Measuring Housing Insecurity: Index Development Using American Housing Survey Data

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Prepared by

James Murdoch, Meghna Brahmachari, and Dennis Okyere

2M Research Services

Fouad Moumen and Sean Streiff

Econometrica, Inc.

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FOREWORD

The U.S. Department of Housing and Urban Development (HUD) is pleased to report on initial research toward the development of a national Housing Insecurity Index. This research constitutes an important step in developing a comprehensive measure of housing insecurity (HI)–a multidimensional concept that has, to date, posed measurement challenges. This work draws primarily from data in the Housing Insecurity Research Module (HIRM), an opt-in, follow-on survey conducted shortly after the 2019 American Housing Survey (AHS). The AHS, sponsored by HUD and conducted by the U.S. Census Bureau, is the largest and most comprehensive regularly collected national longitudinal housing sample survey in the United States.

Since secure housing promotes positive outcomes in health, educational attainment, and employment, deepening our understanding of housing insecurity remains important for researchers and policymakers. However, inconsistent measurement of housing insecurity has made it difficult to track the concept reliably over time. The HIRM was developed by HUD researchers for the 2019 AHS to address this issue by constructing a set of questions, informed by an expert panel and HUD and Census Bureau staff, to measure the continuum of housing insecurity. In the HIRM, researchers measured the concept of housing insecurity based on three dimensions, drawn from the research literature: lack of affordability; lack of stable occupancy, and lack of safety and decency.

Using these three dimensions, the research team developed six distinct profiles of Housing Insecurity. These six profiles represent points along the continuum of HI. At the lower and upper bounds of the continuum are households that are housing secure (very low HI) and those that are housing insecure in all dimensions (very high HI). Profiles in the middle of the continuum represent tradeoffs between these three dimensions of HI. For instance, households in the "HI Instability Only" profile experience extreme residential instability, but live in units that are relatively affordable, safe, and decent. Households in the "HI Safe and Decent" profile live in housing units that are safe and decent, but less affordable and more unstable.

The research presents long-form, medium-form, and short-form versions of the HI questions to estimate the index. The reduced versions are more easily transferable to other survey instruments. While the short-form version is less precise in measuring HI, it has the greatest potential for adoption in other agency surveys. The short form questions are as follows (weights in parenthesis):

Lack of affordability is measured by frequency of worry about mortgage/rent payments (9), recent (in the past 12 months) lapses in housing payments (2.4), and extent of difficulty in making housing payments (3.9). Lack of stable occupancy is measured by previous worry about forced moves (0.9), proportion of persons in the household who have experienced homelessness (2.6), and proportion of persons in the household who are living there temporarily because they have nowhere else to go (1.6). Lack of safety and decency is measured by number of structural deficiencies (1.3) [5 survey items], plumbing breakdowns: toilet (1.5), persons per bedroom (0.3), and feeling unsafe inside home (1.3).

Further data collection, testing, and validation of the medium-form and short-form versions is needed with larger probability samples to optimize the balance between precision and transferability. Once refined and finalized, HUD expects that the HI measurement approach developed in this report will inform how other surveys measure housing insecurity. Consistent measurement will provide crucial information to researchers and policymakers on both the intensity of HI experienced by U.S. households and patterns of experience across the HI continuum. Estimates of HI will shed light on risk factors for HI and its associations with other types of economic insecurity, health, and well-being. Such evidence has direct policy implications, revealing the dimensions of HI problems and informing interventions to mitigate HI.

Solomon Greene
Principal Deputy Assistant Secretary for Policy Development and Research
U.S. Department of Housing and Urban Development

TABLE OF CONTENTS

LIST OF EXHIBITS

ACRONYMS

ACS	American Community Survey
AHS	American Housing Survey
AMI	Area Median Income
AWE	approximate weight of evidence criterion
BCC	boundary characteristic curves
BF	Bayes factor
BIC	Bayesian information criterion
BRFSS	Behavioral Risk Factor Surveillance System
CAIC	consistent Akaike's information criterion
CFA	confirmatory factor analysis
CFI	comparative fit index
cmP	correct model probability
DIF	differential item functioning
EFA	exploratory factor analysis
FHFA	Federal Housing Finance Agency
FIML	full information maximum likelihood
FMR	Fair Market Rent
FSM	food security module
GRM	graded response model
HHS	U.S. Department of Health and Human Services
HI	housing insecurity
HI 1	lack of affordability factor score
HI 2	lack of stable occupancy factor score
HI 3	lack of safety and decency factor score
HIM	housing insecurity measure
HIRM	housing insecurity research module
HUD	U.S. Department of Housing and Urban Development
HUD-HIM	U.S. Department of Housing and Urban Development Housing Insecurity Measure
HUD-HIRM	U.S. Department of Housing and Urban Development Housing Insecurity Research Module
HUD PD&R	U.S. Department of Housing and Urban Development Office of Policy Development and Research
IIF	item information functions
JCHS	Joint Center for Housing Studies of Harvard University
LMR-LRT	Lo-Mendell-Rubin likelihood ratio test
LPA	latent profile analysis
LR	log-likelihood ratio
MAR	missing at random
PSID	Panel Study of Income Dynamics
RMSEA	root mean square error of approximation
SD	standard deviation
SIPP	Survey of Income and Program Participation
SNAP	Supplemental Nutrition Assistance Program

UN	United Nations
VA	U.S. Department of Veterans Affairs
WCN	worst case needs

EXECUTIVE SUMMARY

The purpose of this report is to provide a consistent, transferable, and rigorous way to measure housing insecurity (HI) that accounts for the multidimensionality of the concept, while balancing the need for minimally burdensome measures that can be applied in multiple research and policy contexts. To perform the work, the U.S. Department of Housing and Urban Development's Office of Policy Development and Research (HUD PD&R) contracted with 2M Research Services and its subcontractor Econometrica (hereafter referred to as "the study team") to construct psychometrically sound and practical household-level HI measures, using data from the Housing Insecurity Research Module (HIRM), designed as a supplement to the 2019 American Housing Survey (AHS).

Exhibit ES.1 | Key Takeaways from the Report

- The 2019 AHS and HIRM facilitated the development of valid and reliable scores of three dimensions of HI: lack of affordability, lack of stable occupancy, and lack of safety and decency.
- The concept of HI is different in metro versus non-metro areas and for new construction versus older construction. The study team considers these differences in the development of the scores.
- There are six different profiles of HI that are categories of households with different levels of each HI dimension.
- A household's level of overall HI (very low, low, moderate, high, or very high) can be determined based on the profile of HI the household falls in.
- Households living in an affordable unit will typically have moderate or lower overall HI.
- This report provides simple scores of each dimension of HI that are weighted sums of a reduced set of survey items. These scores perform similarly to scores developed using more sophisticated statistical methods and are much less burdensome to implement.
- This report also provides look-up tables that can identify a household's HI profile using the simple scores.
- Although more research is needed, the simple scores developed are a promising way to measure HI and account for the multidimensionality of the concept while balancing the need for minimally burdensome measures that can be applied in multiple research and policy contexts.

The work in this report builds off previous work done by HUD PD&R, which, based on a review of HI literature and feedback from a panel of experts, developed the definition of HI that this report uses:

> *"Housing Insecurity" is defined as a significant lapse for a given household of one or more elements of secure housing, where "Secure Housing" is stable occupancy of a decent, safe, and affordable housing unit. "Affordable" implies that shelter costs are manageable over the long term without severely burdening or compromising other consumption that normally is essential for health and well-being. "Stable Occupancy" implies that the household does not face substantial risk of involuntary displacement for economic or non-economic reasons. Finally, "Decent and Safe" implies that the unit has physical attributes that satisfy functional needs for well-being related to health, security, and support for activities of daily living. Such attributes include appropriate facilities for excluding external threats, providing climate control, storing and preparing food, maintaining physical and mental hygiene, and developing human potential.* (Watson and Carter, 2020: 8–9)

The study team used the wealth of data in the Core variables of the 2019 AHS and the supplemental HIRM, as well as the flexibility of latent variable modeling, to develop measures of HI with three stages of work:

1. **Stage 1: Develop Gold Standard Factor Scores for Each Dimension of HI.** In the first stage of the work, the study team used household-level indicators of HI constructed from Core AHS and HIRM survey item data to develop scores for three HI dimensions: lack of affordability (HI 1), lack of stable occupancy (HI 2), and lack of safety and decency (HI 3). The study team selected survey items to include in each dimension on the basis of a review of HI literature and in consultation with HUD PD&R experts. The scores developed in stage 1 are "gold standard scores" because the approach was to maximize the precision of the factor scores and include all relevant survey items that increased the validity and reliability of the models. Although highly accurate measures of HI, the gold standard scores are based on many survey items and were developed using complex latent variable modeling. The transferability of the gold standard scores to other research and policy settings is thus limited.
2. **Stage 2: Develop Gold Standard Classification Statuses for General HI.** In the second stage of the work, the study team identified six household-level profiles of overall HI. The profiles are categories that households fall into depending on the score the household has for each of the three gold standard scores. The housing secure profile includes households that have low scores on all three dimensions. The very high HI profile includes households that have high scores on all three dimensions. The remaining profiles include households with different levels for the scores for each dimension. The profiles help to show how households can have different combinations of each dimension of HI and how those combinations relate to the degree to which the household has HI overall. Like the gold standard scores, the gold standard profiles were produced using latent variable modeling that is statistically rigorous and precise but also complex and may not be practical to apply in all research and policy settings.
3. **Stage 3: Develop Reduced Measures of HI.** To develop more transferable, simple, and transparent measures of HI, in the third stage, the study team identified subsets of survey items and used them to develop reduced scores for each dimension of HI. The study team used a simple weighted sum method to develop scores for each dimension of HI based on the reduced survey items. This report includes simple look-up tables that classify households into HI profiles based on the six profiles identified in stage 2, depending on the household's reduced score on each HI dimension. The results from the analyses demonstrate how comparable the reduced scores and the resulting profile classifications are to the gold standards developed in stages 1 and 2.

The sections below include the approach to each of the stages of work and a summary of the results of the analysis for each stage.

Stage 1: Develop Gold Standard Factor Scores for Each Dimension of Housing Insecurity

Guided by a review of recent literature and in consultation with HUD, the study team developed measurement models for the three dimensions of HI (lack of affordability, lack of safety and decency, and lack of stable occupancy). The study team consulted with HUD experts to finalize the measurement model of each dimension. Then, using confirmatory factor analysis (CFA), the study team produced factor scores from each measurement model. Finally, the study team performed differential item functioning (DIF) tests to examine whether the measurement of the scores can be applied across different subpopulations, including the following:

- Race (head of household Black or non-Black).
- Hispanic (head of household Hispanic or non-Hispanic[1]).
- Age (head of household older than 65 or not).
- Gender (head of household female or male).
- Interview language (interview in English or not).
- New construction (home built in 2016 or later or not).
- Metro area (home in a metro or non-metro area).
- Household with children (child in the home or not).
- Tenure (renter-occupied, owner-occupied, occupied without payment).
- Income relative to poverty level (income greater than 300 percent of the poverty line; income between 200 and 300 percent of the poverty line OR less than 80 percent of Area Median Income; or income less than 200 percent of the poverty line).
- Census Division (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, or Pacific).
- Census Region (Northeast, Midwest, South, or West).
- HUD subsidized (not eligible for HUD subsidy, eligible but not subsidized or subsidized).

On the basis of the DIF tests, the study team found that HI should be measured differently (in other words, there were significant differences in the CFA measurement models) for households in metro areas versus non-metro areas and houses that are new construction (built 2016 or later) versus not. This finding is important for this study because it indicates that HI not only differs in terms of degree or intensity for households in metro and non-metro areas and households that are newer and older construction: HI also differs in terms of meaning in these contexts. These groups (metro and non-metro housing, new construction and older construction) represent different housing stocks that likely experience HI differently. In the gold standard models, indicator variables are included for metro status and new construction to account for the differences in measurement in the subgroups. In the reduced scores (see stage 3), this study does not account for the DIF results to preserve the simplicity and transferability of the measures.

Exhibit ES.2 shows the measures selected to produce the gold standard factor scores for each dimension of HI. On the basis of the literature review and discussions with HUD, the study team also modeled subdimensions within each of the three dimensions in the models, which are identified in the exhibit. More information on the specific response options for the measures used to construct the gold standard factor scores is in “Stage 1: Constructing Gold Standard Factor Scores for Each Housing Dimension” in the full report. The specific AHS Core[2] and HIRM survey items that correspond to the measures are described in appendix B.

[1] The study team uses the term *Hispanic* to refer to people of Latin American origin and the term *Black* to describe people of African descent in the United States to align with the language used by the 2019 AHS.

[2] The AHS Core is the set of survey items that are asked of all participants each time the survey is implemented. They are distinct from various topical modules such as the HIRM or Food Security Module, which are not asked each time and are not always asked of the full sample.

Exhibit ES.2 | Dimensions, Subdimensions, and Measures in the Gold Standard HI Factor Scores

HI Dimension	Subdimensions	Measures
HI 1	Worry about inability to pay housing costs	Frequency of worry about mortgage/rent payments
		Extent of worry about mortgage/rent payments
	Lapse in housing payment	Recent (in the past 12 months) lapses in housing payments
		Current lapses in housing payments
	Housing expense hardships	Frequency of difficulty in making housing cost payments
		Extent of difficulty in making housing cost payments
		Difficulty paying utilities
		Housing cost burden
		Perceived severe housing cost burden
		Worst case needs[a]
		Residual income[b]
HI 2	Forced move risk and worry	Risk of eviction or foreclosure
		Previous worry about forced move
		Current worry about forced move
	Residential instability or dislocation	Forced move
		Number of moves
		Proportion of persons in the household who have experienced homelessness
	Household sharing	Proportion of persons in the household who are living there temporarily because they have nowhere else to go
		Proportion of persons in the household who are living there temporarily because of financial difficulties
HI 3	Poor housing quality	Number of structural deficiencies
		Heating breakdowns
		Plumbing breakdowns: toilet
		No running water
		Sewage break
	Overcrowding	Too many people living in unit
		Number of subfamilies
		Persons per room
		Persons per bedroom
		Square feet per person
	Lack of safety	Unsafe for children to play outside
		Feeling unsafe inside home
		Unsafe against break-ins
		Unsafe coming/leaving home at night

HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score.
[a] HUD defines *households with worst case needs* as very low-income renters who do not receive government housing assistance and who pay more than one-half of their income for rent, live in severely inadequate conditions, or both (Alvarez and Steffen, 2021).
[b] The residual income metric is the ratio of residual income to threshold non-shelter housing costs. The threshold non-shelter housing costs are obtained from the Supplemental Poverty Measure (Fox, 2020).
Source: U.S. Census Bureau, 2019 American Housing Survey

Stage 2: Develop Gold Standard Classification Statuses for General Housing Insecurity

After developing the gold standard factor scores for each dimension of HI, the study team identified different “profiles,” or categories of overall HI. Importantly, the study team chose to define overall HI with categories rather than a continuous score (such as a sum of the three dimension scores) because it is not clear from prior research how different combinations of the three dimensions of HI relate to overall HI. One possibility is that the larger the score in each dimension, the higher the level of overall HI, but it is also possible that households make tradeoffs between the dimensions to minimize overall HI. For example, a household may be better off overall if it maximizes the affordability of its unit, even at the expense of stable occupancy and safety and decency. By identifying profiles of HI, the study team was able to identify different combinations of the dimensions of HI and then, based on the relationship of the profiles to external validators, order the profiles in terms of overall HI.

To identify the profiles of HI, the study team used latent profile analysis (LPA). After the researcher specifies the number of profiles, an LPA breaks up the observations in the data into the specified number of groups based on similarities between the observations. In this case, the LPA divided the households into groups based on how similar the households were on the three gold standard factor scores. The study team tested multiple models with different numbers of profiles and found that a model with six profiles fit the data best. Exhibit ES.3 provides a brief definition of each profile identified using LPA, shows whether the gold standard scores tended to be higher (+) or lower (-) for households in the profile, and shows how the study team ranked each profile in terms of overall HI.

Exhibit ES.3 | Six Profiles of HI

Profile	HI 1	HI 2	HI 3	Relationship to Overall HI
Housing Secure: households that have low scores on all three dimensions	-	-	-	Very Low HI
HI Only Instability: households that have high scores for HI 2, but low scores for HI 1 and HI 3	-	+	-	Low HI
HI Affordable: households that have low scores for HI 1 and high scores for at least one other dimension	-	+	+	Moderate HI
HI Stable Housing: households that have low scores for HI 2 and high scores for at least one other dimension	+	-	+	High HI
HI Safe and Decent: households that have low scores for HI 3 and high scores for at least one other dimension	+	+	-	High HI
HI All Dimensions: households that have high scores on all three dimensions	+	+	+	Very High HI

HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score.
Notes: Cells with (+) denote that the gold standard scores are higher for households in the profile. Cells with (-) denote that the gold standard scores are lower for households in the profile.
Source: Authors' summary of the LPA results

To rank the six HI profiles in terms of overall HI, the study team compared households in each profile in terms of average poor self-reported health, food insecurity, and shelter poverty, each of which are established correlates of overall HI.[3] Exhibit ES.4 shows, as expected, that the most secure households (with less poor self-reported health, lower food insecurity, and lower shelter poverty) are those with low scores on all three dimensions, and the most insecure households (higher poor self-reported health, higher food insecurity, and higher shelter poverty) are those with high scores on all three dimensions. Households in profiles that lie between these two poles likely make tradeoffs between the different HI dimensions. Based on the mean poor self-reported health, food insecurity, and shelter poverty of households in these profiles, the study team concluded that households in the HI Instability Only profile are the least insecure after those that are low on all three dimensions (Housing Secure). The means of poor self-reported health, food insecurity, and shelter poverty are not statistically different than the means in the Housing Secure profile.[4] The study team thus labeled these households as having Low HI. Households in the HI Affordable profile are more insecure but not as much as the other profiles. The mean for shelter poverty in the HI Affordable profile (1.06) was lower than the mean in the HI Only Instability profile (1.13) and not statistically different from the Housing Secure profile, but this is understandable given that households living in more affordable units should have less shelter poverty. The means for both poor self-reported health (2.74) and food insecurity (1.31), on the other hand, are higher than the HI Only Instability profile (2.43 and 1.26, respectively) and statistically different from the Housing Secure profile. The study team thus labeled these households as having Moderate HI. Next, households in the HI Stable Housing or HI Safe and Decent profiles are even more insecure. These two profiles had very similar mean values for poor self-reported health, food insecurity, and shelter poverty. Households in either of these profiles were labeled as having High HI. The most insecure households are those that are high on all three dimensions. These households were labeled as having Very High HI.

Exhibit ES.4 | Ranking HI Profiles on Overall HI Using the Mean of Poor Self-Reported Health and Food Insecurity

Overall HI	Profile	Poor Self-Reported Health Mean	Food Insecurity Mean	Shelter Poverty Mean
Very Low HI	Housing Secure	2.56	1.19	1.03
Low HI	HI Only Instability	2.43	1.26	1.13
Moderate HI	HI Affordable	2.74	1.31	1.06
High HI	HI Stable Housing	2.96	1.61	1.18
High HI	HI Safe and Decent	2.97	1.69	1.25

[3] Items regarding poor self-reported health and food insecurity are both included in the 2019 AHS data. The study team constructed the variable indicating shelter poverty from a set of survey items. A household is considered as having shelter poverty if they indicated experiencing any of the following in the previous 12 months: difficulty buying food, difficulty paying for childcare, difficulty paying medical bills, difficulty paying for automobile expenses, difficulty increasing savings, difficulty getting health services, or difficulty paying for other debts.

[4] Statistical significance ($p < 0.05$) was tested using linear regressions with self-reported health, food insecurity, and shelter poverty as the outcome variables and an indicator variable of the profile as the independent variable, with the Housing Secure profile set as the reference category.

Very High HI	HI All Dimensions	3.41	2.43	1.56
	Overall	2.85	1.55	1.17

HI = housing insecurity.
Note: Exhibit ES.4 is exhibit 27 of the main body of the report.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

One interesting finding from stage 2 is that households in homes that are more affordable (Housing Secure, HI Only Instability, or HI Affordable) tend to have lower HI overall. The most secure profiles from this analysis are those with low scores for HI 1; if HI 1 is high and units are unaffordable, the household will either have High or Very High HI. In other words, the cost of the home seems to be the most important factor in overall HI.

Stage 3: Develop Reduced Measures of Housing Insecurity

The gold standard factor scores and profiles are highly robust and precisely measure HI; however, they were produced with data-intensive procedures that are not easily transferable or practical to use. In the final stage of the project, the study team developed practical and transferable methods to score households in terms of HI using a reduced set of measures based on the prior stages of the research. First, the study team developed continuous scores from reduced sets of survey items for each HI dimension. Then, the study team developed look-up tables for classifying households into the profiles identified in stage 2. The look-up tables reflect critical cut points of HI for each of the three dimensions.

To develop the reduced continuous scores for each HI dimension, the study team used graded response models, which helped identify redundancies in the items included in the gold standard measures. After removing redundant items, the study team created reduced scores. The scores are weighted sums of the items included in the reduced models. The weights for each item were developed based on the graded response models that were tested.

Exhibits ES.5, ES.6, and ES.7 show the measures included in the reduced factor scores for each dimension of HI. Each measure comes from at least one survey item in the HIRM or 2019 AHS Core. Measures that are gray were not included in any of the reduced measures. If future researchers are interested in replicating these scores, they could either utilize the specific data from the AHS and HIRM or administer a new survey with the recommended measures included and then develop a weighted sum of the items using the same weights specified in the exhibit.[5] Explicit definitions of each measure are included in appendix B. If developing a new survey, it would be acceptable to generate survey questions that follow the format of the measures developed (in other words, it is not necessary to replicate the exact survey items from the HIRM and AHS Core). A measure with a weight of zero is not required for the reduced factor score.

The exhibits also show three different types of reduced measures: long form, medium form, and short form. The long form reduced measures have the most variables and are thus more data

[5] Ideally, more research will be conducted that tests whether the weights can remain the same across different samples of households.

intensive in terms of both collection of the information via a survey and analysis; however, the results show that the long form typically does a better job of capturing the range of HI for each dimension. The medium form measures fall between the long and short forms in terms of the number of variables and, thus, the degree of nuance captured in terms of HI. The short form measures have the smallest number of survey items and are thus the most practical of the three in ease of data collection and analysis; however, they likely contain the least amount of information compared to the gold standard score. The short form, for example, cannot distinguish between the Housing Secure, HI Instability Only, and HI Affordable profiles nor between the HI Stable Housing and HI Safe and Decent profiles.

Exhibit ES.5 | Measures and Survey Items in HI 1 (Lack of Affordability) and Their Weights in the Reduced Scores

Subdimension	Measures	Survey Items from AHS Core and HIRM Used to Develop Measures	Weight in Long Form	Weight in Medium Form	Weight in Short Form
Worry about inability to pay housing costs	**Frequency of worry about mortgage/rent payments**	HISTPAY	4.1	9	9
	Extent of worry about mortgage/rent payments	HISTNOW	3.8	0	0
Lapse in housing payments	**Recent (in the past 12 months) lapses in housing payments**	HIBFREQ	2.3	2.4	2.4
	Current lapses in housing payments	HICTCHUP	2.2	0	0
Housing expense hardships	**Frequency of difficulty in making housing cost payments**	HIDIFFPAY	12.4	0	0
	Extent of difficulty in making housing cost payments	HIAFFORD	10.2	4	3.9
	Difficulty paying utilities	HIBLLPAY, HIUTLPAY, HIBLLPAY2, HISHUTOFF	0	0	0
	Housing cost burden	TOTHCAMT (HUD created from 40 different housing cost sources), HINCP (HUD created from 19 different sources of income)	0	0	0
	Perceived severe housing cost burden	HIHALF	1.9	2	0
	Worst case needs	WCN (HUD created from income, area median income, assistance, housing cost, and housing adequacy variables)	0	0	0
	Residual income	TOTHCAMT and HINCP	0	0	0

AHS = American Housing Survey. HIRM = Housing Insecurity Research Module.
Notes: Exhibit ES.5 is exhibit 29 of the main body of the report. Items in grey are not included in any of the reduced measures.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit ES.6 | Measures and Survey Items in HI 2 (Lack of Stable Occupancy) and Their Weights in the Reduced Scores

Subdimension	Measures	Survey Items from AHS Core and HIRM Used to Develop Measures	Weight in Long Form	Weight in Medium Form	Weight in Short Form
Forced move risk and worry	**Risk of eviction or foreclosure (see footnote for definitional change in medium form)***	HIMRTFORC, HINFORC, HILVEFORC, HIEVFORC2, HIEVICT, HIEVICPREV, HIEVICLK, HIEVICT2, and HIEVICPREV2	2.1	2.6	0
	Previous worry about forced move**	HIMOVFRC	12	13	0.9
	Current worry about forced move**	HIMOVWR	2.9	2.9	0
Residential instability or dislocation	Forced move	HIEVLNDLD, HIEVFEAR, HIEVCNDM, HIEVCNDM2, HIMVDISAS, HIMVDISAS2, HIEVRAISE, HIEVNOFIX, and HIEVFORC	0	0	0
	Number of moves	HIINTDATE, HIMOVEDATE, and HILIVNUM	0.2	0.2	0
Household sharing	**Proportion of persons in the household who have experienced homelessness**	HIHMLESS, HIHMLESS2, NUMPEOPLE	1.2	1.1	2.6
	Proportion of persons in the household who are living there temporarily because they have nowhere else to go	HINOWHR, HINOWHR2, NUMPEOPLE	0.7	0.7	1.6
	Proportion of persons in the household who are living temporarily because of financial difficulties	NUMPEOPLE, HIFDIFF, HIFDIFF2	0	0	0

AHS = American Housing Survey. HIRM = Housing Insecurity Research Module.
* In the medium-form Stable Occupancy HI measure, the study team kept a simplified measure of eviction or foreclosure that only asked about current risks and removed all questions related to previous risks. The study team also rescaled this variable before developing the reduced index so that the first category was 0 (instead of 1).
** The study team rescaled this variable before developing the reduced index so that the first category of the variable was 0 (instead of 1).
Notes: Exhibit ES.6 is exhibit 33 of the main body of the report. Items in grey are not included in any of the reduced measures.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit ES.7 | Measures and Survey Items in HI 3 (Lack of Safety and Decency) and Their Weights in the Reduced Scores

Subdimension	Measures	Survey Items from AHS Core and HIRM Used to Develop Measures	Weight in Long Form	Weight in Medium Form	Weight in Short Form
Poor housing quality	**Number of structural deficiencies (see footnote for definitional change in medium and short form)***	13 different deficiencies, a total of 18 survey items (see appendix B for more detail). Reduced to 5 items.	2	2.1	1.3
	Heating breakdowns	COLD, COLDEQ, and COLDEQFREQ	0	0	0
	Plumbing breakdowns: toilet	NOTOIL and NOTOILFREQ	0	0	1.5
	Running water	NOWAT and NOWATFREQ	1.2	1.2	0
	Sewage break	SEWBREAK and SEWTYPE	0	0	0
Overcrowding	Too many people living in unit	HIMAXNUM	0	0	0
	Number of subfamilies	NUMSUBFAM	0.3	0.3	0
	Persons per room	TOTROOMS and NUMPEOPLE	0	0	0
	Persons per bedroom**	BEDROOMS and NUMPEOPLE	0.3	0.3	0.3
	Square feet per person	UNITSIZE_IUF and NUMPEOPLE	0	0	0
Lack of safety	Unsafe for children to play outside	HIPLAY	0	0	0
	Feeling unsafe inside home**	HISAFE	0.9	0.9	1.3
	Unsafe against break-ins	HIBRKIN	0	0	0
	Unsafe coming/leaving home at night	HICMING	0	0	0

AHS = American Housing Survey. HIRM = Housing Insecurity Research Module.
* In the medium-form and short-form Safety and Decency HI measure, the study team kept a simplified measure of structural deficiencies in the model. The full measure includes 13 deficiencies, while the simplified measure includes only 5.
** The study team rescaled this variable before developing the reduced index so that the first category of the variable was 0 (instead of 1).
Notes: Exhibit ES.7 is exhibit 38 of the main body of the report. Items in grey are not included in any of the reduced measures.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Lack of Affordability (HI 1)

Exhibit ES 8 compares the long, medium, and short form continuous HI 1 scores in terms of the number of survey items and correlation with key external validators, including poor self-reported health, food insecurity, and shelter poverty. The first option (long form) is the most accurate score; however, it contains a larger number of survey items and is more burdensome in terms of data collection and calculation. In the case of HI 1, the long form score has a lower correlation with the gold standard than the other reduced measures; however, its distribution (see exhibit ES 11) is closer to the gold standard than the other scores. The second option (medium form) is less accurate than the long form score but has fewer survey items. The third option (short form) is the least accurate but most practical in data collection and measurement. Each of the reduced measures has stronger correlations with poor self-reported health, food insecurity, and shelter poverty than the gold standard, but the correlations are in the expected directions and not substantially different from the gold standard correlations (the difference in the reduced measure correlations from the gold standard correlation ranges from 0.04 to 0.08).[6] Importantly, the finding that the reduced measures have stronger correlations with the external validators does not mean they are better measures of HI than the gold standard. Rather, it suggests that the reduced measures may slightly overestimate the relationship between HI and the external validators, although, as stated previously, the difference in the correlations is not substantial.

Exhibit ES.8 | HI 1 Gold Standard and Reduced Scores: Number of Survey Items and Correlations with External Validators

	Gold Standard	Reduced Long	Reduced Medium	Reduced Short
Number of Survey Items	16	7	4	3
Correlation with the Gold Standard	1	0.8257	0.9016	0.8995
Correlations with External Validators				
Poor self-reported health	0.1492	0.1838	0.1868	0.1869
Food insecurity	0.2975	0.3535	0.3757	0.378
Shelter poverty	0.4908	0.5374	0.5444	0.5426

Note: Exhibit ES.8 is a subset of exhibit 30 of the main body of the report.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

[6] The study team did not perform tests of statistical significance for the results shown in exhibit ES 10.

Lack of Stable Occupancy (HI 2)

Exhibit ES.9 compares the gold standard HI 2 measure to long, medium, and short form reduced measures. The reduced measures of HI 2 do not have as strong a relationship to the gold standard measure as the reduced measures of HI 1. The correlations are all around 0.7 (compared to 0.8 or 0.9 for HI 1). The relationships with the external validators are comparable to the gold standard, however.

Exhibit ES.9 | HI 2 Gold Standard and Reduced Scores: Number of Survey Items and Correlations with External Validators

	Gold Standard	Reduced Long	Reduced Medium	Reduced Short
Number of Survey Items	30	20	16	6
Correlation with the Gold Standard	1	0.6823	0.6792	0.6698
Correlations with External Validators				
Poor self-reported health	0.1349	0.2078	0.2065	0.2062
Food insecurity	0.2375	0.3127	0.3124	0.3087
Shelter poverty	0.3033	0.3633	0.3628	0.3418

Note: Exhibit ES.9 is a subset of exhibit 34 of the main body of the report.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Lack of Safety and Decency (HI 3)

Exhibit ES.10 shows the reduced measures the study team developed for HI 3. The reduced score measures of HI 3 are highly related to the gold standard (about 0.9 correlation), and the relationship of the reduced measures to external validators is very comparable to the gold standard.

Exhibit ES.10 | HI 3 Gold Standard and Reduced Scores: Number of Survey Items and Correlations with External Validators

	Gold Standard	Reduced Long	Reduced Medium	Reduced Short
Number of Survey Items	37	24	16	10
Correlation with the Gold Standard	1	0.9167	0.8791	0.8724
Correlations with External Validators				
Poor self-reported health	0.2558	0.2151	0.2133	0.2176
Food insecurity	0.3027	0.2744	0.2714	0.3029
Shelter poverty	0.3016	0.2708	0.2703	0.2927

Note: Exhibit ES.10 is a subset of exhibit 39 of the main body of the report.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Assigning HI Profiles Using the Reduced Measures

After developing the reduced continuous scores, the study team identified the cut points in each dimension that indicated HI. The study team tested several different cut points but found that using the 90th percentile of the Housing Secure profile (the value that 90 percent of all households identified as secure fall under) produced results that most closely matched the gold standard profiles. Using that information, the study team developed a look-up table for the long, medium, and short form measures that researchers can use to classify a household in a profile of HI based on the values of the reduced scores for each HI dimension.

Finally, exhibit ES.11 shows the number and percent of households correctly classified in each profile using the long form, medium form, and short form look-up tables. The study team assumed that the gold standard classification statuses from stage 2 were the correct classification of each household and then compared how each household was classified using the reduced measure look-up table to the gold standard. The table shows that the reduced measures are very robust for correctly classifying households with low HI (90 percent or more are correctly classified). As HI increases, the reduced measures contain more errors; however, the study team found that the error is almost always that the household is classified in a profile that is more secure than the household's true profile. In other words, the reduced measures are not as sensitive to HI as the gold standard, which is expected given that the reduced measures are based on a smaller subset of variables. Despite this error, the reduced measures have strong correlations with the gold standard profile indicator (shown in the last row of exhibit ES.11), and the previous analysis shows that the reduced measures perform similarly to the gold standard measures in terms of external validators.

Exhibit ES.11 | Number and Percent Correctly Classified and Correlation with Gold Standard Profiles for each Set of Reduced Measures

	Long Form		Medium Form		Short Form	
	N	**%**	***N***	**%**	***N***	**%**
Low HI (Housing Secure or HI Instability Only)	900	90.0	900	90.0	1300*	100.0*
Moderate HI (HI Affordable)	200	66.7	200	66.7		
High HI (HI Stable Housing)	500	76.9	500	76.9	750**	68.1**
High HI (HI Safe and Decent)	300	75.0	250	65.5		
Very High HI (HI All Dimensions)	200	57.1	200	57.1	150	42.9
Correlation with Gold Standard Profile Indicator	0.8539		0.8438		0.7021	

HI = housing insecurity.
* Corresponds to Gold Standard Profile 1, 2, and 3 due to loss of information with the short form measures.
** Corresponds to Gold Standard Profiles 4 and 5 due to loss of information with the short form measures.
Note: Exhibit ES.11 is exhibit 45 of the main body of the report.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Conclusion

This report presents an approach to facilitate rigorous and consistent measurement of HI. The modeling results show that the measurement models for the factor scores fit the data well, and all the observed indicators performed as expected. The study team identified some differences in measurement across metro and non-metro areas and among new and older construction, which were incorporated into the estimation of the factor scores. The latent profile analysis finds a model with six profiles that capture housing secure households, housing insecure households, and households that appear to make tradeoffs between the different dimensions of HI. An analysis using poor self-reported health, food insecurity, and shelter poverty as criterion variables shows that the profiles can be ranked on an underlying continuum of HI.

Based on the factor scores, the study team also developed practical and transferable measures of HI. The study team reduced the number of items in each dimension of HI and then used the reduced measures to develop look-up tables that researchers can use to assign households to the HI profiles and determine households' overall level of HI. The analyses show that the reduced measures perform similarly to the gold standard measures and thus provide a promising method to measure HI consistently and rigorously in a way that accounts for the multidimensionality of the concept, while balancing the need for minimally burdensome measures that can be applied in multiple research and policy contexts.

Although these results show promise for identifying a consistent and reliable way of measuring HI, more research is needed to ensure that the results are consistent across multiple samples. This analysis showed that HI is measured differently in metro versus non-metro contexts and for new construction versus older construction. Future research could elucidate these differences and identify potential improvements to the reduced measures of HI, which currently do not incorporate metro or new construction differences. In addition, replicating this analysis on different samples of households is also important to ensure these findings are not sample-specific.

INTRODUCTION

The availability of affordable and decent housing is critical to the well-being of individuals and provides a stable foundation for positive health outcomes for families, educational achievement, and employment (Aurand et al., 2019). However, in 2019, nearly one-half of all renter households and approximately 20 percent of homeowner households spent more than 30 percent of their income on housing (JCHS, 2021). Among low-income households, more than 60 percent of renters and almost one-half of homeowners were severely cost burdened in 2019, spending more than 50 percent of their income on housing (JCHS, 2021).[7] Recent work has also examined the quality of U.S. housing stock. A 2019 study by the Federal Reserve Bank of Philadelphia and Policy Map estimated that more than one-third of all occupied homes in 2017 had structural, plumbing, electrical and heating problems, leaks, or pest infestations (Divringi et al., 2019).

Housing insecurity (HI) likely increased during the COVID-19 pandemic, as the economic fallout had an adverse impact on many households' ability to afford housing payments. The Census Bureau's Household Pulse Surveys found that in early 2021, more than one-half of all low-income renters and 46 percent of low-income homeowners reported having lost employment income since the start of the pandemic (JCHS, 2021). Almost 25 percent of low-income renters and homeowners reported being behind on housing payments at the start of 2021.

Despite the relevance of HI and its use as a concept by researchers, policymakers, program leaders, and practitioners, HI has not been measured consistently through the research literature (Watson and Carter, 2020). The lack of a comprehensive consensus measure makes it impossible to track the prevalence of HI from year to year and to examine the correlation of HI with health, education, employment, and criminal justice outcomes. The American Housing Survey (AHS), launched in 1973, facilitates the rigorous measurement and tracking of the quality, characteristics, and cost of U.S. housing stock over time (Census Bureau, 2019b). However, while many aspects of HI have been measured in AHS, work is still needed to identify a consistent set of HI indicators that are minimally burdensome to collect and easily transferable to various research and policy contexts.

To fill the gap in HI measurement, HUD began developing an HI Research Module (HIRM) for the AHS in 2016 to construct a standardized set of questions to measure the continuum of HI (HUD, 2017). As part of that effort, HUD's Housing as a Platform Knowledge Collaborative undertook an extensive review of the literature published before 2016 (Watson and Carter, 2020). Based on a review of HI literature and feedback from a panel of experts, HUD's Office of Policy Development and Research (PD&R) developed the following definition of HI:

> *"Housing Insecurity" is defined as a significant lapse for a given household of one or more elements of secure housing, where "Secure Housing" is stable occupancy of a decent, safe, and affordable housing unit. "Affordable" implies that shelter costs are manageable over the long term without severely burdening or compromising other consumption that normally is essential for*

[7] The Joint Center for Housing Studies of Harvard University defines low-income households as those earning less than $25,000 in 2019.

> *health and well-being. "Stable Occupancy" implies that the household does not face substantial risk of involuntary displacement for economic or non-economic reasons. Finally, "Decent and Safe" implies that the unit has physical attributes that satisfy functional needs for well-being related to health, security, and support for activities of daily living. Such attributes include appropriate facilities for excluding external threats, providing climate control, storing and preparing food, maintaining physical and mental hygiene, and developing human potential.* (Watson and Carter, 2020: 8–9)

The HUD-HIRM was designed around a conceptual model that presents HI as a multidimensional construct and focuses on three dimensions: lack of affordability, lack of stable occupancy, and lack of safety and decency. Each dimension of HI represents a type of housing challenge faced by households. Data from multiple indicators can be used to assess each dimension, and measures of each dimension can be subsequently combined to create a comprehensive measure of HI.

This project uses the above definition of HI and draws from literature on HI and related fields to construct psychometrically sound and practical household-level measures of HI. Specifically, there are three stages of the work:

1. **Stage 1: Develop Gold Standard Factor Scores for Each Dimension of HI.** In the first stage of the work, the study team used household-level indicators of HI constructed from AHS and HIRM survey item data to develop scores for three different HI dimensions: lack of affordability (HI 1), lack of stable occupancy (HI 2), and lack of safety and decency (HI 3). The study team selected survey items to include in each dimension based on a review of HI literature and in consultation with HUD PD&R experts. The scores developed in stage 1 are "gold standard scores" because the approach was to maximize the precision of the factor scores and include all relevant survey items that increased the validity and reliability of the models. Although highly accurate measures of HI, the gold standard scores are based on many survey items and were developed using complex latent variable modeling. The transferability of the gold standard scores to other research and policy settings is thus limited.
2. **Stage 2**: **Develop Gold Standard Classification Statuses for General HI.** In the second stage of the work, the study team identified six household-level profiles of overall HI. The profiles are categories that households fall into depending on the score the household has for each of the three gold standard scores. The housing secure profile includes households that have low scores on all three dimensions. The very high HI profile includes households that have high scores on all three dimensions. The remaining profiles include households with different levels for the scores for each dimension. The profiles help to show how households can have different combinations of each dimension of HI and how those combinations relate to the degree to which the household has HI overall. Like the gold standard scores, the gold standard profiles were produced using latent variable modeling that is statistically rigorous and precise but also complex and may not be practical to apply in all research and policy settings.

3. **Stage 3: Develop Reduced Measures of HI.** To develop more transferable, simple, and transparent measures of HI, in the third stage, the study team identified subsets of survey items and used them to develop reduced scores for each dimension of HI. The study team used a simple weighted sum method to develop scores for each dimension of HI based on the reduced survey items. This report includes simple look-up tables that classify households into HI profiles based on the six profiles identified in stage 2, depending on the household's reduced score on each HI dimension. The results from the analyses demonstrate how comparable the reduced scores and the resulting profile classifications are to the gold standards developed in stages 1 and 2.

The report is organized as follows. First, the report provides a summary of the literature on HI measurement. Next, the report describes the methods, including the data source, sample, and modeling approaches the study team used as well as the results of the analyses. The report concludes with a summary of findings and avenues for future research.

LITERATURE REVIEW

In 2016, as part of developing a Housing Insecurity Research Module (HUD-HIRM) for the AHS, an extensive review of the literature published before 2016 was undertaken by HUD's Housing as a Platform Knowledge Collaborative (Watson and Carter, 2020). The review presented in this section focuses on literature examining U.S. HI that was published in the past 5 years (in other words, since 2015, when the previous effort of this kind was undertaken). The review consists of five sections: (1) definitions of HI applied in previous literature; (2) outcomes associated with HI; (3) mechanisms related to HI; (4) measurement of HI; (5) HUD's development of HIRM.[8]

Definitions of Housing Insecurity

As mentioned in the introduction, one of the critical challenges to developing a measure of HI is the lack of a universally accepted definition of the term. Cox et al. (2019) traced the historical development of HI back to the U.S. Housing Act of 1949, in which housing was introduced as important for "the general welfare and security of the Nation and the health and living standards of its people." The language of the housing act was lofty, but it provided a rare early example of an attempt to operationally define a construct at the heart of housing policy efforts. More recently, the construct that housing policy targets has been described as HI.

Since 1949, definitions of HI have tended toward defining HI in terms of the dimensions used to measure it. In 1969, the U.S. Department of Health and Human Services (HHS) defined HI in five dimensions: affordability, quality, neighborhood stability, overcrowding, and homelessness (HHS, 1969). In 1997, the United Nations (UN) characterized adequate housing—the UN's construct most closely related to housing security—in terms of six dimensions: affordability, decency and safety (divided into two dimensions), neighborhood stability, protection against forced relocations, and accessibility and protection for cultural expression (UN, 2014).

More recently, HUD has defined HI in terms of three dimensions: affordability, decency and safety, and stable occupancy (Watson and Carter, 2020). While the HUD definition includes fewer dimensions than prior efforts to define HI, the dimensions are broadly articulated to cover the same scope as the HHS and UN definitions, with only one major exception. That exception is the exclusion of concerns for neighborhood quality and stability in the HUD definition.

The neighborhood dimension was excluded from HUD's definition because HUD saw three concerns: "First, including neighborhood factors blurs the conceptual focus on housing needs and would significantly expand the scope and questionnaire length of a pilot module. Second, neighborhood amenities and location are a major part of the bundle of housing services that drives housing prices, which will be captured by the affordability and quality components of the module. Finally, the negative association between neighborhood amenities and affordability means that including both would reduce the explanatory power of a composite housing insecurity indicator" (Watson and Carter, 2020). Concerns related to the assessment of neighborhood quality are well founded. To date, there is no broad consensus regarding what combination of indicators can differentiate high- from low-quality neighborhoods, and in most cases, multiple indicators are used to assess neighborhood quality (for example, Raudenbush, 2003; Talen and

[8] The literature review in this section is a summary of key points from the full literature review, presented in appendix F.

Koschinsky, 2014). The HUD-HIRM includes some indicators of neighborhood safety close to the housing unit, and the AHS Core[9] includes indicators of neighborhood condition.

In addition to defining HI in terms of three dimensions, HUD also states the goal of the HUD Housing Insecurity Measure (HUD-HIM) is to place households on a continuum of HI. Full housing security would denote one end of the continuum and identify households with no significant lapses in any dimensions of secure housing. Households experiencing a lapse in at least one dimension of secure housing would lie at other points along the continuum, and homelessness would denote the other end of the continuum. The HI continuum will allow differentiation of the intensity of HI experienced by households (Watson and Carter, 2020). For example, the HI continuum would be able to characterize households as experiencing housing security, low-intensity HI, moderate-intensity HI, or high-intensity HI.[10] At present, it is unclear how movements along the continuum of HI correspond to changes in the individual dimensions of HI. For example, if households experience housing challenges captured by more than one dimension of HI, are they, therefore, experiencing a higher intensity of HI? Or can housing challenges experienced in only one dimension be so great that they alone produce high-intensity HI?

To assess these questions, which is necessary for the development of the HUD-HIM, the HI construct, including its dimensions, must be well defined. While all major definitions for HI have included multiple dimensions, the vast majority of studies examining HI either examined only one dimension or multiple dimensions independently. For example, Pilkauskas and Michelmore (2019) examined the affordability and stable occupancy dimensions of HI but did not attempt to make any composite measure of the HI construct. Instead, their results provided estimates of how an increase in the earned income tax credit affected the affordability and stable occupancy dimensions separately and were ambiguous regarding the impact on overall HI. Their finding that the tax credit was associated with some—but not all—dimensions increased this ambiguity. Therefore, while there have been calls across the field for studies to employ a multidimensional definition of HI (for example, Cox et al., 2019), examples of multidimensional approaches fall short of examining the HI construct as a whole because HI dimensions are examined separately.

A recent exception to the unidimensional approach extracted four HI dimensions (unaffordability, poor conditions, overcrowding, and forced moves) from the AHS and created a HI index (Routhier, 2019). Routhier (2019) indicated a high rate of HI (more than one-half of U.S. urban renters), defined as the presence of any of the four dimensions measured. Clearly articulating the link between HI severity and the presence of multiple dimensions is a challenge; for example, Routhier's (2019) approach implicitly assumed that the more dimensions of HI that were present, the more intense the HI was, without performing additional analyses to confirm this assumption.

[9] The AHS Core is the set of survey items that are asked of all participants each time the survey is implemented. They are distinct from various topical modules such as the HIRM or Food Security Module, which are not asked each time and are not always asked of the full sample.

[10] HUD has specified that the HUD-HIM should measure HI along a continuum of HI intensity. The example using specific categories is for illustrative purposes only.

Each HI dimension included in HUD's definition of HI has also been assessed using multiple indicators. The stable occupancy dimension has the most variation in how it is assessed. Studies have examined stable occupancy in terms of (1) doubling up[11] (Pilkauskas and Michelmore, 2019; Pilkauskas, Garfinkel, and McLanahan, 2014); (2) overcrowding[12] (Lopoo and London, 2016); or (3) residential instability[13] (Ha et al., 2016; Rose-Jacobs et al., 2019). While all three situations are intended to identify when households are vulnerable to involuntary displacement, each does so to varying degrees. For example, doubling up is common following childbirth and does not always indicate a risk for involuntary displacement. In some cases of doubling up, all parties share expenses more or less equally, while at other times, one household adult member primarily covers all housing burdens (Reyes, 2018).

Affordability and safe and decent dimensions of HI similarly have been assessed in various ways in the literature. Affordability is most frequently measured by the ratio of housing cost to income, but other authors have used the inability to pay bills (Baker, Mason, and Bentley, 2015) or the amount of income left over after paying for housing (Zhang, 2015). The safe and decent dimension has been assessed through a wide variety of housing quality indicators. Most of these indicators, however, have been limited to assessment of the physical adequacy of the house, such as whether the house has working plumbing or heating (Eggers and Moumen, 2013). The measures of physical adequacy are collected in AHS and form the basis for incorporating housing quality in the Worst Case Housing Needs assessment (Watson et al., 2017).

In summary, there is no universally accepted definition for HI, but this work uses HUD's current working definition of HI that defines HI in terms of three dimensions: affordability, safety and decency, and stable occupancy. The dearth of studies utilizing a true multidimensional HI measure (rather than simply examining multiple dimensions independently in the same study) illuminates a clear need for a multidimensional, transferable measure of HI that can easily be incorporated into surveys.

Outcomes Associated with Housing Insecurity

There are many outcomes theorized to be associated with HI. However, due to data availability, the relationship between outcomes and HI has seldom been assessed for most of these outcomes. This section focuses on work since 2015 documenting correlates of HI.

Most correlative studies published since 2015 examined specific subpopulations and dimensions of HI, usually based on data availability. However, some indicators of HI were examined more frequently than others, primarily because of their availability in datasets from large surveys. These indicators include one that measured self-report of worrying about housing expenses that is included in the Behavioral Risk Factor Surveillance System (BRFSS) and a three-question HI screener that asks if households had experienced overcrowding, doubling up, or more than one move in the past 12 months (Cutts et al., 2011). Other indicators of HI were quite varied, and

[11] Typical indicators of doubling up reflect the presence of multiple households living in the same residence.
[12] Overcrowding is usually measured as a ratio of the number of people per room, people per bedroom, or unit square footage per person (Blake, Kellerson, and Simic, 2007).
[13] Usually measured as frequency of moves or length of tenure.

there were no discernable patterns whereby a particular indicator of HI was uniquely associated with specific outcomes.

The most well-documented evidence for correlations with HI exists for health outcomes and measures of health care access. This assessment of the current state of the literature is also consistent with a 2016 review focused on housing evictions (Vásquez-Vera et al., 2017). More than 50 percent of the 47 articles in the 2016 review documented the association between eviction and mental health issues, and 38 percent documented associations with poor physical health, and just under 20 percent of studies examined associations between evictions and health behaviors.

Health outcomes that have been examined in relation to HI can be grouped into several categories:

- Physical and psychiatric conditions.
- Child mental and physical health.
- Self-rated health.
- Prevalence and management of chronic disease and obesity.
- Increased need for acute care.

The associations of mental health indicators with HI appear to be the most robust and diverse. Some studies have documented that foreclosures during the 2007-through-2009 financial recession were associated with increased depression and anxiety; for reviews, see Alhenaidi and Huijts (2019) and Vásquez-Vera et al. (2017). A survey among college students showed that mental disorders were more prevalent among homeless youth and young adults than among stably housed counterparts (Smith and Knechtel, 2019). Self-rated health, diabetes and asthma management (Stupplebeen, 2019), and cardiovascular and lung disease (Charkhchi, Fazeli Dehkordy, and Carlos, 2018) were also poorer for people experiencing HI.

The correlative relationships between HI and health-related outcomes are embedded in contexts frequently characterized by insufficient income, additional non-housing material hardships, addiction, or social vulnerability (Fowler et al., 2019; Johnson et al., 2019). These contexts contribute to deleterious social settings linked to housing quality and condition (Gronlund et al., 2018; Marí-Dell'Olmo et al., 2017; Marquez, Dodge Francis, and Gerstenberger, 2019; Richter et al., 2017).

Many types of social vulnerability appear to place individuals at greater risk for HI. For example, childhood emotional abuse (Curry, 2017), parent separation (Moschion and van Ours, 2019), and loss of a parent (Berman et al., 2015) were associated with greater risk for adult HI. Likewise, families experiencing HI were more likely to have children removed and placed in foster care due to neglect (Wade, 2018). Other groups with a higher incidence of HI included young parents; people with low educational attainment; individuals from minority racial/ethnic groups; people living with HIV; and lesbian, gay, bisexual, or transgender youth (Hrostowski and Camp, 2015; Morton et al., 2018). Correlations between HI and deleterious outcomes appeared strongest for minority groups and older populations (Vásquez-Vera et al., 2017).

Any new measure of HI will likely be used to assess previously documented correlations to connect ongoing work with future developments in HI. The most widely observed correlations included associations with mental health and, in particular, depression and general self-rated health. The most common ways that depression and mental health have been assessed in the literature include the General Health Questionnaire 12-item scale (Goldberg et al., 1997), the 6-item Kessler Screening Scale (Kessler et al., 2010), and self-reported prior depression/diagnosis of poor mental health, such as those used in the BRFSS (Miyakado-Steger and Seidel, 2019). The general self-rated health question is commonly used by researchers as a simple measure of health, in part because it is very easy to implement and has a reasonably high correlation with mortality (Franks, Gold, and Fiscella, 2003; Idler and Benyamini, 1997; Ware, Kosinki, and Keller, 1996). Because of its wide prevalence of use, self-rated health's correlation with HI should also be assessed. In addition, the incidence of HI in socially vulnerable subpopulations is also important to assess for any new measure of HI.

Mechanisms Related to Housing Insecurity

Longitudinal studies allow researchers to examine individuals over time and are, therefore, among the most useful for understanding the mechanisms that create or are created by insecure housing. Two key datasets have been most widely used to study HI from a longitudinal perspective: (1) Journeys Home: A Longitudinal Study of Factors Affecting Housing Stability and (2) Survey of Income and Program Participation (SIPP).[14] Low-income Australians were interviewed every 6 months to collect the Journeys Home data. The data capture indicators of each of the three dimensions of HI that the HUD-HIM also hopes to incorporate. SIPP is a longstanding U.S. longitudinal survey that interviews a nationally representative sample of Americans monthly for 2.5 to 4 years. However, SIPP only captures the affordability dimension of HI.

There is presently no widely accepted theoretical model describing the causal pathways to and from various stages of housing security. These pathways are complex, multidimensional, and varied. Recent work has found that HI has bidirectional relationships with income, employment, and drug and alcohol use (O'Flaherty, 2019; Scutella, Tseng, and Wooden, 2017). The most commonly studied causal pathways for HI were related to individual characteristics, including drug use, alcohol use, or abuse. Drug and alcohol use were robustly found to be likely among people who were insecurely housed; however, two studies found no evidence of a causal link between drug/alcohol use and HI (McVicar, Moschion, and van Ours, 2015, 2019). If anything, results from these studies suggested a reverse causal relationship: HI affected rates of alcohol use in varying ways. Early HI increased the subsequent risk of drug use for women (McVicar, Moschion, and van Ours, 2019). A study examining the Journeys Home data found that after controlling for housing and labor market factors, the likelihood of HI onset was higher for drug users (Johnson et al., 2019).

Another subset of the literature focused on multiple forms of material hardships that resulted from insufficient income and the tradeoff strategies households used to overcome these

[14] Of course, an array of other data sources such as the Panel Study of Income Dynamics, SIPP, the National Longitudinal Study of Adolescent to Adult Health, and other, smaller sources have been used to study HI, but the dimensions of HI available for study in these sources are very limited. Additionally, AHS has a longitudinal structure and incorporates several dimensions of HI, but AHS follows housing units rather than people over time.

hardships. SIPP data allowed comparison of temporal trends in multiple material hardships (in other words, food insecurity, medical hardships, and housing hardships). The trends were imperfectly correlated. For example, from 2003 through 2005, food insecurity decreased while all other hardships increased, and by the end of the financial recession, the incidence of hardships for all hardship types had reached new highs (Heflin, 2016). The 2013 BRFSS[15] study results suggest that food insecurity was more prevalent than HI across all racial/ethnic groups; notably, the data excluded homeless populations (Njai et al., 2017). Among chronically ill patients in the 2015 BRFSS data, however, rates of HI were slightly higher than rates of food insecurity (Charkhchi, Fazeli Dehkordy, and Carlos, 2018). One reason why food insecurity rates might typically be higher than HI rates is that adjustments to the quantity of housing consumed are more difficult; households will often prioritize maintaining housing over additional food purchases (Vold, Lynch, and Martin, 2019). These tradeoffs may influence the relationship between HI and poor chronic disease outcomes (Stupplebeen, 2019).

Utility hardships (for example, difficulty paying the electricity bill) and housing hardships represent another hardship tradeoff that has received considerable attention because the two types of hardship are consumed together in the housing bundle. Using SIPP data, Finnigan and Meagher (2019) noted that utility hardships were much more prevalent and persistent than housing hardships, and households with utility hardships were much more likely to have other disadvantaged characteristics. While empirical studies suggest some consensus that utility hardships, on average, signal risk for HI, qualitative work suggests that housing-insecure households have more nuanced strategic approaches to managing utility costs and rent such that the first occurrence of empirical indicators of utility hardship (in other words, failure to pay a bill or high proportion of income spent on a bill) may not be completely indicative of the onset of the hardship (Desmond, 2016). For example, in Desmond's work, utility payments were often delayed during the winter months, when utility shutoffs were not processed.

While causal mechanisms producing HI have not been clearly defined, there is general agreement that a single pathway does not exist. Rather, a focus on identifying risk factors and conditions that contribute to HI has gained traction in recent work. Risk factors are organized into two categories: structural and individual. Structural risk factors are driven by macro-factors such as state laws, social welfare programs/policies, and markets. In contrast, individual risk factors are associated with individual and household characteristics that are more or less distributed evenly across U.S. states/regions.

The literature shows general agreement that HI is associated with a lack of sufficient income, but income alone does not fully predict HI (Fowler et al., 2019). Part of the challenge in understanding the seemingly simple relationship between HI and income is that lack of income increases the odds of HI, but HI also may impact individuals' abilities to obtain income. In longitudinal analyses, evidence exists supporting links between homelessness and subsequent unemployment (Cobb-Clark and Zhu, 2017) and unemployment that predates and appears to increase the risk of homelessness (Bentley, Baker, and Aitken, 2019; Desmond and Gershenson, 2016).

[15] Perceived food insecurity and HI were assessed with a one-item question for each construct.

Heterogeneity in the HI-income relationship may also be attributed to structural factors such as varying support services and policies. For example, federal income assistance may play an important role in protecting households from experiencing HI. Households with children with special health care needs were more likely to experience HI if they were not recipients of Supplemental Security Income (Rose-Jacobs et al., 2019). Accessibility and availability of support programs may also vary by the diversity and size of the low-income population within a particular community. Another key structural factor important for reducing HI is the availability of subsidized housing (Bailey et al., 2016). Overall, these support programs appear to be effective at reducing the likelihood of the most severe forms of HI for households who are able to receive them.

The dynamics of eviction vary widely based on structural factors, and the repeated threat of eviction versus actual eviction produce dual pathways for HI. Comparative differences in the effects of these pathways on HI intensity are unknown. The legal process of eviction begins with filing an eviction notice and is governed by state law. In some states, filing for eviction is relatively easy, and landlords use this process to induce payment. Therefore, renters may repeatedly be given an eviction notice without an actual eviction; regardless, this creates HI (Garboden and Rosen, 2019). The threat of eviction points to additional facilitators of HI that are embedded in power imbalances between renters and landlords (Soederberg, 2018). These power dynamics are psychologically taxing for the people experiencing HI and may independently contribute to HI (Thomas, Darab, and Hartman, 2016).

One reason evictions and foreclosures resulting in forced household relocation represent such a strong indicator of severe HI is that forced relocation can become another risk factor for additional conditions that contribute to further HI. For example, changes in foreclosure status were associated with an increased risk of food insecurity and HI among SIPP participants during the financial recession (Mykyta, 2015). Panel Study of Income Dynamics (PSID) data revealed that households that were foreclosed upon during this period moved to more residentially disadvantaged neighborhoods, and the effects were strongest for Hispanic[16] households (Hall et al., 2018). Evicted households also typically relocate to disadvantaged neighborhoods (Desmond, 2016).

Measurement of Housing Insecurity

Several authors have made notable attempts toward advancing the development of a comprehensive measure of HI that incorporates multiple dimensions and indicators within each dimension. Multiple indicators provide more stable estimates of HI dimensions that are less prone to random measurement error. However, combining the indicators into a single index can create issues with interpretability.

Routhier (2019) used 11 dichotomous indicators from the 2015 AHS to create an HI index that reflects compounding across different sources of housing stress. These variables were dichotomized to represent identifiers for HI and are summarized in exhibit 1.

[16] The study team uses the term *Hispanic* to refer to people of Latin American origin and the term *Black* to describe people of African descent in the United States to align with the language used by the 2019 AHS.

Exhibit 1 | HI Dimensions and Indicators Extracted from the 2015 American Housing Survey

HI Dimension	Dichotomous Indicators
Unaffordability	▪ Out-of-pocket rent greater than 30 percent of gross income ▪ Out-of-pocket rent greater than 50 percent of gross income ▪ Income less than 133 percent of the federal poverty level (only if rent greater than 30 percent of gross income)
Crowding	▪ More than 1 person per room ▪ More than 1.5 persons per room ▪ One or more subfamilies within household
Poor physical conditions	▪ Objective measure reflecting moderately inadequate conditions (AHS compilation measure) ▪ Objective measure reflecting severely inadequate conditions (AHS compilation measure) ▪ Self-rated physical conditions at 4 or less on a scale of 10
Forced moves (defined only for recent movers)	▪ Forced to move by landlord, bank, government, or disaster ▪ Self-rated current home as worse than previous (only if forced to move)

AHS = American Housing Survey.
Source: Routhier (2019)

Some of these indicators were intentionally ordered to reflect multiple cut points on a single dimension (rent greater than 30 percent and rent greater than 50 percent; more than 1 person per room and more than 1.5 persons per room). Sum scores based on such measures were simple to interpret and clearly identified the severity of HI. However, some indicators contained information that did not perfectly coincide with other indicators (for example, objective and subjective measures of physical conditions). Interpreting a sum score is more difficult for these measures because it is less clear how different values on the score relate to different levels of HI severity. Finally, a sum score that includes multiple dimensions obscures how the dimensions individually contribute to overall HI.

Similar to Routhier (2019), Cox et al. (2017) dichotomized a large set of indicators from the 2005 AHS that captured seven dimensions of HI: housing instability (4 indicators), housing affordability (1 indicator), housing safety (15 indicators), housing quality (33 indicators), neighborhood safety (12 indicators), neighborhood quality (17 indicators), and homelessness (1 indicator). With these indicators, the researchers defined insecurity categories based on (1) the number of dimensions of insecurity experienced (categorical approach) or (2) the total number of insecurity indicators experienced across dimensions (continuous approach).

The HI definition based on the categorical approach in Cox et al. (2017) defined Housing Secure as a household with zero dimensions endorsed and a cost burden of less than 30 percent. Households were defined as having Moderate Security if housing insecure conditions were evident in only one dimension, the household had a cost burden of less than 50 percent, and the household was not identified as homeless. Households were defined as having Low Security if they were not homeless but issues were present in two or three dimensions or if there was a housing cost burden of more than 50 percent. Households were defined as having Very Low Security if they had experienced issues in four or more dimensions or were homeless.

For housing security categories based on the continuous scale approach in Cox et al. (2017), Housing Secure was defined as zero individual issues, a cost burden of less than 50 percent, and not homeless. Moderate Housing Security was defined as one to three issues, cost burden less than 50 percent, and not homeless. Low Housing Security was defined as four to six issues or having a cost burden greater than 50 percent but not homeless. Very Low Security was defined as more than six issues or homeless.

The number of indicators used in these two approaches is both a strength and a limitation. By including many indicators, an approach is unlikely to overlook or misclassify households experiencing insecurity. On the other hand, the full measure requires a great deal of time to administer and presents a considerable cognitive burden. The cut points Cox et al. (2017) selected for the study were based on the distribution of scores and may be sample-specific.[17] Further, based on these cut points, most households were considered at least moderately housing insecure (89 percent).

HUD's Development of the HIRM

HUD constructed the HIRM, which comprises a set of survey items to be implemented as part of a supplement to the 2019 AHS to facilitate the development of the HUD-HIM (Census Bureau, 2019a) . The topic and subtopics of the resulting AHS supplemental HIRM are summarized below.

- Affordable (six measurement questions and eight validating/contextual questions).
  - Housing Stress.
  - Shelter Poverty.
  - Payment Lapses.
- Stable Occupancy (14 questions).
  - Housing Stress/Worry.
  - Eviction and Foreclosure.
  - Residential Instability.
  - Doubling Up.
  - Homelessness.
- Decent and Safe (22 questions).
  - Substandard Physical Environment with Serious Consequences for Daily Living.
  - Objective and Subjective Assessment of Crowding.
  - Housing Safety as Related to Crime and External Threats.

The HUD-HIRM advances the development of the HUD-HIM by providing a way to cross-validate new subjective questions about HI with corresponding measures drawn from large sets of objective items available in the AHS. Questions were developed to minimize the cognitive burden on respondents by anchoring responses on the current housing unit and on experiences concerning that unit within the previous 12 months of the survey. Although most questions could be asked of the full sample, different wording was sometimes required for owners versus renters or for single-person versus multiple-person households, necessitating a system of automatic text fills to simplify the survey completion experience. Some questions applied only to a specific

[17] The issue of sample-specific cut points is also a potential limitation of the research developed for this report and highlights the need for additional research that replicates this approach with different samples of households.

subpopulation (for example, owners, renters, households with dependent children). For these questions, screeners were applied to identify the appropriate respondent group(s).

While HUD tried to order items along a hypothetical continuum of HI, there was some ambiguity in how items representing distinct housing dimensions might be ordered in the "middle" segment between Secure and Severely Insecure. In this middle section, different tradeoff strategies between subdimensions of HI might be possible that could reflect the same general intensity of HI.

HUD requested that the Census Bureau conduct a one-time cognitive pretest of the HUD-HIRM (Virgile et al., 2019), interviewing 15 respondents who were 18 years or older and were below the 300-percent household poverty threshold. As a result of this study, items were reordered to reduce sensitivity to affordability questions; several questions were added (in other words, followup questions evaluating the respondents' levels of difficulty answering questions about the entire household, screener questions accompanying major maintenance and repairs); item wording was altered to focus questions on hardship-related moves; and additional response options were added to include visual cues of disrepair. The HUD-HIRM did not repeat any of the HI-related questions in the Core AHS that have also been used for index development in this study.

The HUD-HIRM was administered as a close-in-time followup survey to AHS participants who completed the Food Security Module, who had incomes below 300 percent of the household federal poverty threshold, who opted in, and who could be reached at followup. While the income of the sample was capped at 300 percent of the federal household poverty threshold, it was more heavily weighted toward lower-income households (below 200 percent) to capture those most impacted by HI. Higher-income households were included to account for geographic differences in the cost of living, which may result in HI. The HIRM was administered to the same half of the AHS sample who received the Food Security Module, and attempts were made to interview the same respondent who responded to the Core survey. Households within the eligible pool were stratified by tenure (owner/renter) and census division. The target sample size was 4,000 households; however, the sample is smaller than anticipated (approximately 70 percent, $N = 2{,}800$). Exhibit 2 in the next section includes information on the demographic characteristics of the HIRM sample.

HUD's HI module is well aligned with common themes and best practices noted in the literature regarding the measurement of HI. Although challenges exist in the construction of the HUD-HIM, many such challenges are described by recent literature—a helpful first step toward solutions. Recent longitudinal studies underscore mechanisms and risk factors for HI, and construct validity of the HUD-HIM will surely benefit from the large body of literature highlighting correlates of HI.

METHODS

Data Source and Sample

The primary data source for all analyses conducted by the study team for this research is the 2019 HIRM and a smaller subset of variables from the 2019 AHS Core data. The final analytical sample includes the 2,800 households that responded to the HIRM. Exhibit 2 provides a summary of the demographic characteristics of the sample.

Exhibit 2 | Sample Characteristics (Unweighted)

Category	Frequency	Percent
Race (head of household, *N* = 2,800)		
Black	600	21.4
Non-Black	2,200	78.6
Ethnicity (head of household, *N* = 2,750)		
Hispanic	550	20.0
Non-Hispanic	2,200	80.0
Gender (head of household, *N* = 2,800)		
Female	1,600	57.1
Male	1,200	42.9
Presence of children (*N* = 2,800)		
Children in the home	900	32.1
No children in the home	1,900	67.9
Age (head of household, *N* = 2,800)		
65 years and older	900	32.1
Younger than 65 years	1,900	67.9
Interview language (*N* = 2,800)		
Non-English	200	7.1
English	2,600	92.9
New construction (*N* = 2,740)		
Home built in 2016 or after	40	1.5
Home built before 2016	2,700	98.5
Metropolitan status (*N* = 2,750)		
Located in a metro area	2,600	94.5
Located outside a metro area	150	5.5
Tenure (*N* = 2,780)		
Occupied without payment	80	2.9
Renter-occupied	1,500	54.0
Owner-occupied	1,200	43.2
Income relative to the poverty level (*N* = 2,850)		
Income greater than 300 percent of federal poverty line	300	10.5
Income between 200 and 300 percent of the federal poverty line OR less than 80 percent AMI	750	26.3
Income less than 200 percent of the poverty line	1,800	63.2
HUD Subsidized (*N* = 1,550)		
Not eligible for HUD subsidy	150	9.7
Eligible for HUD subsidy but not subsidized	900	58.1
HUD subsidized home	500	32.3
Census division (state abbreviations, *N* = 2,800)		
New England (CT, ME, MA, NH, RI, VT)	100	3.6
Middle Atlantic (NJ, NY, PA)	250	8.9

Category	Frequency	Percent
East North Central (IN, IL, MI, OH, WI)	450	16.1
West North Central (IA, KS, MN, MO, NE, ND, SD)	150	5.4
South Atlantic (DE, DC, FL, GA, MD, NC, SC, VA, WV)	600	21.4
East South Central (AL, KY, MS, TN)	150	5.4
West South Central (AR, LA, OK, TX)	400	14.3
Mountain (AZ, CO, ID, NM, MT, UT, NV, WY)	200	7.1
Pacific (AK, CA, HI, OR, WA)	500	17.9
Census region (*N* = 2,750)		
Northeast	350	12.7
Midwest	600	21.8
South	1,100	40.0
West	700	25.5

AMI = area median income.
Notes: Some percentages do not add to 100 due to rounding. The "Percent" column presents percentages based on the rounded counts.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

To develop the HIRM sample, the Census Bureau drew from the sample of AHS respondents that completed the food security module (FSM), referred to as "Split Sample One." Respondents in Split Sample One were deemed eligible to take the HIRM if they (1) opted into the survey and (2) had incomes at or below 300 percent of the federal poverty threshold.[18] The Census Bureau divided the eligible participants into 36 buckets (2 x 2 x 9: owner versus renter, income less than twice the federal poverty level versus income between twice and three times the federal poverty level, and residence in one of nine census divisions). From these 36 buckets, the Census Bureau selected cases such that 45 percent were owners and 55 percent were renters; 80 percent had income less than twice the federal poverty level, and 20 percent had income between twice and three times the federal poverty level; and the sample was divided in proportion to the number of housing units across the census divisions.[19] When the Census Bureau edited the income questions, which included imputation of missing income information, it was found that 300 cases had household incomes greater than three times the poverty level and more than 80 percent of area median income (AMI). This finding meant that the sampled cases fall into three income groups rather than two, expanding the number of buckets to 54 (2 x 3 x 9).

Based on a 20:1 rule-of-thumb ratio of subjects (interviews) to items (questions) and a desired 45 percent versus 55 percent split of owners versus renters, HUD chose a sample size target of 4,000. In the end, 2,800 interviews were completed. This shortfall will reduce the precision of analysis and potentially introduce sampling bias (other than that which is already inherent in the sampling design; for example, bias with respect to household income). Bias could occur due to overall non-response or uneven non-response across important sampling dimensions.

[18] Initially, HUD considered 80 percent of local Area Median Income as the income cap for respondents, but this test was deemed difficult to administer because it varied geographically. Instead, all households at or below 300 percent of the federal poverty level were eligible for inclusion in the sample that was administered the HIRM, which, across the country, captures most households below 80 percent of AMI.
[19] The Census Bureau worked cases that opted in until targets were reached and, for a few cells, past when targets were reached.

To correct any bias in the analytical sample, the study team developed a sampling weight based on each respondent's relative probability of being interviewed for the HIRM.[20] The probability of a case being in the HIRM dataset is the product of three independent probabilities, and the inverse of this product is the sampling weight:

1. The probability of being in Split Sample One.
   - 1 divided by 2 times the base weight.
2. The probability of being in the HIRM sample.
   - (For each bucket) the number of cases targeted for that census division bucket divided by all the cases in that census division bucket that match the tenure- and income-level sample selection criteria for the HIRM.
3. The probability of a completed survey.
   - (For each bucket) the number of completed interviews divided by the number of cases targeted for that bucket.[21]

The study team also forced the weight to sum to 2,800. Using 2,800 as the desired sum has two advantages. First, every frequency distribution using either unweighted or weighted data will sum to the same total. Therefore, frequency distributions can be compared easily without translating counts into percent. Second, all statistical tests will be based on the actual sample size of 2,800.

Exhibit 3 details percentages of households with different characteristics in the unweighted eligible population, weighted eligible population,[22] unweighted analytical sample, and weighted analytical sample. The exhibit also shows the difference in percentage points between the weighted eligible population and the unweighted analytical sample, and the weighted eligible population and the weighted analytical sample for each category. The percent difference in the weighted eligible population and unweighted analytical sample percentages ranges from -18 percent to 149 percent, while the difference between the weighted eligible population and the weighted analytical sample ranges from -22 percent to 81 percent. The tighter range of difference between the weighted eligible population and weighted analytical sample demonstrates the effectiveness of the study team's sampling weight. The analyses below thus report estimates produced with the sampling weight applied unless specifically noted otherwise.[23]

[20] This section provides a summary of the sampling weight. For more detail, see appendix A.
[21] The households that elected out of the followup survey can be ignored. They are implicitly included in "the number of cases targeted for that bucket" term, a term that cancels out in multiplication. Their non-participation is picked up by the last term.
[22] The study team weighted the eligible population percentages using the Split Sample One base weight.
[23] The study team performed all analyses using the unweighted sample as well and found minimal differences between the unweighted and weighted results.

Exhibit 3 | Characteristics of Unweighted Eligible Population, Weighted Eligible Population, Unweighted Analytical Sample, and Weighted Analytical Sample

Income Level as a Percentage of Poverty Threshold	Demographic Variable	Eligible Population		Analytical Sample		% Change (Weighted Eligible to Unweighted Analytical)	% Change (Weighted Eligible to Weighted Analytical)
		Unweighted Percentage	Weighted Percentage	Unweighted Percentage	Weighted Percentage		
Race							
All	Black	18.92	15.76	21.43	16.36	36%	4%
	Not Black	81.08	84.24	78.57	83.64	– 7%	– 1%
Income less than 200% of poverty threshold	Black	23.75	19.19	25.71	20	34%	4%
	Not Black	76.25	80.81	74.29	80	– 8%	– 1%
Income 200–300% of poverty threshold	Black	15.07	12.77	14.29	12.16	12%	– 5%
	Not Black	84.93	87.23	85.71	87.84	– 2%	1%
Income greater than 300% of poverty threshold	Black	13.33	10.63	13.79	12.28	30%	16%
	Not Black	86.67	89.37	86.21	87.72	– 4%	– 2%
Age							
All	> 65 years old	31.33	33.18	32.14	35.71	– 3%	8%
	≤ 65 years old	68.67	66.82	67.86	64.29	2%	– 4%
Income less than 200% of poverty threshold	> 65 years old	34.58	36.11	33.33	36.67	– 8%	2%
	≤ 65 years old	65.42	63.89	66.67	63.33	4%	– 1%
Income 200–300% of poverty threshold	> 65 years old	33.34	35.63	35.71	40	0%	12%
	≤ 65 years old	66.66	64.37	64.29	60	0%	– 7%
Income greater than 300% of poverty threshold	> 65 years old	20.2	22.27	23.08	33.33	4%	50%
	≤ 65 years old	79.8	77.73	76.92	66.67	– 1%	– 14%
Ethnicity							
All	Hispanic	19.83	16.8	20	16.36	19%	– 3%
	Not Hispanic	80.17	83.2	80	83.64	– 4%	1%
Income less than 200% of poverty threshold	Hispanic	22.25	19.28	22.22	17.24	15%	– 11%
	Not Hispanic	77.75	80.72	77.78	82.76	– 4%	3%
Income 200%–300% of poverty threshold	Hispanic	19.63	15.76	20	13.33	27%	– 15%
	Not Hispanic	80.37	84.24	80	86.67	– 5%	3%
Income greater than 300% of poverty threshold	Hispanic	13.57	11.6	13.79	9.09	19%	– 22%
	Not Hispanic	86.43	88.4	86.21	90.91	– 2%	3%
HUD Subsidized							
All	HUD Subsidized	13.21	7.16	17.86	9.09	149%	27%
	Not HUD Subsidized	86.79	92.84	82.14	90.91	– 12%	– 2%

Income Level as a Percentage of Poverty Threshold	Demographic Variable	Eligible Population		Analytical Sample		% Change (Weighted Eligible to Unweighted Analytical)	% Change (Weighted Eligible to Weighted Analytical)
		Unweighted Percentage	Weighted Percentage	Unweighted Percentage	Weighted Percentage		
Income less than 200% of poverty threshold	HUD Subsidized	21.96	12.19	27.78	13.33	128%	9%
	Not HUD Subsidized	78.04	87.81	72.22	86.67	– 18%	– 1%
Income 200–300% of poverty threshold	HUD Subsidized	3.58	1.91	4.11	2.78	115%	46%
	Not HUD Subsidized	96.42	98.09	95.89	97.22	– 2%	– 1%
Income greater than 300% of poverty threshold	HUD Subsidized	1.41	0.72	D	D	D	D
	Not HUD Subsidized	98.59	99.28	83.33	100	– 16%	1%
New Construction							
All	New Construction	1.5	1.65	1.46	1.82	– 12%	10%
	Not New Construction	98.5	98.35	98.54	98.18	0%	0%
Income less than 200% of poverty threshold	New Construction	1.23	1.4	1.16	1.32	– 17%	– 6%
	Not New Construction	98.77	98.6	98.84	98.68	0%	0%
Income 200%–300% of poverty threshold	New Construction	1.44	1.54	2.78	2.78	81%	81%
	Not New Construction	98.56	98.46	97.22	97.22	– 1%	– 1%
Income greater than 300% of poverty threshold	New Construction	2.28	2.43	D	D	D	D
	Not New Construction	97.72	97.57	100	100	2%	2%

Notes: Some percentages do not add to 100 due to rounding. The "Weighted Percentage" and "Unweighted Percentage" columns present percentages based on the rounded counts. For variables where cells are suppressed due to inadequate observations (*N* < 15), the presented percentages are calculated using the rounded sample size as the denominator. "D" signifies a suppressed value.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Stage 1: Constructing Gold Standard Factor Scores for Each Housing Dimension

The study team used confirmatory factor analysis (CFA) to construct gold standard factor scores for each of the three dimensions of HI. The factor scores are referred to as "gold standards" because the goal of this study—unlike that of many statistical analyses that favor parsimony—is to develop valid, precise, and reliable scores for each dimension of HI that extract the maximum amount of variation from the observed indicators for each HI dimension. In stage 3 of the analysis, the study team developed reduced scores of the dimensions of HI that are more applicable in other research contexts that do not benefit from the wealth of data available in the HIRM.

CFA is a statistical modeling technique to explain the covariances or correlations between a set of observed variables with a smaller number of underlying latent variables (Bollen, 1989). The strengths of the CFA approach are two-fold. First, the CFA framework allowed the study team to measure a set of key subdimensions within the lack of affordability, lack of stable occupancy, and lack of safety and decency dimensions. The study team estimated three separate CFA measurement models: one for lack of affordability, one for lack of stable occupancy, and one for lack of safety and decency. In each CFA, the overall dimension was modeled as a "higher-order" latent variable measured by several subdimensions, which were, in turn, measured by the observed items from the HIRM. In other words, the CFA models helped the study team measure and define lack of affordability, lack of stable occupancy, and lack of safety and decency as overall measures, each with a set of subdimensions. Second, the CFA approach allowed the subdimensions and the observed indicators of each subdimension to have different weights. Unlike a composite score that simply sums indicators (for example, Cox et al., 2017), CFA estimates a coefficient (factor loading) for each subdimension and each observed indicator that represents the degree of association with the latent variable being measured. The factor loadings can serve as weights when developing the factor score. For example, the model of lack of affordability includes three subdimensions: worry about inability to pay housing costs, lapse in housing payment, and housing expense hardships. Rather than treat these subdimensions equally in constructing a factor score for lack of affordability, the study team used the CFA factor loadings as weights to construct a score that more accurately represents the observed data.

Lack of Affordability (HI 1) Measurement Model

The study team identified indicators for inclusion in the measurement models based on iterative discussion with external and internal HUD HI subject matter experts. The lack of affordability measurement model divides the concept into three subdimensions: worry about inability to pay housing costs, lapse in housing payment, and housing expense hardships. In the model, lack of affordability is a higher-order factor, referred to as HI 1, that is measured by the three subdimensions, each of which is measured by a set of observed indicators. Exhibit 4 shows the observed indicators the study team selected for each subdimension of lack of affordability.

Exhibit 4 | Lack of Affordability (HI 1): Frequency Distribution of Analysis Variables

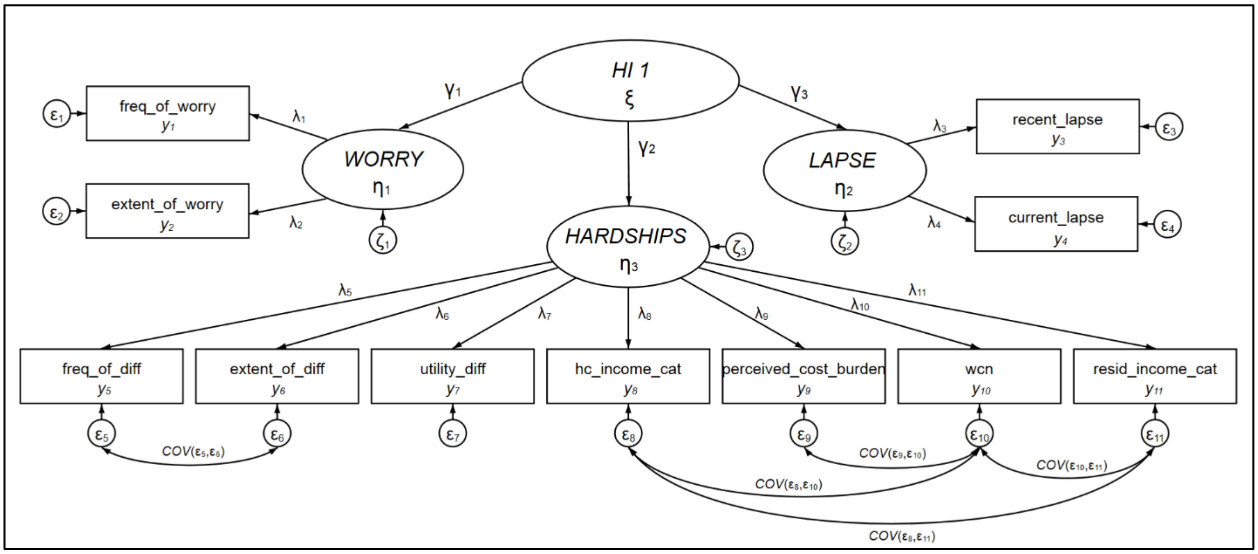
Subdimension	Variable	Categories	Weighted Frequency	Weighted Percent
Worry about inability to pay housing costs (*WORRY*)	**Frequency of worry about mortgage/rent payments (freq_of_worry)**	0: Never	1900	67.9
		1: Rarely	400	14.3
		2: Sometimes	300	10.7
		3: Usually	80	2.9
		4: Always	80	2.9
		Missing	< 15	D
	Extent of worry about mortgage/rent payments (ai_extent_of_worry)	0: Not at all worried	2500	89.3
		1: A little worried	150	5.4
		2: Moderately worried	80	2.9
		3: Very worried	70	2.5
		Missing	0	0.0
Lapse in housing payment (*LAPSE*)	**Recent (in the past 12 months) lapses in housing payments (recent_lapse)**	0: Never	2600	92.9
		1: Only one or two months	90	3.2
		2: Some months but not every month	40	1.4
		3: Almost every month	20	0.7
		4: Every month	20	0.7
		Missing	< 15	D
	Current lapses in housing payments (current_lapse)	0: No	2700	97.8
		1: Yes	60	2.2
		Missing	0	0.0
Housing expense hardships (*HARDSHIPS*)	**Frequency of difficulty in making housing cost payments (freq_of_diff)**	0: Never	2500	89.3
		1: Only 1 or 2 months	90	3.2
		2: Some months but not every month	100	3.6
		3: Almost every month	50	1.8
		4: Every month	50	1.8
		Missing	< 15	D
	Extent of difficulty in making housing cost payments (extent_of_diff)	0: Not at all difficult	2100	75
		1: A little difficult	400	14.3
		2: Moderately difficult	200	7.1
		3: Very difficult	90	3.2
		Missing	< 15	D
	Difficulty paying utilities (utility_diff)	0: No difficulty	2300	82.1
		1: Some difficulty reflecting only difficulty in payment	200	7.1
		2: Notice of shutoff	200	7.1
		3: Incidence of shutoff	80	2.9
		Missing	< 15	D
	Housing cost burden (hc_income_cat)	0: Housing cost less than 30% of income	1,400	50.4
		1: Housing cost 30–50% of income	650	23.4
		2: Housing cost 50–75% of income	300	10.8

Subdimension	Variable	Categories	Weighted Frequency	Weighted Percent
		3: Housing cost 75–90% of income	80	2.9
		4: Housing cost more than 90% of income	350	12.6
		Missing	0	0.0
	Perceived severe housing cost burden (perceived_cost_burden)	0: No	2300	84.2
		1: Yes	400	14.7
		Missing	30	1.1
	Worst case needs[a]	0: No	2500	90.9
		1: Yes	250	9.1
		Missing	0	0.0
	Residual income[b] (resid_income_cat)	0: 500 percent or more	450	16.4
		1: 400 to < 500 percent	200	7.3
		2: 300 to < 400 percent	400	14.6
		3: 200 to < 300 percent	450	16.4
		4: 185 to < 200 percent	90	3.3
		5: 175 to < 185 percent	50	1.8
		6: 150 to < 175 percent	100	3.6
		7: 125 to < 150 percent	150	5.5
		8: 100 to < 125 percent	100	3.6
		9: 75 to < 100 percent	150	5.5
		10: 50 to < 75 percent	100	3.6
		11: < 50 percent	500	18.2
		Missing	0	0.0

[a] HUD has defined households with worst case needs as very low-income renters who do not receive government housing assistance and who pay more than one-half of their income for rent, live in severely inadequate conditions, or both.
[b] The residual income metric is the ratio of residual income to threshold non-shelter housing costs.
Notes: Some percentages do not add to 100 due to rounding. The "Weighted Percent" and "Unweighted Percent" columns present percentages based on the rounded counts. For variables where cells are suppressed due to inadequate observations (*N* < 15), the presented percentages are calculated using the rounded sample size as the denominator. "D" signifies a suppressed value.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 5 shows a path diagram of the lack of affordability or HI 1 model. In the diagram, the latent variables or factors are represented as ovals, the observed indicators are rectangles, and the error terms are circles.

Exhibit 5 | Lack of Affordability (HI 1) Measurement Model



HI 1 = lack of affordability factor score.
Source: Authors' depiction of the HI 1 measurement model using variable names from the U.S. Census Bureau, 2019 American Housing Survey

The measurement model for HI 1 can also be represented with a series of equations. Equation 1 shows the relations between the HI 1 higher-order factor (ξ) and the subdimensions (η_1, η_2, and η_3). Each subdimension has a factor loading (γ_1, γ_2, and γ_3) that estimates the association between HI 1 and the subdimension. The ζs are error terms that reflect measurement error. Equation 2 shows the relations between each subdimension and the observed indicators (y_1 to y_{11}) of the subdimension. Each observed indicator has a factor loading ($\lambda_1$to λ_{11}) that estimates the association between the subdimension and the observed indicator. The ϵs are error terms.

$$\begin{aligned} \eta_1 &= \gamma_1\xi + \zeta_1 \\ \eta_2 &= \gamma_2\xi + \zeta_2 \\ \eta_3 &= \gamma_3\xi + \zeta_3 \end{aligned} \tag{1}$$

$$\begin{aligned} y_1 &= \lambda_1\eta_1 + \epsilon_1 \\ y_2 &= \lambda_2\eta_1 + \epsilon_2 \\ y_3 &= \lambda_3\eta_2 + \epsilon_3 \\ y_4 &= \lambda_4\eta_2 + \epsilon_4 \\ y_5 &= \lambda_5\eta_3 + \epsilon_5 \\ y_6 &= \lambda_6\eta_3 + \epsilon_6 \\ y_7 &= \lambda_7\eta_3 + \epsilon_7 \\ y_8 &= \lambda_8\eta_3 + \epsilon_8 \\ y_9 &= \lambda_9\eta_3 + \epsilon_9 \\ y_{10} &= \lambda_{10}\eta_3 + \epsilon_{10} \\ y_{11} &= \lambda_{11}\eta_3 + \epsilon_{11} \end{aligned} \tag{2}$$

Equations 1 and 2 may be more compactly written in matrix form as follows:

$$\eta = \Gamma\xi + \zeta \tag{3}$$

$$y = \Lambda_y \eta + \epsilon \tag{4}$$

where

$$\eta = \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \end{bmatrix}, \qquad \Gamma = \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix}, \qquad \xi = [\xi_1],\ \zeta = \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \end{bmatrix} \tag{5a}$$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \\ y_7 \\ y_8 \\ y_9 \\ y_{10} \\ y_{11} \end{bmatrix}, \qquad \Lambda_y = \begin{bmatrix} \lambda_1 & 0 & 0 \\ \lambda_2 & 0 & 0 \\ 0 & \lambda_3 & 0 \\ 0 & \lambda_4 & 0 \\ 0 & 0 & \lambda_5 \\ 0 & 0 & \lambda_6 \\ 0 & 0 & \lambda_7 \\ 0 & 0 & \lambda_8 \\ 0 & 0 & \lambda_9 \\ 0 & 0 & \lambda_{10} \\ 0 & 0 & \lambda_{11} \end{bmatrix}, \qquad \epsilon = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \\ \epsilon_7 \\ \epsilon_8 \\ \epsilon_9 \\ \epsilon_{10} \\ \epsilon_{11} \end{bmatrix} \tag{5b}$$

Finally, the model also includes covariance matrices of the error terms in ζ and ϵ. For the HI 1 model and the models for the other two HI dimensions, the study team initially assumed that the error terms did not covary with each other; thus, the two error matrices took the following form:

$$\Psi = \begin{bmatrix} var(\zeta_1) & 0 & 0 \\ 0 & var(\zeta_2) & 0 \\ 0 & 0 & var(\zeta_3) \end{bmatrix} \tag{5c}$$

$$\Theta_\epsilon = \begin{bmatrix} var(\epsilon_1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & var(\epsilon_2) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & var(\epsilon_3) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & var(\epsilon_4) & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & var(\epsilon_5) & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & var(\epsilon_6) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & var(\epsilon_7) & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & var(\epsilon_8) & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & var(\epsilon_9) & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & var(\epsilon_{10}) & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & var(\epsilon_{11}) \end{bmatrix} \tag{5d}$$

In estimating the models, however, the study team assessed whether allowing error terms to covary improved the model fit. In the case of HI 1, the study team found that allowing the error terms for the frequency and extent of difficulty in making payments (ϵ_1 and ϵ_2), housing cost burden and worst case needs (ϵ_8 and ϵ_{10}), housing cost burden and residual income (ϵ_8 and ϵ_{11}), perceived severe housing cost burden and worst case needs (ϵ_9 and ϵ_{10}), and worst case needs and residual income (ϵ_{10} and ϵ_{11}) to covary improved the fit of the model significantly. Covarying errors indicate that the two observed indicators share some common variance beyond that explained by the model's latent variables. The indicators with covarying errors in the HI 1 model all share some aspect of income. It was thus not overly surprising to find that the model was improved with error covariances. The final Θ_ϵ for the HI 1 model is shown in equation 5e below.

$$\Theta_\epsilon =$$

$$\begin{bmatrix} var(\epsilon_1) & cov(\epsilon_2,\epsilon_1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ cov(\epsilon_1,\epsilon_2) & var(\epsilon_2) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & var(\epsilon_3) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & var(\epsilon_4) & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & var(\epsilon_5) & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & var(\epsilon_6) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & var(\epsilon_7) & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & var(\epsilon_8) & 0 & cov(\epsilon_{10},\epsilon_8) & cov(\epsilon_{11},\epsilon_8) \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & var(\epsilon_9) & cov(\epsilon_{10},\epsilon_9) & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & cov(\epsilon_8,\epsilon_{10}) & cov(\epsilon_9,\epsilon_{10}) & var(\epsilon_{10}) & cov(\epsilon_{11},\epsilon_{10}) \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & cov(\epsilon_8,\epsilon_{11}) & 0 & cov(\epsilon_{10},\epsilon_{11}) & var(\epsilon_{11}) \end{bmatrix} \quad (5e)$$

Lack of Stable Occupancy (HI 2) Measurement Model

The study team divided the lack of stable occupancy dimension, HI 2, into three subdimensions that measure forced move risk and worry, residential instability or dislocation, and household sharing. Forced move risk and worry are measured with indicators from the HIRM that capture risk of eviction or foreclosure, previous worry about a forced move, and current worry about a forced move. Residential instability or dislocation is measured by actual forced moves,[24] the number of moves, and the proportion of persons in the household who have experienced homelessness. Finally, household sharing is measured by the proportion of persons in the household who are living in the home temporarily because they have nowhere else to go and the proportion living temporarily because of financial difficulties. Exhibit 6 provides a list of the observed indicators of each dimension of lack of stable occupancy.

[24] The forced moves variable has two values: 0 = not forced to move from current/previous property and 1 = forced to move from current or previous property. It is created as a combination of several items, including whether the landlord forced the respondent to move or whether the city condemned the property. See appendix B for a full description of the forced move variable.

Exhibit 6 | Lack of Stable Occupancy (HI 2): Frequency Distribution of Analysis Variables

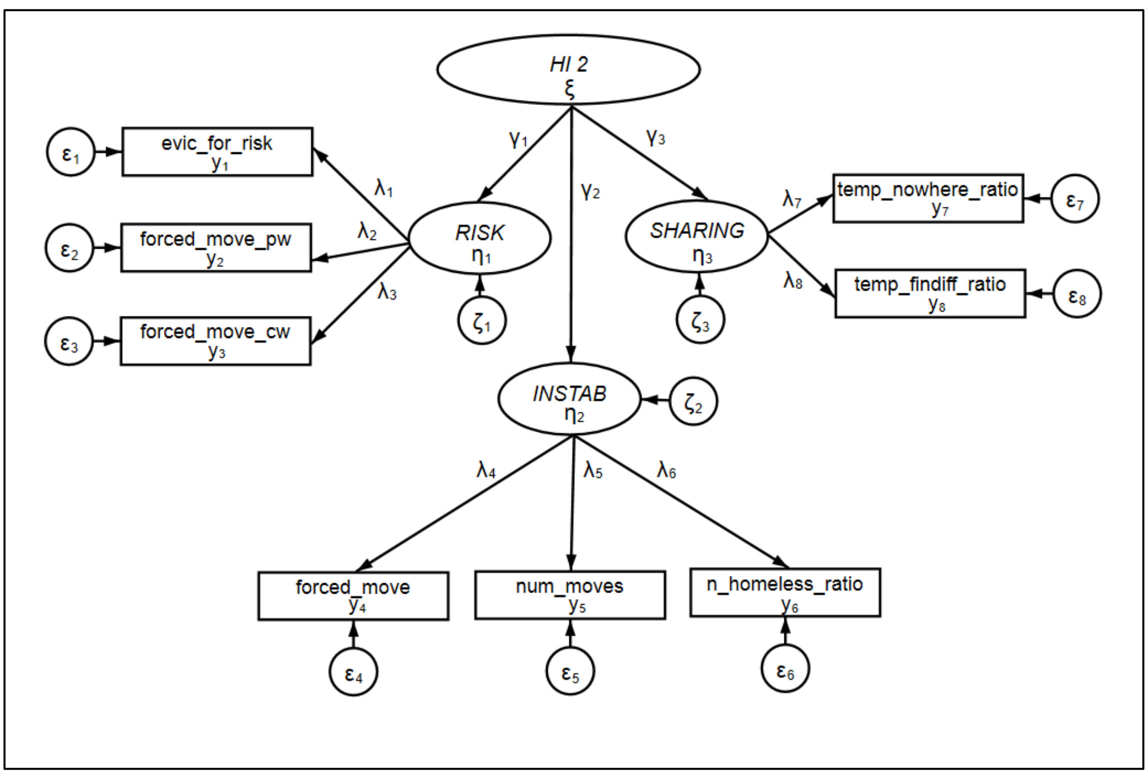
Subdimension	Variable	Categories	Weighted Frequency	Weighted Percent
Forced Move Risk and Worry (*RISK*)	Risk of eviction or foreclosure (evic_for_risk)	0: Low Risk of Eviction or Foreclosure	2600	92.9
		1: Moderate Risk of Eviction or Foreclosure	200	7.1
		3: High Risk of Eviction or Foreclosure	< 15	D
		Missing	< 15	D
	Previous worry about forced move (forced_move_pw)	1: Never	2400	85.7
		2: Rarely	150	5.4
		3: Sometimes	150	5.4
		4: Usually	30	1.1
		5: Always	40	1.4
		Missing	< 15	D
	Current worry about forced move (forced_move_cw)	1: Not at all worried	2400	85.7
		2: A little worried	200	7.1
		3: Moderately worried	80	2.9
		4: Very worried	60	2.1
		Missing	< 15	D
Residential Instability or Dislocation (INSTAB)	Forced move (forced_move)	0: No Forced Move	2700	96.8
		1: Forced Move	90	3.2
	Number of moves (num_moves)	0: None or one move	2500	89.3
		1: Two or More	300	10.7
	Proportion of persons in the household who have experienced homelessness (n_homeless_ratio)	0	2700	96.4
		0.2	< 15	D
		0.25	< 15	D
		0.29	< 15	D
		0.33	< 15	D
		0.5	< 15	D
		0.75	< 15	D
		1	20	0.7
Household Sharing *(SHARING)*	Proportion of persons in the household who are living there temporarily because they have nowhere else to go (temp_nowhere_ratio)	0	2700	96.4
		0.14	< 15	D
		0.17	< 15	D
		0.2	< 15	D
		0.25	< 15	D
		0.29	< 15	D
		0.33	< 15	D
		0.4	< 15	D
		0.5	20	0.7
		0.67	< 15	D
		1	< 15	D
	Proportion of persons in the household who are living temporarily because of financial	0	2600	92.9
		0.13	< 15	D
		0.17	< 15	D
		0.2	< 15	D
		0.22	< 15	D

Subdimension	Variable	Categories	Weighted Frequency	Weighted Percent
	difficulties (temp_findiff_ratio)	0.25	< 15	D
		0.29	< 15	D
		0.33	< 15	D
		0.4	< 15	D
		0.5	20	0.7
		0.67	< 15	D
		1	50	1.8

Notes: Some percentages do not add to 100 due to rounding. The “Weighted Percent” and “Unweighted Percent” columns present percentages based on the rounded counts. For variables where cells are suppressed due to inadequate observations (*N* < 15), the presented percentages are calculated using the rounded sample size as the denominator. “D” signifies a suppressed value.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Like lack of affordability (HI 1), the lack of stable occupancy (HI 2) measurement model can be represented with a series of equations. The equations are virtually identical to those for the HI 1 model and are not included here. The only differences are that there are 8 observed indicators (instead of 11) for HI 2, and the Θ_ϵ matrix does not include any covariance terms. Exhibit 7 shows the path diagram for the stable occupancy measurement model.

Exhibit 7 | Lack of Stable Occupancy (HI 2) Measurement Model



HI 2 = lack of stable occupancy factor score.

Source: Authors' depiction of the HI 2 measurement model using variable names from the U.S. Census Bureau, 2019 American Housing Survey

Lack of Safety and Decency (HI 3) Measurement Model

The study team measured the lack of safety and decency dimension, referred to as HI 3, with three subdimensions, labeled poor housing quality, overcrowding, and lack of safety. Poor housing quality is measured by five observed indicators, including the number of structural deficiencies present in the home, the number of heating breakdowns, the number of plumbing breakdowns, the number of times the unit was without water, and sewage breakdowns. Overcrowding is measured by variables capturing too many people in the unit, the number of subfamilies present in the home, the number of persons per room, the number of persons per bedroom, and the square footage per person. Finally, lack of safety is measured by perceptions of safety, including safety inside the home, safety of children playing outside the home, safety of the home against break-ins, and safety of people coming and going at night. Exhibit 8 lists the observed indicators for each subdimension of lack of safety and decency.

Exhibit 8 | Lack of Safety and Decency (HI 3): Frequency Distribution of Analysis Variables

Variable Name	Variable Label	Categories	Weighted Frequency	Weighted Percent
Poor Housing Quality (*QUALITY*)	Number of structural deficiencies (hs_quality)	0	1500	53.6
		1	700	25
		2	300	10.7
		3	150	5.4
		4	60	2.1
		5	30	1.1
		6	< 15	D
		7	< 15	D
		8	< 15	D
		9	< 15	D
	Heating breakdowns (heat_br)	0: No heating-related service breakdown	2700	96.4
		1–7: One to seven heating-related service breakdowns	80	2.9
		8: Eight or more heating-related service breakdowns	20	0.7
		Missing	< 15	D
	Plumbing breakdowns: toilet (plumb_br)	0: No plumbing-related service breakdown	2700	96.4
		1–7: One to seven plumbing-related service breakdowns	50	1.8
		8: Eight or more plumbing-related service breakdowns	< 15	D
		Missing	< 15	D
	Running water (runwat)	0: If the unit was never without running water for 6+ hours in the past 3 months	2700	96.4

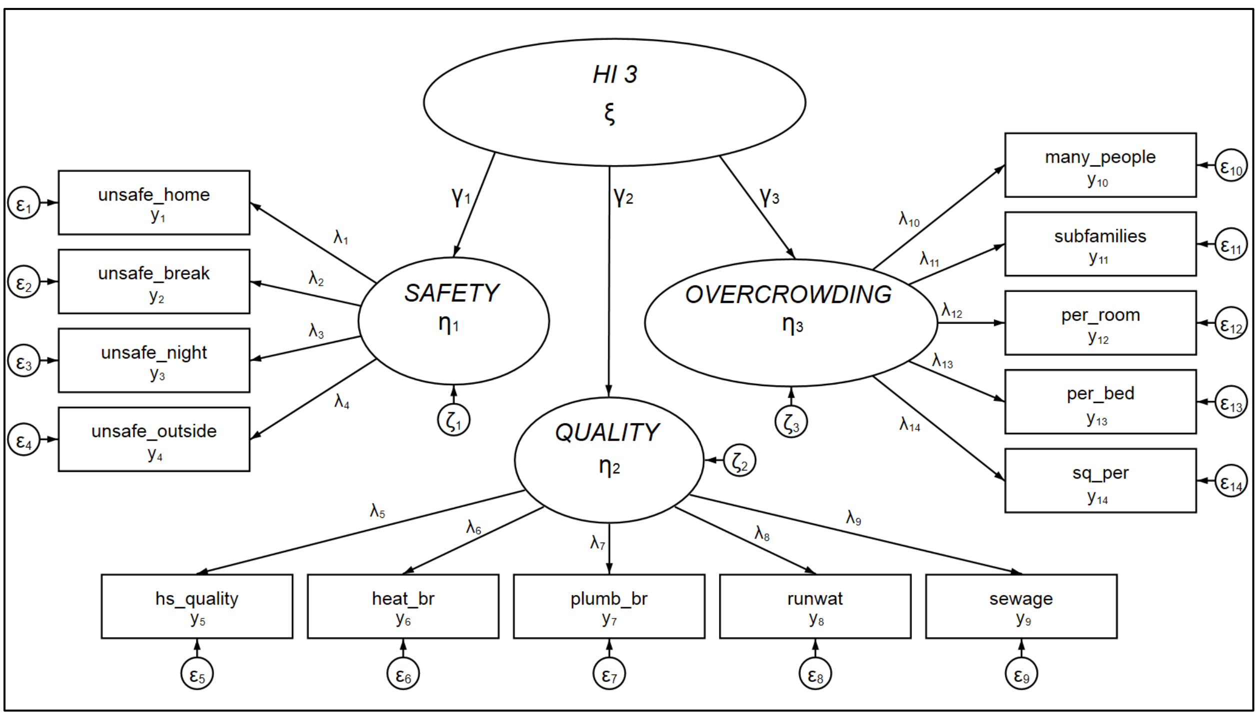
Variable Name	Variable Label	Categories	Weighted Frequency	Weighted Percent
		1–7: One to seven times, the unit was without running water for 6 or more hours in the past 3 months	80	2.9
		8: Eight or more times, the unit was without running water for 6 or more hours in the past 3 months	< 15	D
		Missing	30	1.1
	Sewage break (sewage)	0: No breakdowns that lasted 6 hours or more	2700	96.4
		1: One or more breakdowns that lasted 6 hours or more	40	1.4
		2: Unit is not connected to public sewer, septic tank, or cesspool system	< 15	D
		Missing	< 15	D
Overcrowding (*OVERCROWDING*)	Too many people living in unit (many_people)	0: No	2600	92.9
		1: Yes	150	5.4
		Missing	< 15	D
	Number of subfamilies (subfamilies)	0	2700	96.4
		1	100	3.6
		2	< 15	D
	Persons per room (per_room)	0 to < 0.5	1600	57.3
		0.5 to < 0.75	700	25.1
		0.75 to ≤ 1	400	14.3
		> 1	90	3.2
	Persons per bedroom (per_bed)	0 to < 0.5	300	10.7
		0.5 to < 1	850	30.4
		1	850	30.4
		> 1 to < 1.25	< 15	D
		1.25 to < 1.5	200	7.1
		1.5 to < 1.75	200	7.1
		1.75 to < 2	20	0.7
		2	200	7.1
		> 2	100	3.6
		Missing	30	1.1
	Square feet per person (sq_per)	0: > 185	2400	86.6
		1: ≤ 185	70	2.5
		Missing	300	10.8
Lack of Safety (*SAFETY*)	Unsafe for children to play outside (unsafe_outsid e)	1: Very safe	550	19.9
		2: Moderately safe	250	9
		3: Not very safe	50	1.8
		4: Not at all safe	20	0.7
		Missing	1900	68.6
	Feeling unsafe inside home (unsafe_home)	1: Very safe	2300	83.6
		2: Moderately safe	400	14.5
		3: Not safe	50	1.8
		1: Very safe	1600	57.1
		2: Moderately safe	1000	35.7

Variable Name	Variable Label	Categories	Weighted Frequency	Weighted Percent
	Unsafe against break-ins (unsafe_break)	3: Not safe	200	7.1
		Missing	< 15	D
	Unsafe coming/leaving home at night (unsafe_night)	1: Very safe	1900	68.8
		2: Moderately safe	700	25.4
		3: Not very safe	90	3.3
		4: Not at all safe	50	1.8
		Missing	20	0.7

Notes: Some percentages do not add to 100 due to rounding. The "Weighted Percent" and "Unweighted Percent" columns present percentages based on the rounded counts. For variables where cells are suppressed due to inadequate observations (*N* < 15), the presented percentages are calculated using the rounded sample size as the denominator. "D" signifies a suppressed value.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The equations are virtually the same for the lack of safety and decency, or HI 3, dimension as the other HI dimensions. The only difference is the number of observed indicators. The HI 3 model, like lack of stable occupancy (HI 2), did not have any covariances between error terms. Exhibit 9 provides the path diagram of the HI 3 dimension.

Exhibit 9 | Lack of Safety and Decency (HI 3) Measurement Model



HI 3 = lack of safety and decency factor score.

Source: Authors' depiction of the HI 3 measurement model using variable names from the U.S. Census Bureau, 2019 American Housing Survey

Model Estimation

The study team produced CFA estimates for the models of the HI dimensions in Stata using full information maximum likelihood (FIML) estimation, which, as the name suggests, is an extension of maximum likelihood estimation that uses all information available in the data. Rather than throw out observations with missing information, observations with partial information are included in estimating model parameters. In essence, FIML implies a value for missing information based on the correlation between the variable with missing information and other variables in the dataset. The value of the missing observation is implied based on the value of other non-missing information for that observation. In concept, this is the same as imputation, although no values are imputed with FIML.

Enders and Bandalos (2001) found that FIML performs much better than listwise deletion and results in unbiased parameter estimates. Enders (2010), however, noted that for FIML to produce unbiased estimates, the missing data must be missing at random (MAR), which means that a variable's missingness is not related to the variable itself (in other words, the variable is missing randomly). For example, if higher-income individuals are less likely to report their income on a survey, the variable measuring income would not be MAR because the value of income itself predicts whether the variable is missing. On the other hand, under MAR, a variable's missingness may be explained by other variables in the dataset. Enders (2010) explained that if the variables that predict the missingness of the analytical variables of interest are included in the analytical model as "auxiliary variables," FIML will produce unbiased estimates. This concept is similar to introducing a control variable in a regression model. The control variable may not be of interest to the research question, but the researcher includes it in the analysis to estimate an unbiased coefficient between the variables of interest.

The study team identified auxiliary variables for both the HI 1 model and the HI 3 model. The observed variables in the HI 2 model only contained trivial amounts of missingness (see exhibit 6); thus, auxiliary variables were not required.

For HI 1, the variable measuring perceived severe housing cost burden had the largest amount of missing data (about 1 percent of households). The study team identified measures of receipt of assistance from family or friends and receipt of assistance from charity as auxiliary variables to include to ensure that the model produced the best possible estimates. The assistance from family and friends and from charity as auxiliary variables were included because they both have a high correlation (0.4 or higher) with perceived housing cost burden, and neither are part of the measurement model (Enders, 2010). For HI 3, the variable measuring the degree of safety for children playing outside had the most missing information (about 69 percent of households). This variable had so much missing data because it was not asked of households without children. The study team thus included the number of children present in the household under age 6 and the number of children present in the household aged 6 to 17 as auxiliary variables that predict the missing observations (Enders, 2010). The study team used the saturated correlates method to include the auxiliary variables in the measurement models (each auxiliary variable covaries with the error terms of each observed indicator; the auxiliary variables also covary with each other), which is recommended by Enders (2010). For both HI 1 and HI 3, adding the auxiliary variables had virtually no impact on the model parameters, which suggests that the missing information was already distributed randomly and further justifies the necessary assumption of MAR.

Model Evaluation and Refinement

The study team utilized an iterative approach to arrive at the final estimated CFA models for each dimension of HI. The study team began with the simplest model that replicated the factor structure of the subdimensions presented in the path diagrams above and refined the model until it had an acceptable level of fit to the data. Then the final step was adding in the higher-order factors.

To examine the results of the model, the study team utilized several goodness-of-fit statistics. First, the study team examined the model chi-square, the most rigorous estimate of model fit. The chi-square statistic shows the difference between the model estimated and a model that fits the data perfectly (in other words, a model that perfectly reproduces the covariance matrix of the observed indicators). If the chi-square statistic is insignificant, the model is not significantly different from a perfect-fitting model. Since most models are imperfect representations of the real world, the chi-square statistic is widely recognized as an important but overly restrictive estimate of model fit.

Another commonly used statistic is the comparative fit index (CFI), which estimates how much better the model estimated performs than a baseline model that assumes no relationship between the observed indicators. The CFI can range from 0 to 1, and the common cutoff used in the literature is 0.95, meaning the model performs 95 percent better than the baseline (Acock, 2013). If the CFI is 0.95 or better, there is evidence that the model is a good fit.

One issue with the CFI, however, is that it can indicate a good fit for overly complex models. In other words, it is possible to increase the CFI simply by adding additional indicators to the model, even if they have no substantive value. Another measure of fit, the root mean squared error of approximation (RMSEA), considers how much error there is for each degree of freedom (Acock, 2013). The measure adjusts for the degrees of freedom in the model and thus penalizes models that are overly complex (Acock, 2013). The common cutoff for the RMSEA is 0.05; anything below is considered a good fit (Acock, 2013). Below, the study team reports all three of these measures of model goodness-of-fit.[25]

The study team estimated the models and examined the goodness-of-fit statistics. If the CFI or RMSEA indicated a bad fit, the study team examined modification indices to see how to improve the model fit. Modification indices are Wald tests showing how the model chi-square would improve if a certain parameter were included. Most often, modification indices show that two or more error terms of indicators should covary with one another because the indicators share some variation that is not explained by the underlying latent concept. The model can account for this shared information by correlating the error terms and improving the fit. Another possible improvement from examining modification indices is the identification of an indicator that

[25] In Stata, the goodness-of-fit statistics are not available when applying sampling weights. The study team estimated goodness-of-fit using the unweighted data; however, all parameter estimates reflect the application of the sampling weight. It is possible that the goodness-of-fit statistics would change if they could be estimated with the sampling weight applied; however, the other model parameters do not change significantly after the application of the weight. Thus, the goodness-of-fit statistics reported here are an accurate representation of how well the models fit the data.

measures more than one latent concept in the model. If the indicator has some variation that could be explained by a latent concept in the model, but the indicator is not modeled on that latent variable, the fit of the model would decrease. Modification indices are an easy method to identify what parameters to estimate in a model to ensure that the model fits the data well; however, the study team was careful only to include parameters if they made intuitive sense.

As a final step, the study team evaluated the degree to which the measurement models were invariant across subgroups (for example, gender and race) by conducting differential item functioning (DIF) assessment (Beer, 2004). The study team performed DIF assessment on the subgroups listed in exhibit 2. For this project, DIF evaluation involved regressing the observed items and latent variables on a dummy code for subgroups in the context of the latent variable model (Stark, Chernyshenko, and Drasgow, 2006). A significant regression coefficient on an observed item reveals that, even for households with a similar level on the HI subdimension, households in the subgroup tend to have different values for the indicator. In other words, the measurement of the latent variable is different across subgroups.

Unlike other aspects of the measurement models, the study team was interested in preserving parsimony concerning DIF. If tests revealed weak or no DIF effects, the DIF criterion variable was removed from the model to avoid generating gold standard factor scores that incorporate measurement discrepancies across groups unless those discrepancies are sizable. To determine whether differences were sizable, the study team performed a log-likelihood ratio (LR) test that tested whether a model that allowed measurement differences across subgroups was significantly different from a constrained model that did not allow for differences across the subgroups. If the LR test was statistically significant, indicating a difference between the two models, the criterion variable for the subgroup was included in the final model the study team used to produce factor scores.

Factor Scores

Once the study team arrived at the final measurement models for each of the three dimensions of HI, the model-implied value was estimated for the higher-order factors, HI 1, HI 2, and HI 3. This action resulted in three continuous factor scores that ranked the 2,800 households in the sample on the three dimensions of HI. The study team assessed the relationship of the three gold standard factor scores to a set of validators to ensure that the scores performed as expected. Exhibit 10 lists the validators that the study team examined and the hypothesized relationship to the HI dimensions.

Exhibit 10 | List of External Validators

Category	Expected Relationship with HI	Variable Description
Neighborhood quality 1	Poor neighborhood quality associated with higher HI across all dimensions	1: Neighborhood has good schools, not a lot of petty crime, not a lot of serious crime, AND low risk for serious floods or other disasters 2: Neighborhood has bad schools, a lot of petty crime, a lot of serious crime, OR high risk for serious floods or other disasters

Category	Expected Relationship with HI	Variable Description
Neighborhood quality 2	Poor neighborhood quality associated with higher HI across all dimensions	1: Neighborhood DOES NOT HAVE factories or other industrial structures; buildings with metal bars; abandoned or vandalized buildings; AND trash, litter, or junk in streets, lots, or properties within half a block 2: Neighborhood HAS factories or other industrial structures; buildings with metal bars; abandoned or vandalized buildings; OR trash, litter, or junk in streets, lots, or properties within half a block
Food stamp or SNAP receipt	Recipients should have higher HI across all dimensions	1: Recipient 2: Not a recipient
Household disability	Unclear, but important to understand correlations to see how they change as study team developed a reduced measure	1: No individuals with disabilities in home 2: At least one individual with disabilities in home
Comparison of current housing costs to former	Moving to lower-cost housing may be associated with higher HI 2 Moving to higher-cost housing may be associated with higher HI 1	1: Decreased or stayed about the same 2: Increased
Public assistance income	Unclear, but important to understand correlations to see how they change as study team developed a reduced measure	Min: 0 Median: 0 Max: 14,000 Mean: 116
Amount of annual routine maintenance costs	Low maintenance costs associated with higher levels of HI 1 and HI 2	Min: 0 Median: 500 Max: 9,998 Mean: 853
Rating of neighborhood as a place to live	Low ratings associated with higher HI across all dimensions	Min: 1 Median: 8 Max: 10 Mean: 8
Rating of unit as a place to live	Low ratings associated with higher HI across all dimensions	Min: 1 Median: 8 Max: 10 Mean: 8
Food security of the household	Low food security associated with higher HI across all dimensions	1: High food security among adults 2: Marginal food security among adults 3: Low food security among adults 4: Very low food security among adults
Self-reported health	Poor self-reported health associated with higher HI across all dimensions	1: Excellent health 2: Very good health 3: Good health 4: Fair health 5: Poor health

Category	Expected Relationship with HI	Variable Description
Shelter poverty (composite variable)[a]	Higher shelter poverty associated with higher HI across all dimensions	1: Yes 2: No or other

HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. SNAP = Supplemental Nutrition Assistance Program.
[a] The study team constructed the variable indicating shelter poverty from a set of survey items. A household had shelter poverty if they indicated experiencing any of the following in the previous 12 months: difficulty buying food, difficulty paying for childcare, difficulty paying medical bills, difficulty paying for automobile expenses, difficulty increasing savings, difficulty getting health services, or difficulty paying for other debts.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Model Limitations

One assumption of FIML estimation is that the observed indicators follow a multivariate normal distribution. Many of the indicators in the measurement models are categorical and highly skewed. As a result, the parameter estimates and standard errors may incorporate some bias due to a violation of the multivariate normality assumption. Bollen (1989) noted, however, that FIML estimates ultimately converge to unbiased estimates even in the presence of non-normality, especially with larger sample sizes.

In estimating the measurement models, the study team utilized standard errors that are robust to non-normal data; however, this method would not correct for any potential bias in the coefficients. Little (2013) provided a breakdown of different analytical techniques for handling metric (continuous) and categorical (non-continuous) observed indicators. In the case of this study, many of the categorical indicators are reasonable approximations of an underlying continuous latent variable (for example, housing cost burden is likely a continuous measure that varies from household to household, but the measure is categorical and represents different key cut points; see exhibit 4). In this situation, Little (2013) noted that the researcher can specify a polychoric correlation matrix (rather than the default Pearson) as the baseline. Polychoric correlation theoretically corrects for the loss of information that results from categorizing the otherwise continuous variables; however, this assumes that the underlying latent variable is normally distributed. This study may encounter the same problem—violating the normality assumption. The study team tested models based on polychoric correlations and did not find large differences in the statistical significance or direction of the factor loadings.
Any bias in the estimates is minimal, and the factor scores produced are valid and reliable measures of lack of affordability, lack of stable occupancy, and lack of safety and decency.

Stage 2: Constructing Gold Standard Classification Statuses

With the gold standard factor scores in hand, the study team utilized latent profile analysis (LPA) to identify a set of HI classification statuses or profiles with different combinations of lack of affordability, lack of stable occupancy, and lack of safety and decency. LPA takes a set of continuous observed indicators—in this case, the three factor scores for each dimension of HI—and organizes the data into a set of profiles (the researcher specifies the number) based on each observation's values on the continuous indicators. The profiles represent an unordered, categorical latent variable that explains the relations between the observed indicators. LPA uses the expectation-maximization algorithm to find the solution for the profiles that best fits the data.

Model Formulation

The study team specified an LPA model that takes the form

$$f(y_i) = \sum_{k=1}^{K} [\pi_k \cdot f_k(y_i)] \tag{6}$$

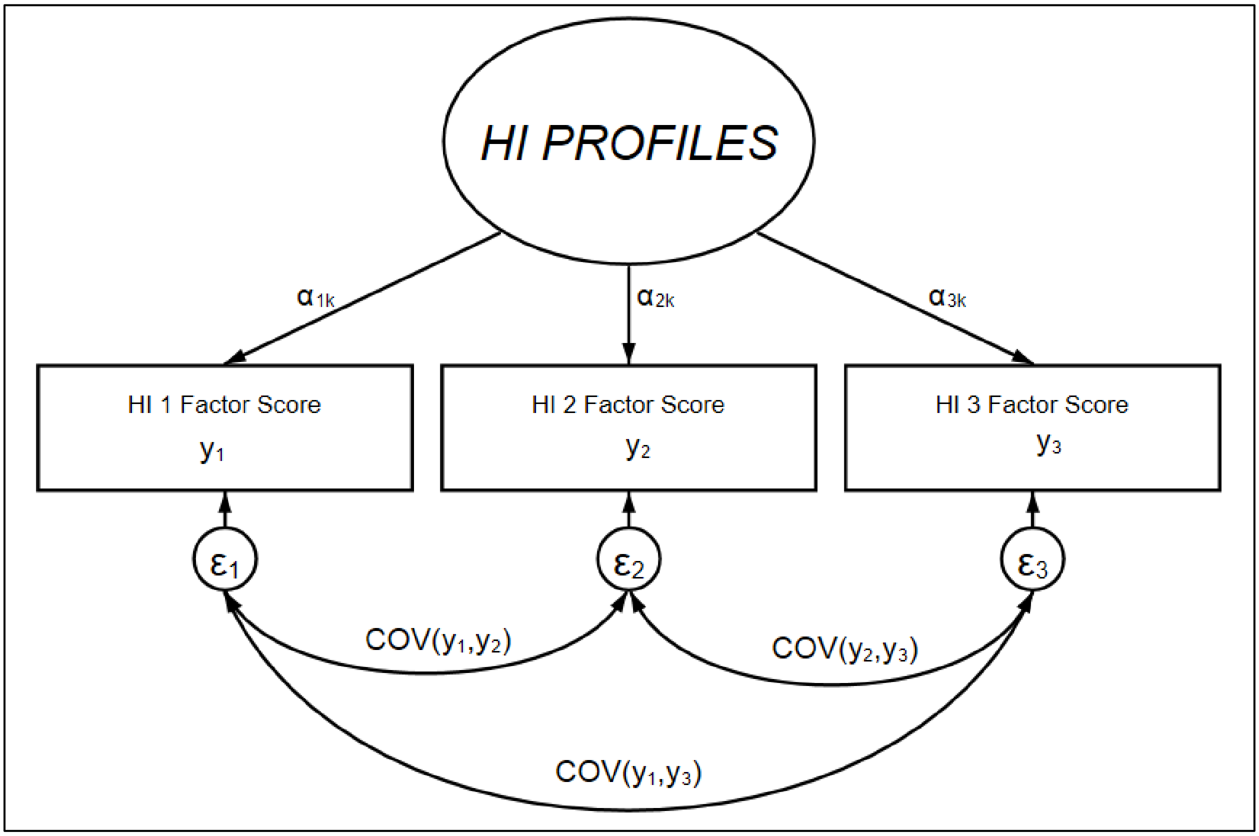
where y_i is the set of continuous observed indicators (in this case, the three factor scores), K is the number of profiles, π_k is the proportion of observations in each profile k, $f(y_i)$ is the multivariate probability density function for the sample, and $f_k(y_i)$ is the profile-specific density function for profile k. The LPA model identifies a probability that each household in the data is in each of the k profiles. In addition, the LPA model identifies the proportion of households estimated to be in each profile (π_k).

LPA assumes that the within-profile distribution of the continuous variables is multivariate normal so that

$$\begin{gathered} y_{i|k} = \alpha_k + \epsilon_{ik}, \\ \epsilon_{ik} \sim MVN(0, \Sigma_k) \end{gathered} \tag{7}$$

where α_k is a vector of the profile k means for each observed indicator and Σ_k is the profile k variance-covariance matrix for the observed indicators. The measurement parameters of an LPA are simply the means, variances, and covariances of the indicators for each profile. Exhibit 11 provides a path diagram representation of the HI LPA.

Exhibit 11 | HI LPA Model



HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score.
Source: Authors' representation

Model Selection

Following Masyn (2013), the study team tested different LPA model types to find the one that best fit the data. There are two primary choices the study team made when developing the final LPA model:

1. **Profile-invariant versus profile-varying standard deviations (SDs):** The study team decided whether to constrain the SD of each factor score to be the same in each profile (in other words, deciding whether to allow each ϵ in exhibit 11 to have a different SD within each profile or not). Profile-invariant SDs assume the range of values for each factor score to be roughly the same in each profile.

2. **Restricted versus unrestricted correlations:** The study team decided whether to constrain correlations between the factor scores in each profile to be zero (in other words, deciding whether to set the COV terms in exhibit 11 to zero or not). Restricted correlations assume that no pattern exists in terms of how the factor scores relate to one another within a profile; the profiles fully capture the relationships between the factors.

There are thus four potential model types, depending on the constraints applied:

1. **Profile-varying, unrestricted:** The observed indicators have different SDs and correlations for each profile.
2. **Profile-invariant, unrestricted:** The observed indicators have the same SDs and correlations for each profile.
3. **Profile-varying, diagonal:** The observed indicators have different SDs for each profile. Correlations between the indicators are constrained to zero for all profiles.
4. **Profile-invariant, diagonal:** The observed indicators have the same SDs for each profile. Correlations between the indicators are constrained to zero for all profiles.

To determine which model was the best, the study team followed the steps outlined in Masyn (2013). First, the study team estimated models with different numbers of profiles for each of the four types. The study team started with one profile and increased the number until the model began to have identification problems. The study team estimated each model 100 times using different random starting values each time and examined the log-likelihood values produced from the 100 different estimations. The study team assumed identification problems if the model did not converge to the maximum log-likelihood value for at least 10 percent of the iterations.

After producing the set of models with different numbers of profiles, the study team compared each model using the relative fit measures recommended by Masyn (2013). These include the Bayesian information criterion (BIC), the consistent Akaike's information criterion (CAIC), and the approximate weight of evidence criterion (AWE). Each of these measures essentially compares the log-likelihood values of the various models. Since a researcher could conceivably keep specifying a more and more complex model to minimize the log-likelihood, each of the fit indices includes a penalty term that considers model complexity (number of parameters and sample size). The fit measures differ slightly in terms of their penalty terms. Masyn (2013) suggested comparing each to ensure that models are compared rigorously and robustly.

The study team also used pairwise comparisons of models with k and $k + 1$ profiles to determine if the increase in the number of profiles significantly improved the model. The study team used the Bayes factor (BF) and the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT) described by Masyn (2013) for this purpose. When comparing model A to model B, a BF of 3 or greater is weak evidence for model A, a BF between 3 and 10 is moderate evidence for model A, and a BF greater than 10 is strong evidence for model A. The LMR-LRT produces a p-value that indicates whether the model with a larger number of profiles significantly improves the model or not. A significant p-value indicates a significant improvement.

Finally, the study team used the correct model probability (cmP) to compare models. The cmP indicates the probability that each model is the correct one compared to all other models in the set. The study team followed Masyn's (2013) advice and estimated the cmP for each group of models within each of the four types. Then the study team identified the best model within each type considering all the different fit indices, which resulted in four potential models (one for each type). As the last step, the study team estimated the cmP for the final four models and identified the best overall model.

Stage 3: Developing a Transferable Measure of HI

After developing and validating gold standard factor scores and classification statuses, the study team worked to develop a set of transferable, reduced measures of HI. The first step taken by the study team was to return to the gold standard measurement models and determine if any redundant variables could be removed from the models without a significant loss of information. To identify redundant variables, the study team estimated a graded response model (GRM) on the set of items in each gold standard measure. The study team chose the GRM model because it assumes categorical data and allows for the observed items to differ in terms of difficulty and discrimination (Engelhard, 2005). In the case of this research, item difficulty corresponds to the proportion of households in the most insecure category for the item. Items that are more "difficult" will have fewer households in the most insecure category than items that are less "difficult." In other words, it is easier to provide an insecure answer to a survey item if the item difficulty is low. Discrimination refers to an item's ability to distinguish between households with high and low HI. Households with low HI will tend to fall into more secure categories, and households with high HI will tend to fall into more insecure categories on an item with strong discrimination. Thus, if an item has weak discrimination, it has less utility as a measure of HI since households with high HI may still be in a secure category, or households with low HI may still be likely to be in an insecure category on the item. The GRM model and the item difficulty and discrimination parameters are described in more detail below.

A GRM is a model type in the item response theory framework that estimates the equivalent of a set of ordered logit models, one for each observed indicator, with a single latent independent variable, referred to as theta (θ). The variable theta is the underlying dimension that is measured by each of the observed indicators (in this study, theta would thus be lack of affordability, lack of stable occupancy, or lack of safety and decency, depending on the model being run).

One of the main parameters in the GRM is the item "difficulties." Each item has $r - 1$ difficulty parameters, where r is the number of response options for the item. For example, an item with four response options will have three difficulty parameters. The difficulty parameters provide the estimated theta value for which a respondent would have a 0.5 probability of answering the response option or any of the response options above it versus answering any of the response options below. For example, if *item a* has four response options, and the difficulty parameter for response option two is -2, that means that someone with a theta value of -2 would be equally as likely to answer item a with response options two, three, or four as they would to answer item a with response option one. Item difficulties are the same as the cut points in an ordered logit model.[26] The study team identified items with similar difficulty parameters for the highest response option as redundant because the items indicate HI at similar points in the dimension. If two items have very different difficulty parameters, one item is more sensitive than another and will identify a household as insecure at a lower point in the distribution of the HI dimension than the other variable.

The second parameter in the GRM is item discrimination. Each item has one discrimination parameter that indicates the degree to which the item discriminates between observations with

[26] In stage 3, unlike stage 1, the study team was not interested in modeling subdimensions of each dimension of HI. Rather, all variables were included in a GRM, and the study team assumed that theta is a unidimensional latent variable: either affordability, stable occupancy, or safety and decency. Based on the gold standard measures, each of the dimensions are multi-dimensional; however, in stage 3 the study team was only interested in identifying redundant variables that capture similar information in terms of the higher-order underlying dimension and do not need to capture the multi-dimensionality of each HI dimension.

higher and lower values of theta. In the GRM, the study team can identify items that are stronger measures of the underlying dimension as those with larger discrimination parameters because they do a better job of distinguishing between insecure and secure households.

The GRM is expressed with the following equation for the probability of selecting the qth option or higher, $P_{j,q}^{+}(\theta)$, on the jth item:

$$P_{j,q}^{+}(\theta) = \frac{exp\{a_j(\theta - b_{j,q})\}}{1 + exp\{a_j(\theta - b_{j,q})\}} \tag{8}$$

In equation 8, a_j is item j's discrimination and $b_{j,q}$ is item j's difficulty for response option q or higher.

After running a GRM on the items in each gold standard measure, the study team identified items with similar difficulty parameters for the highest response option.[27] Items with similar difficulty parameters are potentially redundant. If there was an item with clearly higher discrimination among the items with similar difficulties, the study team identified the items with lower discrimination as candidates for removal. In cases where items with similar difficulties also had similar discrimination, the study team examined each item's total information (similar to the coefficient of variation or r-squared) and selected the item that explained the most information. Using this process, the study team was able to develop reduced measures for lack of affordability, lack of stable occupancy, and lack of safety and decency.

The study team reran a GRM on each reduced set of items and developed reduced scores (weighted sums) for each dimension of HI using the item discrimination parameters from the reduced GRM as the item weights in the sum. The discrimination was used as the weight because variables with higher discrimination are more closely associated with the HI dimension and should thus be weighted more heavily in the score than items with weaker discrimination. Without the weight, the study team would have made an implicit assumption that each item contributes to HI equally, which is not the case based on both the GRM and the stage 1 analyses. The study team then validated the reduced measures by calculating each reduced measure's correlation with the gold standard measures and each reduced measure's correlations with the list of external validators. The reduced measures should have strong correlations with the gold standard measures and correlate with the validators similarly to the gold standard measures.

Finally, after validating the reduced measures, the study team created a look-up table that specifies the ranges of each reduced measure for each HI profile identified in stage 2. The reduced measures and the look-up table are meant to be practical and transferable measures of overall HI and each dimension of HI.

The results in this report provide promising evidence that the reduced measures are good measures of HI that perform similarly to the gold standard factor scores and have comparable distributions. The reduced measures also assign households to the correct HI profiles most of the

[27] Several of the items had multiple categories. Comparing difficulty for just the highest response option helped simplify the reduction process. In addition, the study team was most interested in the highest response option because this is the option that is most clearly related to HI.

misclassification error are virtually always explained by the erroneous classification of a household to a more secure profile than what the gold standard scores would assign. This misclassification is expected since the reduced items contain fewer variables than the gold standard measures and are thus less sensitive to HI. Misclassification also increases if fewer survey items are included in the reduced measure (see results below comparing the long, medium, and short forms reduced measures in exhibit 45). Although these findings show promise for using the reduced measures in HI research, more testing with a larger random sample is needed.

RESULTS

Below are the detailed results of each of the three analytical stages of the Housing Insecurity Research Study. First are the stage 1 results of CFA models for each of the three dimensions of HI and the resulting gold standard factor scores. Then, this report shows the results of the stage 2 LPA that identified six profiles (gold standard classification statuses) of HI based on the gold standard factor scores. The study team examines how each profile relates to poor self-reported health, food insecurity, and shelter poverty to understand whether the profiles can be ordered on an underlying dimension of overall HI. Finally, this report presents results informed by the stage 3 GRM models that facilitated the development of transferable, reduced measures of HI. The study team provides results that show how each reduced measure relates to external validators and how well the reduced measures classify households into the six profiles identified in stage 2.

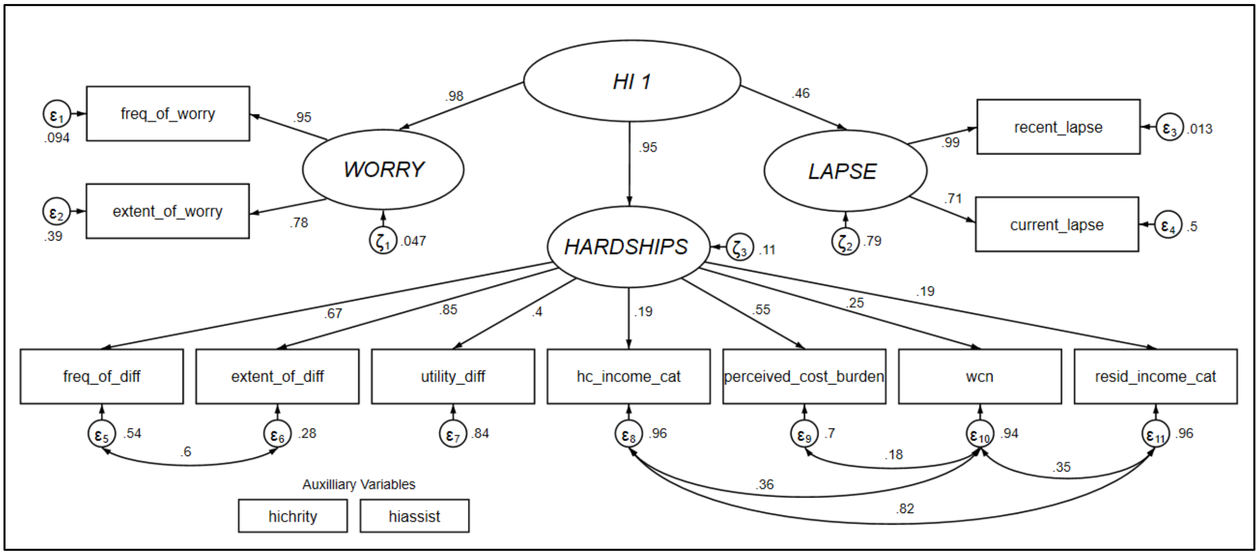
Stage 1: Gold Standard Factor Scores

The first stage of the analysis involved developing and estimating CFA measurement models for each dimension of HI. Below are the results of the measurement models and goodness-of-fit statistics, findings from DIF tests that identify whether the measurement of HI differs for any subgroups present in the sample, and information on the gold standard factor scores estimated from the final stage 1 CFA measurement models.

Measurement Model Results

Exhibit 12 presents the standardized results of the higher-order CFA for lack of affordability (HI 1). Each of the variables in the model is described in exhibit 4 and appendix B. Since the results are standardized (meaning the mean of HI 1 is zero and the variance is 1), the factor loadings in the model can range from -1 to 1, with 1 indicating a perfect positive association, -1 indicating a perfect negative association, and 0 indicating no association. Also, with standardized results, the error variances (shown next to each error term) are the proportion of the indicator's variance that is not explained by the latent variable it measures. For example, the model shows that the subdimension lapse in housing payment (*LAPSE*) explains all but about 1 percent of the variation for recent lapses in housing payments (recent_lapse). All parameters in the model are statistically significant ($p < 0.001$).

Exhibit 12 | Results: Weighted Lack of Affordability (HI 1) Measurement Model



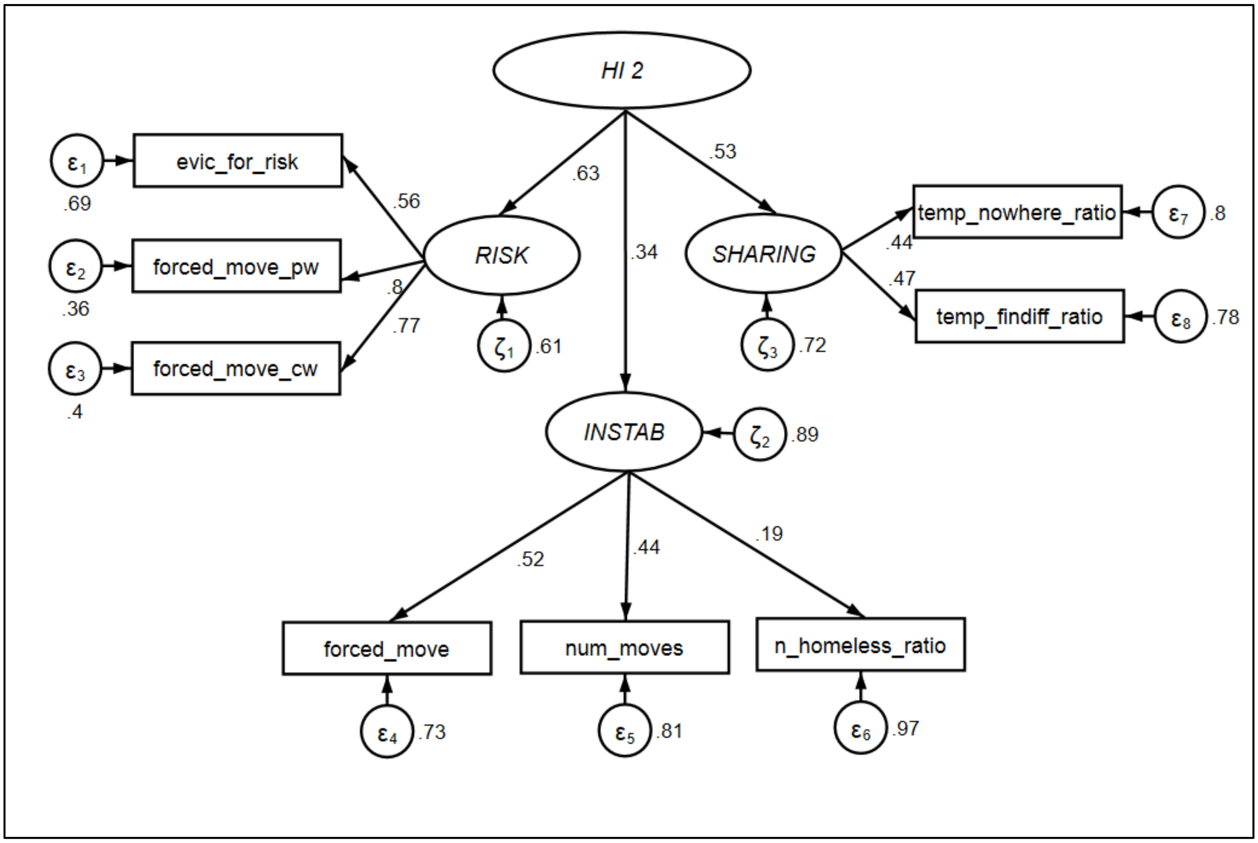
HI 1 = lack of affordability factor score.
N = 2,800.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The results in exhibit 12 show that worry about inability to pay housing costs (*WORRY*) and housing expense hardships (*HARDSHIPS*) are the strongest measures of HI 1, as both have loadings above 0.9. Lapse in housing payment (*LAPSE*) is more moderately associated with HI 1, suggesting that lapses in payments may be caused by circumstances other than lack of affordability issues.

The HI model results also show that each indicator observed is positively associated with the underlying subdimension, as expected. The observed indicators for both lapse in housing payments and worry about inability to pay housing costs have strong loadings (0.7 or higher). Housing expense hardships (*HARDSHIPS*) has some of the weakest measures. For example, housing cost burden and residual income both have factor loadings of 0.19, suggesting that while housing expense hardship is positively related to these objective measures of cost burden, the subdimension is better measured by the subjective measures, such as the reported extent of difficulty in making payments and perceived severe cost burden. This finding highlights that the HI 1 factor score will assign higher levels of HI to households that report higher subjective measures in the HIRM.

Exhibit 13 shows the standardized results for the lack of stable occupancy (HI 2) higher-order CFA. The variables included in the model are discussed in exhibit 6 as well as in appendix B. The model shows that forced move risk and worry (*RISK*) is the strongest measure of stable occupancy HI, with a factor loading of 0.63. Household sharing (*SHARING)* is the next strongest measure, and residential instability or dislocation (*INSTAB*) is the weakest, although still positive and statistically significant. Unlike the HI 1 model, none of the subdimensions are strong measures of HI 2. Additional indicators that are more associated with lack of stable occupancy may improve the measure. However, it is also possible that the subdimensions have other causes beyond HI 2 and that some aspects of stable occupancy—for example, the proportion of people in the household that experienced homelessness—are rare events. If HI 2 is skewed and somewhat bifurcated due to relatively rare indicators, it would result in lower factor loadings since variation in HI 2 would be limited.

Exhibit 13 | Results: Weighted Lack of Stable Occupancy (HI 2) Measurement Model

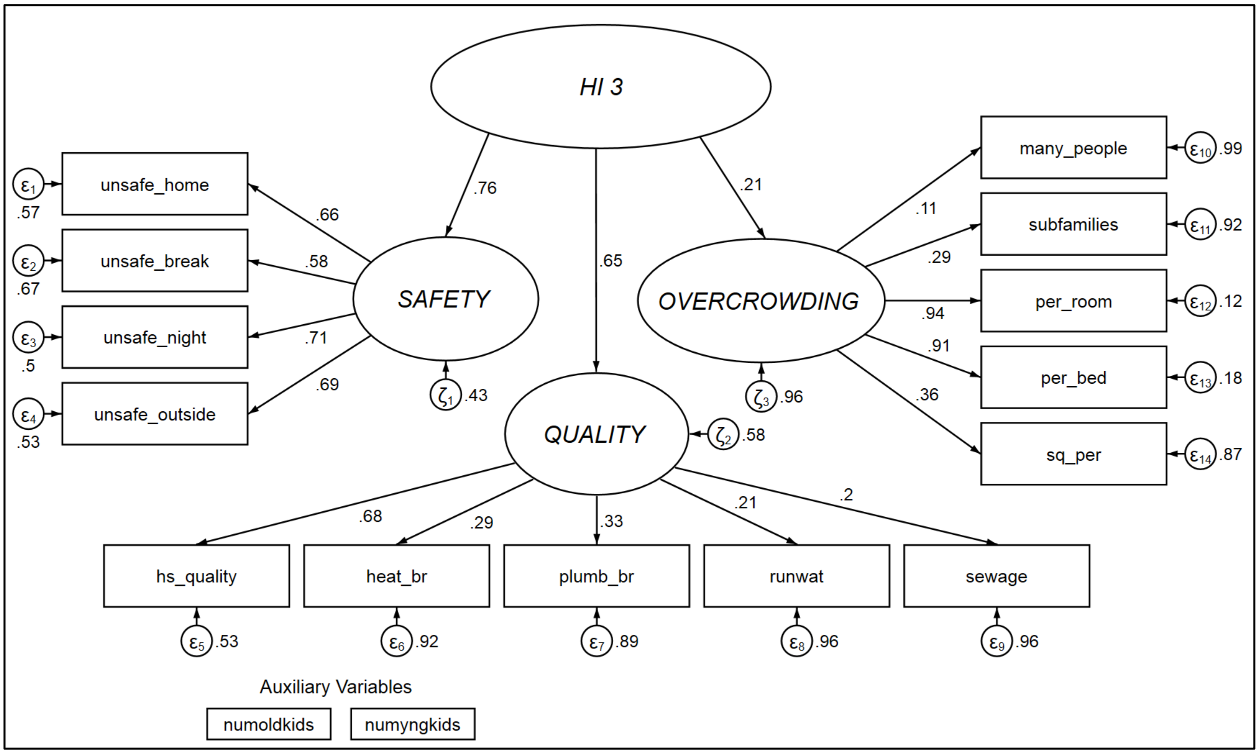


HI 2 = lack of stable occupancy factor score.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The observed indicators for each subdimension of HI 2 are positive and statistically significant. The proportion of people in the home who experienced homelessness (n_homeless_ratio) is the weakest measure, with a factor loading of 0.19, but most households (almost 99 percent) do not have any individuals that have experienced homelessness, so a small loading is expected.

Exhibit 14 shows the standardized results for the lack of safety and decency (HI 3) higher-order CFA. The variables included in the model are described in exhibit 8 as well as in appendix B. The findings show that lack of safety (*SAFETY*) and poor housing quality (*QUALITY*) are the strongest measures of HI 3. Overcrowding (*OVERCROWDING*) is a weaker measure, with a loading of 0.21. In addition, HI 3 only explains about 4 percent of the variation in overcrowding. As stated previously, this is not an indication of a poor model. Instead, it shows that lack of safety and decency is only one potential cause of overcrowding; there are likely many other causes, such as location in a highly dense area, cultural differences, and so on.

Exhibit 14 | Results: Weighted Lack of Safety and Decency (HI 3) Measurement Model



HI 3 = lack of safety and decency factor score.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Like the other measurement models, the observed indicators of the subdimensions of HI 3 are all positive and statistically significant. For lack of safety, the indicators are roughly equal in terms of factor loadings. For overcrowding, the best measures are the number of people per room (per_room) and the number of people per bedroom (per_bed). For poor housing quality, the number of quality issues in the household (hs_quality) is the best measure, although the breakdown measures are also positive and significant, as expected.

Finally, exhibit 15 shows goodness-of-fit statistics that the study team produced from the unweighted results of the measurement models. As discussed in the methods section, these standard goodness-of-fit statistics are not available when a sampling weight is applied; however, since the unweighted and weighted results were very similar, these goodness-of-fit statistics are still useful.

Exhibit 15 | Model Goodness-of-Fit Statistics

	χ^2	CFI	RMSEA
Affordability	285.9*	0.984	0.05
Stable Occupancy	91.61*	0.975	0.04

Safety and Decency	292.2*	0.975	0.033

CFA = confirmatory factor analysis. RMSEA = root mean squared error of approximation.
* $p < 0.05$.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

In all cases, the final higher-order CFA models met the common standards for a good fit. The literature suggests that the CFI should be 0.95 or higher, and the RMSEA should be 0.5 or lower (Acock, 2013). The study team also reports the model χ^2. A model that is no different from a model that fits the data perfectly should have a statistically insignificant χ^2. In practice, most models, especially complex ones such as the higher-order CFAs, have statistically significant χ^2. The CFI and RMSEA offer alternative, but still very robust, estimations of model fit.

DIF Assessment

As described in the methods section, the study team also performed DIF assessment to understand whether the measurement models performed the same way for various subgroups in the sample. Exhibit 16 provides the findings of the LR tests. A statistically significant LR test indicates the presence of DIF.

Exhibit 16 | Likelihood Ratio Test Results: Chi-Square Value and Significance Level by Subgroup and Dimension

No.	Sub-Group	HI 1	HI 2	HI 3
1	Race (Black/Non-Black)	$p > 0.1$	$p > 0.1$	$p > 0.1$
2	Hispanic	$p > 0.1$	$p > 0.1$	$p > 0.1$
3	Age (Over 65)	$p > 0.1$	$p > 0.1$	$p > 0.1$
4	Gender	$p > 0.1$	$p > 0.1$	$p > 0.1$
5	Interview Language (Non-English interview)	$p > 0.1$	$p > 0.1$	$p > 0.1$
6	New Construction	**$p < 0.001$**	**$p < 0.001$**	**$p < 0.001$**
7	Metro Area	**$p < 0.001$**	**$p < 0.001$**	**$p < 0.001$**
8	Household with Children	$p > 0.1$	$p > 0.1$	$p > 0.1$
9	Tenure [Renter; Owner; Occupied Without Payment of Rent]	$p > 0.1$	$p > 0.1$	$p > 0.1$
10	Income Relative to Poverty Level	$p > 0.1$	$p > 0.1$	$p > 0.1$
11	Census Division	$p > 0.1$	$p > 0.1$	$p > 0.1$
12	Census Region	$p > 0.1$	$p > 0.1$	$p > 0.1$
13	HUD Subsidized (only renters) [not subsidized; eligible but not subsidized; eligible and subsidized]	$p > 0.1$	$p > 0.1$	$p > 0.1$

HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score.
Note: Bolded likelihood ratio tests indicate the presence of differential item functioning (DIF).
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Only two group variables, metropolitan status and new construction, had significant DIF, and these findings were consistent across each measurement model. It is understandable that the three different dimensions of insecurity are measured differently in metropolitan areas compared to non-metropolitan areas. For instance, it may be that certain observed indicators, such as housing cost burden, are more important in determining lack of affordability in metropolitan areas compared to non-metropolitan areas. Further, observed indicators such as unsafe against break-ins or persons per room relate differently to the lack of safety and decency indicators in metropolitan areas compared to non-metropolitan areas. Similarly, the share of people that experienced homelessness may relate differently to lack of stable occupancy in metropolitan areas compared to non-metropolitan areas.

In the case of new construction, it is likely that observed indicators such as housing quality and service breakdowns related differently to lack of safety and decency when the unit is newly constructed compared to when it is not.

The study team incorporated both grouping variables in the measurement models before estimating the gold standard factor scores to account for the presence of DIF in new construction and non-metropolitan areas.

Factor Scores

The study team estimated the model-implied scores for each dimension of HI from each higher-order CFA. Exhibit 17 shows summary statistics describing the factor scores. The study team standardized the factor scores to have means of zero and variances of one to increase interpretability. The exhibit shows that the factor scores are skewed to the right, so the medians all tend to be lower than the mean. HI 1 has the least skew (and kurtosis), while HI 2 has the most (which also helps explain the lower factor loadings in exhibit 13). HI 3 has the largest spread in terms of values, ranging from -1.54 to 10.54.

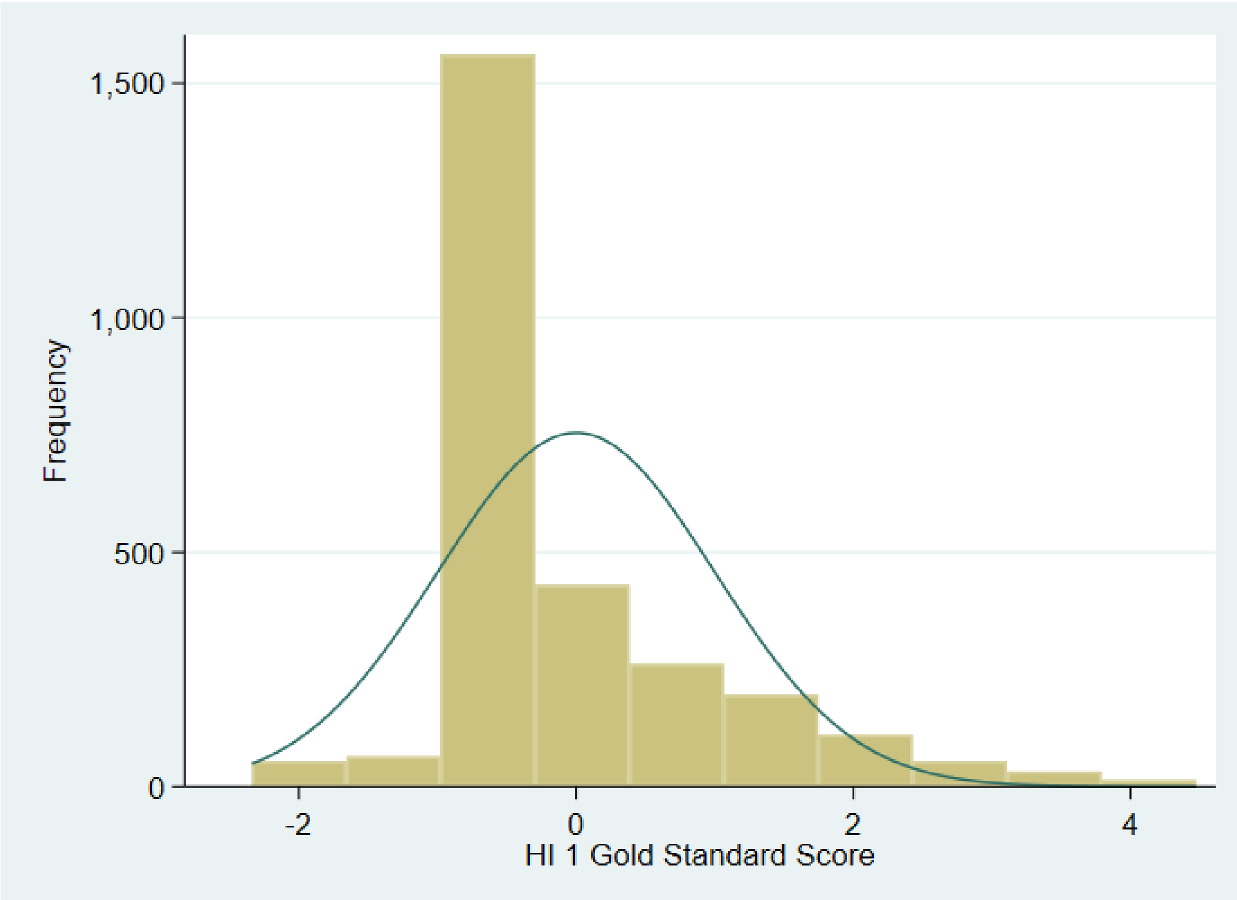
Exhibit 17 | Gold Standard Factor Score Descriptive Statistics

	Minimum	Median	Maximum	Mean	Variance	Skewness	Kurtosis
HI 1	– 2.34	– 0.46	4.47	0	1	1.54	5.65
HI 2	– 0.95	– 0.45	7.77	0	1	2.91	13.02
HI 3	– 1.54	– 0.24	10.54	0	1	2.13	11.86

HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

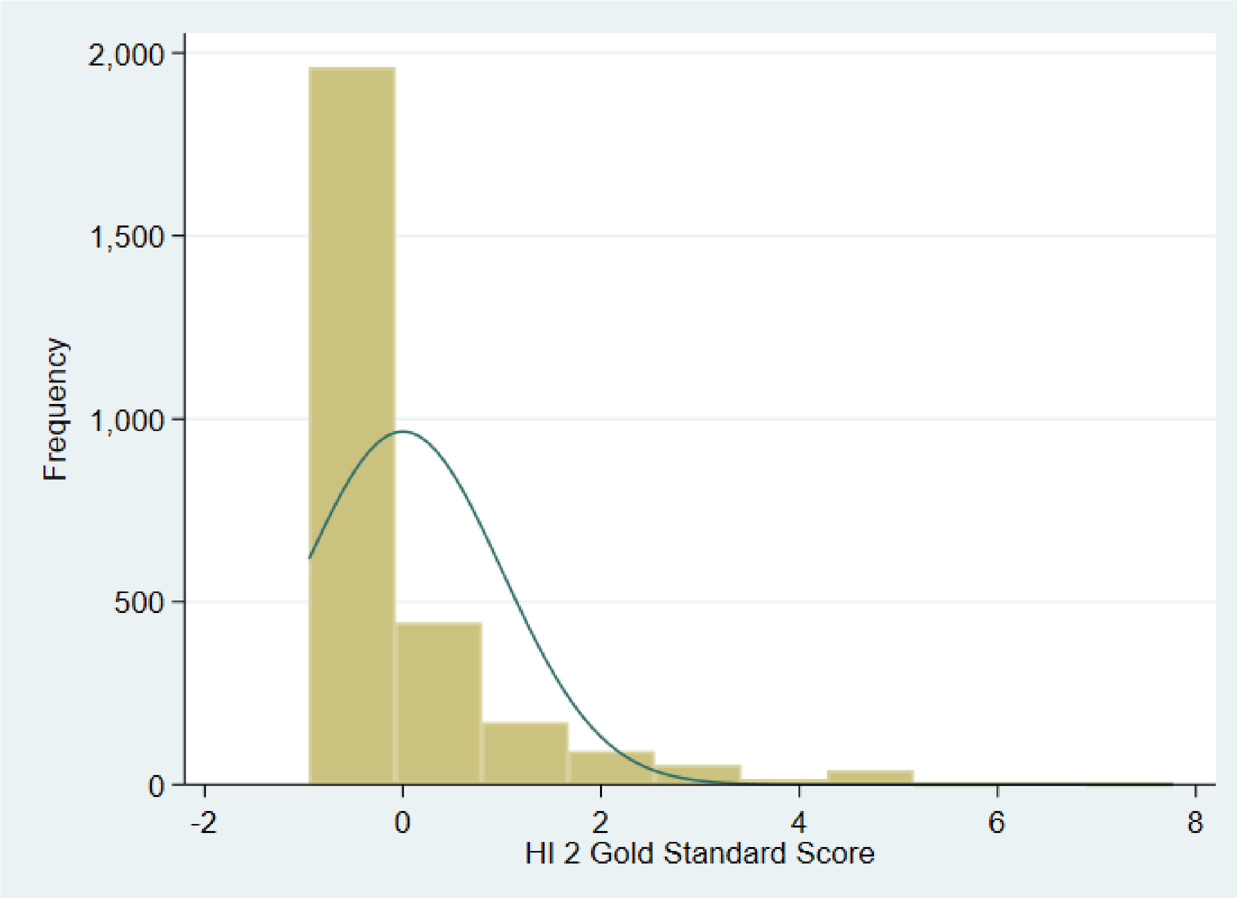
Exhibits 18, 19, and 20 show histograms of each of the three factor scores against a standard normal distribution. The exhibits further demonstrate the skewness of the scores, suggesting that many households have relatively low HI; however, a small number have extremely high levels. Exhibit 19 is also striking in that it shows that more than half of the sample has identical values for HI 2. These households have an identical response pattern for the HI 2 questions in the HIRM. The factor score value for these households is -0.45 (the median value of the distribution, highlighting one downside of using categorical data: there is likely to be less variation in the scores across the sample.

Exhibit 18 | Affordability Factor Score Histogram



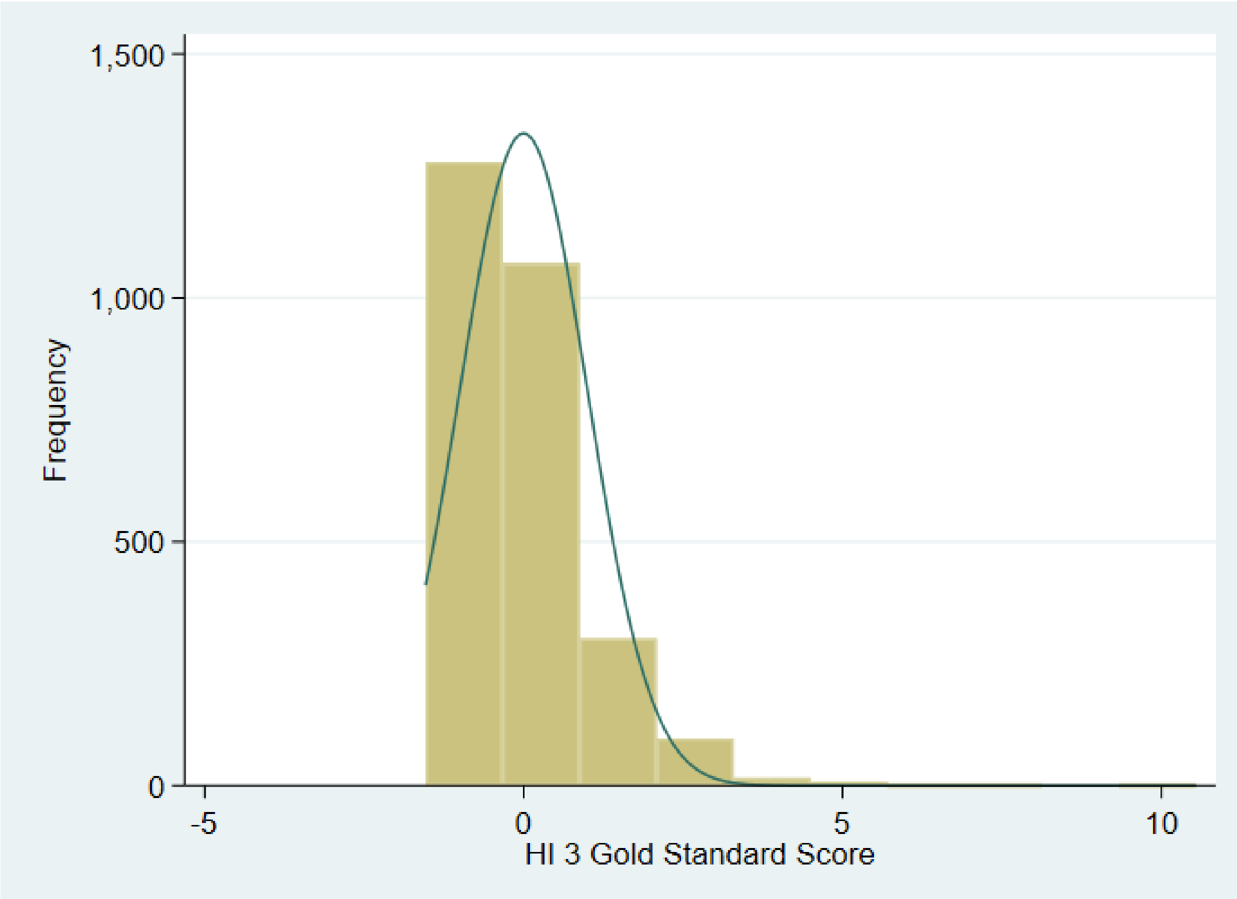
HI 1 = lack of affordability factor score.
Notes: Subtracted mean and divided by standard deviation to standardize factor scores for comparison purposes. Factor scores rounded to four significant digits.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 19 | Stable Occupancy Factor Score Histogram



HI 2 = lack of stable occupancy factor score.
Notes: Subtracted mean and divided by standard deviation to standardize factor scores for comparison purposes. Factor scores rounded to four significant digits.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 20 | Safety and Decency Factor Score Histogram



HI 3 = lack of safety and decency factor score.
Notes: Subtracted mean and divided by standard deviation to standardize factor scores for comparison purposes. Factor scores rounded to four significant digits.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The study team assessed the relationship between the standardized gold standard factor scores for the three dimensions of HI against a set of validators to see whether the scores performed as expected. For binary validators—that is, validators with only two categories—for each HI dimension, the study team compared the mean factor score in one category with the mean factor score in another category and conducted a one-way *t*-test to test whether the scores were significantly different from each other across categories. For categorical validators with more than two categories, the study team examined the Spearman correlation between the validators and dimensions of HI. For continuous validators, the study team examined the Pearson correlation between the validators and dimensions of HI. Exhibit 21 provides a list of the validators that the study team examined, the hypothesized relationship to the HI dimensions, and the direction and statistical significance of the relationship between the validators and the HI dimensions.

Most of the external validators have the expected relationships with the three HI dimensions. For some external validators, even though the direction of the relationship with an HI dimension is as expected, the relationship is not statistically significant. For instance, poor neighborhood quality (1) is associated with higher HI 2, as expected, but this relationship is not statistically significant. In the case of the validator that compares current housing costs to former housing costs, moving to higher-cost housing is associated with higher HI 2, contrary to expectations. However, this relationship is not statistically significant. Finally, in the case of one external validator (lower maintenance costs), the results indicate a statistically significant relationship, contrary to expectations. Lower maintenance costs were expected to be associated with higher levels of HI 1 and HI 2. However, the results indicate that housing with higher maintenance costs is associated with higher HI 1, and this relationship is statistically significant.

Exhibit 21 | External Validators and Factor Scores for Dimensions of HI: Direction and Significance of Correlation

Validator	Expected Relationship with HI	Actual Relationship with HI
Neighborhood quality 1 (binary)	Poor neighborhood quality associated with higher HI across all dimensions	Poor Neighborhood Quality 1 is associated with— Higher HI 1 $p < 0.0001$ Higher HI 2 $p < 0.0001$ Higher HI 3 $p < 0.0001$
Neighborhood quality 2 (binary)	Poor neighborhood quality associated with higher HI across all dimensions	Poor Neighborhood Quality 2 is associated with— Higher HI 1 $p < 0.0001$ Higher HI 2 $p < 0.0001$ Higher HI 3 $p < 0.0001$
Food stamp or SNAP receipt (binary)	Recipients should have higher HI across all dimensions	Households that are food stamp recipients also have— Higher HI 1 $p < 0.0001$ Higher HI 2 $p < 0.0001$ Higher HI 3 $p < 0.0001$
Household disability (binary)	Unclear, but important to understand correlations to see how they change as study team developed a reduced measure	Households with at least one individual with disabilities also have— **Higher HI 1** $\boldsymbol{p > 0.1}$ Higher HI 2 $p < 0.01$ Higher HI 3 $p < 0.0001$
Comparison of current housing costs to former (binary)	Moving to lower-cost housing may be associated with higher HI 2; Moving to higher-cost housing may be associated with higher HI 1	Moving to higher-cost housing is associated with— Higher HI 1 $p < 0.01$ **Higher HI 2** $\boldsymbol{p > 0.1}$ Higher HI 3 $p > 0.1$
Public assistance income (continuous)	Unclear, but important to understand correlations to see how they change as a reduced measure is developed	Higher public assistance income is associated with— Higher HI 1 $p < 0.05$ Higher HI 2 $p > 0.1$ Higher HI 3 $p < 0.01$
		Higher maintenance cost is associated with—

Validator	Expected Relationship with HI	Actual Relationship with HI	
Amount of annual routine maintenance costs (continuous)	Low maintenance costs associated with higher levels of HI 1 and HI 2	**Higher HI 1** Higher HI 2 Higher HI 3	$\boldsymbol{p < 0.01}$ $p > 0.1$ $p < 0.01$
Rating of neighborhood as a place to live (continuous)	Low ratings associated with higher HI across all dimensions	Lower ratings are associated with— Higher HI 1 Higher HI 2 Higher HI 3	 $p < 0.0001$ $p < 0.0001$ $p < 0.0001$
Rating of unit as a place to live (continuous)	Low ratings associated with higher HI across all dimensions	Lower ratings are associated with— Higher HI 1 Higher HI 2 Higher HI 3	 $p < 0.0001$ $p < 0.0001$ $p < 0.0001$
Food insecurity of the household (categorical)	Food insecurity associated with higher HI across all dimensions	Food insecurity is associated with— Higher HI 1 Higher HI 2 Higher HI 3	 $p < 0.0001$ $p < 0.0001$ $p < 0.0001$
Poor self-reported health (categorical)	Poor self-reported health associated with higher HI across all dimensions	Poor self-reported health is associated with— Higher HI 1 Higher HI 2 Higher HI 3	 $p < 0.0001$ $p < 0.0001$ $p < 0.0001$
Shelter poverty (composite variable)	Shelter poverty associated with higher HI across all dimensions	Difficulty paying for any non-housing needs is associated with— Higher HI 1 Higher HI 2 Higher HI 3	 $p < 0.0001$ $p < 0.0001$ $p < 0.0001$

HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score. SNAP = Supplemental Nutrition Assistance Program.
Note: Bold text indicates a finding counter to expectations.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Certain measures are widely used in the literature to capture dimensions of HI. Housing Cost Burden, a categorical measure of the share of housing cost to household income, is a widely used measure of HI 1; number of moves is a measure of HI 2; and housing adequacy is a measure of HI 3. Exhibit 22 presents the correlation between standard measures of HI and gold standard factor scores for each dimension of HI. The correlations are positive and statistically significant, as expected, though they are weak (between 0.3 and 0.4). The gold standard scores were developed from many different variables that capture different aspects of each of the three dimensions of HI. On the other hand, the standard measures of housing cost burden, number of moves, and housing adequacy measure only one aspect of each dimension (housing expense hardships, residential instability or dislocation, and poor housing quality, respectively). The study team thus did not expect the gold standard scores to have strong correlations with the standard measures, which may miss much of the nuance of HI.

Exhibit 22 | Spearman Correlation Between Factor Scores and Corresponding Standard HI Measure

Factor Score	Standard HI Measure	Spearman Correlation
Affordability Insecurity	Housing Cost Burden	0.3493***
Stable Occupancy Insecurity	Number of Moves	0.3343***
Safety and Decency Insecurity	Housing Adequacy	0.3925***

HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score.
*** Indicates *p*-value < 0.01.
Notes: Housing Cost Burden has three categories: housing cost < 30 percent of household income, housing cost 30–50 percent of household income, and housing cost > 50 percent of household income. Number of moves has two categories: none or one move, and two moves or more.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The study team also evaluated the gold standard factor scores and the standard HI measures against established correlates of HI: food insecurity of the household and poor self-reported health. Exhibit 23 presents the Spearman correlation between food insecurity, poor self-reported health, and the measures of HI. All measures of HI have a statistically significant relationship with food insecurity and poor self-reported health at the 5-percent significance level. However, the standard measures have much weaker correlations and a negative correlation with the external validators in the case of the number of moves. The gold standard measures, which have stronger positive correlations with the external validators, are likely better and more nuanced measures of HI.

Exhibit 23 | Spearman Correlation Between HI Measures and Food Insecurity and Poor Self-Reported Health

HI Measures	Food Insecurity of the Household	Poor Self-Reported Health
Factor Score HI Dimensions		
HI 1	0.2745***	0.1414***
HI 2	0.2614***	0.1517***
HI 3	0.2741***	0.2622***
Standard HI Measures		
Housing Cost Burden	0.1210***	0.0405**
Number of Moves	0.0598***	– 0.0473**
Housing Adequacy	0.1626***	0.1169***

HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score.
** Indicates *p*-value < 0.05.
*** Indicates *p*-value < 0.01.
Notes: Housing Cost Burden has three categories: housing cost < 30 percent of household income, housing cost 30–50 percent of household income, and housing cost > 50 percent of household income. Number of moves has two categories: none or one move, and two moves or more.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Stage 2: Gold Standard Classification Statuses

After producing the gold standard factor scores based on the stage 1 analyses, the study team implemented an LPA that identified six profiles of HI. Below is a discussion of the results identifying the LPA model with the best fit for the data and the LPA results for a six-profile model. The labels for each profile explain how the profile relates to overall HI.

Model Selection

The study team followed the process Masyn (2013) recommended to identify the best model for the LPA used to identify gold standard classification statuses. Exhibit 24 provides the results of the model selection process, comparing relative fit indices, including the Bayesian information criterion (BIC), consistent Akaike's information criterion (CAIC), and the approximate weight of evidence criterion (AWE), as well as pairwise comparisons between models with k and $k + 1$ profiles, including the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT) and Bayes factor (BF). Finally, the study team examines the correct model probability (cmP), which identifies the best-fitting model among a set of models with different constraints or different numbers of profiles. As described in the methods section, lower values for each of the relative fit indices indicate a model with a better fit to the data. A statistically significant (< 0.01) LMR-LRT and a BF less than 0.10 indicates that the model with one more class (the row below) is a better fit. A cmP closer to 1 also indicates a good model. First, the study team calculated the cmP for models within each of the four model types and identified the best model. Then the study team calculated the cmP for those four models again and identified the best model of the second group. The yellow rows in the exhibit are the best models based on all the criteria for the specific model type. The green is the best model overall and is the final model selected to perform the LPA.

Exhibit 24 also shows that for the strictest model—the profile-invariant, diagonal model—the study team was able to estimate models with up to three profiles before facing identification issues. This outcome was expected, given the large variation in the factor scores. The profile-invariant models constrain the variance of the indicators to be the same across the profiles, which is not a good assumption in the presence of skewed data. The study team was able to estimate models with up to five profiles with the profile-varying, diagonal model; up to four profiles with the profile-invariant, unrestricted model; and up to six profiles with the profile-varying, unrestricted model.

Finally, exhibit 24 shows that relative fit statistics almost always improved with the number of profiles in the models. The four best models were the models with the largest number of profiles for each model type. The final best model was the profile-varying, unrestricted model with six profiles.

Exhibit 24 | Model Selection Criteria

Model Type	# of Profiles	Log Likelihood	# of Parameters	BIC	CAIC	AWE	Adj. LMR-LRT *p*-value	BF	cmP	cmP (Best 4 models)
Profile-invariant, diagonal	1	– 10670	7	23690	23690	23760	< 0.01	< 0.10	< 0.01	
	2	– 10150	14	21440	21460	21600	< 0.01	< 0.10	< 0.01	
	3	– 11820	21	20459	20480	20690	--	--	> 0.99	< 0.01
Profile-varying, diagonal	1	– 11820	7	23690	23690	23760	< 0.01	< 0.10	< 0.01	
	2	– 6569	14	13250	13260	13400	< 0.01	< 0.10	< 0.01	
	3	– 5527	21	11220	11240	11450	< 0.01	< 0.10	< 0.01	
	4	– 4505	28	9232	9260	9538	< 0.01	< 0.10	< 0.01	
	5	– 4216	35	8710	8745	9093	--	--	> 0.99	< 0.01
Profile-invariant, unrestricted	1	– 11530	10	23130	23140	23240	< 0.01	< 0.10	< 0.01	
	2	– 10580	20	21330	21350	21550	< 0.01	< 0.10	< 0.01	
	3	– 10050	30	20340	20370	20670	< 0.01	< 0.10	< 0.01	
	4	– 9786	40	19890	19930	20330	--	--	> 0.99	< 0.01
Profile-varying, unrestricted	1	– 11530	10	23130	23140	23240	< 0.01	< 0.10	< 0.01	
	2	– 6485	18	13110	13130	13310	< 0.01	< 0.10	< 0.01	
	3	– 5498	28	11220	11250	11520	< 0.01	< 0.10	< 0.01	
	4	– 5329	38	10360	10100	11370	< 0.01	< 0.10	< 0.01	
	5	– 4149	46	8663	8709	9166	< 0.01	< 0.10	< 0.01	
	6	– 4069	56	8592	8638	9194	--	--	> 0.99	> 0.99

AWE = approximate weight of evidence criterion. BF = Bayes factor. BIC = Bayesian information criterion. CAIC = consistent Akaike's information criterion. cmP = correct model probability. LMR-LRT = Lo-Mendell-Rubin likelihood ratio test.

Notes: Highlighted rows are the best models within each type. These four models were compared against one another using the $\widehat{cmP}$ measure. The final model selected is the green row. Cells at the maximum number of profile for each model type have a "—" in the cell for Adj.LMR-LRT p-value and BF because they do not have a $k + 1$ profile with which a pairwise comparison can be made.

Source: U.S. Census Bureau, 2019 American Housing Survey

Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Profiles of Housing Insecurity

Exhibit 25 provides a brief definition of each profile identified using LPA, shows whether the gold standard scores tended to be higher (+) or lower (-) for households in the profile, and shows how the study team ranked each profile in terms of overall HI.

Exhibit 25 | HI Profiles

Profile	HI 1	HI 2	HI 3	Relationship to Overall HI
Housing Secure: households that have low scores on all three dimensions	-	-	-	Very Low HI
HI Only Instability: households that have high scores for HI 2, but low scores for HI 1 and HI 3	-	+	-	Low HI
HI Affordable: households that have low scores for HI 1 and high scores for at least one other dimension	-	+	+	Moderate HI
HI Stable Housing: households that have low scores for HI 2 and high scores for at least one other dimension	+	-	+	High HI
HI Safe and Decent: households that have low scores for HI 3 and high scores for at least one other dimension	+	+	-	High HI
HI All Dimensions: households that have high scores on all three dimensions	+	+	+	Very High HI

HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score.
Notes: Cells with (+) denote that the gold standard scores are higher for households in the profile. Cells with (-) denote that the gold standard scores are lower for households in the profile.
Source: Authors' summary of the LPA results

Exhibit 26 provides detailed results from the six-profile LPA model. The exhibit first shows the means, standard deviations (SDs), and correlations of the gold standard factor scores for the entire sample. Since the scores were standardized, each had an overall mean of zero and an SD of one. The correlations between the gold standard scores show that they are all positively related to one another. Specifically, H1 and H2 have a correlation of 0.323, H1 and H3 have a correlation of 0.246, and H2 and H3 have a correlation of 0.250.

The exhibit then shows the means, SDs, and correlations of the factor scores for households within each of the six profiles. If the profile has a negative and statistically significant mean, it means that households in the profile typically have smaller values on the gold standard factor score than the overall sample; and if the profile has a positive and statistically significant mean, then it includes households that typically have higher values on the gold standard factor score. The SDs show the degree of variability in the factor scores in each profile. If the SD is larger, the range of values that the score takes within the dimension is much more variable. In all profiles except for the HI All Dimensions profile, the SDs are smaller than the overall sample, implying that within each profile, the range of values of each factor score is relatively tight. In the case of HI All Dimensions, the SDs are likely larger because the profile includes households with very extreme values for each of the gold standard factor scores. Finally, the correlations within each profile show how the factor scores are related to one another for households in the profile. In some profiles, the correlations are positive and statistically significant, similar to the overall sample; however, in other cases, the correlations are insignificant (bolded red text), indicating no relationship, or negative, indicating that households with higher scores on one dimension will typically have lower scores on the other. Profiles with negative correlations may include households making tradeoffs between the different dimensions. For example, the HI Affordable profile, which shows a negative correlation between HI 1 and H2, may include households that choose to live in affordable housing that is less stable rather than housing that is more stable and less affordable. Below, the specific findings for each profile are described in more detail.

Exhibit 26 | LPA Results

	Variable	Mean	SD	Correlations		
				HI 1	HI 2	HI 3
Overall Sample	HI 1	0	1	1		
	HI 2	0	1	0.323	1	
	HI 3	0	1	0.246	0.250	1
Profiles	**Variable**	**Mean**	**SD**	**Correlations**		
				HI 1	**HI 2**	**HI 3**
Housing Secure (32.8%)	HI 1	– 0.525	0.043	1		
	HI 2	– 0.450	0.032	**0**	1	
	HI 3	– 0.483	0.449	**– 0.039**	**0**	1
HI Instability Only (1.7%)	HI 1	– 0.307	0.857	1		
	HI 2	4.662	0.834	0.765	1	
	HI 3	**0.096**	0.705	0.466	0.568	1
HI Affordable (11.8%)	HI 1	– 0.511	0.047	1		
	HI 2	– 0.174	0.560	– 0.453	1	
	HI 3	– 0.190	0.728	– 0.172	0.162	1
HI Stable Housing (23.9%)	HI 1	0.146	0.932	1		
	HI 2	– 0.450	0.032	**0**	1	
	HI 3	0.195	0.951	**– 0.020**	**0**	1
HI Safe and Decent (15.7%)	HI 1	0.394	0.987	1		
	HI 2	0.106	0.542	0.135	1	
	HI 3	– 0.249	0.525	0.173	0.216	1
HI All Dimensions (14.0%)	HI 1	1.002	1.537	1		
	HI 2	1.297	1.153	0.265	1	
	HI 3	1.223	1.443	**– 0.083**	– 0.232	1

HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score. SD = standard deviation.
Note: **Bolded red text** indicates a result that is not statistically different from zero ($p > 0.05$).
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The most common of the six profiles is Housing Secure (32.8 percent of households), which includes households with low scores on all three dimensions that live in secure housing. The means of the three dimensions of HI are all below the overall mean, indicating a low level of HI. The SD and correlations are also small/statistically insignificant.

HI Instability Only includes households that are extremely insecure in terms of stable occupancy but live in relatively affordable and safe, decent homes. The profile is the smallest and only includes about 1.7 percent of households in the sample. Households in this profile have much higher levels of HI 2 than households in the overall sample (mean of 4.662). On the other hand, they have lower levels of HI 1 (-0.307) and about average levels of HI 3 (the mean is not statistically different from zero). The correlations show that the dimensions are all positively related to one another. Households with higher levels of HI 2 will tend to have higher levels of HI 1 and HI 3, but HI 2 is always much larger (more insecure) than the other two dimensions, which are much more likely to be on the secure end of the distribution.

About 11.8 percent of the sample falls in the HI Affordable profile. Households in this profile live in affordable housing. The mean of HI 2 is negative (-0.174), but, importantly, because HI 2 is so skewed, households in this profile are more instable than the overall sample (the median value of HI 2 is -0.45, which is lower than the HI Affordable profile mean of -0.174). Also, HI 2 and HI 3 negatively correlate with HI 1 in this profile, which indicates that households in the profile with lower levels of HI 1 tend to have higher levels of HI 2 and HI 3. The HI Affordable profile thus likely includes households that choose to live in more affordable homes, despite those homes being more instable and less safe and decent.

The HI Stable Housing profile is the second largest after Housing Secure, with about 23.9 percent of households. Households in this profile live in stable homes that typically are slightly less affordable and less safe and decent. The mean of HI 2 is low (-0.45), while the mean of HI 1 and H3 are higher than the overall sample (0.146 and 0.195, respectively). There is virtually no relationship between the HI dimensions in this profile (the correlations are all statistically insignificant). Thus, regardless of the severity of HI 1 or HI 3, households in this profile live in stable housing.

The HI Safe and Decent profile has about 15.7 percent of households in the sample. Households in this profile live in safe and decent homes that are more unaffordable and instable. The mean of HI 3 is low (-.249), while the means of the other dimensions are higher than the overall sample (.394 and .106, respectively). The correlations between the scores for households in this profile are all positive, suggesting that as any of the dimensions increase or decrease, the others do the same. Thus, households in this profile always have lower levels of HI 3 (in other words are more safe and decent) compared to the other dimensions.

Finally, HI All Dimensions, which includes about 14 percent of the households in the sample, clearly represents households that are very housing insecure on all dimensions. The means of the HI dimensions are all well above the overall sample means. The variance of the HI dimensions in this profile is also large, indicating that a small number of households have very high insecurity relative to most of the sample. One interesting finding is that HI 2 and HI 3 negatively correlate in this profile, which could indicate that there are potentially two types of insecure households in this profile: households that have very high HI 3 and moderately high HI 2, and households that have moderately HI 3 and very high HI 2. This attribute could have been explored more in a model with seven profiles; however, the model with seven profiles was not well-identified, and thus the study team could not pursue this line of thought further with the LPA.

Exhibit 27 provides the mean of poor self-reported health, food insecurity, and shelter poverty scores from the AHS data for each of the profiles the study team identified in the LPA. Both poor self-reported health and food insecurity range from 1 to 5, with 1 indicating the highest or best level of health/food security and 5 indicating the worst. The study team expects profiles with more HI to have higher scores for all three variables. Thus, poor self-reported health, food insecurity, and shelter poverty serve as criterion variables that can help show the relationship of each of the profiles to an underlying HI continuum. Profiles with higher means for the poor self-reported health, food insecurity, and shelter poverty variables should have higher overall HI.

Exhibit 27 | Mean of Poor Self-Reported Health and Food Insecurity for Each HI Profile

Overall HI	Profile	Poor Self-Reported Health Mean	Food Insecurity Mean	Shelter Poverty Mean
Very Low HI	Housing Secure	2.56	1.19	1.03
Low HI	HI Instability Only	2.43	1.26	1.13
Moderate HI	HI Affordable	2.74	1.31	1.06
High HI	HI Stable Housing	2.96	1.61	1.18
High HI	HI Safe and Decent	2.97	1.69	1.25
Very High HI	HI All Dimensions	3.41	2.43	1.56
	Overall	2.85	1.55	1.17

HI = housing insecurity.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 27 shows, as expected, that the most secure households (with less poor self-reported health, lower food insecurity, and lower shelter poverty) are those with low scores on all three dimensions, and the most insecure households (higher poor self-reported health, higher food insecurity, and higher shelter poverty) are those with high scores on all three dimensions. Households in profiles that lie between these two poles likely make tradeoffs between the different HI dimensions. Based on the mean poor self-reported health, food insecurity, and shelter poverty of households in these profiles, the study team concluded that households in the HI Instability Only profile are the least insecure after those that are low on all three dimensions (Housing Secure). The means of poor self-reported health, food insecurity, and shelter poverty are not statistically different from the means in the Housing Secure profile.[28] These households are labeled as having Low HI. Households in the HI Affordable profile are more insecure but not as much as the other profiles. The mean for shelter poverty in the HI Affordable profile (1.06) was lower than the mean in the HI Only Instability profile (1.13) and not statistically different from the Housing Secure profile, but this is understandable given that households living in more affordable units should have less shelter poverty. The means for both poor self-reported health

[28] The study team tested for statistical significance ($p < 0.05$) using linear regressions with self-reported health, food insecurity, and shelter poverty as the outcome variables and an indicator variable of the profile as the independent variable with the Housing Secure profile set as the reference category.

(2.74) and food insecurity (1.31), on the other hand, are higher than the HI Only Instability profile (2.43 and 1.26, respectively) and statistically different from the Housing Secure profile. These households are labeled as having Moderate HI. Next, households in the HI Stable Housing or HI Safe and Decent profiles are even more insecure. These two profiles had very similar mean values for poor self-reported health, food insecurity, and shelter poverty. The households in either of these profiles are labeled as having High HI. The most insecure households are those that are high on all three dimensions. These households are labeled as having Very High HI.

Stage 3: Reduced Measure of Housing Insecurity

This section describes the reduced measures developed that capture each dimension of HI. For each dimension, the study team details the measures that have the highest correlation with the gold standard factor score, as these measures are strong candidates to retain in the reduced measures. Then, the study team provides the list of variables ultimately selected for the reduced measures based on the graded response models. The study team developed long, medium, and short forms reduced measures. The long form reduced measures have the most variables and are thus more burdensome to collect via a survey and may involve more complex analysis; however, the results show that the long form typically does a better job of capturing the range of HI for each dimension. The medium form measures fall between the long and short forms in terms of the number of variables and, thus, the degree of nuance captured in terms of HI. The short form measures have the smallest number of survey items and are thus the most practical of the three in ease of data collection and analysis; however, they likely contain the least amount of information compared to the gold standard score.

Included for each reduced measure is a weight for each item in the measure that researchers can use to develop a composite score. Researchers who wish to replicate the reduced scores presented could either use existing AHS and HIRM data or conduct a new survey data collection with a different sample. If conducting a new survey data collection, the researcher can include questions that correspond to the items included in the reduced scores. The specifics of each item in each HI dimension are included in appendix B.

In addition to presenting the reduced scores, the study team also validated the scores against a series of external validators and compared how the reduced scores compare with the gold standards. Each reduced score performed similarly to the gold standard factor scores. The study team also analyzed whether the measurement of the reduced scores differed across subgroups in the data. As with the gold standard scores, metro areas and new construction were found to differ from non-metro areas and older construction for the reduced scores. The study team experimented with developing different sets of weights for different subgroups of the data to account for the measurement variance; however, this quickly became time consuming, and the practicality of the scores was significantly reduced. Moreover, the resulting scores did not appear to perform any better than scores produced from weights that did not vary across subgroups. The study team thus elected not to incorporate measurement variance in the reduced scores; however, future research may investigate how HI can be measured in different contexts and how this impacts findings from statistical analyses using scores of HI.

After validating the reduced scores, look-up tables were developed to show which HI profile a household should be classified in based on the values from the reduced scores for each dimension of HI. look-up table for the long, form, and short form reduced scores. Finally, the study team the number and percent of households that are correctly classified into each of the HI profiles with each of the reduced scores and how each of the profiles developed from the reduced scores compare to one another and the gold standard profiles in terms of poor self-reported health, food insecurity, and shelter poverty.

Building a Reduced Lack of Affordability (HI 1) Measure

To build a reduced and more transferable measure of lack of affordability, which the study team refers to as HI 1, it is helpful to first look at the Pearson correlations that each of the items in the HI 1 model has with the gold standard factor score. Items with the largest correlations will likely need to be in the reduced model to ensure that the reduced model retains the same information as the gold standard model. Exhibit 28 shows how each of the HI 1 indicators correlates with the gold standard score. Variables with the highest correlation include frequency of worry about payments, extent of worry about payments, frequency of difficulty in making payments, and extent of difficulty in making housing payments. A reduced measure that includes these items will likely have a higher correlation with the gold standard than a measure that excludes them.

Exhibit 28 | Pearson Correlations of Lack of Affordability (HI 1) Items with the Gold Standard

Indicator	Label	Correlation (Pearson)
ai_freq_of_worry	Frequency of worry about mortgage/rent payments	0.8849
ai_extent_of_diff	Extent of difficulty in making housing cost payments	0.7548
ai_extent_of_worry	Extent of worry about mortgage/rent payments	0.7341
ai_freq_of_diff	Frequency of difficulty in making housing cost payments	0.6254
ai_perceived_cost_burden	Perceived severe housing cost burden	0.4973
ai_recent_lapse	Recent (in the past 12 months) lapses in housing payments	0.4365
ai_utility_diff	Difficulty paying utilities	0.3603
ai_current_lapse	Current lapses in housing payments	0.3150
ai_wcn	Worst case needs	0.2064
ai_residual_income	Residual income	0.1509
ai_hc_income_cat	Housing cost burden	0.1383

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 29 provides the weights for each measure in the long, medium, and short form reduced scores. The weights correspond to the measure's discrimination in the graded response models estimated for each reduced score (see appendix G for more detail on how the reduced set of variables was determined and the weights applied). The long, medium, and short form reduced scores differ in terms of the measures included in the composite score and the weights for each measure included. Variables that the study team excluded from all three reduced scores include difficulty paying utilities, housing cost burden, worst case needs, and residual income. The study team identified these variables as having redundancy with at least one other item based on the results of the graded response model (see appendix G).

Exhibit 29 | Measures and Survey Items in the Lack of Affordability (HI 1) Dimension and Their Weights in the Reduced Scores

Subdimension	Measures	Survey Items from AHS Core and HIRM Used to Develop Measures	Weight in Long Form	Weight in Medium Form	Weight in Short Form
Worry about inability to pay housing costs	**Frequency of worry about mortgage/rent payments**	HISTPAY	4.1	9	9
	Extent of worry about mortgage/rent payments	HISTNOW	3.8	0	0
Lapse in housing payments	**Recent (in the past 12 months) lapses in housing payments**	HIBFREQ	2.3	2.4	2.4
	Current lapses in housing payments	HICTCHUP	2.2	0	0
Housing expense hardships	**Frequency of difficulty in making housing cost payments**	HIDIFFPAY	12.4	0	0
	Extent of difficulty in making housing cost payments	HIAFFORD	10.2	4	3.9
	Difficulty paying utilities	HIBLLPAY, HIUTLPAY, HIBLLPAY2, HISHUTOFF	0	0	0
	Housing cost burden	TOTHCAMT (HUD created from 40 different housing cost sources), HINCP (HUD created from 19 different sources of income)	0	0	0
	Perceived severe housing cost burden	HIHALF	1.9	2	0
	Worst case needs	WCN (HUD created from income, area median income, assistance, housing cost, and housing adequacy variables)	0	0	0
	Residual income	TOTHCAMT and HINCP	0	0	0

AHS = American Housing Survey. HIRM = Housing Insecurity Research Module.
Note: Items in grey are not included in any of the reduced measures.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 30 compares the long, medium, and short form scores in terms of the number of survey items and correlation with key external validators. The exhibit shows that the gold standard measure is based on 16 items in the AHS and HIRM, while the reduced measures are based on significantly fewer items. In the case of HI 1, the long form score has a lower correlation with the gold standard than the other reduced measures; however, its distribution (see exhibit 31) is closer to the gold standard than the other scores. The long form likely has a lower correlation with the gold standard because of the different weights applied to each item in the measure (see exhibit 29). The weights ensure that the measure accurately captures the distribution of the gold standard but may result in some deviation around the mean, which is less present in the medium and short form reduced measures. Each reduced measure has very similar correlations with the external validators and is highly comparable to the gold standard score. This finding is strong evidence that the reduced measures would perform similarly to the gold standard in statistical analyses.

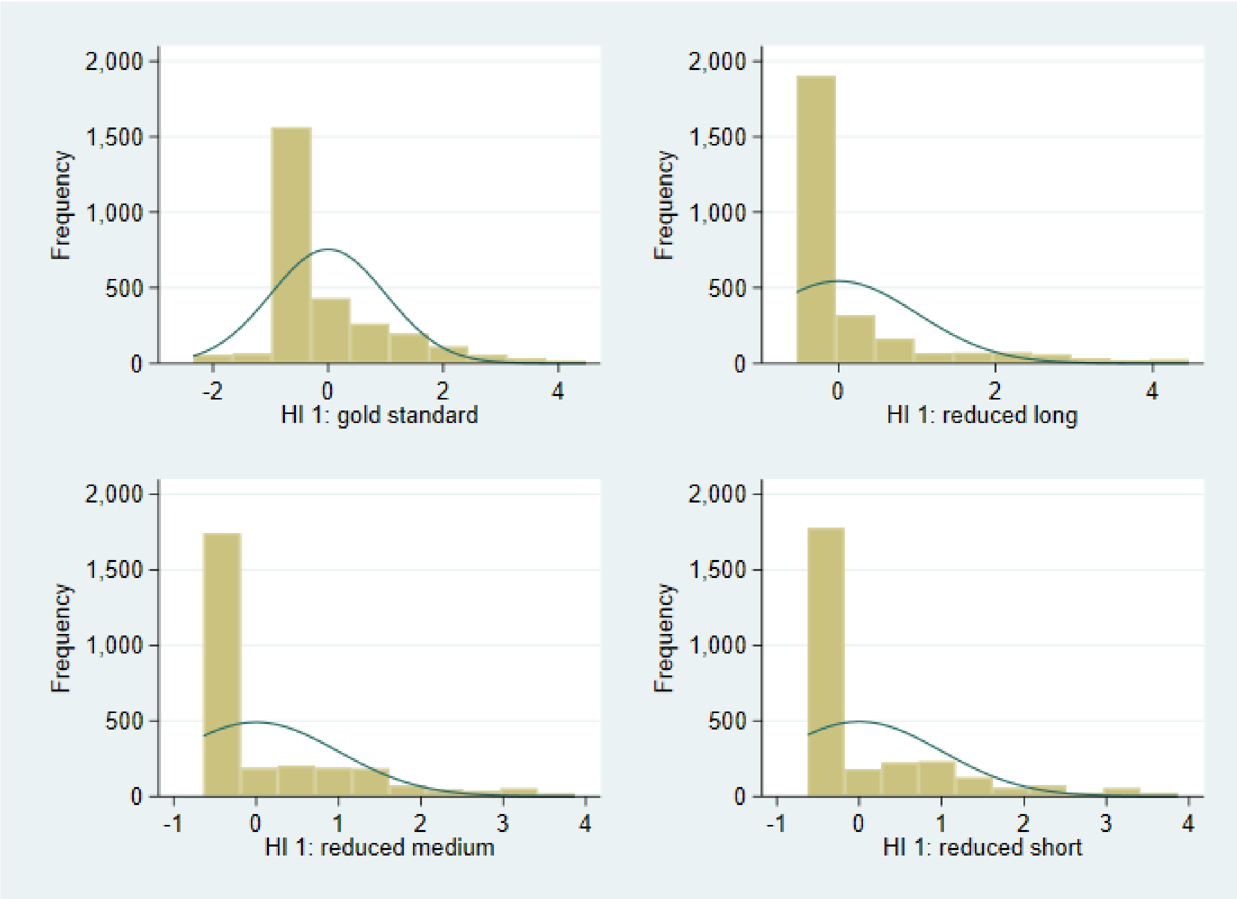
Exhibit 30 | | Lack of Affordability (HI 1) Gold Standard and Reduced Scores: Number of Survey Items and Correlations with External Validators

	Gold Standard	Reduced Long	Reduced Medium	Reduced Short
Number of Survey Items	16	7	4	3
Correlation with the Gold Standard	1	0.8257	0.9016	0.8995
Correlations with External Validators				
Poor self-reported health	0.1492	0.1838	0.1868	0.1869
Food insecurity	0.2975	0.3535	0.3757	0.378
Shelter poverty	0.4908	0.5374	0.5444	0.5426
Neighborhood quality 1	0.1572	0.162	0.1786	0.1767
Neighborhood quality 2	0.1117	0.0999	0.1188	0.1156
Food stamp or SNAP receipt (1 = yes, 2 = no)	– 0.1096	– 0.1406	– 0.1643	– 0.1628
Household disability (1 = yes, 2 = no)	– 0.0097	– 0.0339	– 0.0144	– 0.017
Comparison of current housing costs to former	0.1182	0.0896	0.1111	0.1095
Public assistance income	0.046	0.0571	0.0669	0.066
Amount of annual routine maintenance costs	0.078	0.0638	0.0442	0.0545
Rating of neighborhood as a place to live	– 0.1651	– 0.1954	– 0.2055	– 0.2098
Rating of unit as a place to live	– 0.2076	– 0.2253	– 0.2436	– 0.2441

SNAP = Supplemental Nutrition Assistance Program.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 31 shows the distribution of the gold standard factor score and the reduced factor scores for lack of affordability (HI 1) in histograms. Each score was standardized to have a mean of 0 and an SD of 1 to make the scores more comparable across the graphs. While the standardized scale of each score is the same, the range of values on the x-axis varies because the range of possible values of each score differed slightly. The long form reduced measure is closest to the gold standard; however, there is still some loss of information, especially at the more housing secure end of the measure. Each of the reduced measures is similar in terms of the range of values it captures.

Exhibit 31 | Lack of Affordability (HI 1) Histograms: Gold Standard and Reduced Scores



HI 1 = lack of affordability factor score.
Notes: Subtracted mean and divided by standard deviation to standardize factor scores for comparison purposes. Factor scores rounded to four significant digits.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Building a Reduced Lack of Stable Occupancy (HI 2) Measure

Exhibit 32 shows the correlations between the lack of stable occupancy items and the lack of stable occupancy gold standard factor score (HI 2). Previous worry about a forced move is the strongest correlation, followed by current worry about a forced move. At least one of these items will likely need to be included in the reduced measure.

Exhibit 32 | Pearson Correlations of Lack of Stable Occupancy (HI 2) Items with the Gold Standard

Indicator	Label	Correlation (Pearson)
so_forced_move_pw	Previous worry about a forced move	0.6456
so_forced_move_cw	Current worry about a forced move	0.6301
so_evic_for_risk	Risk of eviction or foreclosure	0.4698
temp_findiff_ratio	Proportion of persons in the housing living there because of financial difficulties	0.3110
temp_nowhere_ratio	Proportion of people in the household living there because they have nowhere else to go	0.2911
so_forced_move	Forced move	0.2581
so_num_moves	Number of moves	0.1731
n_homeless_ratio	Proportion of people in the household that have experienced homelessness	0.1563

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 33 provides the weights from the graded response models for each measure of HI 2 for the long, medium, and short form reduced scores. The study team found that a forced move and the proportion of persons living in the household living there because of temporary financial difficulties were redundant with other variables and removed these from the reduced measures (see appendix G for more detail). In addition, in the medium form and short form measures, the risk of eviction or foreclosure variable was reduced by removing all questions related to previous risks and the eviction notice variable.

Exhibit 33 | Measures and Survey Items in the Lack of Stable Occupancy (HI 2) Dimension and Their Weights in the Reduced Scores

Subdimension	Measures	Survey Items from AHS Core and HIRM Used to Develop Measures	Weight in Long Form	Weight in Medium Form	Weight in Short Form
Forced move risk and worry	**Risk of eviction or foreclosure (see footnote for definitional change in medium form)***	HIMRTFORC, HINFORC, HILVEFORC, HIEVFORC2, HIEVICT, HIEVICPREV, HIEVICLK, HIEVICT2, and HIEVICPREV2	2.1	2.6	0
	Previous worry about forced move**	HIMOVFRC	12	13	0.9
	Current worry about forced move**	HIMOVWR	2.9	2.9	0
Residential instability or dislocation	Forced move	HIEVLNDLD, HIEVFEAR, HIEVCNDM, HIEVCNDM2, HIMVDISAS, HIMVDISAS2, HIEVRAISE, HIEVNOFIX, and HIEVFORC	0	0	0
	Number of moves	HIINTDATE, HIMOVEDATE, and HILIVNUM	0.2	0.2	0
Household sharing	**Proportion of persons in the household who have experienced homelessness**	HIHMLESS, HIHMLESS2, NUMPEOPLE	1.2	1.1	2.6
	Proportion of persons in the household who are living there temporarily because they have nowhere else to go	HINOWHR, HINOWHR2, NUMPEOPLE	0.7	0.7	1.6
	Proportion of persons in the household who are living there temporarily because of financial difficulties	NUMPEOPLE, HIFDIFF, HIFDIFF2	0	0	0

AHS = American Housing Survey. HIRM = Housing Insecurity Research Module.

* In the medium form Stable Occupancy HI measure, the study team kept a simplified measure of eviction or foreclosure that only asked about current risks and removed all questions related to previous risks. The study team also removed the eviction notice question (HIEVICPREV) from the medium form. The study team did test a model with the eviction notice question included, but the results were virtually unchanged. Finally, the study team also rescaled the eviction or foreclosure variable before developing the reduced index so that the first category was 0 (instead of 1).

** The study team rescaled this variable before developing the reduced index so that the first category of the variable was 0 (instead of 1).

Note: Items in grey are not included in any of the reduced measures.

Source: U.S. Census Bureau, 2019 American Housing Survey

Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 34 compares the gold standard HI 2 measure to long, medium, and short form reduced measures. The reduced measures of HI 2 do not have as strong a relationship with the gold standard measure as the reduced measures of HI 1. The correlations are all around 0.7 (compared to 0.8 or 0.9 for HI 1). The relationships with the external validators are comparable to the gold standard, however.

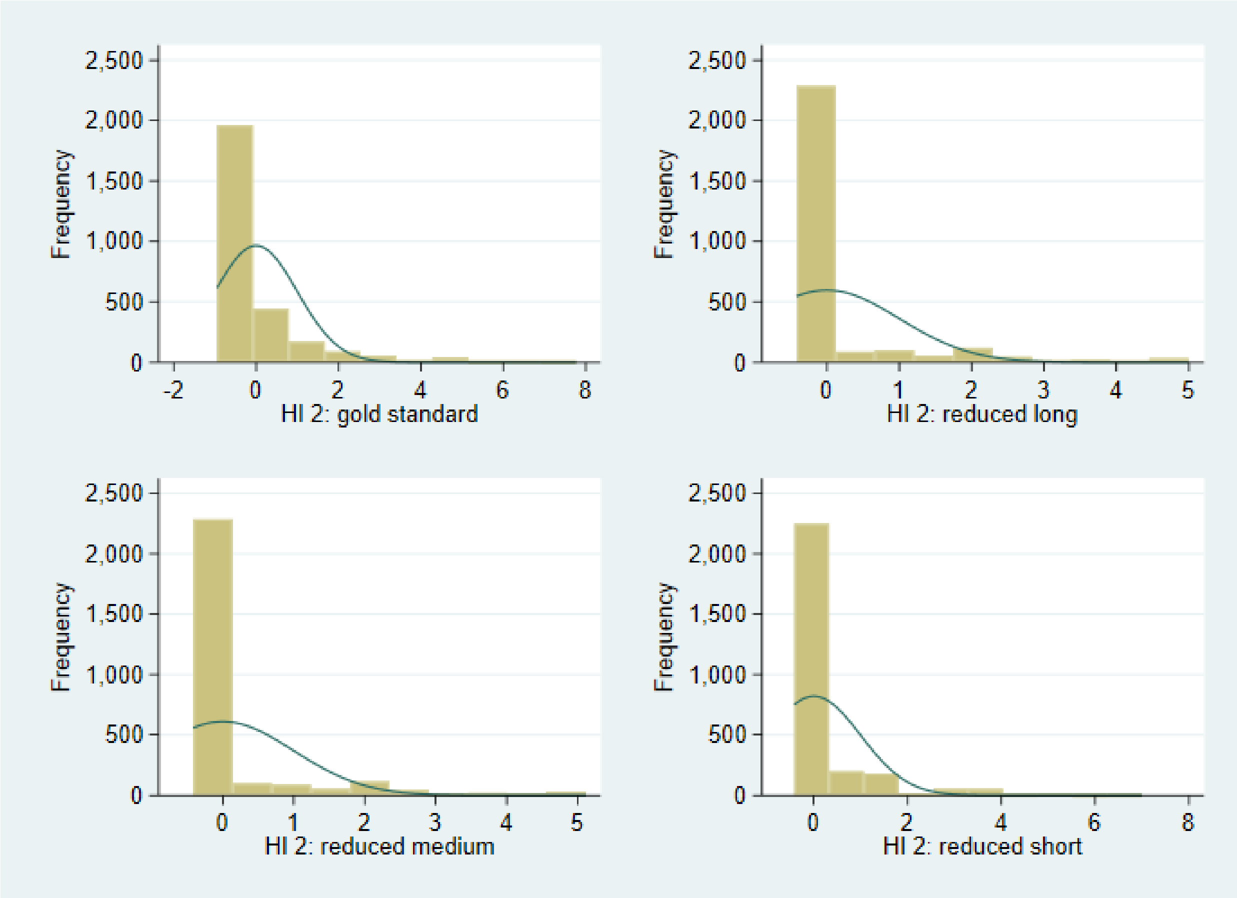
Exhibit 34 | Lack of Stable Occupancy (HI 2) Gold Standard and Reduced Scores: Number of Survey Items and Correlations with External Validators

	Gold Standard	Reduced Long	Reduced Medium	Reduced Short
Number of Survey Items	30	20	16	6
Correlation with the Gold Standard	1	0.6823	0.6792	0.6698
Correlations With External Validators				
Poor self-reported health	0.1349	0.2078	0.2065	0.2062
Food insecurity	0.2375	0.3127	0.3124	0.3087
Shelter poverty	0.3033	0.3633	0.3628	0.3418
Neighborhood quality 1	0.1283	0.1461	0.1461	0.1539
Neighborhood quality 2	0.0905	0.1139	0.1129	0.1094
Food stamp or SNAP receipt (1 = yes, 2 = no)	– 0.0972	– 0.1457	– 0.1468	– 0.1406
Household disability (1 = yes, 2 = no)	– 0.0586	– 0.0990	– 0.0977	– 0.1082
Comparison of current housing costs to former	0.0366	0.0290	0.0270	0.0089
Public assistance income	0.0222	0.0302	0.0307	0.0484
Amount of annual routine maintenance costs	0.0155	0.0505	0.0496	0.0418
Rating of neighborhood as a place to live	– 0.1263	– 0.1595	– 0.1591	– 0.1654
Rating of unit as a place to live	– 0.1521	– 0.2108	– 0.2116	– 0.2160

SNAP = Supplemental Nutrition Assistance Program.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The histograms in exhibit 35 of standardized scores of the reduced measures better illuminate why the study team found a lower correlation between the reduced measures of HI 2 and the gold standard. The reduced measures appear to lose some information around 0 (the average score), as the bars in the reduced measure histograms are flatter. The bar just below 0 with a large frequency of households is taller in the reduced measures, as well, suggesting that some households that have average or slightly above average HI 2 based on the gold standard would shift to being measured as having slightly below average HI 2 in the reduced measures. This discrepancy is important to note; however, the histograms show that the range of values is comparable between the reduced measures and the gold standard. Thus, although the reduced measures may have some errors, especially around the mean, they still do a good job of measuring the range of HI 2. Moreover, the reduced measures have expected relationships with external validators and are thus still strong measures for statistical analysis of HI 2.

Exhibit 35 | Lack of Stable Occupancy (HI 2) Histogram: Gold Standard and Reduced Scores



HI 2 = lack of stable occupancy factor score.
Notes: Subtracted mean and divided by standard deviation to standardize factor scores for comparison purposes. Factor scores rounded to four significant digits.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%,%20Weighting,%20and%20Error%20Estimation.pdf.

Building a Reduced Lack of Safety and Decency (HI 3) Measure

Exhibit 36 shows the Pearson correlations of each item of HI 3 with the overall gold standard factor score. The number of structural deficiencies is strongly correlated with the gold standard measure. The reduced measure will likely need to retain this variable, although this is not ideal since the measure is a combination of 13 deficiencies measured in the AHS.

Exhibit 36 | Pearson Correlations of Lack of Safety and Decency (HI 3) Items with the Gold Standard

Indicator	Label	Correlation (Pearson)
hs_quality	Number of structural deficiencies	0.8729
sd_unsafe_home	Feeling unsafe inside home	0.4644
sd_unsafe_outside	Feeling it is unsafe for children to play outside	0.4279
sd_unsafe_night	Feeling unsafe coming/leaving the home at night	0.4226
sd_unsafe_break	Feeling unsafe against break-ins	0.4149
sd_heat_br	Heating breakdowns	0.3417
sd_plumb_br	Plumbing breakdowns: toilet	0.3091
sd_sewage	Sewage breakdowns	0.244
per_bed	Persons per bedroom	0.2388
sd_runwat	Frequency unit was out of running water for 6 hours or more	0.2325
per_room	Persons per room	0.2303
sq_per	Square feet per person	0.1221
sd_many_people	Too many people living in the unit	0.0801
sd_subfamilies	Number of subfamilies	0.0771

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 37 lists the 13 structural deficiencies included in the structural deficiencies measure and the individual item correlation with the overall variable. Items with the strongest correlation include that the unit has inside leaks, outside leaks, an open crack wider than a dime, rats recently seen in the unit, and musty smells in the unit. The study team developed a reduced measure that was a simple sum of these five items to replace the full structural deficiency variable in the reduced HI 3 measure.

Exhibit 37 | Correlation of Each Deficiency with the Overall Structural Deficiency Variable

Deficiency	Correlation with Overall Measure
Electricity is not used	(no households selected this item)
Musty smells	**0.6335**
Crack in wall wider than a dime	**0.5447**
Rats seen recently	**0.5297**
Inside water leaks	**0.5121**
Outside water leaks	**0.509**
Peeling paint	0.4375
Holes in the floor	0.387
Some rooms with no working electric plugs	0.221
Exposed wiring	0.2179
Unvented room heater	0.136
No sink OR no fridge OR no cooking equipment OR no exclusive use	0.1352
No hot/cold running water OR no full bathroom OR no exclusive use bathroom	0.1303

Note: Items in bold have the strongest correlation with the overall variable.
Source: U.S. Census Bureau, 2019 American Housing Survey

Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 38 provides the weights used to develop the reduced scores and lists the survey item(s) from the AHS Core or HIRM on which each variable is based. Based on the graded response models, the study team found that heating breakdowns, sewage breaks, too many people living in the unit, persons per room, square feet per person, unsafe for children to play outside, unsafe against break-ins, and unsafe coming/leaving home at night all had some redundancy with other lack of safety and decency measures, and thus these measures were removed from all the reduced scores (see appendix G for more detail on variable redundancy in the graded response models).

Exhibit 38 | Measures and Survey Items in the Lack of Safety and Decency (HI 3) Dimension and Their Weights in the Reduced Scores

Subdimension	Measures	Survey Items from AHS Core and HIRM Used to Develop Measures	Weight in Long Form	Weight in Medium Form	Weight in Short Form
Poor housing quality	**Number of structural deficiencies (see footnote for definitional change in medium and short form)***	13 different deficiencies, a total of 18 survey items (see Appendix B for more detail). The study team reduced to 5 items in the medium form and short form versions.	2	2.1	1.3
	Heating breakdowns	COLD, COLDEQ, and COLDEQFREQ	0	0	0
	Plumbing breakdowns: toilet	NOTOIL and NOTOILFREQ	0	0	1.5
	Running water	NOWAT and NOWATFREQ	1.2	1.2	0
	Sewage break	SEWBREAK and SEWTYPE	0	0	0
Overcrowding	Too many people living in unit	HIMAXNUM	0	0	0
	Number of subfamilies	NUMSUBFAM	0.3	0.3	0
	Persons per room	TOTROOMS and NUMPEOPLE	0	0	0
	Persons per bedroom**	BEDROOMS and NUMPEOPLE	0.3	0.3	0.3
	Square feet per person	UNITSIZE_IUF and NUMPEOPLE	0	0	0
Lack of safety	Unsafe for children to play outside	HIPLAY	0	0	0
	Feeling unsafe inside home**	HISAFE	0.9	0.9	1.3
	Unsafe against break-ins	HIBRKIN	0	0	0
	Unsafe coming/leaving home at night	HICMING	0	0	0

AHS = American Housing Survey. HIRM = Housing Insecurity Research Module.
* In the medium and short form Safety and Decency HI measure, the study team kept a simplified measure of structural deficiencies in the model. The full measure includes 13 deficiencies, whereas the simplified measure includes only 5.
** The study team rescaled this variable before developing the reduced index so that the first category of the variable was 0 (instead of 1).
Note: Items in grey are not included in any of the reduced measures.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 39 shows that the reduced score measures of HI 3 are highly related to the gold standard (about 0.9 correlation), and the relationship of the reduced measures to external validators is very comparable to the gold standard.

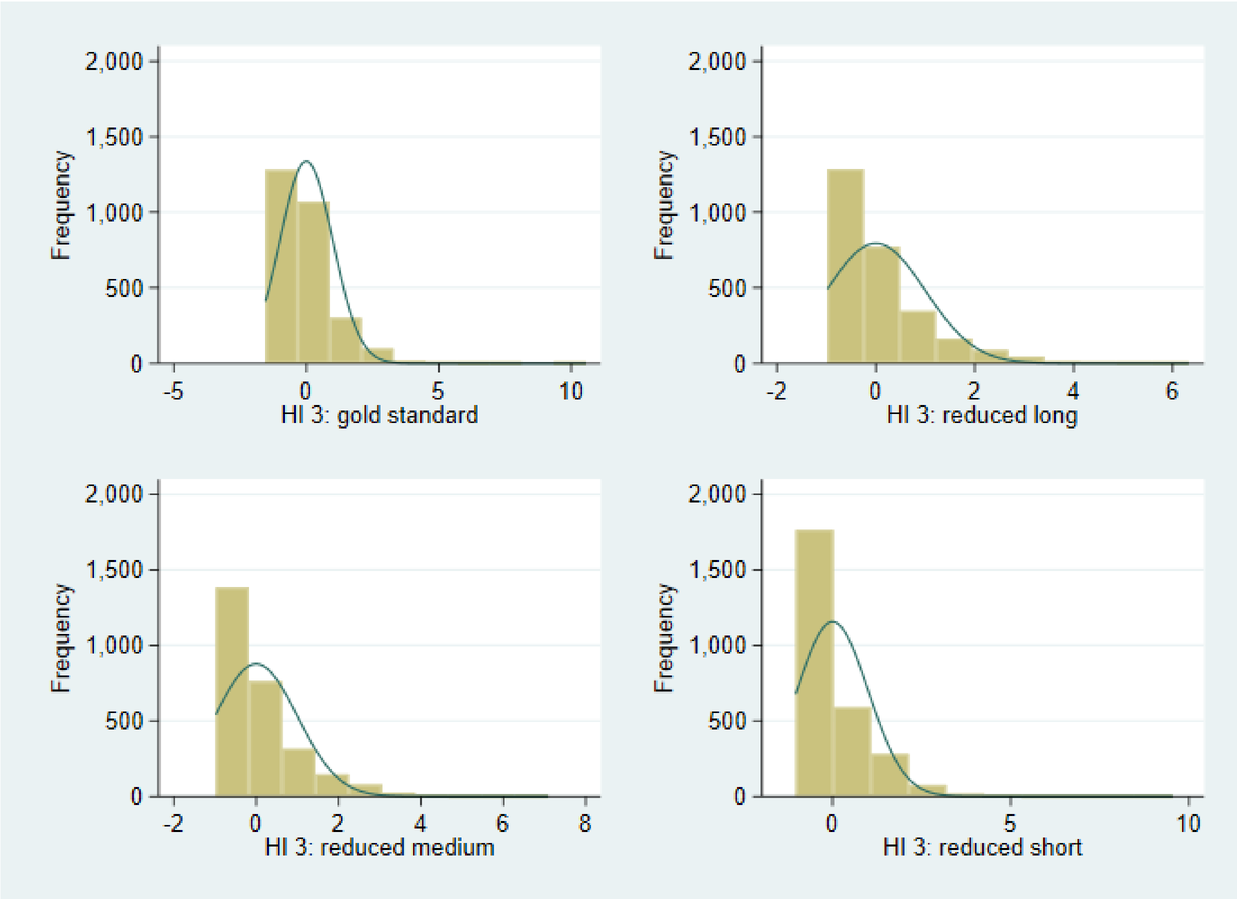
Exhibit 39 | Lack of Safety and Decency (HI 3) Gold Standard and Reduced Scores: Number of Survey Items and Correlations with External Validators

	Gold Standard	Reduced Long	Reduced Medium	Reduced Short
Number of Survey Items	37	24	16	10
Correlation with the Gold Standard	1	0.9167	0.8791	0.8724
Correlations with External Validators				
Poor self-reported health	0.2558	0.2151	0.2133	0.2176
Food insecurity	0.3027	0.2744	0.2714	0.3029
Shelter poverty	0.3016	0.2708	0.2703	0.2927
Neighborhood quality 1	0.2540	0.2167	0.2093	0.2223
Neighborhood quality 2	0.2508	0.2142	0.2099	0.2257
Food stamp or SNAP receipt (1 = yes, 2 = no)	– 0.1282	– 0.1440	– 0.1518	– 0.1526
Household disability (1 = yes, 2 = no)	– 0.1163	– 0.0830	– 0.0747	– 0.0563
Comparison of current housing costs to former	0.0278	0.0124	0.0075	0.0351
Public assistance income	0.0564	0.0763	0.0680	0.0719
Amount of annual routine maintenance costs	0.0985	0.1024	0.0981	0.0869
Rating of neighborhood as a place to live	– 0.2980	– 0.2443	– 0.2395	– 0.2781
Rating of unit as a place to live	– 0.4222	– 0.3988	– 0.3935	– 0.4097

SNAP = Supplemental Nutrition Assistance Program.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 40 shows that the distribution of the reduced scores for HI 3 is also very similar to the gold standard. Interestingly, the short form reduced measure has a larger range of values than the other reduced measures. This outcome results from the weights applied when developing the reduced short form measure, but it seems that the overweighting only happened for a very small number of households. Overall, all the reduced measures do a good job of capturing the distribution of the gold standard.

Exhibit 40 | Lack of Safety and Decency (HI 3) Histograms: Gold Standard and Reduced Scores



HI 3 = lack of safety and decency factor score.
Notes: Subtracted mean and divided by standard deviation to standardize factor scores for comparison purposes. Factor scores rounded to four significant digits.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Assigning HI Profiles from the Reduced Measures

After validating the reduced measures, the study team developed an approach to assign the HI profiles to households using the reduced measures. The HI Profiles identify the category of HI of each household and the overall level of HI of each household. Based on the work performed in stage 2, the study team defined six HI profiles, each with increasing HI. Exhibit 41 provides this information for review.

Exhibit 41 | Overall HI Level for Each HI Profile

HI Profiles	Overall HI Level
Housing Secure	Very Low HI
HI, Only Instability	Low HI
HI Affordable	Moderate HI
HI Stable Housing	High HI
HI Safe and Decent	High HI
HI All Dimensions	Very High HI

HI = housing insecurity.
Source: Authors' summary of the stage 2 results

To identify the profile of each household based on the reduced measures, the study team first had to identify a cutoff in each reduced measure, a score indicating the point at which the household would be classified as insecure on that dimension. To identify the cutoffs, the study team summarized the reduced measures for households in the Housing Secure profile based on the gold standard analysis performed in stage 2. The study team found that over 90 percent of the households in the Housing Secure profile had a score of 0 for the reduced measures of both HI 1 and HI 2 (this was consistent for the long, medium, and short form reduced measures). For HI 3, 90 percent of households in the Housing Secure profile had a reduced score of 4.6 or lower in the long form measure, 4.5 or lower in the medium form measure, and 4.5 or lower in the short form measure. Based on this information, the study team defines households as insecure for the HI 1 and HI 2 dimension if they have a reduced score above 0 (in other words, if households did not answer all survey items in the reduced measure with the secure option, they are classified as having some level of insecurity). For the HI 3 dimension, the study team define households as insecure if they have a score above 4.6 (4.5 for the medium and short form) on the reduced measure. Unlike the other two dimensions, this means that households may provide some responses to the survey items in the reduced score that indicate insecurity and still be classified as secure for HI 3. This occurrence is not surprising given that the reduced score of HI 3 is based on a larger number of survey items than the other dimensions, and many of the HI 3 items in the reduced measure have more non-zero response options (for example, number of persons per bedroom has nine response options).

Exhibit 42 shows the look-up table using the long form reduced measures. For this table, the cut points are zero for both HI 1 and HI 2 (if the household has a score above zero, it is classified as insecure for that dimension). For HI 3, the cut point is 4.6. In addition, the study team found that households with extreme HI 3 values above 6.4 on the long form reduced measure should be assigned to either the HI Stable Housing or HI All Dimensions profile, depending on the values for the other two dimensions. When developing the look-up table, the study team also found that the reduced measures did not have enough sensitivity to properly classify households in HI Instability Only, which was the smallest profile (less than 2 percent of the sample). As a result, the study team combine Housing Secure and HI Instability Only in the look-up table. If a household falls within the values specified in the first row of exhibit 42, then the household is classified as being in the Housing Secure or HI Instability Only profile and having "low HI." If a household has values that correspond to HI Affordability, the household is classified as having "moderate HI," while households with values that correspond to the HI Stable Housing or HI Safe and Decent profile in the look-up table are classified as having "high HI." Finally, households with values corresponding to HI All Dimensions are classified as having "very high HI."

Exhibit 42 | HI Look-Up Table Using Long Form Reduced Measures

	HI 1 Reduced Score	HI 2 Reduced Score	HI 3 Reduced Score
Low HI (Housing Secure or HI Instability Only)	Score = 0	Score = 0	Score ≤ 4.6
Moderate HI (HI Affordable)	Score = 0	Score > 0	Score ≤ 4.6
		OR	
	Score = 0	Score ≥ 0	4.6 < Score ≤ 6.4
High HI (HI Stable Housing)	Score > 0	Score = 0	Score ≥ 0
		OR	
	Score = 0	Score = 0	Score > 6.4
High HI (HI Safe and Decent)	Score > 0	Score > 0	Score ≤ 4.6
Very High HI (Profile 6)	Score > 0	Score > 0	Score > 4.6
		OR	
	Score = 0	Score > 0	Score > 6.4

HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibits 43 shows the look-up table for the medium form reduced measures. The table is virtually the same as the long form look-up table. The only difference is that with the medium form reduced measure, the cut points for HI 3 change slightly.

Exhibit 43 | HI Look-Up Table Using Medium Form Reduced Measures

	HI 1 Reduced Score	HI 2 Reduced Score	HI 3 Reduced Score
Low HI (Housing Secure or HI Instability Only)	Score = 0	Score = 0	Score ≤ 4.5
Moderate HI (HI Affordable)	Score = 0	Score > 0	Score ≤ 4.5
		OR	
	Score = 0	Score ≥ 0	4.5 < Score ≤ 6
High HI (HI Stable Housing)	Score > 0	Score = 0	Score ≥ 0
		OR	
	Score = 0	Score = 0	Score > 6
High HI (HI Safe and Decent)	Score > 0	Score > 0	Score ≤ 4.5
Very High HI (HI All Dimensions)	Score > 0	Score > 0	Score > 4.5
		OR	
	Score = 0	Score > 0	Score > 6

HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 44 shows the look-up table using the short form reduced measures. The short form did not have enough sensitivity to distinguish between Housing Secure, HI Instability Only, and HI Affordable or between HI Stable Housing and HI Safe and Decent. The table thus provides values that classify households as having "low to moderate HI" (Housing Secure, HI Instability Only, or HI Affordable), "high HI" (HI Stable Housing or HI Safe and Decent), or "very high HI" (HI All Dimensions). Researchers who are particularly interested in more fine-grained distinctions between the HI profiles are thus advised to use either the long form or medium form reduced measures.

Exhibit 44 | HI Look-up Table Using Short Form Reduced Measures

	HI 1 Reduced Score	HI 2 Reduced Score	HI 3 Reduced Score
Low to Moderate HI (Housing Secure, HI Instability Only, or HI Affordable)	Score = 0	Score ≥ 0	Score ≤ 4.5
High HI (HI Stable Housing or HI Safe and Decent)	Score > 0	Score = 0	Score ≥ 0
		OR	
	Score = 0	Score = 0	Score > 4.5
		OR	
	Score > 0	Score > 0	Score ≤ 3.4
Very High HI (HI All Dimensions)	Score > 0	Score > 0	Score > 3.4
		OR	
	Score = 0	Score > 0	Score > 4.5

HI = housing insecurity. HI 1 = lack of affordability factor score. HI 2 = lack of stable occupancy factor score. HI 3 = lack of safety and decency factor score.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 45 shows the number and percentage of households correctly classified in each profile using the long, medium, and short form look-up tables. The study team assumed that the gold standard classification statuses from stage 2 were the correct classification of each household and then compared how each household was classified using the reduced measure look-up table to the gold standard. The table shows that the reduced measures are very strong at correctly classifying households with low HI (90 percent or more are correctly classified). As HI increases, the reduced measures contain more errors; however, the study team found that the error is almost always that the household is classified in a profile that is more secure than the household's true profile. In other words, the reduced measures are not as sensitive to HI as the gold standard, which is expected since the reduced measures are based on a smaller subset of variables. Despite this error, the reduced measures strongly correlate with the gold standard profile indicator (shown in the last row of exhibit 45). The previous analysis shows that the reduced measures perform similarly to the gold standard measures in terms of external validators.

Exhibit 45 | Number and Percent Correctly Classified and Correlation with Gold Standard Profiles for Each Set of Reduced Measures

	Long Form		Medium Form		Short Form	
	N	%	*N*	%	*N*	%
Low HI (Housing Secure or HI Instability Only)	900	90.0	900	90.0	1300*	100.0*
Moderate HI (HI Affordable)	200	66.7	200	66.7		
High HI (HI Stable Housing)	500	76.9	500	76.9	750**	68.1**
High HI (HI Safe and Decent)	300	75.0	250	65.5		
Very High HI (HI All Dimensions)	200	57.1	200	57.1	150	42.9
Correlation with Gold Standard Profile Indicator	0.8539		0.8438		0.7021	

HI = housing insecurity.
* Corresponds to Gold Standard Profile 1, 2, and 3 due to loss of information with the short form measures.
** Corresponds to Gold Standard Profiles 4 and 5 due to loss of information with the short form measures.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit 46 compares the mean self-reported health, food insecurity, and shelter poverty for profiles developed from the gold standard and reduced measure scores. The table shows that the means of the external validator variables increase with each profile (and, as a result, they increase as the overall level of HI increases) regardless of whether the profiles are predicted from the gold standard or the reduced measures. The means are also very comparable to one another, which provides additional evidence that the reduced measures would perform like the gold standard in statistical analyses examining questions around HI.

Exhibit 46 | Comparison of Gold Standard, Long Form, and Medium Form: Mean Poor Self-Reported Health, Food Insecurity, and Shelter Poverty for Each HI Profile

	Poor Self-Reported Health				Food Insecurity				Shelter Poverty			
	Gold Standard	Long Form	Medium Form	Short Form	Gold Standard	Long Form	Medium Form	Short Form	Gold Standard	Long Form	Medium Form	Short Form
Low HI (Housing Secure or HI Instability Only)	2.56	2.61	2.61	2.68*	1.20	1.23	1.23	1.29*	1.03	1.03	1.03	1.05*
Moderate HI (HI Affordable)	2.74	2.84	2.88		1.31	1.42	1.46		1.06	1.11	1.12	
High HI (HI Stable Housing)	2.96	2.97	2.97	3.04**	1.61	1.62	1.61	1.79**	1.18	1.21	1.21	1.30**
High HI (HI Safe and Decent)	2.97	3.03	3.04		1.70	1.92	1.92		1.25	1.36	1.36	
Very High HI (HI All Dimensions)	3.41	3.39	3.36	3.38	2.43	2.39	2.41	2.54	1.56	1.54	1.56	1.59

HI = housing insecurity.
* Corresponds to Gold Standard Profiles 1, 2, and 3 due to loss of information with the short form measures.
** Corresponds to Gold Standard Profiles 4 and 5 due to loss of information with the short form measures.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

CONCLUSION

Summary of Findings

This report presents an approach to facilitate rigorous and consistent measurement of HI. Based on a literature review and discussion with HUD experts, the study team defined HI as a multidimensional concept measured by three dimensions: lack of affordability, lack of stable occupancy, and lack of safety and decency. Using household-level responses from the 2019 AHS, which included the HIRM, the study team presented measurement models of each dimension of HI. The study team provided goodness-of-fit information that show the models map well to the data and are statistically sound measures of HI. The study team estimated three factor scores from the measurement models referred to throughout this report as the "gold standard" factor scores.

In stage 2 of the research, the study team used the factor scores in an LPA that identified six profiles of HI. The six profiles categorized households with different combinations of the three dimensions of HI and facilitated the ordering of households on a continuum of overall HI. The six profiles include a profile with housing secure households, a profile with housing insecure households, and four profiles with households that appear to make tradeoffs between the different dimensions of HI. To understand how each profile related to overall HI, the study team examined means of poor self-reported health, food insecurity, and shelter poverty, which are variables with established relationships with HI, for each profile. The study team found that profiles that are insecure on more than one dimension had higher means for each of the three variables, which is evidence that households that are insecure on more than one dimension have higher overall HI. The analysis of poor self-reported health, food insecurity, and shelter poverty also shows that households living in affordable housing typically have lower overall HI than households living in unaffordable housing.

Finally, in stage 3 of the analysis, the study team estimated scores of the three dimensions with reduced numbers of survey items to increase the transferability of HI measures across surveys with limited space for such questions. The goal of the research was for these reduced measures to inform a consistent and statistically rigorous method of measuring HI while minimizing the burden of data collection. The study team performed an analysis that compared the reduced scores to the gold standards on several external validators to ensure that the reduced measures would perform like the gold standards in analyses of HI. For each reduced score, list the items included in the measure and the weights assigned to each item are listed. To develop the reduced scores, a researcher can simply create a weighted sum of the survey items the study team recommended in the reduced measures. Look-up tables (one for each version of the reduced measures, which include long form, medium form, and short form) are provided that offer a method for assigning households to the profiles the study team identified in the LPA in stage 2. Thus, the reduced measures capture both continuous measures of each dimension of HI and the profiles of HI that correspond to the degree of overall HI for each household.

Analysis of Open-Ended Questions in the Housing Insecurity Research Module

Although not the main focus of this research, the study team identified five open-ended questions from the HIRM survey that could potentially have been useful for measuring HI. Each question was examined to determine whether the responses contained information that can be applied to categories in the analysis variables used in the measurement models for the three dimensions of HI and to understand whether additional closed-ended items could be added in future HIRM data collections. In the five open-ended questions, respondents were asked either about reasons for a previous move or about reasons that cause worry about their current housing situation. The study team examined these narrative responses and first classified them as one of the following: (a) indicating greater residential instability, (b) indicating less residential instability, or (c) irrelevant to residential instability. Appendix E provides more details.

Next, with a special focus on reasons indicating greater residential instability and in collaboration with HUD, the study team determined whether the response fit an existing response category, whether a new category should be created in future iterations of the HIRM to represent a novel response, or whether the information was not usable for measuring HI. The study team determined that most of the open-ended responses either fit an existing response category or were not usable for measuring HI. For example, for questions related to previous reasons for a move, some open-ended responses were coded as “Bad Neighborhood” or “Lack of Upkeep.” However, closely related questions are already asked in the HIRM survey. For the question related to reasons that cause worry about the current housing situation, several open-ended responses cited childcare expenses, health-related expenses, or car-related expenses as causing worry about the housing situation. However, these coded responses do not affect any of the observed indicators used in the measurement models. Based on this analysis, the study team do not have any recommendations for updates to future iterations of the HIRM.

Avenues for Future Research

Although the results show promise for identifying a consistent and reliable way of measuring HI, more research is needed to ensure that the results are consistent across multiple samples. In this analysis, the study team found evidence that HI is measured differently in metro versus non-metro contexts and for new construction versus older construction. Future research could elucidate these differences. In the reduced scores, it was difficult to incorporate metro/non-metro and new construction/older construction differences without creating different weights for different subgroups of the population. Future research could identify potential improvements to the reduced HI measures that incorporate these differences. In addition, replicating this analysis on different samples of households is also important to ensure that these findings are not sample-specific.

A second potential line of research could focus on understanding the difference between individual-level and household-level insecurity. The study team’s analysis used household-level data from the AHS, which presented some limitations, especially in the measurement of lack of stable occupancy. One clear limitation is that the AHS, as a household survey, does not capture homeless populations. In addition, for non-family households, instability is likely better expressed at the individual level as some individuals may be less stable than others, even within the same household. The study team found that lack of stable occupancy is a highly skewed phenomenon, with most households living in stable housing and a small number experiencing extremely high levels (for example, households with individuals who experienced homelessness in the past, households with large numbers of individuals temporarily staying) of instability. One important question that the study team were not able to answer in this research is whether the experience of lack of stable occupancy is as skewed if the data is collected at the individual level.

Finally, a third avenue that the study team hope this research spurs is work utilizing the measures of HI the study team developed to understand the prevalence of HI and strategies better to reduce HI. This work could investigate numerous questions, such as what the spatial concentrations of HI are in the United States, what the external influences on the dimensions of HI are, and how HI relates to social, economic, health, and other outcomes.[29] Although this work is perhaps the most interesting to the study team, the study team recommend more research replicating this study's findings on other samples first to ensure that the proposed measures are consistent and statistically reliable.

[29] AHS does not report geographic information smaller than census division and metropolitan area. For analysis of the spatial concentration of HI, more detailed data are needed. Another option is to develop models using small area estimation and related techniques that could estimate HI scores at smaller levels of geography.

APPENDIXES

Appendix A: Sample Weights

Overview

The study team constructed weights with the following objectives:

1. To create one or more sets of weights to adjust the Housing Insecurity Research Module (HIRM) data for deviations from the eligible population or the sampling design.
2. To check whether the unweighted or weighted sample differs in important ways from the population of interest.

Sample weights are designed to adjust for the differences in the probability of being interviewed. If a sampled case has a low probability, then it should have a higher weight because that interviewed case represents more universe cases. Typically, the weight is the inverse of the probability of being interviewed. If the probability of being interviewed is 1 percent (0.01), then the weight should be 100 (1/0.01).

Sampling Plan

The Census Bureau drew 36 buckets (2 x 2 x 9) from Split Sample One: owner versus renter, income less than twice the federal poverty level versus income between two and three times the federal poverty level, and residence in one of nine census divisions. HUD instructed the Census Bureau to sample at the following rates: 55 percent renters and 45 percent owners; 2/3 with income less than two times the federal poverty line, and 1/3 with income between two and three times the federal poverty level income. The Census Bureau set the sampling rates by division. Using these guidelines, the Census Bureau set a target sample for each bucket, and the percent of successful interviews from the target sample varied across buckets from a low of 46 percent to a high of 150 percent. Overall, the Census Bureau planned to interview 4,000 households. Only 2,800 households were successfully interviewed.

HUD went through two steps in developing the sample targets. The first consideration was to restrict the sample to cases with household income below 80 percent of Area Median Income (AMI) because these households constitute most households eligible for HUD assistance. The Census Bureau judged the implementation of that universe in the instrument too difficult. The second approach was to use household income in relation to the poverty line to determine eligibility. HUD looked at unweighted data from the 2017 American Housing Survey (AHS) to see what level of poverty nationwide captures most of the units below 80 percent of AMI and settled on the value of three times the federal poverty level. This value captured most but not all (above 95 percent) of the households below 80 percent of AMI. Due to regional variations in the cost of living, this approach also provided a sample where respondents were likely to be more housing secure. HUD wanted the sample to focus on housing insecure units but have enough variation to be able to order cases on a continuum.

The HIRM survey was a follow-on survey, conducted after the AHS. Respondents had to opt in to HIRM. At the end of the AHS survey, respondents deemed eligible for HIRM were asked if they would be willing to participate in the follow-on survey. To increase participation, survey administrators promised respondents a $40 incentive upon completion of the follow-on survey. Only households with income less than or equal to three times the poverty level were eligible for the follow-on survey. This income determination was based on unedited responses to the income questions in the AHS.

An additional complication caused the interviewed sample to differ from the planned sample. When the Census Bureau edited the income questions, it found that 300 of the interviewed cases had household incomes higher than three times the poverty level, indicating that the sampled cases fell into three income groups rather than two, expanding the number of buckets to 54 (2 x 3 x 9).

Multiple datasets were used to construct the sampling weights. The HIRM and the Food Security modules were administered to Split Sample One of the 2019 AHS. The weights are constructed of two subsamples of Split Sample One:

(1) ELIGIBLES—all cases that were offered the opportunity to participate in HIRM, identified by HISCREEN = {1 = interviews, 2 = refusals}, a total of 19,500 households, and

(2) INTERVIEWS—all cases on the HIRM file, a total of 2,800 households. INTERVIEWS is a proper subset of ELIGIBLES.

Exhibit A.1 | Relevant Dataset for the Construction of Weights

Dataset	Variable to Identify Relevant Cases	Number of Cases
National AHS 2019 (AHS2019nat)	SPLITSAMP = 1	31,500
Skinny file	HISCREEN = (1,2)	19,500
Eligible	Cases (cases common to both datasets)	14,500

AHS = American Housing Survey.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

As shown in exhibit A.1 above, the 2019 AHS IUF SAS file AHS2019nat (Split Sample One) had 31,500 Household cases. The skinny file provided by HUD to identify the eligible cases had 19,500 cases where the variable HISCREEN = {1,2}. There were 14,500 cases common to both datasets. The remaining cases in the skinny file matched the Metro AHS 2019 data. These cases were inadvertently included in the skinny file and were excluded from the weighting analysis. Hence, the number of Eligible cases was 14,500.

To create the proposed weight, ELIGWT, the study team starts with the pure weight, PWT19, from the data file AH2019nat. Because of the split sample, they identify the corresponding pure weight for the selected cases (Split Sample One) as SP1PWT = 2 * PWT19. The final weight for Split Sample group 1, SP1WEIGHT, is also from the AHS2019nat file.

The interviewed cases were identified from the HIRM dataset provided by the Census Bureau. After excluding the metro households, the remaining 2,800 interviewed cases were left for future analysis. The study team also needed the poverty level income variable POVLVLINC from the

HADS2019 SAS data file to calculate the income to poverty level percent variable used to identify adjustment buckets discussed below.

The study team merged all these files into one merged file and identified two variables called IN_ELIGIBLE and IN_INTERVIEW to select the appropriate eligible and interviewed cases from the merged file. Exhibit A.2 shows that the ELIGIBLES subset contains fewer than half the AHS cases in Split Sample One. The INTERVIEWS subset contains roughly 1 in 5 of the cases in ELIGIBLES.

Exhibit A.2 | Merged Datasets for the Construction of Weights

Dataset	Unweighted Counts	Relevant Weights
Split Sample One	31,500	SP1WEIGHT, SP1PWT
Eligibles	14,500	SP1WEIGHT, SP1PWT
Interviews	2,800	SP1WEIGHT, SP1PWT, ELIGWT, TARGETWT

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

For cases not in INTERVIEWS, ELIGWT is equal to 0. In other words, ELIGWT applies only to interviewed cases. Exhibit A.3 shows the differences in weighted estimates when datasets are weighted by the split sample weight (SP1WEIGHT) and the split sample basic weight (SP1PWT) and the ratio between these weighted estimates.

Exhibit A.3 | Weighted Counts

Dataset	Weighted by SP1WEIGHT	Weighted by SP1PWT	Ratio of Weighted Counts: SP1WEIGHT TO SP1PWT
Split Sample One	139,700,000	100,100,000	1.396
Eligibles	66,310,000	45,120,000	1.47
Interviews	12,420,000	8,459,000	1.468

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The subset ELIGIBLES and INTERVIEWS can each be subdivided into 54 buckets that are exhaustive and mutually exclusive. The buckets are defined by three variables: household income (HINCP relative to POVLVLINC—3 levels), tenure (TENURE—2 options), and Census Division (DIVISION—9 options), or (54 = 3 * 2 * 9).[30] The three income levels are defined as shown in exhibit A.4:

[30] The study team merged the National AHS Split Sample One with the HADS2019 data and kept only the cases where HINCP was not "N" and Division is not "N." An owner bucket is defined by TENURE = "1"; a renter bucket is defined by TENURE IN {"2," "3"}.

Exhibit A.4 | Income Levels

Income Group	Definition
Low	Household income less than twice the federal poverty level [(HINCP ÷ POVLVLINC) LE 2]
Modest	Household income between 2 and 3 times the federal poverty level, or household income greater than 3 times the federal poverty level and less than 80% AMI [2 LT (HINCP ÷ POVLVLINC) LE 3 OR ((HINCP ÷ POVLVLINC) GT 3 AND INCRELAMICAT IN {1, 2, 3, 4})]
Higher	Household income greater than 3 times the federal poverty level and greater than 80% AMI [(HINCP ÷ POVLVLINC) GT 3 AND INCRELAMICAT IN {5,6}]

AMI = area median income.

Construction of Weights

This section explains the construction and development of ELIGWT.

Use of Relative Weights

The HIRM sample was not designed to produce counts of households with housing insecurity (HI); it was designed to define what HI means and how to identify households with HI. Once one knows how to diagnose HI, subsequent surveys can count the households that are housing insecure.

For the planned analysis, it is the relative weight that is important. If the probability of being interviewed for case A is "a" and probability of being interviewed for case B is "b," then the weight of case B should be b/a times the weight of case A. If a is 0.01 and b is 0.02, then the weight of case A should be twice that of case B (0.02/0.01). The weights should reflect the relative probabilities of being interviewed. Relative weights have the advantage of discouraging interpreting findings in absolute terms.

The final step in creating ELIGWT was to force the weight to sum over INTERVIEWS to 2,800. Using 2,800 as the desired sum has two advantages. First, every frequency distribution using either unweighted or weighted data will sum to the same total. Therefore, frequency distributions can be compared easily without translating counts into percentages. Second, all statistical tests will be based on the actual sample size, 2,800.

The sample design recognizes that sample cases will represent different numbers of households in the relevant population. ELIGWT is designed to allow each interviewed case to enter the analysis with a weight proportionate to the number of cases it represents. The following are two examples to explain further.

1. There might be 500,000 households in the modest income, owner, East South-Central Division (AL, KY, MS, TN) bucket. The AHS might contain 100 households in Split Sample One and 20 in the HIRM dataset. On average, each sample case in this bucket represents 25,000 households.
2. There might be 800,000 households in the low income, renter, East North Central Division (IL, IN, MI, OH, WI) bucket. The AHS might contain 160 of these households

in Split Sample One, and 80 of them may be in the HIRM dataset. On average, each of the sample cases in this bucket represents 10,000 households.

The differences in these hypothetical examples result from the combined influence of several factors, some planned and some unplanned.

1. HUD asked the Census Bureau to sample twice as many eligible low-income households as modest-income households.
2. HUD asked the Census Bureau to sample households such that 55 percent are renters and 45 percent are owners. Owner households are roughly 60 percent of all households.
3. The Census Bureau may have sampled at a higher rate in less populous divisions.
4. In some buckets, a higher percentage of households may have volunteered for the HIRM followup.
5. The percent of volunteers selected for followup by the Census Bureau may have differed by bucket.
6. In some buckets, a higher percentage of volunteer households may have declined the HIRM interview when contacted (or the Census Bureau could not contact the volunteer household).

Factors 1, 2, and 3 were part of the sample design; factors 4, 5, and 6 were unplanned deviations from the sample design. Whether planned or unplanned, sample cases represent a different number of actual households across buckets.

The first step in computing the ELIGWT is to calculate a gross weight for every case in every bucket—that is, the number of eligible households represented by an interviewed case.

The weighted sum of all eligible cases in bucket *i*/weighted sum of all interviewed cases in bucket *i* are shown in exhibit A.5:

Exhibit A.5 | Weighted Counts for Eligibles and Interviewed Groups

INCRELPOVCAT	TENURE	DIVISION	ELIGIBLE_SUM_SP1PWT	INTERVIEW_SUM_SP1PWT
1	1	1	412,000	65,500
1	1	2	1,044,000	166,000
1	1	3	1,763,000	397,000
1	1	4	635,000	121,000
1	1	5	2,481,000	502,000
1	1	6	1,010,000	193,000
1	1	7	1,582,000	350,000
1	1	8	861,000	111,000
1	1	9	1,260,000	275,000
1	2	1	495,000	95,000
1	2	2	1,638,000	269,000
1	2	3	1,744,000	446,000
1	2	4	817,000	208,000

INCRELPOVCAT	TENURE	DIVISION	ELIGIBLE_SUM_SP1PWT	INTERVIEW_SUM_SP1PWT
1	2	5	2,335,000	592,000
1	2	6	958,000	274,000
1	2	7	1,639,000	402,000
1	2	8	742,000	231,000
1	2	9	2,024,000	492,000
2	1	1	286,000	67,500
2	1	2	895,000	156,000
2	1	3	1,180,000	307,000
2	1	4	605,000	132,000
2	1	5	1,692,000	311,000
2	1	6	595,000	121,000
2	1	7	821,000	188,000
2	1	8	490,000	130,000
2	1	9	940,000	169,000
2	2	1	170,000	51,000
2	2	2	581,000	106,000
2	2	3	458,000	123,000
2	2	4	265,000	58,500
2	2	5	838,000	188,000
2	2	6	203,000	36,500
2	2	7	451,000	54,500
2	2	8	317,000	72,500
2	2	9	914,000	168,000
3	1	1	307,000	32,000
3	1	2	984,000	102,000
3	1	3	1,093,000	89,000
3	1	4	397,000	44,000
3	1	5	1,386,000	140,000
3	1	6	352,000	22,000
3	1	7	758,000	45,500
3	1	8	393,000	19,500
3	1	9	920,000	76,000
3	2	1	105,000	8,000
3	2	2	466,000	34,000
3	2	3	280,000	31,500
3	2	4	147,000	17,000
3	2	5	532,000	44,500

INCRELPOVCAT	TENURE	DIVISION	ELIGIBLE_SUM_SP1PWT	INTERVIEW_SUM_SP1PWT
3	2	6	110,000	11,000
3	2	7	181,000	41,000
3	2	8	161,000	10,000
3	2	9	465,000	63,000

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The first step weight (STEP1EGWT) for a case in bucket *i* is as follows:

> STEP1EGWT = SP1PWT*(Weighted sum of all eligible cases in bucket i/weighted sum of all interviewed cases in bucket *i*)

SP1PWT is used for the weighted sums in this formula. This product is the specific AHS weight of an interviewed case times the average number of households in ELIGIBLES represented by an interviewed case in that bucket.

The final step is to make ELIGWT a relative weight.

ELIGWT = (2,800 / the sum of STEP1EGWT over all cases in INTERVIEWS) * SP1PWT * (Weighted sum of all eligible cases in bucket *i* / weighted sum of all interviewed cases in bucket *i*) = (2,800 / the sum of STEP1EGWT over all cases in INTERVIEWS) * STEP1EGWT.

Appendix B: Constructing Observed Indicators for Measurement Models

This section presents the construction of observed indicators for the measurement models of the three dimensions of housing insecurity (HI): lack of affordability, lack of stable occupancy, and lack of safety and decency.

Existing variable names are given in parentheses and listed in all caps. When the existing codes will be used for analysis without recoding, codes are displayed in purple text. However, some observed indicators required recoding or construction across multiple survey items. For these cases, black text is used for the existing codes and purple text to highlight the codes of the proposed final variables.

The study team have conceptualized the analysis variables as reflecting a "higher is worse" valence. An ordered placement of categories is assumed, in which codes associated with larger numbers indicate conditions of more insecurity than those with lower numbers.

Lack of Affordability (HI 1)

The lack of affordability dimension is conceptualized as a higher-order latent variable (HI 1); it is directly indicated by other latent variables rather than manifest indicators. Specifically, the HI 1 latent factor is a function of three latent variables: Worry About Inability to Pay Housing Costs, Lapse in Housing Payments, and Housing Expense Hardships. Below the study team describe the construction of the observed indicators of each of these three latent variable measures of lack of affordability.

Worry About Inability to Pay Housing Costs

Frequency of Worry

The study team constructed the subjective frequency of housing cost stress measured with the following item: "How often [in the last 12 months/since you've lived here] would you say you were worried or stressed about having enough money to pay your [mortgage/rent]?" (HISTPAY). This item is asked of respondents who were responsible for the mortgage payment (HIMORT > 0) or rent (HITENURE = 2). The study team coded the response options for this survey item as 0 = never, 1 = rarely, 2 = sometimes, 3 = usually, and 4 = always. Respondents who were skipped out of this question (no mortgage/rent) were assigned a code of 0 (never worry).

Extent of Worry

The study team constructed current housing cost stress with the following item: "How worried are you right now about not being able to pay your [mortgage/rent] payment? Are you ..." (HISTNOW). Only those respondents who expressed some degree of worry about making housing payments (HISTPAY > 0) were asked this question. The study team coded the response options for this question as 0 = not at all worried, 1 = a little worried, 2 = moderately worried, and 3 = very worried. Respondents who were skipped out of this question because they had no mortgage or rent or they had indicated never having been worried in the past 12 months or since they moved to their current home (if they moved within the past year) were assigned a code of 0 (not at all worried).

Lapse in Housing Payment

Recent Lapse

Respondents who were responsible for rent or mortgage payments were asked whether they had been behind in making housing payments in the last 12 months: "Thinking about [the last 12 months/since you've lived here], was there ever a time when [you/you and your household] were a month or more behind in making a [mortgage/rent] payment?" (HIBEHIND). Response options were 1 = yes and 2 = no. Respondents indicating a lapse (HIBEHIND = 1) were asked the following question: "How often [in the last 12 months/since you've lived here] would you say [you/you and your household] were behind on your [mortgage/rent] payments?" (HIBFREQ). Response options for this survey item were 1 = only 1 or 2 months, 2 = some months but not every month, 3 = almost every month, and 4 = every month. Respondents who were skipped out of this question because they do not have rent or mortgage or were not behind in payments were given a code of 0, implying a response of "never" (0 = never).

Current Lapse

Respondents indicating a lapse in housing payment (HIBEHIND = 1) were also asked the following question: "Are [you/you and your household] currently caught up on your [mortgage/rent] payments?" (HICTCHUP). The observed indicator is constructed as "Are you currently in lapse of housing payment?" and assigned a code of 0 = no (if HUCTCHUP = yes) and 1 = yes (if HICTCHUP = no) to conform to a convention of a "higher is worse" coding valence. A code of 0 is assigned to respondents who were skipped out of this question because they were not responsible for rent or mortgage and respondents who indicated they were not behind in payments.

Housing Expense Hardships

Household income is an important component of calculating different measures of housing expense hardships. This section begins with a description of how household income can be defined for use in the observed indicators. This description is followed by descriptions of the proposed construction of analysis variables that capture housing expense hardships.

Total Household Income or Household Wage Income

Household income can be expressed in several ways: as a difference score reflecting income after housing costs are paid (residual income) or as a ratio of calculated or estimated housing costs. Collecting income data from impoverished respondents is difficult. Wage income is a common income measure that has promise for transferability, so the study team will consider wage among the options for assessing income. Household-level wage income can be constructed from person-level wage data (WAGP), summed across persons in a household.

A fuller picture of household income can be obtained by considering other income sources beyond wages (see exhibit B.1).

Exhibit B.1 | Sources of Income

- Wage and salary income of person.
- Person has alimony or child support income.
- Person has dividends.
- Received interest, dividends, royalty income.
- Person has interest income.
- Received VA payments/unemployment/child support/alimony/other income.
- Person has unemployment/workers comp/VA/other pay.
- Other income received by nonrelative.
- Person has rental income.
- Received retirement or survivor pension.
- Wages/salary received by reference person/relative.
- Salary received by nonrelative.
- Received self-employment income.
- Received self-employment income by nonrelative.
- Received Social Security or Railroad Retirement pension
- Received Supplemental Security Income.
- Received Aid to Families with Dependent Children, Temporary Assistance for Needy Families, or other public assistance or welfare program payments.
- Received Social Security Disability Income, workers compensation, VA, or other disability payments.
- Sum of a person's other income.

VA = U.S. Department of Veterans Affairs.

HUD calculated household income in the past 12 months (HINCP) as the sum of all types of income for all household members aged 16 and older. This indicator is expected to be too complex to be considered for a transferable version of the measure, but the study team will use the fuller measure to construct gold standard factor scores.

The following few sections describe how total household income was combined with indicators of housing cost to derive indicators of HI. Several proposed analysis variables under housing expense hardships are calculated using household income. The following are analysis variables under housing expense hardships that do not use household income: perceived severe housing cost burden, extent of difficulty making housing payments, frequency of difficulty making housing payments, and difficulty paying utilities.

Housing Cost to Household Income Ratio

HUD calculated monthly total housing costs (TOTHCAMT) as the sum of all the amount variables in the "Total Housing Costs" subtopic (see exhibit B.2). The study team obtained a ratio of annual housing costs to household income. The sample did not have any negative values for household income. Household income was set to 1 when it was equal to zero.

In consultation with HUD, the research team developed a categorical measure that binned the responses based on meaningful cutoffs. The final categories were as follows: 0 = 30 percent or less of income spent on housing costs; 1 = more than 30, but 50 percent or less of income spent on housing costs; 2 = more than 50, but 75 percent or less of income spent on housing costs; 3 = more than 75, but 90 percent or less of income spent on housing costs; and 4 = more than 90 percent of income spent on housing costs.

Exhibit B.2 | Sources of Housing Costs

- Monthly total mortgage amount (all mortgages).
- Monthly rent amount.
- Monthly total utility amount.
- Monthly property tax amount.
- Monthly homeowner or renter insurance amount.
- Monthly homeowners or condominium association amount.
- Monthly lot rent amount.
- Monthly total housing costs.
- Annual real estate tax payment.
- Annual cost of homeowners insurance.
- Manager provides personal care assistance.
- Frequency of association/mobile home park fee.
- Monthly condo/homeowner's association/mobile home fee.
- Frequency of land/site rent payment.
- Frequency of other mobile home fee payments.
- Meals included in rent paid to household.
- Frequency of rent payment.
- Lodger contributes to household for food.
- Lodger contributes to household for mortgage/rent.
- Lodger contributes to household for other costs.
- Lodger contributes to household for utilities.
- Condo/co-op/association/mobile home park fee required.
- Other mobile home fees required.
- Pay separate rent for land.
- Rent paid by lodgers (rounded).
- Amount lodger pays to household.
- Lodger pays fixed amount to household.
- Land/site rent.
- Amount of other required mobile home fees.
- Ownership shared with person not living there.
- Person not living there helps pay mortgage/utilities.
- Amount of rent actually paid.
- Rent adjusted because of relationship with owner.
- Frequency of lodger's rent payment to household.
- Received real estate property tax rebate.
- Household has homeowners insurance.
- Monthly housing costs.
- Land rent included with mortgage payment.
- Monthly payment for principal and interest.

Residual Income

The residual income metric is the ratio of residual income to threshold non-shelter housing costs and is a way to capture housing affordability. Residual income is the difference between household income and annualized housing costs (12*TOTHCAMT). Threshold non-shelter housing costs are the basic, minimum level of non-housing spending needs and are determined by the size and the number of children in the household.

The conceptual basis of the residual income metric is the idea of having enough income left over to meet basic non-housing costs after paying for housing (JCHS, 2019). This operationalization can be used to distinguish between high-income households that have high housing burdens due to consumer choice to purchase more expensive housing and low-income households that have high burdens due to limited affordable housing options. Such a household may have a substantial cost-to-income ratio, but the residual income metric will be higher than a lower-income household with the same cost-to-income ratio. The research team calculated the residual income metric: residual income as a percentage of threshold non-shelter costs. Higher values of the residual income metric indicate lower levels of Affordability HI. For example, if the residual income metric is greater than 100 percent, the household's residual income is more than the minimum required to meet the household's non-housing spending needs.

In consultation with HUD, the research team used a categorical measure that binned the responses based on meaningful cutoffs: 0 = residual income is greater than 500 percent of threshold non-shelter costs, 1 = residual income is 400–500 percent of threshold non-shelter costs, 2 = residual income is 300–400 percent of threshold non-shelter costs, 3 = residual income is 200–300 percent of threshold non-shelter costs, 4 = residual income is 185–200 percent of threshold non-shelter costs, 5 = residual income is 175–185 percent of threshold non-shelter costs, 6 = residual income is 150–175 percent of threshold non-shelter costs, 7 = residual income is 125–150 percent of threshold non-shelter costs, 8 = residual income is 100–125 percent of threshold non-shelter costs, 9 = residual income is 75–100 percent of threshold non-shelter costs, 10 = residual income is 50–75 percent of threshold non-shelter costs, and 11 = residual income is less than 50 percent of threshold non-shelter costs.

Worst Case Needs

HUD has defined households with worst case needs (WCN) as very low-income renters who do not receive government housing assistance and who pay more than one-half of their income for rent, live in severely inadequate conditions, or both. The response options for this HUD-constructed variable include the following: 1 = assisted (self-reported); 2 = unassisted, incomes less than 50 percent of Area Median Income, and worst case needs; 3 = unassisted, incomes less than 50 percent of Area Median Income, not worst case needs; 4 = unassisted, incomes between 51 and 80 percent of Area Median Income; and 5 = renters not in the above categories. The study team constructed the following response categories for analysis: 0 = not worst case needs and 1 = worst case needs (wcn=2). All other cases were assigned 0 (not worst case needs).

Perceived Severe Housing Cost Burden

In addition to the HUD-constructed indicators of housing burden, respondents who reported being responsible for mortgage or rent (HIMORT > 0 or HITENURE = 2) were offered a direct question: "In a typical month, is the [mortgage/rent] payment more than half of your household's monthly income?" (HIHALF). The response options for this survey item were coded 0 = no and 1 = yes. Respondents who were skipped from this question because they do not have rent or mortgage payments were coded 0.

Extent of Difficulty Making Housing Payments

Respondents who reported being responsible for mortgage or rent (HIMORT > 0 or HITENURE = 2) were asked about difficulty in making payments: "Overall [in the last 12 months/since you've lived here], how difficult was it for you to afford your [mortgage/rent] payments?" (HIAFFORD). The study team coded the response options for this question as 0 = not at all difficult, 1 = a little difficult, 2 = moderately difficult, and 3 = very difficult. Respondents who were skipped from this question because they do not have rent or mortgage payments were coded 0, representing "not at all difficult."

Frequency of Difficulty Making Housing Payments

Among respondents who indicated having had difficulty affording housing payment (HIAFFORD = 1 or 2), the frequency of such difficulties was assessed with the item "How often was it difficult for you to afford your [mortgage/rent]?" (HIDIFFPAY). Response options were 1

= only one or two months, 2 = some months but not every month, 3 = almost every month, and 4 = every month. Respondents who were skipped from this question because they do not have rent or mortgage payments and those who were skipped because they reported having had no difficulty with making housing payments in the past 12 months in the current housing unit were coded 0, representing an implied response of "never."

Difficulty Paying Utilities

In addition to rent or mortgage payments, essential housing costs include utility payments, usually electricity. All respondents in the HIRM were asked the following question: "[In the last 12 months\Since you've lived here], has there been a time when [you were/your household was] behind on your electricity bill?" (HIBLLPAY). Response options were 1 = yes, 2 = no, and 3 = not responsible for electricity bill. Respondents who indicated that they had been behind on the electric bill were asked two additional questions: "[In the last 12 months/Since you've lived here], have [you/you and your household] received a notice that your electricity would be shut off because the bill was not paid?" (HIBLLPAY2) and "[In the last 12 months/Since you've lived here], have [you/your household] had your electricity shut off because the bill was not paid?" (HISHUTOFF). Response options for both questions were 1 = yes and 2 = no. Respondents who were not behind on electricity bills or not responsible for the electric bill (HIBLLPAY = 2, 3, don't know, or refused) but expressed current worry about housing payment (HISTNOW = 1 or 2) were asked an additional question: "[In the last 12 months/Since you've lived here], has it ever been extremely difficult for [you/your household] to pay for your utility bills, besides electricity?" (HIUTLPAY). Response options were 1 = yes, 2 = no, and 3 = not responsible for paying utility bills.

The study team constructed a single observed indicator from these items to reflect difficulty in paying utilities. The study team coded the following categories: 0 = no difficulty (HIBILLPAY = 2 or 3 or HIUTLPAY = 2 or 3), 1 = some difficulty reflecting only difficulty in payment (either HIBLLPAY = 1 and both HIBLLPAY2 and HISHUTOFF = 2 or [HIUTLPAY=1]), 2 = notice of shut off (HIBLLPAY2 = 1 and HISHUTOFF = 2), and 3 = incidence of shut off (HISHUTOFF = 1).

Lack of Stable Occupancy (HI 2)

The lack of stable occupancy dimension is a higher-order latent variable (HI 2) that can be represented using three latent variables: Forced Move Risk and Worry, Residential Instability or Dislocation, and Household Sharing. Below, the study team describes the construction of the observed indicators of each of these three latent variable measures of HI 2.

Forced Move Risk and Worry

Risk of Eviction or Foreclosure

The HIRM asks a series of items on past eviction, the receipt of eviction notice, and the likelihood of being evicted. The following items were assigned codes to define risk of eviction.

> "An eviction is when your landlord forces you to move. Have you been threatened with eviction in this home [in the last 12 months/ since you've lived here]?" (HIEVICT). The response options for this survey item included 1 = yes, 2 = no. This item was asked of renters only.

Of the respondents with an affirmative response to HIEVICT (HIEVICT =1, threatened with eviction), a followup question asked whether they received an eviction notice. The second item asked, "In the last 12 months/ since you've lived here, have you received an eviction notice?" (HIEVICPREV). The response options for this item included 1 = yes, 2 = no.

The third item included in this construct was the following: "How likely is it that you will have to leave this home because of eviction?" (HIEVICLK). The response options were 1 = very likely, 2 = somewhat likely, 3 = not very likely, 4 = not likely at all. This item was asked of renters only. Respondents who were skipped out of this question (HITENURE = 1) were assigned a code 0 = no: skipped, homeowner.

In addition to being asked questions about the current home, households who moved 2 years before the interview were asked about eviction. "Earlier you said you moved in the last 2 years. Did you move away from that home because you, or anyone you were staying with in your previous home, were evicted from that home? (Read as necessary: A landlord not renewing the lease should not be counted as an eviction.)" (HIEVICT2). The response options were 1 = yes, 2 = no. This item was not asked of respondents who did not move in the last 2 years.

The fifth item was the following: "Did you, or anyone you were staying with, receive an eviction notice while living at that home?" (HIEVICPREV2). The response options were 1 = yes, 2 = no.

The HIRM also lists a series of questions on foreclosure. The correlation between the following items needs to be explored before combining the items to construct a single measure of the risk of foreclosure as households with high, medium, and low risk of leaving home due to foreclosure.

The first item to be included under this measure was, "[In the last 12 months/since you lived here], have you received a notice that the current mortgage was going to be foreclosed on?" (HIMRTFORC). The response options were 1 = yes, 2 = no. This item was asked of respondents who were responsible for the mortgage payment (HIMORT > 0) and homeowners (HITENURE = 1).

The second item to construct the risk of foreclosure was, "Is your current mortgage in foreclosure now?" (HINFORC). The response options were 1 = yes, 2 = no. This item was asked of respondents who were responsible for the mortgage payment (HIMORT > 0) and homeowners (HITENURE = 1).

The third item was: "How likely is it that you will have to leave your home because of foreclosure?" (HILVEFORC).[31] The response options were 1 = very likely, 2 = somewhat likely, 3 = not very likely, 4 = not at all likely. This item was asked of respondents who were responsible for the mortgage payment (HIMORT > 0) and homeowners (HITENURE = 1).

[31] The variable HILVEFORC does not include households that face foreclosure due to unpaid property taxes.

> The last item included in this measure was: “Earlier you said you moved in the last 2 years. Now the study team are going to ask you some questions about your previous home. Did you move away from that home because it was foreclosed upon?” (HIEVFORC2). The response options were 1 = yes, 2 = no.

The analysis variable derived to define risk of eviction or foreclosure is as follows:

> 1 = low risk of foreclosure (HIMRTFORC = 2 and HINFORC = 2 and HILVEFORC = 3 or 4 and HIEVFORC2 = 2)/low risk of eviction (HIEVICT = 2 and HIEVICPREV = 0 and HIEVICLK = 3 or 4 and HIEVICT2 = 0 or 2 and HIEVICPREV2 = 0 or 2).
>
> 2 = moderate risk of foreclosure (HIMRTFORC = 1 or HINFORC = 1 or HILVEFORC = 1 or 2 or HIEVFORC2 = 0 or 1 [but not all conditions satisfied])/moderate risk of eviction (all other combinations of HIEVICT, HIEVICPREV, HIEVICLK, HIEVICT2, and HIEVICPREV2 not given in definition of low or high risk).
>
> 3 = high risk of foreclosure (HIMRTFORC = 1 and HINFORC = 1 and HILVEFORC = 1 or 2 and HIEVFORC2 = 0 or 1)/high risk of eviction (HIEVICT = 1 and HIEVICPREV = 1 and HIEVICLK = 1 or 2 and [HIEVICT2 = 0 or 1 or HIEVICPREV2 = 0 or 1]).

The study team also developed a reduced form of risk of eviction or foreclosure that focuses on current risks:

> 1 = low risk of foreclosure (HIMRTFORC = 2 and HINFORC = 2 and HILVEFORC = 3 or 4)/low risk of eviction (HIEVICT = 2 and HIEVICLK = 3 or 4).
>
> 2 = moderate risk of foreclosure (HIMRTFORC = 1 or HINFORC = 1 or HILVEFORC = 1 or 2 [but not all conditions satisfied])/moderate risk of eviction (all other combinations of HIEVICT, HIEVICLK, not given in definition of low or high risk).
>
> 3 = high risk of foreclosure (HIMRTFORC = 1 and HINFORC = 1 and HILVEFORC = 1 or 2)/high risk of eviction (HIEVICT = 1 and HIEVICLK = 1 or 2).

Previous Worry About Forced Move

Analogous to the item on worry about forced move today, this measure is intended to capture worry about a forced move in the past. “How often [in the last 12 months/since you've lived here] would you say you were worried or stressed about being forced to move]?” (HIMOVFRC). The response options for this survey item included 1 = always, 2 = usually, 3 = sometimes, 4 = rarely, and 5 = never. This item is asked of all respondents. The study team constructed the observed indicator as 1 = never, 2 = rarely, 3 = sometimes, 4 = usually, and 5 = always to conform to the convention of “higher is worse.”

Current Worry About Forced Move

The subjective frequency of worry about being forced to move was measured with the following item: “How worried are you right now about being forced to move?” (HIMOVWR). The response options for this survey item include 1 = very worried, 2 = moderately worried, 3 = a little worried, and 4 = not at all worried. This item is asked of all respondents. The study team constructed the observed indicator as 1 = not at all worried, 2 = a little worried, 3 = moderately worried, and 4 = very worried.

Residential Instability or Dislocation

Forced Move[32]

Households can be forced to move due to various reasons, such as condemned property, disaster, and increased rent, to name a few. Respondents who moved were asked followup questions to determine the cause of the move. The response options for these items were 1 = yes, 2 = no.

> This item was asked of respondents who did not receive an eviction notice in their previous home (HIEVICPREV2= 2 or don't know or refused): "Did you move away from that home because your landlord told you, or a person you were staying with, to leave?" (HIEVLNDLD).
>
> This item is answered by those who were not asked to move by the landlord (HIEVLNDLD = 2 or don't know or refused): "Did you move away because you, or a person you were staying with, missed a rent payment and thought that if you didn't move you would be evicted?" (HIEVFEAR).
>
> This item was asked of respondents who did not move because of missed rent payment (HIEVFEAR = 2 or don't know or refused): "Did you move away because the city condemned the property and forced you to leave?" (HIEVCNDM).
>
> This item was asked of respondents whose previous home did not go into foreclosure (HIEVFORC2 = 2 or don't know or refused): "Did you move away because the city condemned the property and forced you to leave?" (HIEVCNDM2).
>
> This item is answered by those who moved from a previous home for reasons other than their property being condemned (HIEVCNDM = 2 or don't know or refused): "(Did you move away) because of a natural disaster or fire?" (HIMVDISAS).
>
> This item is answered by those who moved from a previous home for reasons other than their property being condemned (HIEVCNDM2 = 2 or don't know or refused): "(Did you move away) because of a natural disaster or fire?" (HIMVDISAS2).
>
> This item was asked of respondents who did not move due to property condemnation (HIEVCNDM = 2 or don't know or refused): "(Did you move away) because the landlord raised the rent?" (HIEVRAISE).
>
> This item was asked of respondents who did not move due to property condemnation (HIEVCNDM = 2 or don't know or refused): "(Did you move away) because the landlord did not make repairs?" (HIEVNOFIX).
>
> This item was asked of respondents who did not move due to property condemnation (HIEVCNDM = 2 or don't know or refused): "(Did you move away) because the landlord went into foreclosure?" (HIEVFORC).

[32] Forced moves could be modified to distinguish between formal evictions, informal evictions, and responsive and forced moves depending on further exploration of data (Desmond and Shollenberger, 2015). It is yet to be determined whether certain types of forced moves would indicate greater instability in the future.

The observed indicator was created as a combination of the items above. The categories were as follows: 0 = not forced to move from current/previous property and 1 = forced to move from current or previous property (HIEVLNDLD = 1 or HIEVFEAR = 1 or HIEVCNDM = 1 or HIEVCNDM2 = 1 or HIMVDISAS = 1 or HIMVDISAS2 = 1 or HIEVRAISE = 1 or HIEVNOFIX = 1 or HIEVFORC = 1).

Number of Moves

The study team constructed an observed indicator for the number of moves in the past 12 months from the following items:

"When did you move to this [house, apartment, manufactured/mobile home, living quarters]?" (HIWHENYR). The response options range from 1890 to 2030 and were asked of all respondents.

"What month was that?" (HIWHENMON). The response options were the months January through December.

> HIMOVEDATE is the move-in date constructed using HIWHENMON / move day / HIWHENYR. The move day could be the first, middle, or end of the month. For cases where the move-in date was missing in the HIRM, the move-in month and year from the American Housing Survey (AHS) Core was used to generate the move-in date as of the 15th day of the month.

"About how many months would you say you lived there?" (HILIVNUM). The response options were integers in the range 1 to 11. Respondents could answer this question if HIPREVHO (How long did you live in your previous home) = 2 (less than a year).

HIINTDATE is the interview date.

The number of moves is calculated as follows:

> Number of moves = 0 if (HIINTDATE) – (HIMOVEDATE)[33] ≥ 12. The number of moves in the last 12 months was coded as 0 if the difference between the interview date and move-in date was greater than or equal to 12 months.

If ([HIINTDATE] – [HIMOVEDATE]) < 12, then the number of moves was calculated as follows:

> Number of moves = 1 if [(HIINTDATE) – (HIMOVEDATE)] + (HILIVNUM) ≥ 12. The number of moves in the last 12 months was coded as 1 if the sum of the duration of stay in current home (when duration of stay in current home is less than 12) and months in previous home is greater than 12.
>
> Number of moves = 2 or more if [(HIINTDATE) – (HIMOVEDATE)] + (HILIVNUM) < 12. The number of moves in the last 12 months was coded as 2 or more if the sum of the duration of stay in current home (when duration of stay in current home was less than 12) and months in previous home was less than 12.

[33] Estimated move-in date was adjusted depending on the month.

The observed indicator "Number of Moves" is coded as 0 = none or one move, and 1 = two or more moves.

Proportion of Persons in the Household Who Have Experienced Homelessness

The proportion of persons in the household who have experienced homelessness was constructed as follows. All respondents in the HIRM were asked the following question: "At any time in the last 12 months did you or anyone else in this [house/apartment/manufactured or mobile home/living quarters] experience homelessness?" (HIHMLESS). The response options for this item were 1 = yes, 2 = no. Respondents who answered that someone in the household had experienced homelessness in the last 12 months (HIHMLESS) were asked, "How many people, including yourself, experienced homelessness?" (HIHMLESS2). The Core AHS includes a variable that captures the number of persons living in the unit (NUMPEOPLE). The response options for both HIHMLESS2 and NUMPEOPLE were integers from 1 to 29. The responses were truncated to a maximum of 30 people living in the unit. Respondents who were skipped from HIHMLESS2 (HIHMLESS = 2) were assigned a code 0 (no one experienced homelessness in the past year). The proportion of persons in the household who have experienced homelessness was calculated as the number of people who experienced homelessness divided by the number of persons living in the unit.

Household Sharing

Proportion of Persons in the Household Who Are Living There Temporarily Because They Have Nowhere Else to Go

The proportion of persons in the household who are living there temporarily because they have nowhere else to go was constructed using two items, one from the HIRM and the other from the Core AHS. All respondents in the HIRM were asked, "Is anyone staying there because they had to leave where they were living before and had no other place to stay?" (HINOWHR). The response options for this item were 1 = yes and 2 = no. Respondents who answered yes were asked, "How many people, including yourself, are staying here because they had to leave where they were living before and had no other place to stay?" (HINOWHR2). The Core AHS includes a variable that captures the number of persons living in the unit (NUMPEOPLE). The response options for both HINOWHR2 and NUMPEOPLE were integers from 1 to 29. The responses were truncated to a maximum of 30 people staying in the current home because they had nowhere else to go. Respondents who were skipped (HINOWHR = 2) were assigned a code 0 (no one staying temporarily). The proportion of persons in the household who are living there temporarily because they have nowhere else to go was calculated as the number of people who are living there temporarily because they have nowhere else to go divided by the number of persons living in the unit.

Proportion of Persons in the Household Who Are Living There Temporarily Because of Financial Difficulties

The proportion of persons in the household who are living there temporarily because of financial difficulties was constructed using two items, one from the HIRM and the other from the Core AHS. All respondents in the HIRM were asked, "Is anyone temporarily staying in your current home because of financial difficulties?" (HIFDIFF). The response options for this item were 1 = yes and 2 = no. Respondents who answered yes were asked, "How many people, including yourself (are temporarily staying there because of financial difficulties)?" (HIFDIFF2). The response options were integers in the range 1 to 29. The responses were top coded to include a maximum of 30 people staying in the current home because of financial difficulties. Respondents who were skipped out of this question (HIFDIFF=1) were assigned a code of 0 to reflect no one in the household was living there temporarily due to financial difficulties. The proportion of persons in the household who are living there temporarily because of financial difficulties was calculated as the number of people who are living there temporarily because of financial difficulties divided by the number of persons living in the unit.

Lack of Safety and Decency (HI 3)

The lack of safety and decency dimension is a higher-order latent variable (HI 3) that is a function of three other latent variables: Poor Housing Quality, Overcrowding, and Lack of Safety. Below, the study team describes the construction of the observed indicators of the three latent variables measuring HI 3.

Poor Housing Quality

Number of Structural Deficiencies

The research team developed a composite variable capturing electricity, heating, structural (inside), and other deficiencies captured in the HIRM and Core AHS. To develop the variable, the research team mirrored the development of the ADEQUACY measure in the AHS. The variable counts the number of deficiencies present, including the following:

1. Electricity is not used (ELECAMT = 0).
2. Exposed wiring (NOWIRE = 2).
3. Some rooms with no working electric plugs (PLUGS = 2).
4. Unvented room heater (HEATTYPE = 7).
5. Inside water leaks (LEAKI = 1).
6. Outside water leaks (LEAKO = 1).
7. Holes in the floor (FLOORHOLE = 1).
8. Crack in wall wider than a dime (WALLCRACK = 1).
9. Peeling paint (PAINTPEEL = 1).
10. Rats seen recently (RODENT = 1, 2, 3, or 4).
11. Musty smells (HIMUST = 1, 2, 3, 4).
12. No hot/cold running water OR no full bathroom OR no exclusive use bathroom (BATHROOMS = 7, 8, 9, 10, 11, 12, 13 OR HOTWATER = 7 OR BATHEXCLU = 1, 2).
13. No sink OR no fridge OR no cooking equipment OR no exclusive use (KITCHSINK = 2 OR FRIDGE = 2 OR COOKTYPE = 4 OR KITEXCLU = 2).

Thus, the number of structural deficiencies is a continuous variable that ranges from 0 to 13.[34]

[34] The team also tested a model using a composite variable that applied a weight to each deficiency. The weight was based on work done to develop the Poor Quality Index (Eggers and Moumen, 2013). The correlation between the simple count and weighted count was very high (0.91), so the team did not include both in the same model. The model with the simple count performed slightly better than the model with the weighted count.

The study team developed a reduced form of the structural deficiency variable, which counts only the following number of deficiencies present:

1. Inside water leaks (LEAKI = 1).
2. Outside water leaks (LEAKO = 1).
3. Crack in wall wider than a dime (WALLCRACK = 1).
4. Rats seen recently (RODENT = 1, 2, 3, or 4).
5. Musty smells (HIMUST = 1, 2, 3, 4).

Thus, the reduced number of structural deficiencies is a continuous variable that ranges from 0 to 5.

Heating Breakdowns

Besides structural deficiencies, housing quality is also reflected in the number of service breakdowns that residents experience. The study team measured the number of heating-related service breakdowns as the number of times the unit was uncomfortably cold for more than 24 hours because of a heating equipment breakdown. Three items from the Core AHS were used to construct this measure.

The first item is, “Last winter, for any reason, was your unit so cold for 24 hours or more that you were uncomfortable?” (COLD). This item was asked when the unit is occupied (INTSTATUS = 1) and if the household has some type of main heating equipment (HEATTYPE ≠ 13). The response options for this item were 1 = yes, 2 = no, 3 = household did not live in the unit last winter. The second item from Core AHS used is, “Was that because the main heating equipment broke down?” (COLDEQ). This item was only asked of respondents who reported being uncomfortably cold for 24 hours or more last winter (COLD = 1). The response options for this item were 1 = yes, 2 = no. The third item is “Number of times main heating equipment broke down for 6 hours or more” (COLDEQFREQ). This item was only asked of respondents who reported being uncomfortably cold for 24 hours or more last winter because of a heating equipment breakdown (COLDEQ = 1). The response options for this question were integers between 0 and 7. The responses were top coded, where 8 indicates there were eight or more heating equipment breakdowns lasting 6 hours or more.

The three items from the Core AHS were used to construct a measure of the number of heating-related service breakdowns in the unit. The constructed measure was coded into nine response options as follows: 0 = no heating-related service breakdown (COLD = 2, 3 or COLDEQ = 2), 1–7 = one to seven heating-related service breakdowns (COLDEQFREQ = 1–7), 8 = eight or more heating related service breakdowns (COLDEQFREQ = 8). Respondents in units that did not have any type of main heating equipment were skipped out of these questions. They were coded as being out of universe.

Plumbing Breakdowns: Toilet

The study team constructed three different measures of plumbing-related service breakdowns in the unit. The first analysis variable measures the number of times the unit was without a toilet for more than 6 hours. This measure uses two items from the Core AHS. The first item is, “Flag indicating if unit had any toilet breakdowns in last 3 months” (NOTOIL). The response options were 1 = yes and 2 = no. Respondents were skipped out of this question if the unit does not have a flush toilet (in other words, if BATHROOMS = 7, 10, 11, 13). The second item from the Core

AHS is "Number of toilet breakdowns within last 3 months that lasted 6 hours or more." The response options were 0 = never broke down for 6 hours, 1–7 = one to seven breakdowns lasting 6 hours or more, 8 = eight or more breakdowns lasting 6 hours or more. Respondents were skipped out of this question if the unit did not have any toilet breakdowns in the last 3 months (NOTOIL = 2). The observed indicator measuring the number of times the unit was without a toilet for more than 6 hours was coded into nine response options as follows: 0 = if the unit was never without a toilet for 6 or more hours in the last 3 months (NOTOIL = 2 or NOTOILFREQ = 0), 1–7 = one to seven breakdowns lasting 6 hours or more (NOTOILFREQ = 1–7), 8 = eight or more breakdowns lasting 6 hours or more (NOTOILFREQ = 8). Respondents in units without a flush toilet were skipped out of this question and were coded as being out of universe (INTSTATUS=1 and BATHROOMS=7,10,11,13).

Running Water Breakdowns

The second analysis variable measures the number of times the unit was completely without water for 6 hours or more in the last 3 months. This measure uses two items from the Core AHS. The first item is "Flag indicating if unit was completely without running water in the last 3 months" (NOWAT). The response options were 1 = yes, 2 = no. Respondents were skipped out of this question if the unit does not have hot or cold water or has fewer than 2 bathrooms. The second item from the Core AHS is, "Number of times unit was completely without running water in the last 3 months" (NOWATFREQ). The response options were 0 = never broke down for 6 hours, 1–7 = one to seven breakdowns lasting 6 hours or more, 8 = eight or more breakdowns lasting 6 hours or more. Respondents were skipped out of this question if the unit was not without running water in the last 3 months (NOWAT = 2). The observed indicator measuring the number of times the unit was completely without water for 6 hours or more in the last 3 months was coded into nine response options as follows: 0 = if the unit was never without running water for 6+ hours in the last 3 months (NOWAT = 2 or NOWATFREQ = 0), 1–7 = one to seven times the unit was without running water for 6 or more hours in the last 3 months (NOWATFREQ = 1–7), 8 = eight or more times the unit was without running water for 6 or more hours in the last 3 months (NOWATFREQ = 8). Respondents for whom the NOWAT variable was missing were coded as out of universe.

Sewage Breakdowns

The third measure of plumbing-related service breakdowns is the number of sewage disposal breakdowns in the last 3 months that last 6 hours or more. It was assessed using the item SEWBREAK from the Core AHS: "Number of sewer breakdowns within last 3 months that last 6 hours or more" (SEWBREAK). The response options were 1 = one breakdown in the last 3 months for 6 hours or more; 2 = two breakdowns in the last 3 months for 6 hours or more; 3 = three breakdowns in the last 3 months for 6 hours or more; 4 = four or more breakdowns in last 3 months for 6 hours or more; 5 = sewage system broke down in the last 3 months, but never for 6 hours or more; and 6 = no breakdowns in the last 3 months. Respondents were skipped out of this question if the unit was not connected to the public sewer, septic tank, or cesspool system (SEWTYPE = 7, 8, 9, 10).

The constructed observed indicator measuring the number of sewage disposal breakdowns in the last 3 months was coded into three response options as follows: 0 = no sewage system breakdowns in the last 3 months that lasted 6 hours or more (SEWBREAK = 5, 6), 1 = one or more breakdown in the last 3 months for 6 hours or more (SEWBREAK = 1, 2, 3, 4), and 2 = unit is not connected to public sewer, septic tank, or cesspool system (SEWTYPE = 7, 8, 9, 10).

Overcrowding

Too Many People Living in Unit

This measure of overcrowding is subjective and was assessed with the following item: “Thinking about the number of people in your home and the space you have, are there more people staying here than can live comfortably in this unit?” (HIMAXNUM). This item was asked of all respondents. The response options for this question were 1 = yes and 2 = no. This item was recoded to 0 = no and 1 = yes.

Number of Subfamilies

The number of subfamilies living in the same unit was assessed with the following item from the Core AHS: “Number of subfamilies living in this unit” (NUMSUBFAM). This item was asked of respondents when the unit was occupied (INTSTATUS = 1). The response options for this question were numeric, ranging between 0 and 5. The study team has provided the frequency counts of number of subfamilies.

Persons per Bedroom

The objective measure of overcrowding was constructed using two items from the Core AHS, the number of bedrooms in the unit and the number of persons living in the unit: “How many bedrooms are in this unit?” (BEDROOMS). The item is asked of all respondents. The response options for this question were integers between 0 and 9. The responses were top coded, where 10 indicates 10 or more bedrooms in the unit.

The second item is “Number of people living in this unit?” (NUMPEOPLE). This question is asked of respondents when the unit is occupied (INTSTATUS = 1). The response options for this question were integers between 1 and 29. The responses were top coded, where 30 indicates 30 or more people living in the unit. Persons per bedroom was calculated as the number of persons living in the unit divided by the number of bedrooms in the unit. When the number of bedrooms in the unit was equal to zero (BEDROOMS=0), persons per bedroom was coded as missing. The study team created a categorical variable that bins the responses of this variable. To develop meaningful categories, the study team used cut points identified by Blake, Kellerson, and Simic (2007). The categories for persons per bedroom were: 1 = 0 to < 0.5; 2 = 0.5 to < 1; 3 = 1; 4 = > 1 to < 1.25; 5 = 1.25 to < 1.5; 6 = 1.5 to < 1.75; 7 = 1.75 to < 2; 8 = 2; 9 = > 2.

Persons per Room

Persons per room was constructed using two items from the Core AHS, the number of rooms in the unit and the number of persons living in the unit: “The total number of rooms is the sum of all rooms reported by the respondent” (TOTROOMS). The item was asked of all respondents. The response options for this question were integers between 0 and 44. The responses were top coded, where 45 indicates 45 or more rooms in the unit. The second item was “Number of people living in this unit?” (NUMPEOPLE). This item was asked of respondents when the unit was occupied (INTSTATUS = 1). The response options for this question were integers between 1 and 29. The responses were top coded, where 30 indicates 30 or more people living in the unit. Persons per room was calculated as the number of persons living in the unit divided by the number of rooms in the unit. When the number of rooms in the unit was equal to zero (TOTROOMS=0), persons per room was coded as missing. The study team created a categorical variable that bins the responses of this variable. To develop meaningful categories, the study team used cut points identified by Blake, Kellerson, and Simic (2007). The categories for persons per room were: 1 = 0 to < 0.5; 2 = 0.5 to < 0.75; 3 = 0.75 to ≤ 1; 4 = > 1.

Unit Square Foot Per Person

Unit square foot per person is another objective measure of overcrowding. It was constructed using two items from the Core AHS, the size of the unit (in square feet) and the number of persons living in the unit: "Thinking about all the rooms you mentioned earlier, as well as the hallways and entryways in this housing unit, about how many square feet is that?" (UNITSIZE_IUF). This item was asked of all respondents. The response options for this question were numeric, ranging from 99 to 99,998 square feet. Units that were 99,999 square feet or larger were top coded as 99999. The second item is "Number of people living in this unit?" (NUMPEOPLE). This item was asked of respondents when the unit was occupied (INTSTATUS = 1). The response options for this question were integers between 1 and 29. The responses were top coded, where 30 indicates 30 or more people living in the unit. Unit square feet per person was calculated as the size of the unit in square feet divided by the number of persons living in the unit. The study team created a categorical variable that bins the responses of this variable. To develop meaningful categories, the study team used 165 square feet per person as the cut point because this was identified by Blake, Kellerson, and Simic (2007) as the point at which a unit becomes overcrowded. The categories for square feet per person were 0 = > 165 square feet per person, 1 = ≤ 165 or less square feet per person.

Lack of Safety

Unsafe for Children to Play Outside

The respondent's assessment of the security of their home for children was measured using the following item from the HIRM: "How safe is it for children to play outside around your home during the day?" (HIPLAY). The response options were 1 = very safe, 2 = moderately safe, 3 = not very safe, and 4 = not at all safe. Respondents who were skipped out of this question because the household does not have children under 18 (MINCHILD = 0) were coded as missing.

Feeling Unsafe Inside Home

The respondent's overall feeling of security inside their home was measured using the following item from HIRM: "How safe do you feel inside your home?" (HISAFE). The response options were 1 = very safe, 2 = moderately safe, 3 = not very safe, and 4 = not at all safe. For the observed indicator in the measurement model, the study team include the following categories: 1 = very safe (HISAFE = 1), 2 = moderately safe (HISAFE = 2), and 3 = not safe (HISAFE = 3, 4).

Unsafe Against Break-Ins

The respondent's assessment of the security of their home against break-ins was measured using the following item from the HIRM: "How secure is your home against break-ins?" (HIBRKIN). The response options were 1 = very secure, 2 = moderately secure, 3 = not very secure, and 4 = not at all secure. For the observed indicator in the measurement model, the study team includes the following categories: 1 = very safe (HIBRKIN = 1), 2 = moderately safe (HIBRKIN = 2), and 3 = not safe (HIBRKIN = 3, 4).

Coming/Leaving Home at Night

The respondent's assessment of the security of the area around their home was measured using the following item from the HIRM: "How safe do you feel coming and going from your home at night?" (HICMING). The response options were 1 = very safe, 2 = moderately safe, 3 = not very safe, and 4 = not at all safe.

Appendix C: Descriptive Statistics: Observed Indicators

Lack of Affordability (HI 1): Descriptive Statistics

This section provides summary statistics for all observed variables in HI 1 and the Pearson correlations between each of the variables.

Exhibit C.1 | Lack of Affordability (HI 1): Weighted Summary Statistics of Observed Variables

Observed Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Frequency of worry about mortgage/rent payments	2,800	0.56	1.00	0	4
Extent of worry about mortgage/rent payments	2,800	0.20	0.61	0	3
Recent lapse in housing payments	2,800	0.11	0.49	0	4
Current lapse in housing payments	2,800	0.02	0.15	0	1
Frequency of difficulty making housing payments	2,800	0.23	0.76	0	4
Extent of difficulty making housing payments	2,800	0.39	0.76	0	3
Difficulty paying utilities	2,800	0.30	0.72	0	3
Housing cost burden	2,800	1.08	1.39	0	4
Perceived severe housing cost burden	2,700	0.15	0.35	0	1
Worst case needs	2,800	0.09	0.29	0	1
Residual income	2,800	4.73	3.98	0	11

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit C.2 | Lack of Affordability (HI 1): Weighted Pearson Correlation Between Observed Variables

	Pearson Correlation Between Observed Variables for Affordability Insecurity										
	Frequency of worry about mortgage/ rent payments	Extent of worry about mortgage/ rent payments	Recent lapse in housing payments	Current lapse in housing payments	Frequency of difficulty making housing payments	Extent of difficulty making housing payments	Difficulty paying utilities	Housing cost burden	Perceived severe housing cost burden	Worst case needs	Residual income
Frequency of worry about mortgage/rent payments	1										
Extent of worry about mortgage/rent payments	0.7459*	1									
Recent lapse in housing payments	0.4252*	0.3577*	1								
Current lapse in housing payments	0.3043*	0.2972*	0.6996*	1							
Frequency of difficulty making housing payments	0.589*	0.5423*	0.2996*	0.2237*	1						
Extent of difficulty making housing payments	0.7491*	0.6171*	0.3582*	0.2441*	0.807*	1					
Difficulty paying utilities	0.35*	0.3005*	0.3243*	0.2394*	0.2524*	0.3255*	1				
Housing cost burden	0.1571*	0.1466*	0.0372*	0.0055	0.1334*	0.1482*	0.0555*	1			
Perceived severe housing cost burden	0.4832*	0.3797*	0.1908*	0.0995*	0.3518*	0.4775*	0.1999*	0.2161*	1		
Worst case needs	0.2194*	0.1918*	0.1016*	0.0305	0.1647*	0.2063*	0.0992*	0.4079*	0.3198*	1	
Residual income	0.1636*	0.1472*	0.0608*	0.0261	0.1282*	0.147*	0.0994*	0.8275*	0.1899*	0.3917*	1

* Indicates *p*-value < 0.05.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Lack of Stable Occupancy (HI 2): Descriptive Statistics

This section provides summary statistics for all observed variables in HI 2 and the Pearson correlations between each of the variables.

Exhibit C.3 | Lack of Stable Occupancy (HI 2): Weighted Summary Statistics of Observed Variables

Observed Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Risk of eviction or foreclosure	2,800	1.07	0.27	1	3
Previous worry about forced move	2,800	1.26	0.73	1	5
Current worry about forced move	2,800	1.19	0.58	1	4
Forced move	2,800	0.03	0.18	0	1
Number of moves	2,800	0.11	0.32	0	1
Proportion of persons in the household who have experienced homelessness	2,800	0.01	0.08	0	1
Proportion of persons in the households who are living there temporarily because they have nowhere else to go	2,800	0.02	0.11	0	1
Proportion of persons in the households who are living there temporarily because of financial difficulties	2,800	0.03	0.15	0	1

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit C.4 | Lack of Stable Occupancy (HI 2): Weighted Pearson Correlation Between Observed Variables

Pearson Correlation Between Observed Variables for Stable Occupancy Insecurity								
	Risk of eviction or foreclosure	Previous worry about forced move	Current worry about forced move	Forced move	Number of moves	Proportion of persons in the household who have experienced homelessness	Proportion of persons in the households who are living there temporarily because they have nowhere else to go	Proportion of persons in the households who are living there temporarily because of financial difficulties
Risk of eviction or foreclosure	1							
Previous worry about forced move	0.4447*	1						
Current worry about forced move	0.4282*	0.6190*	1					
Forced move	0.0723*	0.1136*	0.0764*	1				
Number of moves	0.0782*	0.0202	0.0276	0.2374*	1			
Proportion of persons in the household who have experienced homelessness	0.1051*	0.0837*	0.0966*	0.0604*	0.0865*	1		
Proportion of persons in the households who are living there temporarily because they have nowhere else to go	0.1394*	0.1022*	0.0993*	0.0186	0.0574*	0.1010*	1	
Proportion of persons in the households who are living there temporarily because of financial difficulties	0.0779*	0.1292*	0.1284*	0.0334	-0.0097	0.1183*	0.2100*	1

* Indicates *p*-value < 0.05.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Lack of Safety and Decency (HI 3): Descriptive Statistics

This section provides summary statistics for all observed variables in HI 3 and the Pearson correlations between each of the variables.

Exhibit C.5 | Lack of Safety and Decency (HI 3): Weighted Summary Statistics of Observed Variables

Observed Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Structural deficiencies	2,800	0.78	1.14	0	9
Heating breakdowns	2,800	0.1	0.72	0	8
Toilet breakdowns	2,800	0.05	0.48	0	8
Running water breakdowns	2,800	0.07	0.54	0	8
Sewer breakdowns	2,800	0.02	0.13	0	2
Persons per bedroom	2,700	3.44	2.17	1	9
Too many people living in unit	2,800	0.06	0.24	0	1
Number of subfamilies	2,800	0.04	0.21	0	2
Persons per room	2,800	1.63	0.84	1	4
Unit square feet per person	2,500	0.03	0.17	0	1
Feeling unsafe inside home	2,800	1.18	0.43	1	3
Unsafe against break-ins	2,800	1.5	0.62	1	3
Unsafe coming/leaving home at night	2,800	1.37	0.64	1	4
Unsafe for children to play outside	850	1.47	0.73	1	4

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit C.6 | Lack of Safety and Decency (HI 3): Weighted Pearson Correlation Between Observed Variables

Pearson Correlation Between Observed Variables for Safety and Decency Insecurity														
	Structural deficiencies	Heating breakdowns	Toilet breakdowns	Running water breakdowns	Sewer breakdowns	Persons per bedroom	Too many people living in unit	Number of subfamilies	Persons per room	Unit square feet per person	Feeling unsafe inside home	Unsafe against break-ins	Unsafe coming/ leaving home at night	Unsafe for children to play outside
Structural deficiencies	1													
Heating breakdowns	0.1743*	1												
Toilet breakdowns	0.2075*	0.1297*	1											
Running water breakdowns	0.1376*	0.1611*	0.0716*	1										
Sewer breakdowns	0.1321*	0.0384*	0.1464*	0.0279	1									
Persons per bedroom	0.0743*	0.0711*	0.0388*	0.0057	0.0074	1								
Too many people living in unit	0.0382*	0.0548*	0.0214	-0.0099	-0.0086	0.0985*	1							
Number of subfamilies	0.0476*	-0.013	0.026	0.0224	-0.0061	0.2468*	0.0035	1						
Persons per room	0.087*	0.0827*	0.0218	-0.0094	0.0189	0.851*	0.1054*	0.2789*	1					
Unit square feet per person	0.0816*	0.0693*	0.0291	0.0782*	-0.0012	0.3272*	0.0401*	0.1711*	0.3254*	1				
Feeling unsafe inside home	0.2432*	0.0975*	0.0854*	0.0222	0.0347	0.104*	0.1013*	-0.045*	0.0751*	0.0466*	1			
Unsafe against break-ins	0.2544*	0.0617*	0.1012*	-0.0006	0.08*	0.1092*	0.0193	0.0001	0.1057*	0.0094	0.3947*	1		
Unsafe coming/leaving home at night	0.2414*	0.0573*	0.0705*	0.007	0.0141	0.0995*	0.06*	-0.0169	0.082*	0.0272	0.4648*	0.4041*	1	
Unsafe for children to play outside	0.2445*	0.1146*	0.0981*	0.0938*	0.0783*	0.1509*	0.1453*	-0.0313	0.1568*	0.1137*	0.4319*	0.3083*	0.5687*	1

* Indicates *p*-value < 0.05.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Appendix D: Exploratory Factor Analysis

This section presents the results of the exploratory factor analysis (EFA) of the three dimensions of housing insecurity (HI). The exploratory analysis includes variables from an earlier iteration of the measurement models. Results from the EFA informed the development of the final measurement models presented in this report.

The study team produced EFA estimates for each dimension of HI in Stata using the principal component factor analysis method. Principal component factor analysis is one of the most common EFA approaches and assumes that the factors produced explain all variation in the observed items. In other words, the approach assumes that no variation is unique to each item. In addition to principal component factor analysis, the team also tried the "principal factor" method, which is the default in Stata. This approach allows for variance unique to the observed items (in other words, the factors may explain some of the variance but not all in the observed items). The study team found that the results did not change substantively with the principal factor method.

Exploratory Analysis: Lack of Affordability (HI 1)

Exhibit D.1 shows the results of an exploratory factor analysis of the HI 1 indicators with the oblique rotation. The first factor explains 29.9 percent of the variation in the observed indicators, factor 2 explains 16.6 percent of the variation, factor 3 explains 16.4 percent of the variation, and factor 4 explains 15.3 percent of the variation.

Exhibit D.1 | Exploratory Analysis: Lack of Affordability (HI 1) Dimension

	Proportion of Variance Explained by Factor			
Factor 1	29.9%			
Factor 2	16.6%			
Factor 3	16.4%			
Factor 4	15.3%			
	Factor Loading			
	Factor 1 (Worry about inability to pay and subjective housing expense hardships)	**Factor 2 (Lapse in payment)**	**Factor 3 (Income)**	**Factor 4 (Objective housing expense hardships)**
Frequency of worry	**0.8287**	0.1156	0.0102	0.0174
Extent of worry	**0.7699**	0.1223	0.0161	– 0.0201
Recent lapse in payment	0.1524	**0.8306**	– 0.0163	0.0153
Current lapse in payment	– 0.0307	**0.9119**	– 0.0042	0.0234
Frequency of difficulty making payments	**0.8228**	– 0.0107	0.0338	– 0.0714
Extent of difficulty making payments	**0.8968**	0.0159	0.0215	– 0.0381

Difficulty paying utilities	**0.3907**	0.2499	0.0292	-0.049
Perceived cost burden	**0.6638**	– 0.1617	– 0.09	0.2481
Housing cost burden	0.0542	– 0.009	0.1328	**0.8288**
WCN	0.3038	– 0.152	– 0.0709	**0.5954**
Ratio of FMR to income (categorical)	– 0.2144	0.1471	– 0.0045	**0.763**
Income to AMI ratio (reverse coded)	– 0.0024	– 0.0139	**0.9618**	0.0515
Income to poverty ratio (reverse coded)	0.0134	– 0.0009	**0.9818**	– 0.0235

AMI = Area Median Income. FMR = Fair Market Rent. WCN = worst case needs.
Note: Bolded cells indicate factor loadings > .30.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Frequency of worry about inability to pay housing costs and the extent of worry both load heavily on factor 1, with factor loadings of 0.83 and 0.77, respectively. The frequency of difficulty making payments, extent of difficulty making payments, difficulty paying utilities, and perceived cost burden also all load heavily on factor 1. This finding suggests that factor 1 captures the measures of Worry About Inability to Pay housing costs and the subjective measures of Housing Expense Hardships.

However, worry about inability to pay housing costs is conceptually distinct from the experience of housing expense hardships. A household may be very worried about paying housing costs even if they have not experienced any difficulty paying them. In the final measurement model, the study team has retained both the latent variables, Worry About Inability to Pay and Housing Expense Hardships, which gives the team flexibility to weigh the two concepts differently.

The Recent Lapse and Current Lapse in Payment variables load heavily on factor 2. This finding suggests that factor 2 captures the measures of the Lapse in Payment latent variable.

Income to Area Median Income (AMI) Ratio and Income to Poverty Ratio load heavily on factor 3, with factor loadings of 0.96 and 0.98, respectively. None of the other analysis variables load heavily onto factor 3. Thus, these two variables are driven by an underlying factor unrelated to the other analysis variables. These variables have been removed from the final measurement model.

Housing Cost Burden, Worst Case Needs, and Ratio of Fair Market Rate (FMR) to Income (categorical) load heavily on factor 4. The factor loading of Housing Code Burden is 0.83, and the factor loading for Worst Case Needs is 0.6, suggesting that factor 4 captures objective measures of housing expense hardships. The Ratio of FMR to Income also loads heavily on factor 4. This measure includes a geographically adjusted benchmark of housing costs. However, this measure does not include information about housing cost of the individual household. The Ratio of FMR to Income (categorical) variable has been removed from the final measurement model of the gold standard factor scores and replaced with the categorical Residual Income variable that considers household income, housing costs of the household, and a basic minimum level of non-housing spending needs for the household.

Exploratory Analysis: Lack of Stable Occupancy (HI 2)

Exhibit D.2 shows the result of an EFA on the HI 2 indicators in an earlier version of the measurement model with the oblique rotation. The first factor explains 21.6 percent of the variation in the observed indicators, factor 2 explains 19.8 percent of the variation, factor 3 explains 18.8 percent of the variation, and factor 4 explains 13.5 percent of the variation.

Exhibit D.2 | Exploratory Analysis: Lack of Stable Occupancy (HI 2) Dimension

	Proportion of Variance Explained by Factor			
Factor 1	21.6%			
Factor 2	19.8%			
Factor 3	18.8%			
Factor 4	13.5%			
Factor Loading				
	Factor 1 (Forced move risk and worry)	**Factor 2 (Household sharing)**	**Factor 3 (Homelessness)**	**Factor 4 (Residential Instability /Dislocation)**
Risk of eviction or foreclosure	**0.7358**	0.0312	– 0.006	0.0223
Forced move	0.0471	– 0.0088	0.0334	**0.7816**
Previous worry about forced move	**0.8747**	0.001	– 0.0113	0.0058
Current worry about forced move	**0.8594**	– 0.0183	0.0174	– 0.0229
Anyone experienced homelessness	0.0301	0.0298	**0.9268**	0.0014
Number of people who experienced homelessness	– 0.0272	– 0.0265	**0.9462**	0.007
Doubling up	0.0504	**0.8268**	– 0.0033	0.007
Temporary housing, financial difficulty	– 0.0502	**0.7397**	0.0614	– 0.1036
Temporary housing, nowhere else to go	– 0.0101	**0.7817**	– 0.0412	0.0805

Number of moves (3 categories)	– 0.044	0.0091	– 0.0142	**0.8158**

Note: Bolded cells indicate factor loadings > .30.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The Risk of Eviction or Foreclosure, Previous Worry About Forced Move, and Current Worry About Forced Move variables load heavily on factor 1, with factor loadings of 0.74, 0.87, and 0.86, respectively. This factor appears to capture the Forced Move Risk and Worry latent variable. Doubling Up, Temporary Housing Financial Difficulty, and Temporary Housing Nowhere Else to Go all load heavily on factor 2. This factor appears to capture the Household Sharing latent variable in the final measurement model.

The Doubling Up variable measures whether at least one person is staying temporarily in the household due to either financial difficulties or because they have nowhere else to stay. The response options for the Doubling Up variable are 1 = no one is staying in the household temporarily due to financial difficulties or because they have nowhere else to stay, 2 = at least one person is staying temporarily due to financial trouble but not because they have nowhere else to stay, 3 = at least one person is staying temporarily because they have nowhere else to stay but not due to financial trouble, and 4 = at least one person is staying temporarily because they have nowhere else to stay and due to financial trouble. While all variables in the final measurement model follow the convention "higher is worse," it is unclear in the case of Doubling Up whether the response options are indeed ordered such that higher values indicate greater HI. The Temporary Housing Financial Difficulty and Temporary Housing Nowhere Else to Go variables measure the number of people staying temporarily in the house due to financial difficulties and because they have nowhere else to go, respectively. However, these variables do not account for the overall size of the household. Thus, households of different sizes that have the same number of people staying temporarily will have the same level of Household Sharing insecurity. The EFA shows that these three variables load heavily on the same factor. Due to the issues mentioned above, in the final measurement model, Doubling Up, Temporary Housing Financial Difficulty, and Temporary Housing Nowhere Else to Go are replaced with the Proportion of Persons in the Household Who Are Living Temporarily Due to Financial Difficulties and Proportion of Persons in the Household Who Are Living Temporarily Because They Have Nowhere Else to Go.

Forced Move and Number of Moves load heavily on factor 4, with factor loadings of 0.78 and 0.82, respectively. This factor appears to capture the Residential Instability or Dislocation latent variable. Anyone Experienced Homelessness and Number of People Experienced Homelessness load heavily on a separate factor, factor 3. Conceptually, variables related to homelessness should also measure Residential Instability. However, this is not captured in the EFA in exhibit D.2. Notably, Number of People Who Experienced Homelessness does not account for the size of the household. In the final measurement model, the study team replaced Anyone Experienced Homelessness and the Number of People Who Experienced Homelessness with the Proportion of Persons in the Household Who Have Experienced Homelessness.

In the EFA in exhibit D.2, the Number of Moves variable has three categories: no moves, one move, and two or more moves. In the final measurement model, the Number of Moves variable was collapsed to two categories (less than two moves, two or more moves) in keeping with standard practice in the HI literature.

Exploratory Analysis: Lack of Safety and Decency (HI 3)

Exhibit D.3 shows the results of an EFA of the HI 3 indicators in an earlier version of the measurement model with the oblique rotation. The analysis found seven factors that explain variation in the HI 3 indicators.

The first factor reflects the lack of safety concept, as it has strong positive loadings for each lack of safety variable. The factor also has a moderate loading for the variable measuring musty smells and the variable measuring issues related to overcrowding. In the confirmatory analysis of an earlier version of the measurement model, the team found that the variable Issues Related to Overcrowding had a cross-loading on the lack of safety concept. The exploratory analysis also shows this and further justifies the removal of this variable from the final measurement model.

Exhibit D.3 | Exploratory Analysis: Lack of Safety and Decency (HI 3) Dimension

Proportion of Variance Explained by Factor				
Factor 1	13.5%			
Factor 2	12.3%			
Factor 3	7.7%			
Factor 4	6.5%			
	Factor Loading			
	Factor 1 (Lack of safety)	**Factor 2 (Overcrowding)**	**Factor 3 (Heating and water breakdowns)**	**Factor 4 (Cooling and electrical deficiencies)**
Feeling unsafe inside home	**0.7585**	0.0173	0.0594	0.0422
Unsafe against break-ins	**0.6684**	– 0.0854	– 0.1329	0.1038
Unsafe coming/leaving home at night	**0.7936**	0.0104	– 0.0118	– 0.1007
Unsafe for children to play outside	**0.715**	0.0606	0.0153	– 0.0755
Lack of upkeep	0.1588	– 0.0907	**0.5404**	0.0474
Musty smells	**0.448**	– 0.05	0.1007	0.255
Kitchen deficiencies	– 0.0427	0.0454	– 0.0767	0.1344
Cooling deficiencies	0.0661	0.1126	– 0.0967	**0.3966**
Quality of wiring	– 0.0311	– 0.0079	– 0.0021	**0.6766**

Adequacy of electrical outlets/plugs	0.0274	– 0.0304	– 0.0272	– **0.6812**
Heating breakdowns	– 0.0242	0.0135	**0.6955**	0.0375
Toilet breakdowns	– 0.037	0.0401	0.1667	– 0.0748
Running water breakdowns	– 0.0337	0.0028	**0.7636**	– 0.038
Sewer breakdowns	0.0202	– 0.0916	– 0.001	0.1506
Issues related to overcrowding	**0.3588**	0.174	0.183	0.0155
Number of people per bedroom	0.0035	**0.8965**	0.0086	0.0138
Too many people living in unit	0.2391	0.1355	0.0429	0.0185
Number of subfamilies	– 0.0964	**0.3101**	0.1255	– 0.1979
Number of people per room	– 0.0216	**0.9265**	– 0.0077	– 0.0042
Unit square feet per person	– 0.0623	– **0.7345**	0.0289	– 0.0241

Note: Bolded cells in factor loadings > .30.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The second factor has strong loadings for the variables measuring overcrowding. The variable measuring too many people living in the unit has the weakest loading of the overcrowding measures, which reflects the confirmatory results of the final measurement model (exhibit 14 shows that the coefficient for too many people living in the unit is only 0.11). In the EFA, the Number of People per Bedroom, the Number of People per Room, and the Unit Square Feet per Person variables are continuous. However, in the final measurement model, they are categorical, coded using the cut points identified by Blake, Kellerson, and Simic (2007).

The third factor has strong loadings for heating and running water breakdowns as well as lack of upkeep, while the fourth factor has strong loadings for cooling deficiencies, adequate outlets/plugs (negative loading), and poor-quality wiring. These two factors point to breakdowns (heating and water) and deficiencies (cooling and electrical) that are most likely to occur together. It is also likely that many breakdowns/deficiencies may occur separately, which would explain the lack of correlation between indicators such as kitchen, cooling, and electrical deficiencies. Further, in an earlier iteration of the measurement model, confirmatory factor analysis showed that the presence of Musty Smells and Lack of Upkeep both loaded strongly onto a Structural Deficiencies latent variable along with electrical deficiencies, with a statistically significant but weaker loading. In the final measurement model, the study team combined these indicators to create the Structural Deficiencies variable.[35]

[35] For a full description of the construction of the Structural Deficiencies variable, see appendix B.

Appendix E: Coding Open-Ended Items

The study team identified five open-ended questions from the Housing Insecurity Research Module (HIRM) Survey that might be useful for analysis.[36] Each question was examined to determine whether the responses contained information that could be applied to codes in variables of interest. Specifically, respondents might have volunteered an uncoded reason for a previous move or a reason that causes worry about the current housing situation. The study team examined these narrative responses and determined, in collaboration with HUD, whether the response fit an existing response category, whether a new category should be created to represent a novel response, or whether the information was not usable for HI measurement.

The rest of the section describes the five open-ended questions identified from the HIRM survey, the universe for each question, and the categories into which the open text responses were coded.

HIMVOSP

The HIMVOSP question asks respondents about reasons for a previous move. The text of the HIMVOSP question is, "What were the other reasons?" The question is asked of respondents who had moved in the last 2 years, said yes to one of the reasons listed for moving, and have HIMVOTH=1 (respondent had other reasons to move) and HIXTEN in (2,3) (previous home rented or occupied without payment of rent).

There were 90 open-ended responses to this question. The study team coded the responses into a new variable, HIMVOSP_Other. Each response is coded into either a reason for moving already listed in the HIRM survey or a newly created reason. The reason "Other" includes reasons for moving, such as lack of parking space, no pet policy, and changed apartments. The frequency distribution for HIMVOSP_Other is provided below. The first column of exhibit E.1 lists the reasons under HIMVOSP_Other, the second column provides the frequency count, and the third column provides the frequency percent as a share of the total number of open-ended responses. The fourth column presents the level of residential instability indicated by the reason. The fourth column is discussed in detail below.

Exhibit E.1 | HIMVOSP_Other: Frequency Distribution

HIMVOSP_Other	Frequency Count	Percent	Level of Residential Instability Indicated by the Reason
Bad neighborhood (bad = dangerous, conflicts, violence); not affordable; overcrowding; temporary living	20	22.22%	Greater residential instability
HIEVFORC; HIEVNOFIX; HIMVDISAS; homeless; lack of upkeep	20	22.22%	Greater residential instability

[36] There were six open ended questions in the HIRM survey. The open-ended question that was not examined by the study team was CATI_OTHER, which recorded reasons for exiting the interview other than those listed in the SCREENOUT question.

Bought a house; increased standard of living; wanted bigger space; wanted own place; wanted to buy house	20	22.22%	Less residential instability
Closer to family; closer to medical help; closer to work; housing assistance; job-related reasons; relocation; schooling-related reasons; senior housing facilities; single story needed; lease end; personal reasons; other.	30	33.33%	Irrelevant to residential instability
Grand Total	**90**	100.00%	

Notes: Some percentages do not add to 100 due to rounding. The “Percent” column presents percentages based on the rounded counts.

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Some of the responses in HIMVOSP are coded as reasons for moving already listed in the HIRM survey: HIEVFORC (moved away because landlord went into foreclosure), HIEVNOFIX (moved away because landlord did not make repairs), and HIMVDISAS (moved away because of a natural disaster or fire). The study team created three new variables—HIEVFORC_new, HIEVNOFIX_new, and HIMVDISAS_new—that are equal to the original variables (HIEVFORC, HIEVNOFIX, and HIMVDISAS) for most cases and incorporate the relevant recodes from the HIMVOSP_Other. The three items—HIEVFORC_new, HIEVNOFIX_new, and HIMVDISAS_new—are used to construct the observed indicators on forced moves (so_forced_move) in the stable occupancy dimension.

The newly coded reasons under HIMVOSP_Other do not affect any observed indicators used in the analysis. However, it is useful to analyze the newly coded reasons to determine whether any of them should be included in future iterations of the HIRM as a reason for moving. To aid this analysis, in column (4) of exhibit E.1, the newly created reasons were first classified as one of the following:[37] (a) indicating greater residential instability, (b) indicating less residential instability, or (c) irrelevant to residential instability.

Of particular interest are reasons classified as indicating greater residential instability. The study team examined these reasons and determined that none of them should be included as reasons for moving in future iterations of the HIRM.

Some open-ended responses were coded as either Bad Neighborhood or Lack of Upkeep. However, closely related questions are already asked in the HIRM survey. The HIEVDNGR item asks whether the respondent moved away because the neighborhood was dangerous, and the

[37] This classification was created through consultations between HUD and the study team.

HIEVNOFIX item asks whether the respondent moved away because the landlord did not make repairs.

HIMVNON

The HIMVNON question also asks respondents about reasons for a previous move. The text of the HIMVNON question is, "I see that none of these reasons fit your case. Why did you move away from this place?" The question is asked of respondents who had moved in the last 2 years, said no (or don't know/refused) to all the reasons listed for moving, and have HIXTEN in (2, 3) (previous home rented or occupied without payment of rent).

There were 300 open-ended responses to this question. The study team coded the responses into a new variable HIMVNON_Other. The open text responses are coded into one of the reasons listed under HIMVNON_Other in exhibit E.2. The reason "Other" includes reasons for moving such as too far away, washer/dryer in apartment, and owner passed away. The frequency distribution for HIMVNON_Other is provided below.

Exhibit E.2 | HIMVNON_Other: Frequency Distribution

HIMVNON_Other	Frequency Count	Percent	Level of Residential Instability Indicated by the Reason
Bad neighborhood; not affordable; overcrowding; temporary living	< 15	D	Greater residential instability
Downsize; homeless; lack of upkeep; lower rent	< 15	D	Greater residential instability
Availability of senior housing; closer to family; closer to school; closer to work; job-related reasons; pet friendly; received housing assistance; relocation; schooling-related reasons	80	26.67%	
Bought a house; earn higher wages; wanted a bigger place; wanted own space; wanted to buy house	80	26.67%	Less residential instability
Lease end; owner/landlord was selling; personal reasons; other	90	30.00%	Irrelevant to residential instability
Grand Total	**300**	**100%**	

Notes: Some percentages do not add to 100 due to rounding. The "Percent" column presents percentages based on the rounded counts. Since cells are suppressed due to inadequate observations (*N* < 15), the presented percentages are calculated using the rounded sample size as the denominator. "D" signifies a suppressed value.
Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The newly coded reasons under HIMVNON_Other do not affect any observed indicators used in the analysis. The fourth column of exhibit E.2 presents the level of residential instability indicated by each reason. As in the case of HIMVOSP, the reasons were classified as one of the following:[38] (a) indicating greater residential instability, (b) indicating less residential instability, or (c) irrelevant to residential instability.

The study team examined the newly coded reasons classified as indicating greater residential instability and determined that none of them should be included as reasons for moving in future iterations of the HIRM.

HIMVOSP2

The HIMVOSP2 question asks respondents about reasons for a previous move. This question is very similar to the HIMVOSP question, but the universe of respondents is slightly different. The text of the HIMVOSP2 question is, "What were the other reasons?" The question is asked of respondents who had moved in the last 2 years, said yes to one of the reasons listed for moving, and have HIMVOTH2=1 (respondent had other reasons to move) and HIXTEN=1 (previous home owned).

The study team coded the responses into a new variable HIMVOSP2_Other. Each response was coded into a reason for moving already listed in the HIRM survey or into a new reason listed under HIMVOSP2_Other in exhibit E.3. The reason "Other" includes responses whose meaning was not very clear, such as "age." The frequency count for HIMVOSP2_Other is provided below.

Exhibit E.3 | HIMVOSP2_Other: Frequency Distribution

HIMVOSP2_Other	Frequency Count	Level of Residential Instability Indicated by the Reason
Affordability; HIWMINC2; lack of space; temporary housing; landlord was selling home	< 15	Greater residential instability
Better neighborhood; closer to family; relocation; wanted more space; personal reasons; other	20	Neutral/Less residential instability/Irrelevant to residential instability

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

[38] This classification was created through consultations between HUD and the study team.

Some responses in HIMVOSP2 are coded as a reason for moving already listed in the HIRM survey, HIWMINC2 (moved away because income decreased). However, this does not affect any of the observed indicators. The newly coded reasons under HIMVOSP2_Other also do not affect any of the observed indicators used in the analysis. The third column of exhibit E.3 presents the level of residential instability indicated by each reason. As in the case of HIMVOSP and HIMVNON, reasons were classified as one of the following:[39] (a) indicating greater residential instability, (b) indicating less residential instability, (c) neutral (could indicate instability, but the direction is unclear), or (d) irrelevant to residential instability.

The study team examined the newly coded reasons classified as indicating greater residential instability and determined that none of them should be included as reasons for moving in future iterations of the HIRM.

HIMVNON2

The HIMVNON2 question also asks respondents about reasons for a previous move. The text of the HIMVNON2 question is, “I see that none of these reasons fit your case. Why did you move away from this place?” The question is asked of respondents who had moved in the last 2 years, said no (or don't know/refused) to all the reasons listed for moving, and have HIXTEN=1 (previous home owned).

The open text responses are coded into one of the reasons listed under HIMVNON_Other in exhibit E.4. The reason “Other” includes reasons for moving, such as retired and wanted to move away, interested in more diversity, and opportunity to lease a room. The frequency count for HIMVNON2_Other is provided below.

Exhibit E.4 | HIMVNON2_Other: Frequency Distribution

HIMVNON2_Other	Frequency Count	Level of Residential Instability Indicated by the Reason
Conflicts with landlord; downsize; owner/landlord was selling; upkeep	< 15	Greater residential instability
Better neighborhood; closer to family; closer to work; convenience; job-related reasons; moved to a smaller place; relocation; schooling-related reasons; schooling-related reasons + closer to family; schooling-related reasons + personal reasons	40	Neutral
Bought a house; income increased; wanted more space; wanted own space	20	Less residential instability
Personal; other	30	Irrelevant to residential instability

[39] This classification was created through consultations between HUD and the study team.

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The newly coded reasons under HIMVNON2_Other do not affect any of the observed indicators used in the analysis. The third column of exhibit E.4 presents the level of residential instability indicated by each reason. As in the case of HIMVOSP2, reasons were classified as one of the following:[40] (a) indicating greater residential instability, (b) indicating less residential instability, (c) neutral (could indicate instability, but the direction is unclear), or (d) irrelevant to residential instability.

The study team examined the newly coded reasons classified as indicating greater residential instability and determined that none of them should be included as reasons for moving in future iterations of the HIRM.

HICAUSESP

The HICAUSESP question asks respondents about the reasons that cause them to worry about their housing situation. The text of the HICAUSESP question is, "Specify other causes of worry not listed in HIWCAUSE." This question is asked to respondents who choose the option something else (HIWCAUSE=8) when presented with different reasons for cause of worry about housing payment situation. The text of the HIWCAUSE question is, "Do any of the following currently cause you to worry about your housing situation?"

The study team coded the responses into a new variable, HICAUSESP_Other. Each open text response was coded either into one of the causes of worry listed under the HIWCAUSE question or into a new cause of worry. The frequency count for HICAUSESP_Other is provided in exhibit E.5.

Exhibit E.5 | HICAUSESP_Other: Frequency Distribution

HICAUSESP_Other	Frequency Count	Percent
HIWCAUSE = 2, 5, 6; childcare expenses; car-related expenses; health-related expenses; health-related + car-related expenses	20	50.00%
Limited income; job security; personal; conflicts with neighbors; schooling-related expenses; general cost of living; other	20	50.00%
Grand Total	**40**	**100.00%**

Source: U.S. Census Bureau, 2019 American Housing Survey

[40] This classification was created through consultations between HUD and the study team.

Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The newly coded reasons indicate that several responses cited either childcare expenses, health-related expenses, or car-related expenses as causing worry about the housing situation. However, the coded responses under HICAUSESP_Other do not affect any of the observed indicators used in the analysis. The HIWCAUSE question is also not included in the analysis.

Appendix F: Full Literature Review

Introduction

Housing is a basic fundamental need, and the role of government and policymakers in providing or regulating housing has a long history. Historians date the first housing regulations in the United States as occurring in 1624—over a century before the United States would become a sovereign nation. Most early laws were focused on fire prevention and hygiene, and housing policy quickly began to focus on efforts to ensure the availability of adequate housing for low-income and vulnerable populations (Plunz, 2016). During the mid-20th century, discrimination and segregation in housing were a key focus of housing policy, and while these have remained important considerations, more recent efforts have focused on affordable housing for all. More recently, *housing insecurity* (HI) has become a key term to describe the target malady that housing policy hopes to address.

Despite longstanding efforts to improve how all U.S. citizens are housed, measurement of the scope of the housing problem in the United States has lagged. The American Housing Survey (AHS) was launched in 1973[41] to facilitate more rigorous measurement and tracking of the quality, characteristics, and cost of the U.S. housing stock over time (Census Bureau, 2019b). The AHS is a joint product of HUD and the U.S. Census Bureau. This literature review aims to establish a foundation for developing a comprehensive HI measure: the HUD Housing Insecurity Measure (HUD-HIM).

To fill the gap in HI measurement, HUD began developing the HUD Housing Insecurity Research Module (HUD-HIRM) for the AHS in 2016 (HUD, 2017). As part of that effort, HUD's Housing as a Platform Knowledge Collaborative undertook an extensive review of the literature published before 2016 (Virgile et al., 2019). Since then, the research module has been developed and administered to a subset of 2019 AHS participants whose household income was below 300 percent of the federal poverty threshold. Data from this module will be used to inform the construction of the HUD-HIM.

The current review focuses on literature examining U.S. HI and published in the past 5 years (in other words, since 2015, when the last such effort was undertaken).[42] On January 3, 2020, the Web of Science was queried to obtain all full-text articles published in English since 2015 using the keywords "housing insecurity" and "housing security." This search resulted in 158 articles, which were subsequently considered for inclusion in this review. Additional articles were added based on citations from key manuscripts, querying the Survey of Income and Program Participation (SIPP) manuscript database and, similarly, querying the Panel Study of Income Dynamics database. From these articles, a conceptual review has been developed. A review of article abstracts revealed four themes as important for bolstering rigorous development of an HI measure, and only articles supporting these themes were reviewed: (1) state of HI in the United States; (2) outcomes correlated with HI; (3) mechanisms related to HI; and (4) measurement of HI.

[41] In 1973, the AHS was called the "Annual Housing Survey." The name was changed to the "American Housing Survey" in 1983.

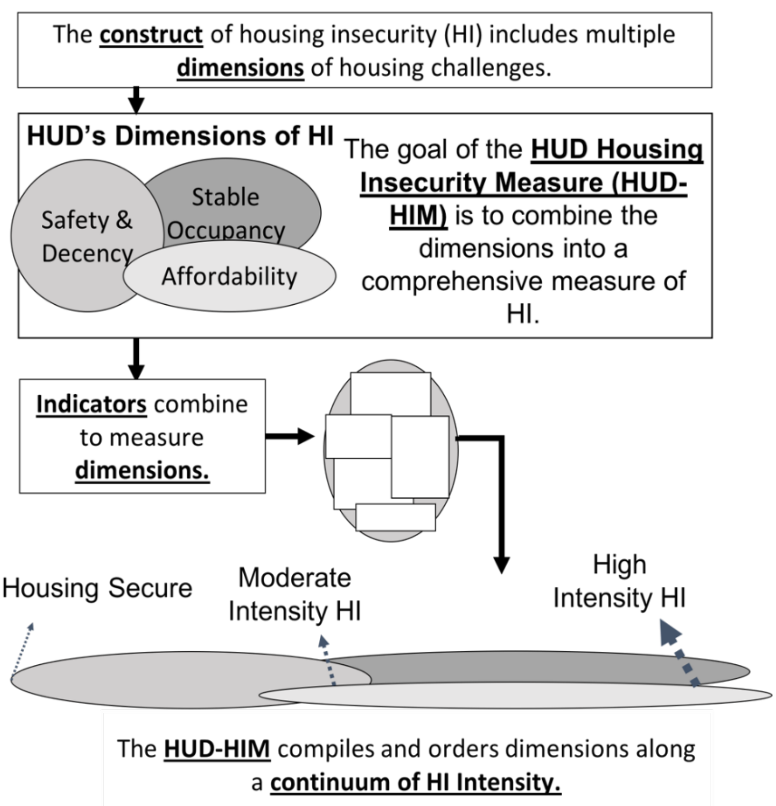
[42] These boundaries were sometimes extended when necessary to elucidate key points.

Housing Insecurity in the United States

Definitions of HI

The HUD-HIRM was designed around a conceptual model that presents HI as a multidimensional construct. Each dimension of HI represents a type of housing challenge faced by households, such as lack of housing affordability or low-quality housing. Data from multiple indicators can be used to assess each dimension, then measures of each dimension can be combined to create a comprehensive measure of HI. HUD has already identified three key dimensions for inclusion in the HUD-HIM, and the goal of the HUD-HIM is to combine the dimensions into a comprehensive measure of HI. Exhibit F.1 illustrates how indicators (squares) can be combined to measure dimensions (ovals), which are combined in the HUD-HIM to form an HI continuum. The goal of the development of the HUD-HIM is to provide systematic structure to the indicators and dimensions to assess HI accurately.

Exhibit F.1 | Multidimensional Structure of HI



Source: Authors' representation

One of the critical challenges to developing a measure of HI is the lack of a universally accepted definition of the term. Cox et al. (2019) traced the historical development of HI back to the U.S. Housing Act of 1949, in which housing was introduced as important for "the general welfare and security of the Nation and the health and living standards of its people." Improvements in what the study team now refers to as the various dimensions of HI were purported to have the goal of "development and redevelopment of the communities and to the advancement of the growth, wealth, and security of the Nation."[43] The language of the housing act was lofty, but it provided a rare early example of an attempt to operationally define a construct that is at the heart of housing policy efforts. More recently, the construct that housing policy targets has been described as HI.

Since 1949, definitions of HI have tended toward defining HI in terms of the dimensions used to measure it. In 1969, the U.S. Department of Health and Human Services (HHS) defined HI in

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[43] U.S. Congress. 1949. "Housing Act of 1949." https://www.govinfo.gov/app/details/COMPS-10349.

five dimensions: affordability, quality, neighborhood stability, overcrowding, and homelessness (HHS, 1969). In 1997, the United Nations (UN) characterized adequate housing, the UN's construct most closely related to housing security, in terms of six dimensions: affordability, decency and safety (divided into two dimensions), neighborhood stability, protection against forced relocations, and accessibility and protection for cultural expression (UN, 2014).

More recently, HUD has defined HI in terms of three dimensions: affordability, decency and safety, and stable occupancy (Watson and Carter, 2020). The dimensions in HUD's definition can trace their origins back to the 1949 Housing Act (described above) and are seen in each of the subsequent definitions put forth by HHS and the UN. Although the HUD definition includes fewer dimensions than previous efforts to define HI, the dimensions are broadly articulated to cover the same scope as the HHS and UN definitions, with only one major exception. That exception is the exclusion of concerns for neighborhood quality and stability in the HUD definition.

The neighborhood dimension was excluded from HUD's definition because HUD saw three concerns: "First, including neighborhood factors blurs the conceptual focus on housing needs and would significantly expand the scope and questionnaire length of a pilot module. Second, neighborhood amenities and location are a major part of the bundle of housing services that drives housing price, which will be captured by the affordability and quality components of the module. Finally, the negative association between neighborhood amenities and affordability means that including both would reduce the explanatory power of a composite housing insecurity indicator" (Watson and Carter, 2020). Concerns related to the assessment of neighborhood quality are well founded. To date, there is no broad consensus regarding what combination of indicators can differentiate high- from low-quality neighborhoods, and in most cases, multiple indicators are used to assess neighborhood quality (for example, Raudenbush, 2003; Talen and Koschinsky, 2014). In addition, there is substantial evidence that neighborhood quality is capitalized in housing prices (for example, Bayer, Ferreira, and Mcmillan, 2007; Emrath and Taylor, 2012; Greenstone and Gallagher, 2008; Nguyen-Hoang and Yinger, 2011; Yinger, 2015). However, housing prices—which, when combined with income, are a key indicator of the affordability dimension—alone are not a sufficient means of assessing neighborhood quality because neighborhood quality is only one of many characteristics of housing upon which house price is based (Leonard et al., 2016).

Market segmentation in residential housing markets also creates differential hedonic pricing of housing attributes, including neighborhood quality (for example, Farmer and Lipscomb, 2010; Galster, 1997; Islam and Asami, 2009; Quillian, Lee, and Honoré, 2020). Due to market segmentation, housing affordability is better interpreted alongside consideration of the factors that distinguish housing market segments. One of these key factors is neighborhood quality. Desmond (2016) asserts that rental units in high- and low-quality neighborhoods may rent at comparable prices because rental price, in part, reflects perceptions of different risk levels associated with the likelihood that tenants will be able to maintain rent payments and not contribute to neighborhood problems. Landlords in low-quality neighborhoods may be willing to rent to tenants with a history of eviction or arrests, but landlords in higher-quality neighborhoods may not. Recent work examining variations in the structure of Section 8 voucher rental allowances showed that voucher holders with allowances that were adjusted based on local neighborhood rents were able to move to higher-quality neighborhoods, but these households remained in neighborhoods that were lower quality relative to the metropolitan area as a whole (Collinson and Ganong, 2018). The authors concluded that barriers or preferences that create market segmentation may have prevented households from using the more generous rental allowances to improve the neighborhood quality dimension more fully.

In light of these considerations related to neighborhood quality (safety, condition), it might be useful for HUD to consider including neighborhood quality as an additional dimension of HI. Fortunately, the HUD-HIRM already includes some indicators of neighborhood safety, and the core AHS has included other indicators of neighborhood condition for many years. Development of the HUD-HIM can proceed by assessing the ability of these indicators to improve the quality of HI measurement and weigh this improvement against the costs of measuring a fourth dimension (neighborhood quality). This approach is preferred to simply excluding neighborhood quality from consideration before developing the HUD-HIM because the approach allows researchers and policymakers to more clearly understand the consequences of inclusion/exclusion of the neighborhood quality dimension. The extant literature suggests that neighborhood quality may have important independent and correlative relationships with other HI dimensions.

The approach to defining HI in terms of the dimensions used to measure it has a critical weakness: it does not allow for an understanding of how the intensity of HI should be assessed or interpreted. HUD states the goal of the HUD-HIM is to place households on a continuum of HI. Full housing security would denote one end of the continuum and identify households with no significant lapses in any dimensions of secure housing. Households experiencing a lapse in at least one dimension of secure housing would lie at other points along the continuum, and homelessness would denote the other end of the continuum. The HI continuum will allow differentiation of the intensity of HI experienced by households (Virgile et al., 2019). For example, the HI continuum would be able to characterize households as experiencing housing security, low-intensity HI, moderate-intensity HI, or high-intensity HI.[44] At present, it is unclear how movements along the continuum of HI correspond to changes in the individual dimensions of HI. For example, if households experience housing challenges captured by more than one dimension of HI, are they, therefore, experiencing a higher intensity of HI, or can housing challenges experienced in only one dimension be so great that they alone produce high-intensity HI?

To assess these questions necessary for the development of the HUD-HIM, the HI construct, including its dimensions, must be well-defined. To this end, the goals first put forth in the 1949 Housing Act continue to provide a basis for a general framework for assessing HI intensity: More intense HI should be judged based on its association with more precarious and deleterious outcomes. Despite ambiguity regarding exactly what constitutes varied intensities of HI, there is consensus that homelessness represents the most extreme form of HI. Homelessness occurs in different modalities, as exemplified by the ETHOS (European Typology on Homelessness and Housing Exclusion) typology, which lists 13 possible conditions through which homelessness

[44] HUD has specified that the HUD-HIM should measure HI along a continuum of HI intensity. The example using specific categories is for illustrative purposes only.

could occur (European Federation of National Organizations Working with the Homeless [FEANTSA], 2005). HUD has adopted a definition of homelessness that uses three of the ETHOS modalities, including people living either (1) in rough accommodations, (2) in emergency accommodations, or (3) in accommodations for the homeless. In contrast, most other developed countries use a broader definition of homelessness that expands the HUD definition to people living in insecure accommodations and temporary or nonconventional structures (O'Flaherty, 2019). This review uses the term *homelessness* to refer to the current HUD definition unless specifically stated otherwise. Studies that utilized the more expansive definition are referred to as studying HI more generally.

While all major definitions for HI have included multiple dimensions, the vast majority of studies examining HI either examined only one dimension or multiple dimensions independently. For example, Pilkauskas and Michelmore (2019) examined the affordability and stable occupancy dimensions of HI but did not attempt to make any composite measure of the HI construct. Instead, results provided estimates of how an increase in the earned income tax credit affected the affordability and stable occupancy dimensions separately and were ambiguous regarding the impact on overall HI. Ambiguity is enhanced because the tax credit was found to be associated with some but not all dimensions. Therefore, while there have been calls across the field for studies to employ a multidimensional definition of HI (for example, Cox et al., 2019), examples of multidimensional approaches fall short of examining the HI construct as a whole because HI dimensions are examined separately.

A recent exception to the unidimensional approach extracted four HI dimensions (unaffordability, poor conditions, overcrowding, and forced moves) from the AHS and created an HI index (Routhier, 2019). Routhier (2019) indicated a high rate of HI (more than half of U.S. urban renters), defined as the presence of any of the four dimensions measured. However, the author could not make conclusive statements about the severity of HI because the link between HI severity and the presence of multiple dimensions has not been clearly articulated. Routhier's (2019) approach implicitly assumed that the more dimensions of HI that were present, the more intense the HI was. Development of the HUD-HIM must explicitly determine whether or not such an assumption is warranted.

Each HI dimension included in HUD's definition of HI has also been assessed using multiple indicators. The stable occupancy dimension has the most variation in how it is assessed. Studies have examined stable occupancy in terms of (1) doubling up[45] (Pilkauskas, Garfinkel, and McLanahan, 2014; Pilkauskas and Michelmore, 2019); (2) overcrowding[46] (Lopoo and London, 2016); or (3) residential instability[47] (Ha et al., 2016; Rose-Jacobs et al., 2019). While all three situations are intended to identify when households are vulnerable to involuntary displacement, each does so to varying degrees. For example, doubling up is common following childbirth and does not always indicate a risk for involuntary displacement. In some cases of doubling up, all parties share expenses more or less equally, while at other times, one household adult member primarily covers all housing burdens (Reyes, 2018). Similarly, it has been documented that

[45] Typical indicators of doubling up indicate the presence of multiple households residing in the same residence.
[46] Overcrowding is usually measured as a ratio of the number of people per room, people per bedroom, or unit square footage per person (Blake, Kellerson, and Simic, 2007).
[47] Usually measured as frequency of moves or length of tenure.

public housing dwellers in the United States are less likely to move than similar households receiving other forms of housing assistance, such as Section 8 vouchers, which are highly portable. This finding suggests that residential stability, and therefore the stable occupancy dimension of HI, may be more positive for public housing residents. However, it is unclear if this apparent residential stability obtained via public housing is beneficial, particularly if public housing is located in resource-deprived neighborhoods (Gold, 2018).

Affordability and safe and decent dimensions of HI similarly have been assessed in various ways in the literature. Affordability is most frequently measured by the ratio of housing cost to income, but other authors have used the inability to pay bills (Baker, Mason, and Bentley, 2015) or the amount of income left over after paying for housing (Zhang, 2015). The decent and safe dimension has been assessed through a wide variety of housing quality indicators. Most of these indicators, however, have been limited to assessment of the physical adequacy of the house, such as whether the house has working plumbing or heating (Eggers and Moumen, 2013). The measures of physical adequacy are collected in the AHS and form the basis for incorporating housing quality in the Worst Case Housing Needs assessment, which is discussed more fully in the next section (Watson et al., 2017).

In summary, a universally accepted definition for HI is not apparent, but in this work, the study team will defer to HUD's current working definition of HI, which defines HI in terms of the dimensions measured. The study team also believes the literature supports the consideration of neighborhood quality as a fourth dimension of HI and note that exploring the costs and benefits of adding this additional dimension can be undertaken using existing indicators available in the HUD-HIRM and the core AHS. The dearth of studies utilizing a true multidimensional HI measure (rather than simply examining multiple dimensions independently in the same study) illuminates a clear need for a comprehensive, transferable measure of HI that can easily be incorporated into surveys. Work to develop such a measure must contend with some challenges that are likely responsible for the current shortfall in defining HI. First, agreement on a comprehensive HI definition is necessary for directing choices that must be made regarding how dimensions combine and inform the intensity of HI. Second, the extant work suggests that multiple indicators exist even within a singular dimension that is clearly defined. Careful empirical work must be done to inform how the dimension is optimally assessed before inclusion in a composite measure of HI. Next, the study team explores aspects of the extant literature that are useful for informing progress to overcome these challenges.

Monitoring of Levels and Trends Related to HI

Without a comprehensive measure of HI, the current discussion of HI is primarily informed by reports of individual dimensions of HI. In what follows, the study team attempts to distinguish between (1) measurement of HI dimensions and tabulation of those results and (2) use of those data to systematically and regularly study HI. Measurement and tabulation are an important first step, and systematic, regular study provides greater depth and rigor to HI assessment. Of all of the dimensions of HI, affordability is the dimension most frequently and thoroughly studied for the nation as a whole, owing primarily to the availability of national data on housing affordability. Affordability is more widely reported, and data are routinely collected for more indicators related to affordability. The AHS has an extensive history of collecting data on housing quality, and there have been significant efforts in formulating recommendations for using the AHS data to provide a richer characterization of housing quality (for example, Eggers and Moumen, 2013; Emrath and Taylor, 2012; Newman and Garboden, 2013). These housing quality data provide indicators of the decency and safety dimension. This dimension is assessed every 2 years in the form of indicators of severe and moderate housing inadequacy as part of the Worst Case Housing Needs reports. The stable occupancy dimension is measured via a few routinely collected indicators. Exhibit F.2 summarizes the indicators that are routinely measured and reported relative to HI.

Exhibit F.2 | Dimensions and Indicators of HI that Are Frequently Reported in the United States

Dimension	Indicators	Available in American Housing Survey Public Use Data?	Other Data Source(s)*
Affordability	Changes in housing supply and demand	No	U.S. Census Bureau Housing Vacancy Survey, New Residential Construction, New Residential Sales Data
	House price indices	No	FHFA
	Median house price-to-income ratio	Yes	National Association of REALTORS® Metropolitan Median Area Prices
	Debt-to-income ratios	Yes	Mortgage origination data from Fannie Mae, Freddie Mac, and the Federal Housing Administration
	Homeownership rates	Yes	U.S. Census Bureau ACS
	Housing cost burden	Yes	U.S. Census Bureau ACS
	Housing affordability reflected in Worst Case Housing Needs	Yes	NA
Stable Occupancy	Population migration	Yes	U.S. Census Migration and Geographic Mobility Statistics
	Overcrowding	Yes	NA
Decency & Safety	Housing quality and adequacy	Yes	NA

ACS = American Community Survey. FHFA = Federal Housing Finance Agency. NA = not applicable.
* List of other data sources reflects major sources used in routine reporting; it is not an exhaustive list of sources.
Source: Authors' compilation based on a review of the HI literature

The purpose of this section is to present a snapshot of the state of HI from the available reports examining indicators of the dimensions of HI during the same period as the focus of this literature review (in other words, 2015 through 2019). This synthesis helps contextualize the discussion of housing affordability and illuminate the extent to which indicators of the dimensions of HI are routinely measured and reported. Two key regular reports provide periodic summaries of conditions in the U.S. housing market: The State of the Nation's Housing annual report (JCHS, 2019) and the Worst Case Housing Needs Report (Watson et al., 2017). The following sections examine these reports in turn and then briefly describe other indicators collected that relate to the stable occupancy dimension of HI.

State of the U.S. Housing Market

The State of the Nation's Housing (JCHS, 2019) is an annual report produced by the Joint Center for Housing Studies at Harvard University (JCHS). It provides an annual update of current housing market trends related to supply, demand, cost, and affordability. Next, the study team separately summarizes these trends for owner-occupied and rental housing markets. Statistics and facts contained within the remainder of this section come from the 2019 State of the Nation's Housing report unless otherwise noted.

State of the U.S. Housing Market for Owner-Occupied Housing

In 2019, growth in the supply of housing units primarily intended for the owner-occupied market was modest. Furthermore, as has been the trend for some time, new construction was primarily focused on the higher end of the home price distribution. This focus translated into growth in affordable owner-occupied housing being reliant upon housing units "cycling down" from more expensive strata. The cycling down effect has slowed because the number of senior households is at an all-time high, and due to shifts and innovations in health care, senior households are remaining in their homes and "aging in place" at a higher rate than prior cohorts.

Increases in the demand for all owner-occupied housing appear to be outpacing supply. After falling since 2005, homeownership rates increased in 2017 and 2018. This trend was fueled by improvements in the affordability of homeownership among middle- and upper-income new homebuyers. Since the financial crisis of 2007 through 2009, falling or steady home prices and low interest rates have combined with large income growth among 25- to 44-year-olds. If homeownership rates for the Millennial generation are comparable to previous generations, 2018 through 2028 is projected to see an increase in demand of 8 million owner-occupied units attributable to new homeowners in this age group alone. This increase amounts to a sustained 10-year growth rate in homeownership among the Millennial cohort alone, equaling the 2016-through-2018 growth rate experienced across all age groups combined.

Increased demand and slower growth in supply have resulted in rising house prices. In 2018, the Federal Housing Finance Agency (FHFA) house price index indicated that home prices nationally in real terms (in other words, inflation adjusted) were within 2 percent of their 2006 prerecession high. The ratio of median house price to median household income is a common measure of housing affordability, with higher ratios indicating more unaffordable housing. This ratio peaked at 4.7 in 2005 amid the house price run-up before the financial recession and bottomed out at 3.3 in 2011, following the recession. In 2018, the ratio was 4.1. High median price-to-income ratios are concentrated on the east and west coasts and a few metropolitan areas in Arizona and Colorado. The rest of the nation still has moderate median price-to-income metrics. Along with prices, borrower risk has increased. The share of Fannie Mae loans made to borrowers with debt-to-income ratios higher than 43 percent (the typical metric for high-risk lending) has increased from 13 percent in 2013 to 29 percent in 2018; the trend for Freddie Mac is similar. The ability of Fannie Mae and Freddie Mac to offer these high-risk loans is made possible by a waiver from the federal government; that waiver expired in 2021, which may cause a decrease in homebuying among high-risk borrowers.

Despite these trends suggesting future risk in affordability and lending in the owner-occupied market, housing cost burden remains low for homeowners. At the end of 2017, the number of homeowners with high housing cost burden (measured as the share of households paying more than 30 percent of income for housing) was down to its lowest level since 2000 and down 8 percentage points from its high in 2010.

State of the U.S. Housing Market for Rental Housing

Indicators measuring the increase in the supply of new rental units are near all-time highs. However, absorption has also been high, as many single-family homes and rental units in buildings with four or fewer units have been converted back to owner-occupied housing. Thus, absorption remains in line with supply increases, so the supply of housing units is not increasing substantially. In particular, the supply of low-cost units remains a concern. The number fell by more than 4 million units from 2011 through 2017.

Alongside the trend of increasing homeownership rates, demand for rental units fell every year from 2015 through 2018, after average increases of around 850,000 units per year from 2003 through 2015. However, house price gains and worsening credit risk in the owner-occupied market suggest that demand for rental units will begin increasing. The data from 2019 suggest that this is already occurring. During the first quarter of 2019, the Consumer Price Index indicated a 3.6-percent annual increase in rental rates, and RealPage data indicated a decline in vacancy rates. Despite the recent trend of decreases in demand, demand for middle- and high-income renters (anyone making more than $75,000 annually) has increased for 8 consecutive years, leaving the question of how low-income renters are affected.

With new construction targeting the upper-income housing market and a decline in overall rental demand, there has been hope that some additional units might filter down to the lower-income rental market, thereby alleviating upward price pressure. However, these hopes have not come to fruition. Vacancy rates for low-quality rental units had fallen to only 4.8 percent at the start of 2019. Furthermore, the share of rental units renting for less than $800/month has steeply declined in the post-recession period.

As of 2017, 47.4 percent of renter households were cost burdened (in other words, greater than 30 percent of their income is spent on housing). That number was down just 3.4 percentage points from the post-recession peak in 2011. The proportion of cost-burdened households is highest among African-American and Hispanic renter households, among which more than half are cost burdened. The share of cost-burdened households is affecting more middle-income groups, with the proportion of households cost burdened increasing by 4.6 percent between 2011 and 2017 among households making $30,000 to $44,999 and 2.9 percent among households making $45,000 to $74,999. Among the nation's most expensive markets along the east and west coasts, 46 percent of renters making $45,000 to $74,999 were cost burdened.

Homelessness, in many ways, results from unsustainable housing affordability challenges. Overall, the number of people who are homeless has been declining in the United States since 2008, resulting in a decrease of 87,000 people in the homeless population. However, high-cost housing markets along the west coast are seeing a rise in homelessness. Between 2014 and 2018, the number of unsheltered homeless people grew by 25 percent in California.

Worst Case Housing Needs

A focus on HI necessitates a closer examination of the group of renters experiencing the most challenges related to housing affordability. Worst case housing needs are quantified based on AHS data and summarized in a report to Congress every 2 years; the most recently available report was submitted in 2017 and is based on data collected in the 2015 AHS (Watson et al., 2017). Worst case housing needs are defined as renters with very low incomes (at or below 50 percent of the Area Median Income) who do not receive government assistance and who spend more than half of their incomes on rent, live in severely inadequate conditions, or both. By this definition, there are three possible ways households could be counted as having worst case needs: (1) housing that is expensive relative to income, (2) inadequate housing, or (3) both. In the most recent Worst Case Housing Needs report, severely inadequate housing alone accounted for only 2 percent of worst case needs cases, although this proportion has changed over time. The trend in worst case housing needs continues to increase, with a 10-year growth rate of just under 40 percent. In 2015 (the latest estimates available), 43 percent of low-income renters in the United States experienced worst case housing needs. The rising incidence of worst case needs extends to all major racial/ethnic groups and age groups. Growth in the number of people experiencing worst case housing needs could be caused by growth in the low-income population as a whole or by worsening affordability conditions in the rental housing market. From 2013 to 2015, it was estimated that growth in the population susceptible to worst case housing needs accounted for 70 percent of the rise in worst case needs, and a shrinking supply of affordable rental units relative to demand accounted for the other 30 percent of the increase. Despite the overall trend of growth in rental supply, the supply of units considered affordable to low- and very low-income renters has been decreasing.

Trends in Stable Occupancy

The AHS collects indicators of overcrowding (the persons-per-room ratio) and frequency of moves. These indicators may be tabulated using the AHS table creator and have been used to assess trends in overcrowding. The last report of this nature analyzed data before the 2007-to-2009 financial recession (Blake, Kellerson, and Simic, 2007). HUD’s Annual Homelessness Assessment Report provides proximal indicators of the state of stable occupancy in the United States. In addition, the U.S. Census Bureau reports statistics describing migration and geographic mobility of households, and data on foreclosures are available at a national level from RealtyTrac (Attom Data Solutions, n.d.). Desmond’s eviction lab also is a potential source of eviction data (https://evictionlab.org/). However, these statistics are not routinely examined to regularly monitor overall trends in mobility related to housing for low-income populations.

Current Gaps in Assessment and Monitoring the State of HI in the United States

During the period of this literature review (2016 to present), the affordability of owner-occupied housing has, for the most part, improved for most households. However, there are signs that this trend may be reversing in the near future. At the same time, rental housing for low-income households has continued to suffer increasing affordability challenges.

Although the current data aid in understanding the market forces and trends related to housing affordability, trends in other dimensions of HI are either less frequently monitored or monitored less comprehensively. The development of the HUD-HIM appears to be very useful for improving more comprehensive monitoring of all dimensions of HI.

Overall, the development of a robust measure of HI can build on the indicators already frequently measured in the United States. In addition to the dimension of HI currently included in HUD's definition, the exclusion of neighborhood condition should be evaluated. Housing market segmentation could render neighborhood condition an important dimension of HI that is substantively distinct from the affordability dimension. In the long term, the HUD-HIM will provide a much-needed bridge over a gap in holistically assessing HI levels and trends and informing how levels and trends in individual dimensions affect overall HI.

Exhibit F.3 | Key Points

How are the dimensions of HI currently monitored in the United States?

- Housing **Affordability** and its underlying causes are assessed in the AHS, and a variety of other sources and indicators are summarized and reported annually.
- The **Safety and Decency** dimension of HI is incorporated with affordability in the Worst Case Housing Needs report, which focuses on identifying situations of severely inadequate housing.
- The **Stable Occupancy** dimension of HI is assessed in the AHS and by the Census Bureau, and indicators can be tabulated using the AHS table creator.

Outcomes Associated with Housing Insecurity

There are many outcomes theorized to be associated with HI. However, the relationship between outcomes and HI has seldom been assessed for most of these outcomes due to data availability. The development of HUD's Housing Insecurity Measure (HUD-HIM) will no doubt facilitate the closure of this gap in the literature. For now, the study team surveyed articles published since 2015 documenting correlates of HI. The body of evidence produced by these correlative studies is useful for constructing a comprehensive strategy for assessing the validity of the HUD-HIM.

Correlative studies were distinguished from other studies that examined mechanisms and risk factors for HI, which are reviewed in *Correlates of HI*, primarily because correlative studies are typically cross-sectional and exploratory. Although some of the correlative studies reviewed suggested a causal interpretation of the results, the analysis presented did not take the necessary steps to prove a causal pathway. The majority of correlative studies identified examined health outcomes. This result, however, should be interpreted with caution. During the period covered by this literature review, there was an increased focus on social determinants of health. Within that focus, documenting correlations between health outcomes and constructs such as HI was a key subfocus. In contrast, other fields have focused more intently on elucidating causal mechanisms linking HI and outcomes; thus, discussion of outcomes associated with HI outside of health have been examined, with a more deliberate attempt to elucidate causality. These outcomes are the subject of *Correlates of HI*.

Correlates of HI

Most correlative studies published since 2015 have examined specific subpopulations and dimensions of HI, usually based on data availability. However, some indicators of HI were examined more frequently than others, primarily because of their availability in large surveys. These included an indicator measured by self-report of worrying about housing expenses that is included in the Behavioral Risk Factor Surveillance System (BRFSS) and a three-question housing insecurity screener that asks if households had experienced overcrowding, doubling up, or more than one move in the past 12 months (Cutts et al., 2011). Other indicators of HI were quite varied, and there were no discernable patterns whereby a particular indicator of HI was uniquely associated with specific outcomes.

Because the study team is interested in identifying correlates of the HI construct (rather than single dimensions in isolation), the team focuses on correlative relationships found across multiple studies examining diverse populations and different HI dimensions. From this perspective, the most well-documented evidence for correlations with HI exists for health outcomes and measures of health care access. The assessment of the current state of the literature here is also consistent with a 2016 review focused on housing evictions (Vásquez-Vera et al., 2017). More than 50 percent of the 47 articles in the 2016 review documented the association between eviction and mental health issues, 38 percent documented associations with poor physical health, and just under 20 percent of studies examined associations between evictions and health behaviors.

Health outcomes that have been examined in relation to HI can be grouped into a few categories:

- Physical and psychiatric conditions.
  - Alhenaidi and Huijts, 2019; Crumé, Nurius, and Fleming, 2019; Hallett and Freas, 2018; Marí-Dell'Olmo et al., 2017; Marquez, Dodge Francis, and Gerstenberger, 2019; Park and Jung, 2019; Pobutsky, Baker, and Reyes-Salvail, 2015; Vásquez-Vera et al., 2017.
- Child mental and physical health.
  - Covington et al., 2019; Fowler et al., 2018; Fuller et al., 2019; Higginbotham, Davis Crutcher, and Karp, 2019; Kelleher, Reece, and Sandel, 2018.
- Self-rated health.
  - Clair et al., 2016; Holman and Walker, 2018; Martin et al., 2019; Park and Jung, 2019; Stahre et al., 2015; Vásquez-Vera et al., 2017.
- Prevalence and management of chronic disease and obesity.
  - Charkhchi, Fazeli Dehkordy, and Carlos, 2018; Chhabra et al., 2020; Kronfli et al., 2017; Liu et al., 2019; Martin et al., 2019; Stupplebeen, 2019; Vásquez-Vera et al., 2017; Yelin et al., 2019.
- Increased need for acute care.
  - Collinson and Reed, 2018; Jackson et al., 2017; Malecha et al., 2018.

The mental health relationships with HI appear to be the most robust and diverse. Several studies have documented that foreclosures during the 2007-through-2009 financial recession were associated with increased depression and anxiety; for reviews, see Alhenaidi and Huijts (2019) and Vásquez-Vera et al. (2017). A survey among college students showed that mental disorders were more prevalent among homeless youth and young adults than among stably housed counterparts (Smith and Knechtel, 2019). Self-rated health, diabetes and asthma management (Stupplebeen, 2019), and cardiovascular and lung disease (Charkhchi, Fazeli Dehkordy, and Carlos, 2018) were also poorer for people experiencing HI. Two studies noted significant HI concerns among emergency room (ER) patients (Jackson et al., 2017; Malecha et al., 2018). One other study compared housing secure and housing insecure individuals and found that housing insecure individuals utilized the ER more (Collinson and Reed, 2018).

The relationship between HI and health care access has also been examined in a number of studies (Charkhchi, Fazeli Dehkordy, and Carlos, 2018; Duke and Borowsky, 2018; Martin et al., 2019; Mkandawire et al., 2015; Poghosyan et al., 2019; Surratt et al., 2015; Vold, Lynch, and Martin, 2019). Disruptions in health care access created by HI and HI itself contribute to significant challenges for receiving needed care and adhering to care regimens.

This finding was particularly true of individuals with serious medical challenges, such as those associated with HIV or other chronic conditions (Mkandawire et al., 2015; Surratt et al., 2015). For these chronically ill patients, the high cost of rent, discrimination, and poor landlord-tenant relationships undermined the ability to meet dietary needs, stay healthy, and adhere to treatment. Examining the U.S. population as a whole, BRFSS data revealed that adults who experienced HI were more likely to forgo routine check-ups, and they lacked usual sources of care (Charkhchi, Fazeli Dehkordy, and Carlos, 2018; Martin et al., 2019).

The correlative relationships between HI and health-related outcomes are embedded in contexts frequently characterized by insufficient income, additional non-housing material hardships, addiction, or social vulnerability (Fowler et al., 2019; Johnson et al., 2019). These contexts contribute to deleterious social settings linked to housing quality and condition (Gronlund et al., 2018; Marí-Dell'Olmo et al., 2017; Marquez, Dodge Francis, and Gerstenberger, 2019; Richter et al., 2017). Some studies have more generally studied the relationships between HI and various types of social vulnerability that characterize particular contexts in which HI is embedded, including parenthood (SmithBattle, 2019; Warren and Font, 2015), victimization (Breiding et al., 2017; Curry, 2017; Diette and Ribar, 2018; Katsulis et al., 2015; Logie et al., 2018; Schwarz et al., 2019; Webb, 2018), familial relationship instability (Berman et al., 2015; Dwyer Emory, 2018; Moschion and van Ours, 2019; Wade, 2018), personal identity or social exclusion (Alba et al., 2019; Glick et al., 2019; Theodore et al., 2018) and substance abuse or addiction (Chhabra et al., 2020; Christensen et al., 2017; Harris et al., 2017; Keane, Magee, and Lee, 2015).

Many types of social vulnerability appear to place individuals at greater risk for HI. For example, childhood emotional abuse (Curry, 2017), parent separation (Moschion and van Ours, 2019), and loss of a parent (Berman et al., 2015) were associated with greater risk for adult HI. Likewise, families experiencing HI were more likely to have children removed and placed in foster care due to neglect (Wade, 2018). Sexual exploitation (Breiding et al., 2017; Schwarz et al., 2019) and elder abuse (Webb, 2018) were also associated with a higher incidence of HI. Other groups with a higher incidence of HI included young parents; people with low educational attainment; individuals from minority racial/ethnic groups; people living with HIV; and lesbian, gay, bisexual, or transgender youth (Hrostowski and Camp, 2015; Morton et al., 2018). Correlations between HI and deleterious outcomes appeared strongest for minority groups and older populations (Vásquez-Vera et al., 2017). Additionally, HI was associated with increased vulnerability to adverse effects of other stresses, such as losing a loved one (Bindley et al., 2019).

Limitations and Gaps in the Understanding of Correlates of HI

Infrequent and inconsistent measurement of HI has likely limited the extent to which correlates of HI have been documented. Health researchers have increasingly begun exploring the "social determinants of health," among which HI is often included. As a result, most studies assessing HI correlates have come from this field. Nevertheless, health researchers usually have little formal training related to housing markets or the factors underlying HI, producing a potential weakness in the extant work. These limitations can be addressed by developing an HI measure that can be reproduced in multiple surveys and is informed by the significant number of studies conducted in non-health fields that inform risk factors and mechanisms through which HI occurs.

Any new measure of HI will likely be used to assess previously documented correlations to connect ongoing work with future developments in HI. The most widely observed correlations included associations with mental health—in particular, depression and general self-rated health. The most common ways that depression and mental health have been assessed in the literature include the General Health Questionnaire 12-item scale (GHQ-12) (Goldberg et al., 1997), the 6-item Kessler Screening Scale (K6) (Kessler et al., 2010), and self-reported prior depression diagnoses of poor mental health, such as those used in the BRFSS (Miyakado-Steger and Seidel, 2019). The general self-rated health question is commonly used by researchers as a simple measure of health, in part because it is very easy to implement and has a reasonably high correlation with mortality (Franks, Gold, and Fiscella, 2003; Idler and Benyamini, 1997; Ware, Kosinki, and Keller, 1996). Because of its wide prevalence of use, self-rated health's correlation with HI should also be assessed. The incidence of HI in socially vulnerable subpopulations is also important to assess for any new measure of HI.

There is presently no widely accepted theoretical model describing the causal pathways to and from various stages of HI. These pathways are complex, multidimensional, and varied (Fowler et al., 2019). The literature providing the strongest evidence to elucidate causal pathways can be viewed from two perspectives. First, there are longitudinal studies that investigate patterns of HI entry and exit alongside attempting to disentangle the often-bidirectional relationships between deleterious household outcomes or circumstances and HI. Second, another body of work has sought to identify key risk factors for HI. The next two sections will discuss the published work using these approaches.

Longitudinal Studies

Longitudinal studies allow for the examination of individuals over time and are, therefore, among the most useful for understanding the mechanisms that create or are created by insecure housing. However, the very nature of HI makes longitudinal data regarding individuals and households experiencing HI difficult to obtain. Despite these challenges, the number of longitudinal studies related to HI has increased in recent years. Most of these studies have examined newly available data from Australia's Journeys Home dataset or the Survey of Income and Program Participation (SIPP) (O'Flaherty, 2019). Next, the study team reviews the limited knowledge available from recent studies that focused on understanding causal pathways that lead to HI, including the major data sources available for this endeavor, investigations of the duration of HI, and studies attempting to unpack complex mechanisms related to HI.

Exhibit F.4 | Key Longitudinal Data Sources for the Study of HI

Journeys Home: A Longitudinal Study of Factors Affecting Housing Stability

- Purpose: The survey was designed to support investigation of a theory-informed conceptual model of causes and consequences of homelessness.
- Sample: 1,682 Australians at 6-month intervals for 2.5 years during 2011 through 2013; all participants were low-income and at risk for HI, but 50 percent were stably housed when the study began. HI Dimensions: Data include indicators of all three dimensions of HI included in HUD's working definition.

Source: Melbourne Institute: Applied Economic & Social Research

Survey of Income and Program Participation (SIPP)

- Purpose: Assess levels and trends in the distribution of income and impact of government assistance programs.
- Sample: Nationally representative sample of 14,000 to 52,000 U.S. households that are interviewed monthly for 2.5 to 4 years. The sample size and duration has varied by panel, with more recent panels including more households but observing them for a shorter duration. HI Dimensions: Affordability as indicated by missed utility and medical bills, missed rental payments, foregone medical treatments, food insecurity, and financial assistance provided by friends and family members.

Source: U.S. Census Bureau, SIPP

The only dataset intentionally designed to follow housing insecure households over time is the Journeys Home data (Scutella, Tseng, and Wooden, 2017). The study, conducted by the Melbourne Institute, followed 1,682 Australians at 6-month intervals for 2.5 years, from 2011 through 2013 (https://melbourneinstitute.unimelb.edu.au/journeys-home). Respondents were included in the study because they were currently housing insecure or statistically determined to be at risk for or vulnerable to HI. At the first wave, 24 percent were classified as "homeless" according to the European definition of homelessness, which classifies people as homeless if they are sleeping rough; are living in cars or abandoned buildings; are living doubled up; or are living in shelters, hotels, boarding houses, or caravans. Fifty percent of the sample was classified as "stably housed" at wave 1, but 94 percent of the wave 1 sample had experienced HI during their lifetimes. While only 62 percent of people invited to participate in the study did so, overall, study retention was high: 83 percent of the sample continued through wave 6 (Ribar, 2017). This dataset can potentially be a valuable source of information regarding how multiple dimensions of HI interact, as the dataset includes indicators of all three dimensions of HI. However, the dataset was developed to study homelessness and was designed around a theoretically informed model of the causes and consequences of homelessness (Scutella and Johnson, 2012). Thus far, the conceptual model of homelessness has been the focus of studies utilizing the data. Nevertheless, the dataset has begun to provide important evidence related to the causes and consequences of HI.

SIPP[48] is another longitudinal dataset that has frequently been used to study HI. While SIPP was not designed to study HI in particular, its sampling frame does allow for a focus on low-income populations. SIPP data provides a detailed account of household spending and income that has allowed researchers to extract indicators of multiple material hardships (in other words, missed utility and medical bills, missed rental payments, foregone medical treatments, and food insecurity), as well as financial assistance provided by friends and family members.

Findings from longitudinal studies examining the causes of HI illuminate conditions that speak to the challenges inherent in measuring HI using a self-report survey instrument. First, the onset of severe HI (measured as doubling up, homelessness, or living in a shelter or other substandard accommodation) generally co-occurred with other deleterious outcomes, which tended to vary across contexts and social/demographic individual characteristics (Ribar, 2017). In all of the studies reviewed, there appears to be no consensus or strong evidence for any dominant pattern of behavior or conditions that predate severe HI. In contrast, strong evidence was presented that private individual information (in other words, information not routinely or easily collected in survey data) was quite important for predicting severe HI (O'Flaherty, 2019; O'Flaherty, Scutella, and Tseng, 2018). The private information examined was collected in the Journeys Home data—so it is not impossible to collect this information. However, the information was considered difficult to collect in routine survey efforts because the list of indicators was very long, required historical information that is only possible in a longitudinal survey design, or was subject to response bias if collected in the context of receipt of social services. A complete list of the private information can be found in table 1 of O'Flaherty, Scutella, and Tseng (2018). This suggests that there may not be systematic transitions along the HI continuum that the HUD Housing Insecurity Measure (HUD-HIM) hopes to measure.

Exits from HI are also heterogeneous. For example, exit rates from HI change over time. Initially, exit rates in the Journeys Home data increased and peaked 4 to 6 months after the onset of HI (measured as doubling up, homelessness, living in a shelter or other substandard accommodation). Beyond 6 months, exit rates leveled off and then fell. Exit rates were lower among older populations and for men (Cobb-Clark et al., 2016). Individual characteristics that have been associated with increased odds of leaving homelessness are related to an individual's ability to earn income, including recent employment, welfare receipt, and job training, while female gender and shorter work history were most closely linked to returns to homelessness (Piliavin et al., 1996). Nevertheless, homelessness was often merely one component of larger patterns of HI that included frequent, brief stays in dwellings of varied quality (Sosin, Piliavin, and Westerfelt, 1990).

[48] https://www.census.gov/programs-surveys/sipp.html.

The most commonly studied causal pathways for HI were related to individual characteristics, including drug use, alcohol use, or abuse. Drug and alcohol use were robustly found to be likely among people who were insecurely housed; however, two studies found no evidence of a causal link between drug/alcohol use and HI (McVicar, Moschion, and van Ours, 2015, 2019). If anything, results from these studies suggested a reverse causal relationship: HI affected rates of alcohol use in varying ways. Homelessness reduced the likelihood of heavy drinking (McVicar, Moschion, and van Ours, 2015), and early HI increased the subsequent risk of drug use for women (McVicar, Moschion, and van Ours, 2019). A third study examining the same Journeys Home data found that after controlling for housing and labor market factors, the likelihood of HI onset was higher for drug users (Johnson et al., 2019). Similarly, rates of physical abuse were comparatively higher among households facing HI, particularly among woman-headed households. However, evidence of links between physical abuse and HI was only weakly present for men: Only the initial onset of physical abuse increased the risk of subsequent HI in the Journeys Home study (Cobb-Clark and Zhu, 2017; Diette and Ribar, 2018).

Another subset of the literature focused on multiple forms of material hardships that resulted from insufficient income and the tradeoff strategies households used to overcome these hardships. SIPP data allowed comparison of temporal trends in multiple material hardships (in other words, food insecurity, medical hardships, and housing hardships). The trends were imperfectly correlated. For example, from 2003 through 2005, food insecurity decreased while all other hardships increased, and at the end of the financial recession, the incidence of hardships for all hardship types reached new highs (Heflin, 2016).

Several studies have examined food security alongside HI. The 2013 BRFSS[49] allowed for the study of both constructs, and results suggest that food insecurity was more prevalent across all racial/ethnic groups than HI; notably, the data excluded homeless populations (Njai et al., 2017). Among chronically ill patients in the 2015 BRFSS data, however, rates of HI were slightly higher than rates of food insecurity (Charkhchi, Fazeli Dehkordy, and Carlos, 2018). One reason why food insecurity rates might typically be higher than HI rates is that adjustments to the quantity of housing consumed are more difficult; households will often prioritize maintaining housing over additional food purchases (Vold, Lynch, and Martin, 2019). These tradeoffs may influence the relationship between HI and poor chronic disease outcomes (Stupplebeen, 2019). In Journeys Home data, homelessness was found to increase the risk of food insecurity and lead to decreased food expenditures but only for men; no statistically significant relationship between homelessness and food security was observed for women (Herault and Ribar, 2017).

Utility hardships (for example, difficulty paying the electricity bill) and housing hardships represent another hardship tradeoff that has received considerable attention because the two types of hardship are consumed together in the housing bundle. In fact, utility costs are included in calculating total housing costs when assessing housing cost burden. Using SIPP data, Finnigan and Meagher (2019) noted that utility hardships were much more prevalent and persistent than housing hardships, and households with utility hardships were much more likely to have other disadvantaged characteristics. The strongest, most robust predictor of both housing and utility hardships was entries into poor health among household member(s) (Finnigan and Meagher,

[49] Perceived food insecurity and HI were assessed by a one-item question for each construct.

2019). Data from the Panel Study of Income Dynamics (PSID) provided further evidence that utility hardships (operationalized as spending 10 percent or more on utilities) were associated with an increased likelihood of remaining in poverty, controlling for household-specific fixed effects (Bohr and McCreery, 2019). While empirical studies suggest some consensus that utility hardships, on average, signal risk for HI, qualitative work suggests that housing insecure households have more nuanced strategic approaches to managing utility and rent such that the first occurrence of empirical indicators of utility hardship (in other words, failure to pay a bill or high proportion of income spent on a bill) may not be completely indicative of the onset of the hardship (Desmond, 2016). For example, in Desmond's work, utility payments were often delayed during the winter months, when utility shutoffs were not processed. Although this pattern may not be observed in southern cities, other similar tradeoffs could emerge when utility assistance programs are more generous during the summer months in regions with extreme heat.

Risk Factors for Insecure Housing

While causal mechanisms producing HI are not clearly defined, there is general agreement that a single pathway does not exist. Rather, a focus on identifying risk factors and conditions that contribute to HI has gained traction in recent work. Risk factors are organized into two categories: structural and individual. Structural risk factors are driven by macro factors, such as state laws, social welfare programs/policies, and markets. In the U.S. context, many structural risk factors vary geographically. This geographic variation deserves important consideration when developing and interpreting the HUD-HIM. In contrast, individual risk factors are associated with individual and household characteristics that are more or less distributed evenly across U.S. states/regions.

The literature shows general agreement that HI is associated with a lack of sufficient income, but income alone does not fully predict HI (Fowler et al., 2019). Part of the challenge in understanding the seemingly simple relationship between HI and income is that income increases the odds of HI, but HI also may impact individuals' abilities to obtain income. In longitudinal analysis, evidence exists supporting the link between homelessness and subsequent unemployment (Cobb-Clark and Zhu, 2017) and unemployment that predates and appears to increase the risk of homelessness (Bentley, Baker, and Aitken, 2019; Desmond and Gershenson, 2016). Stability and amount of income flows are also likely important factors affecting the income-HI relationship. A one-time injection of income in the form of the earned income tax credit produced mixed results: Doubling up and crowding among single mothers decreased, but there was no impact on eviction or homelessness (Pilkauskas and Michelmore, 2019).

Heterogeneity in the HI-income relationship may also be attributed to structural factors, such as varying support services and policies. For example, federal income assistance may play an important role in protecting households from experiencing HI. Households of children with special healthcare needs were more likely to experience HI if they were not recipients of Supplemental Security Income (Rose-Jacobs et al., 2019). Additionally, exits from homelessness were more likely for people with a documented mental health diagnosis because additional programs were in place to support them (Cobb-Clark et al., 2016). Accessibility and availability of support programs may also vary by the diversity and size of the low-income population within a particular community. Another key structural factor important for reducing HI is the availability of subsidized housing (Bailey et al., 2016). Reeves et al. (2016) examined changes in the United Kingdom's private-sector rental housing support and found that reductions in housing support produced an increase in the prevalence of depressive symptoms. On average, households who could secure subsidized housing remained in the program for 6 years. This figure ranged from 9 years for elderly households to a 4-year average stay for nonelderly families with children (McClure, 2018). Demand for subsidized housing grows when the supply of affordable rental units is insufficient (McClure, 2018). Since subsidized housing has a generally fixed supply, increased demand usually only results in longer waiting lists. Overall, these support programs appear to be effective at reducing the likelihood of the most severe forms of HI for households who can receive them; the development of the HUD-HIM will allow a more detailed assessment of the impact of these programs, including their impact on the overall intensity and prevalence of HI.

Exhibit F.5 | Key Points

What is known about transitions and tradeoffs along the HI continuum?

- Transitions into severe HI are difficult to predict and may not be systematic.
- People who are insecurely housed move frequently among dwellings of various quality, which might result in frequent changes to the intensity of HI.
- HI has a bidirectional relationship with income, employment, and drug and alcohol use; existence of deleterious outcomes in these domains both increases likelihood of HI and is more probable following the onset of HI.
- HI frequently co-occurs alongside other material hardships, and there are some general patterns in prevalence among these hardships:
    - Food security rates are generally higher than HI rates (measured as difficulty paying rent).
    - Occurrences of missed utility bills were more persistent and prevalent than missed rent payments.
- Structural factors (housing and labor markets or local policies and programs) can produce variation in transitions and tradeoffs along the HI continuum; the HUD-HIM must be able to assess HI independent of structural factors so that it can be used to study these factors' implications for HI.
    - Income and housing support programs reduce the likelihood of the most severe forms of HI, but their impact along the entire HI continuum is unknown.
    - The dynamics of eviction vary widely based on structural factors, and repeated threat of eviction versus actual eviction produce dual pathways for HI. Comparative differences in the effects of these pathways on HI intensity are unknown.
    - Following foreclosure or eviction, households typically relocate to lower-quality neighborhoods.

Johnson et al. (2019) examined the interplay between structural and individual risk factors for homelessness. Prior work has been split on whether structural factors, such as housing and labor markets, or individual-level factors were more prominent in perpetuating HI (Early and Olsen, 2002; Nisar et al., 2019; Quigley and Raphael, 2001; Wang, 2016; Wong and Piliavin, 1997). Journeys Home data allowed a more nuanced contribution to this debate. Individual-level factors, including risky behaviors (such as drug/alcohol use and violence) and adverse life experiences (such as low educational attainment, past homelessness, and unemployment), were linked to HI alongside structural factors, which included housing affordability, housing assistance programs, and labor market tightness as measured by the local unemployment rate. Results suggest that structural factors most impact HI for minority groups and those without mental illness (Johnson et al., 2019).

Evictions increase the risk of extreme HI, and structural and individual factors influence the likelihood of eviction. The legal process of eviction begins with filing an eviction notice and is governed by state law. In some states, filing for eviction is relatively easy, and landlords use this process to induce payment. Therefore, renters may repeatedly be given an eviction notice without an actual eviction; regardless, this creates HI (Garboden and Rosen, 2019). There is some evidence that a landlord's preference for eviction or threat of eviction is a function of the neighborhood condition: In neighborhoods where property turnover is higher (and properties are likely being upgraded), actual eviction may be more likely, whereas, in other low-income neighborhoods, the threat of eviction may be an economically optimal way for landlords to collect rents (Immergluck et al., 2019). The threat of eviction points to additional facilitators of HI that are embedded in power imbalances between renters and landlords (Soederberg, 2018). These power dynamics are psychologically taxing for the people experiencing HI and may independently contribute to HI (Thomas, Darab, and Hartman, 2016).

One reason evictions and foreclosures resulting in forced household relocation represent such a strong indicator of severe HI is that forced relocation can become another risk factor for additional conditions that contribute to further HI. For example, changes in foreclosure status were associated with an increased risk of food and housing insecurity among SIPP participants during the financial recession (Mykyta, 2015). PSID data revealed that households that foreclosed during this period moved to more residentially disadvantaged neighborhoods, and the effects were strongest for Hispanic households (Hall et al., 2018). Evicted households also typically relocate to disadvantaged neighborhoods (Desmond, 2016). Evictions have been associated with lower earnings, but there is little evidence that evictions substantially worsened employment outcomes or increased receipt of public assistance (Collinson and Reed, 2018). Finally, foreclosure risk is not limited to severely economically disadvantaged households; foreclosure rates were also found to be associated with parental investment in higher education during the financial recession (Faber and Rich, 2018).

Another significant subsection of the literature has focused exclusively on individual risk factors and individual trigger events for HI. These include high medical costs (Bilodeau et al., 2018; Bona et al., 2016), incarceration (Dwyer Emory, 2018; Moschion and Johnson, 2019), and an inclination toward risk taking (risky sexual conduct, gambling, suicidal ideation, substance abuse, and aggression; Harris et al., 2017). The dynamics of the relationship between the risk factor and HI likely vary within each risk factor. For example, HI risk increased 3 percentage points upon immediate release from incarceration and four times as much 6 months after release (Moschion and Johnson, 2019).

Key Gaps in Knowledge About Causes of HI

To date, the Journeys Home data are the only large longitudinal data source following individuals over time that is available for studying HI from multiple dimensions.[50] Therefore, the

[50] Of course, an array of other data sources such as PSID, SIPP, ADD-Health, and other, smaller sources have been used to study HI, but the dimensions of HI available for study in these sources are very limited. Additionally, the AHS has a longitudinal structure and incorporates several dimensions of HI, but the AHS follows housing units rather than people over time.

array of individual and structural factors available for investigation is limited to this one dataset and to the Australian context. In the literature, a significant number of potential individual risk factors have been identified (for example, unemployment, high healthcare costs, incarceration, and multiple forms of risky behavior), but causal studies assessing the pathway(s) between these risk factors and multiple dimensions of HI in the U.S. context are lacking.

In addition, available evidence suggests significant, important interactions between structural and individual risk factors must be understood to more fully inform effective policy and practice targeting the individual and societal challenges associated with HI. HI measurement must achieve some level of independence from structural risk factors if the HI measure is to help elucidate the implications of structural factors on HI risk. Concerns for independence take many forms. First, structural factors could cause equivalent levels of HI to be observed as different endpoints in the data. A prime example is the eviction process, which is used more/less frequently depending on state law. Second, subjective measures of HI may be biased by context. High/low density of similar struggling, low-income households may impact the degree to which individuals subjectively evaluate their situation due to social comparison mechanisms.

Results from the Journeys Home studies (for example, O'Flaherty, Scutella, and Tseng, 2018; Ribar, 2017) indicated that transitions into and out of severe HI are difficult to predict and may not be systematic. Previous evidence also suggests that a clearer understanding of how households navigate multiple forms of material hardships in coping with income shortfalls holds promise for producing a more complete understanding of HI risk factors. Importantly, these tradeoffs between different material hardships may evolve as structural factors change. For example, enforcement of utility disconnect orders or code violations may vary over time and across locations; tradeoff strategies between housing and utility hardships are also likely to evolve when these programs evolve. A comparison of results from qualitative and quantitative studies of dual utility and housing hardship indicates that mixed-method research approaches might be useful in this endeavor. To date, however, there are few examples of these methods applied rigorously to the study of material hardships or HI.

Measurement of Housing Insecurity

In this section, the study team review recent articles that show promise for contributing to the development of an HI measure, focusing on articles that contribute to the conceptual framework in fundamental ways or add new features or approaches. In addition, the study team outline a few promising approaches in other fields. The review of the literature outside the field of HI is not intended to be exhaustive; the study team have included two specific measures that seem particularly relevant.

Recent Advances in the Field of HI Measurement

Several authors have made notable attempts toward advancing the development of a comprehensive measure of HI that incorporates multiple dimensions and indicators within each dimension. This work has principally taken two forms: (1) empirical investigations that seek to estimate the sensitivity of HI prevalence to different methods of combining indicators that measure HI and (2) development of the HUD-HIRM as a resource for more rigorously investigating the multidimensional construction of HI and related measurement approaches.

Sensitivity of HI to Alternative Measurement Approaches

Refining Cut Points for Income-to-Housing Costs

Indicators of housing cost burden typically rely on a single cut point applied to housing cost-to-income ratios to classify households as housing secure or insecure. Households with a housing-cost-to-income ratio greater than 30 percent are generally classified as having a high cost burden indicative of HI. However, continuous-level measures with a somewhat arbitrary cut point can result in "churn" of households into and out of recognized HI when they are near the cut point value. For these households, small changes in income could result in a household changing its affordability status between measurement periods. These measures may classify households that have temporary poor housing affordability as having a similar experience to households that have deeper and more persistent affordability issues (in other words, households that chronically experience difficulty affording housing are combined with households for which difficulty affording housing is an acute event).

Baker and colleagues (Baker, Mason, and Bentley, 2015) sought to address this issue by refining the traditional income-to-housing-costs ratio, which does not differentiate between lower-income households that are housing insecure and higher-income households that elect to spend a large proportion of their income on more expensive housing. This method is akin to how the Worst Case Housing Needs report examines housing cost burdens while accounting for the level of household income relative to Area Median Income. A traditional approach also does not account for differences in household size or composition. Instead, Baker, Mason, and Bentley (2015) used a "30/40 approach" to measuring housing affordability. Households are considered housing cost burdened if they spend more than 30 percent of their gross household income on housing and have an equivalized disposable household income in the lower 40 percent of the national income distribution.

Even after refining the cut point to increase sensitivity to HI, the authors found a significant difference in demographic variables and income status between households that were definitionally housing insecure over 5 years and households that churned between HI statuses. They also found that 30 percent of households identified as housing insecure using this cut point in a given year may not be housing insecure the following year. Even when using a carefully chosen cut point, HI status may change frequently for many households. This finding echoes an earlier finding by Susin (2007) that suggests that the duration of rent burden is an important indicator of HI, where a short period of 1 or 2 years may have fewer deleterious consequences than a longer period of rent burden. Assessment of HI may be improved by incorporating followup questions to assess the duration of housing difficulties.

Multidimensional Indexes

Using a multiple-item aggregation may help combat the limitations of single-item indicators. A multiple-item measure may better reflect severity and scope as it manifests in simultaneously occurring housing issues. Routhier (2019) used 11 dichotomous indicators from the 2015 AHS to create an HI index that reflects compounding across different sources of housing stress. These variables were dichotomized to represent identifiers for HI and are summarized in exhibit F.6.

Exhibit F.6 | HI Dimensions and Indicators Extracted from the 2015 American Housing Survey

HI Dimension	Dichotomous Indicators
Unaffordability	▪ Out-of-pocket rent greater than 30 percent of gross income ▪ Out-of-pocket rent greater than 50 percent of gross income ▪ Income less than 133 percent of federal poverty level (only if rent greater than 30 percent of gross income)
Crowding	▪ More than 1 person per room ▪ More than 1.5 persons per room ▪ One or more subfamilies within household
Poor Physical Conditions	▪ Objective measure reflecting moderately inadequate conditions (AHS compilation measure) ▪ Objective measure reflecting severely inadequate conditions (AHS compilation measure) ▪ Self-rated physical conditions at 4 or lower on a scale of 10
Forced Moves (defined only for recent movers)	▪ Forced to move by landlord, bank, government, or disaster ▪ Self-rated current home as worse than previous (only if forced to move)

AHS = American Housing Survey. HI = housing insecurity.
Source: Authors' compilation of information, based on a review of Routhier (2019)

Some of these indicators were intentionally ordered to reflect multiple cut points on a single dimension (rent greater than 30 percent and rent greater than 50 percent; more than 1 person per room and more than 1.5 persons per room). Sum scores based on such measures were simple to interpret and clearly identified the severity of HI. However, some indicators contained information that did not perfectly coincide with other indicators (for example, objective and subjective measures of physical conditions). Also, a sum score (for the HI construct) with unordered or ambiguously ordered measures can produce unclear statements about relative standing. Including multiple dimensions in the HI aggregated score also results in difficulty in making straightforward comparisons across scores for individual dimensions.

Using the 2005 AHS, Cox et al. (2017) identified and dichotomized a large set of indicators from seven dimensions of HI: housing instability (4 indicators), housing affordability (1 indicator), housing safety (15 indicators), housing quality (33 indicators), neighborhood safety (12 indicators), neighborhood quality (17 indicators), and homelessness (1 indicator). With these indicators, the researchers defined insecurity categories based on (1) the number of dimensions of insecurity experienced (categorical approach) or (2) the total number of insecurity indicators experienced across dimensions (continuous approach).

Based on the categorical approach, the HI definition defined Housing Secure as a household with zero dimensions endorsed and a cost burden of less than 30 percent. Households were defined as having Moderate Security if housing insecure conditions were evident in only one dimension, the household had a cost burden of less than 50 percent, and the household was not identified as homeless. Households were defined as having Low Security if they were not homeless, but issues were present in two or three dimensions; or there was a housing cost burden of more than 50 percent. Households were defined as having Very Low Security if they had experienced issues in four or more dimensions or were homeless.

For housing security categories based on the continuous scale approach, Housing Secure was defined as zero individual issues, a cost burden of less than 50 percent, and not homeless.

Moderate Housing Security was defined as one to three issues, cost burden less than 50 percent, and not homeless. Low Housing Security was defined as four to six issues or having a cost burden of greater than 50 percent but not homeless. Very Low Security was defined as having more than six issues or being homeless.

The number of indicators used in these two approaches is both a strength and a limitation. By including many indicators, households experiencing insecurity will not likely be overlooked or misclassified. On the other hand, the full measure requires a great deal of time to administer and presents a considerable cognitive burden. The cut points selected for the study were based on the distribution of scores and were sample-specific. Further, based on these cut points, most households were considered at least moderately housing insecure (89 percent). Too much sensitivity to variability may exist in less policy-relevant portions of the underlying continuum.

HUD's Development of the HIRM

HUD constructed the HIRM, which is composed of a set of survey items to be implemented as part of a supplement to the AHS to facilitate the development of the HUD-HIM (Census Bureau, 2019a). Watson and Carter (2020) provide a thorough overview of this effort, and the study team summarize their overview in this section.

Critically, Watson and Carter supplied a strong initial operational definition to guide the work.

> *"Housing Insecurity" is defined as a significant lapse for a given household of one or more elements of secure housing, where "Secure Housing" is stable occupancy of a decent, safe, and affordable housing unit. "Affordable" implies that shelter costs are manageable over the long term without severely burdening or compromising other consumption that normally is essential for health and well-being. "Stable Occupancy" implies that the household does not face substantial risk of involuntary displacement for economic or non-economic reasons. Finally, "Decent and Safe" implies that the unit has physical attributes that satisfy functional needs for well-being related to health, security, and support for activities of daily living. Such attributes include appropriate facilities for excluding external threats, providing climate control, storing and preparing food, maintaining physical and mental hygiene, and developing human potential." (2020: 233) "[H]ousing insecurity under any one dimension (affordability, stable occupancy, or decent and safe housing) could be understood as housing insecurity in general. Therefore, the study team envision scoring survey responses for each dimension of secure housing separately. Further scale analysis will provide additional insight into the feasibility of scoring households across a single latent dimension of housing insecurity." (2020: 236)*

The topic and subtopics of the resulting AHS supplemental HIRM are summarized below:

- Affordable (six measurement questions and eight validating/contextual questions).
    - Housing Stress.
    - Shelter Poverty.

    - Payment Lapses.
- Stable Occupancy (14 questions).
    - Housing Stress/Worry.
    - Eviction and Foreclosure.
    - Residential Instability.
    - Doubling Up.
    - Homelessness.
- Decent and Safe (22 questions).
    - Substandard Physical Environment with Serious Consequences for Daily Living.
    - Objective and Subjective Assessment of Crowding.
    - Housing Safety as Related to Crime and External Threats.

The HUD-HIRM advances the development of the HUD Housing Insecurity Measure (HUD-HIM) by providing a way to cross-validate new subjective questions of HI with corresponding measures drawn from large sets of objective items available in the AHS. Questions were developed to minimize the cognitive burden on respondents by anchoring responses on the current housing unit and on experiences concerning that unit that occurred within the previous 12 months of the survey. While most questions could be asked of the full sample, different wording was sometimes required for owners versus renters or for single-person versus multiple-person households, motivating a system of automatic text fills to simplify the experience of completing the survey. Some questions applied only to a specific subpopulation (for example, owners, renters, households with dependent children). For these questions, screeners were applied to identify the appropriate respondent group(s).

While HUD tried to order items along a hypothetical continuum of HI, there was some ambiguity about how items representing distinct housing dimensions might be ordered in the "middle" segment between Secure and Severely Insecure. In this middle section, different tradeoff strategies might reflect the same general intensity of HI.

HUD requested that the Census Bureau conduct a one-time cognitive pretest of the HUD-HIRM (Virgile et al., 2019), interviewing 15 respondents who were 18 years or older and were below the 300-percent household poverty threshold. As a result of this study, items were reordered to reduce sensitivity to affordability questions, several questions were added (in other words, followup questions evaluating the respondents' levels of difficulty answering questions about the entire household, screener questions accompanying major maintenance and repairs), item wording was altered to focus questions on hardship-related moves, and additional response options were added to include visual cues of disrepair.

The HUD-HIRM was administered as a close-in-time followup survey to AHS participants who completed the Food Security Module, who had incomes below 300 percent of the household federal poverty threshold, who opted in, and who could be reached at followup. While the income of the sample was capped at 300 percent of the federal household poverty threshold, it was more heavily weighted toward lower-income households (below 200 percent) to capture those most impacted by HI. Higher-income households were included to account for geographic differences in the cost of living, which may result in HI. Interviewers tried to re-interview respondents who had taken the AHS/Food Security Module, but other household members were substituted if the original respondent was unavailable. Households within the eligible pool were stratified by tenure (owner/renter) and census division. The target sample size was 4,000 households; one recent status update from HUD is that the obtained sample is somewhat smaller than anticipated (approximately 70 percent, $N = 2{,}779$).

Promising Approaches from Other Fields

This section introduces general statistical measurement frameworks used in other fields that may contribute in novel ways to the development of the HUD-HIM. Due to the expected similarities in substance and structure between food insecurity and HI, the *Household Food Security Measure* developed by the U.S. Department of Agriculture (USDA-FSM) provides a strong referent. To incorporate multiple dimensions of HI into the planned measure, the study team need to identify strategies for scoring and classification that account for qualitatively different housing experiences and strategies for meeting housing needs. The efforts toward developing the global Multidimensional Poverty Index (MPI) seem particularly appropriate as a guide for this work. For this literature review, the study team provide a conceptual description of the issues and approaches as they apply to the current effort; the study team do not attempt a comprehensive review of these measures or associated studies.

U.S. Department of Agriculture—Food Security Measure

According to a report by the National Research Council (2006: 44), “Food insecurity is experienced when there is (1) uncertainty about future food availability and access, (2) insufficiency in the amount and kind of food required for a healthy lifestyle, or (3) the need to use socially unacceptable ways to acquire food.” The USDA-FSM may be administered as an 18-item (households with children), 10-item (households without children), or 6-item (all households) survey instrument that is used widely to assess household-level food security in the United States (ERS, 2012a, 2012b). The USDA-FSM can also be used to obtain continuous scores equal to the number of endorsed items (in other words, 0 to 10 for the 10-item screener) and to classify the severity of households’ food insecurity into four categories. Designed to provide a straightforward way to obtain survey data for monitoring household food insecurity in the United States and assessing the impact of food assistance and other intervention programs, the USDA-FSM can provide valuable guidance for the current effort to monitor HI. Specifically, the ongoing measurement development of the USDA-FSM may contribute insight into methods that will contribute to the transferability, ease of administration, validity and reliability assessment, and scaling of the HUD-HIM.

Initial Psychometric Analysis and Refinement

The selection of items for inclusion in the USDA-FSM reflected a strong theory about the underlying measurement model, namely a Rasch measurement model. Specifically, items were chosen to reflect a set of ordered items that capture distinct segments of the underlying continuum of food security. Because it was designed to reflect multidimensionality in HI, the items selected for inclusion in the HUD-HIRM did not conform to such a strict model. However, there may be a candidate set of items within each housing dimension that does conform to a Rasch structure. Next is an overview of the development of the items, missing data handling, scoring, and classification of the USDA-FSM if a Rasch structure can be applied to the HUD-HIM.

From 1992 through 1994, in consultation with substantive researchers and measurement experts (for example, the National Conference on Food Security Measurement and Research), USDA constructed an operational definition of food security (ERS, 2019). In defining the scope of the measure, it was important to identify what would *not* be covered and what would be central in the operational definition. For example, the USDA-FSM does not distinguish features of the timing of periods of food insecurity (cyclical, episodic, prolonged, brief but intense). It also does not address food safety, nutritional quality, or social acceptability of food sources and does not distinguish coping strategies. It does not account for assistance programs, food expenditures, or emergency food resources.

Instead, items were created that, when the aggregate score is calculated, reflect a continuum of food insecurity and hunger due to financial resource constraints. Item choice reflects the findings of previous research that showed that households go through “different experiential and behavioral stages as food insecurity becomes more severe” (Bickel et al., 2000: 9). The developers attempted to identify potential items that spanned the full range of severity with which food insecurity and hunger are experienced in the United States. Item content was chosen to represent anxiety that the food budget or supply might be insufficient to meet basic needs, perceptions that food was inadequate in quality or quantity, and reported instances or consequences (hunger) of reduced food intake for adults and children in the household. Items assessed household conditions, events, behaviors, and subjective reactions. Each was bounded by experiences in either the past 12 months or the past 30 days. Items concerning child food security were asked only of households with dependent children.

The first psychometric assessment of this initial pool of 30 items was conducted from 1995 through 1997 using interview survey data collected from households in a supplement to the 1995 Current Population Survey (CPS) (Hamilton et al., 1997a, 1997b, 1997c). The initial food security items were embedded in a module that included food assistance and coping strategy sections. Before analysis, the obtained responses were dichotomized to reflect affirmative (at or above the selected cut point response category for the item or food insecure), negative (below the selected cut point or not food insecure), or missing. Item nonresponse was rare for food insecurity. Using exploratory linear factor analysis and Rasch modeling to determine the underlying dimensional structure, the authors identified 18 questions with the desired characteristic of being “modally” ordered. In other words, response patterns for these items typically displayed a clear sequencing of endorsement with few violations (Ohls, Radbill, and Schirm, 2001). In this process, households first note “serious inadequacy in their food supply, feel anxiety about the sufficiency of their food to meet basic needs, and adjust their food budget and food served. As the situation becomes more severe, adults experience reduced food intake and hunger, but they spare the children this experience. In the third stage, children also suffer reduced food intake and hunger and adults’ reductions in food intake are more dramatic” (Hamilton et al., 1997a: v). Importantly, hunger is seen as a severe stage or level of food insecurity rather than representing a separate dimension of food security. In this way, the concept of a single underlying dimension is retained.

With Rasch modeling, households and items are simultaneously ordered along a single underlying dimension, and households with and without children could share the same underlying scale, despite having different sets of items. Leveraging the assumption of the modal sequencing of items, the developers of the scale created a table that assigned an estimated food security score, ranging by design from 0 to 10, to each possible item-sum score. This table is presented in exhibit F.7. Due to the differences in the number of items across households with and without children, a separate column was provided for each, but the resulting food security scores were interpreted in the same way. It may be possible to develop a similar table that associates hand-calculated HI dimension scores with model-derived values and HI classification statuses.

For population monitoring of insecurity, a classification scheme can intuitively represent the scores derived from the continuous scale. Initially, the developers of the scale identified four categories of food security status, representing distinct behavioral stages associated with the managed process of food insecurity and hunger. Based on item content and estimated model parameters, the developers selected cut points for the number of items endorsed that reflect households that were (1) food secure, in which there was no or minimal evidence of food insecurity; (2) food insecure without hunger, in which food insecurity was evident (concerns and adjustments to household food management), but there was little or no reduction in food intake; (3) food insecure with moderate hunger, in which food intake for adults in the household had been reduced but only for adults; and (4) food insecure with severe hunger, in which both children and adults in the household had reduced food intake. The final two categories are frequently combined to draw a parallel between households with and without children.

Exhibit F.7 | Mapping of United States Department of Agriculture—Food Security Measure Sum Scores onto Continuous Scale Values and Categorical Statuses

Number of “Yes” Responses		1998 Scale Value		Food Security Status Category
Household with Child	Household with No Child	Standard Computational Metric	Standard 0–10 Metric	
0	0	0.0*	0.0*	Food secure
1		1.4	1.0	
	1	1.7	1.2	
2		2.6	1.8	
	2	3.1	2.2	
3		3.4	2.4	Food insecure without hunger
4		4.1	3.0	
	3	4.2	3.0	
5		4.8	3.4	
	4	5.2	3.7	
6		5.4	3.9	
7		6.0	4.3	
	5	6.2	4.4	
8		6.6	4.7	Food insecure with hunger, moderate
	6	7.1	5.0	
9		7.2	5.1	
10		7.7	5.5	
	7	8.0	5.7	
11		8.3	5.9	
12		8.8	6.3	
	8	9.0	6.4	
13		9.3	6.6	

Number of “Yes” Responses		1998 Scale Value		Food Security Status Category
Household with Child	Household with No Child	Standard Computational Metric	Standard 0–10 Metric	
14		9.8	7.0	Food insecure with hunger, severe
	9	10.1	7.2	
15		10.4	7.4	
	10	11.1*	7.9*	
16		11.1	8.0	
17		12.2	8.7	
18		13.0*	9.3*	

* Scale scores for extreme households—that is, those affirming no items or all items—cannot be calculated under Rasch model assumptions. Here, the score of 0 for no affirmatives is arbitrary, and researchers should omit the category from associative analyses or use appropriate techniques to allow the implied scale value to be estimated in the equation. There are very few households that affirmed all items. Scores for these households are calculated at 17.5 affirmatives for households with children and 9.5 for households without children.
Source: Reproduced from Bickel et al. (2000: 71)

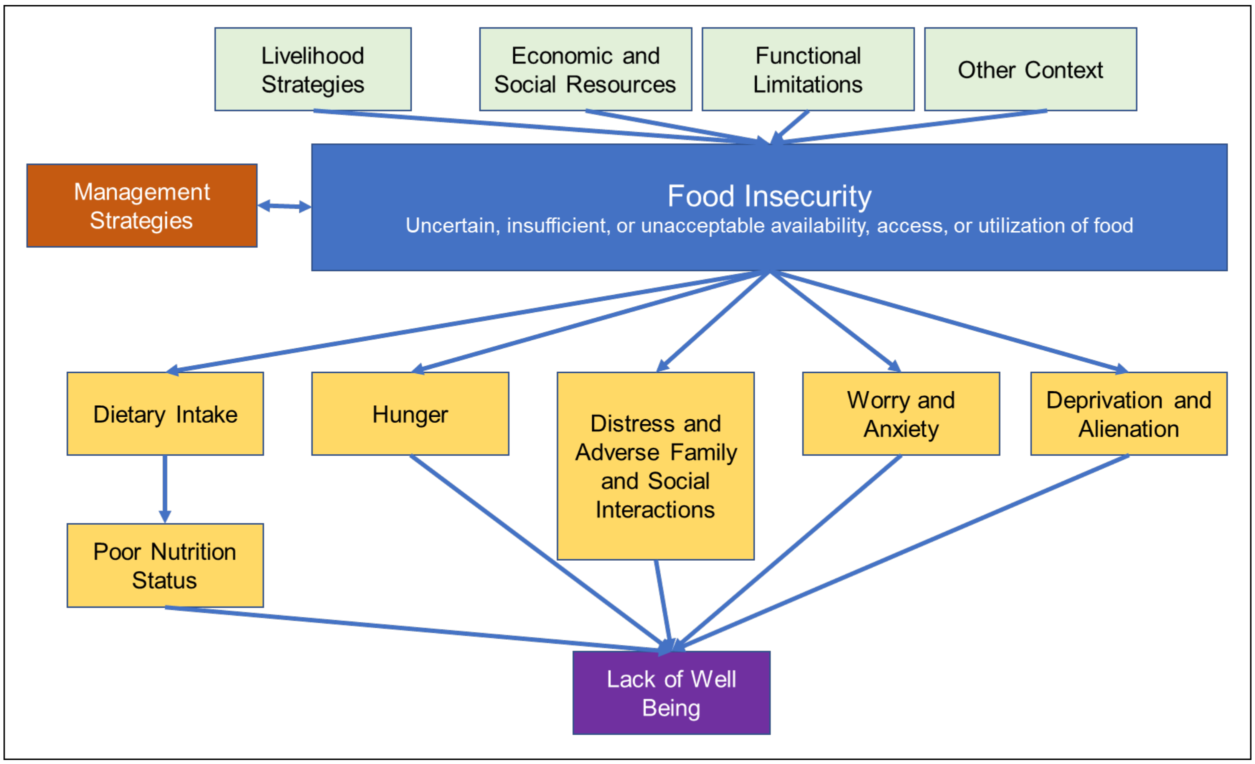
In the psychometric analysis, missing data were handled statistically within the Rasch modeling paradigm. Based on the confirmed modality of responses, the developers offered a simpler and more readily accessible way to handle missing data when a statistical model was not required (for example, for tracking purposes). Specifically, an affirmative response was assumed for all items below an observed affirmative response in the modal sequence. The assignment rubric for missing values not following this rule was set to be conservative to minimize false positives, and a maximum number of missing items for reliable measurement was specified. If a Rasch model applies to the HI data, the study team may also develop recommendations for replacing missing data using this approach.

From 1997 through 2001, survey data collected through annual CPS assessments were used to assess the stability and consistency of the USDA-FSM (Ohls, Radbill, and Schirm, 2001). Ongoing measurement development work on the HUD-HIM may benefit from approaches and lessons learned from this work. This study showed that item calibration values and item sequencing were stable across replications. However, because continuous score estimates varied somewhat based on data and sample variations, the analysts recommended that cut points for food security classification status be assigned based on sum scores rather than continuous scores. The study also evaluated subgroup invariance (race and Hispanic ethnicity, household composition, metropolitan status, and region). Although no formal statistical test was conducted, subgroups showed very similar patterns and estimated parameters, leading to the conclusion that the scale was generalizable across these characteristics.

From 2003 through 2006, a Committee on National Statistics of the National Academy of Sciences was convened to critically evaluate the USDA-FSM in light of a decade of general use in policy and research efforts (National Research Council, 2006). The Council’s reflections on the measurement development process, consideration of multidimensionality, and critical evaluation of simplifying model assumptions prospectively informs the HIM project and is reflected in the modeling approach proposed here for characterizing each housing insecurity dimension. Some of this wisdom will apply to the immediate HIM measurement development work, and some may be a focus of future data collection efforts to continue the work.

Based on substantive findings during this time, an overarching conceptual model of food insecurity was constructed (see exhibit F.8). This exhibit shows the disaggregation of hunger from food insecurity itself. The council stated that "hunger is a concept distinct from food insecurity. . . . Hunger itself is an important concept that should be measured at the individual level distinct from, but in the context of, food insecurity" (National Research Council, 2006: 5). They also suggested the development of dimensions of frequency and duration as separate but related measures.

Exhibit F.8 | Conceptual Model of Food Security and Its Predictors and Outcomes



Source: Authors' adaptation of a figure from Habicht et al., 2004

The council members recognized important advances in statistical modeling that should be brought to bear on the USDA-FSM, recommending a more general model than the Rasch model originally used. Instead, generalized latent variable modeling, which covers such techniques as factor analysis, latent class analysis, and item response theory, was recommended to better model measurement error in the items by adding a discrimination or loading parameter. The council members suggested examining the possibility that the structure of measurement error may differ across subgroups, including households with and without children; this variation is referred to as differential item functioning (DIF). The distribution of the latent food security variable might also differ across subgroups. In particular, it may be important to model the underlying variable as a truncated Gaussian distribution to account for individuals who were not included in the sampling pool (homeless) and individuals who were screened out of the study due to a very low likelihood of food insecurity.

Further, the council recommended using all ordered categories in a polytomous factor model rather than restricting the available information by dichotomizing the items. The council also identified pairs of items representing an internal screener (did an event happen?) and followup (how often did the event happen?), which were originally modeled as independent. As a more appropriate alternative, the council recommended combining the information in each non-independent pair into a single item for use in analysis and scoring.

In line with its recommendation to examine the measure with less restrictive statistical models, the council recommended empirically validating food security classification cut points. Since the assignment of households to classifications is probabilistic (in other words, there is measurement error or uncertainty in the assignment, even in cases with complete data), uncertainty in the assignment can be used to validate potential cut points. Using a less restrictive statistical model also smooths the estimated food security scores, allowing for finer distinctions between cut points than is available for simple sum scores.

In 2012, the USDA Economic Research Service (ERS) conducted a formal evaluation of the council's recommended enhancements (Nord, 2012). This study found that combining the screener/followup pairs improved the measure, and this recommendation was adopted. Many other suggested enhancements did not substantially change the status assignments; these were rejected in favor of simplicity and transparency, which are measurement characteristics also highly prized in the development of the HIM:

> *Transparency and simplicity in high-visibility Federal Government measures of well-being are of great importance. Discrete assignment of food security status offers, in a sense, the best of both worlds. It allows the measure to draw on the scientific merits and statistical advantages of latent-trait measurement while supporting explanation of the measure to public and policy audiences based on raw score. The value of being able to say, "To be classified as food insecure, households must report at least these three conditions: . . . " is enormous. USDA places considerable value on the public's ability to replicate published prevalence estimates directly from the public-use data. (Nord, 2012: 92)*

The ERS evaluation study found that improving the precision of classification status based on correct trichotomies over dichotomies and using discrimination parameters (loadings) did not significantly improve. However, if precision is needed, the use of model-based estimates over a sum-score look-up table is recommended: "Food security survey data . . . typically include only a small number of items (rarely more than 15, often 10 or fewer), with the result that measurement of the latent trait is not very precise. Furthermore, the measurable range of food insecurity includes only a small proportion of the population; a large proportion of responses (typically up to 80 percent) have raw score of zero. . . . [S]ome distortion of the measure may result if the distribution is not modeled correctly" (Nord, 2012: 48). Generally, statistically derived probabilities of classification status are not markedly improved over assignment based on a look-up table. However, there is a tendency toward greater food insecurity among households with children when accounting for measurement error. These considerations suggest that there may be an opportunity to develop versions of the HIM suited for different purposes.

An important consideration for the USDA-FSM and the HUD-HIM is the degree to which the measures are interpretationally equivalent across subpopulations of households. A measure must be adaptable for use with different languages and cultures to be fully transferable. Items interpreted differently across language or cultural subgroups, if not appropriately adjusted, will result in composite scores that are not strictly comparable across subgroups. When evaluating the possibility that the measurement structure differs across subgroups (household composition, race and Hispanic ethnicity, household income relative to poverty threshold, metropolitan residence, and census region), the study found only one substantial differential item functioning effect related to how Hispanic and non-Hispanic households reported eating balanced meals. However, the practical implication of that DIF was determined to be negligible for prevalence estimates:

> *Even though the statistical basis for these adjustments may be quite strong, making such adjustments might raise questions about the validity of the comparisons, introducing something of a "black box" quality at the expense of the transparency and ease of explanation of the current method. It may be more appropriate to use the estimates from this study to comment on observed relationships, or to give an approximation of what bias between two types of households may be, in cases where the bias appears to be large enough to affect the conclusions of a study or public perceptions of the importance of a reported difference in prevalence rates. (Nord, 2012: 75)*

Rabbitt and Coleman-Jensen (2017) examined the USDA-FSM for language and citizenship effects using Rasch modeling. This method of testing DIF involves fitting separate Rasch models for Hispanic and non-Hispanic households, equating the scales across these two models, and comparing the resulting item calibration parameters. The authors found that two items showed evidence of DIF but that the implication on scoring was minimal.

The National Research Council identified potentially important dimensions currently missing from the USDA-FSM and should be considered for further development: duration and chronicity of insecurity over time. These dimensions may also play an important role in housing insecurity. Exploratory analyses showed that timing attributes of food insecurity appear to represent a different dimension than the severity of food insecurity: "Households that experienced frequent or chronic food insecurity had different economic and demographic characteristics than those that experienced more severe food-insecure conditions but of shorter duration" (Nord, 2012: 15).

Violations of the expected modal patterns of responses may give insight into alternative tradeoff strategies for coping with moderate levels of insecurity. A recent study (Coleman-Jensen, Rabbitt, and Gregory, 2017) examined the issue of logically ambiguous response patterns. Specifically, the authors examined a subset of household responses in which the two adult hunger items and the one child hunger item were discordant with the status assigned by the combined number of affirmatives. Households for which the hunger items and assigned food security classification status were discordant were statistically compared with respect to food insufficiency, unmet food needs, use of a food pantry, dietary quality, and demographic characteristics relative to two comparison groups: (1) those who were concordantly assigned to secure status and (2) those who were concordantly assigned to insecure status. The study concluded that the discordant group was more like the concordant insecure group for both validators and demographics.

An ongoing study (Rabbitt, 2020) utilizes bifactor modeling to further explore multidimensionality in the USDA-FSM among households with children. Bifactor modeling allows the researchers to disaggregate the variability in factor indicators to capture two (or more) sources of shared variation with other indicators. Such an approach might allow greater flexibility for modeling complexities in measuring HI, so the study team provides a brief review of the approach.

For USDA-FSM, the indicators were hypothesized to have two component factors: (1) a general household food insecurity factor common to all items and (2) a subfactor common to a subset of items representing either adult food insecurity (eight items) or child food insecurity (seven items).[51] Results of modeling showed evidence of a strong general food security factor and coherent subfactors that can be leveraged to probe dynamics specific to child hunger. Further, bifactor modeling allowed the authors to recommend several alternative formulations of the general food insecurity scale that omit indicators that were more heavily influenced by subfactors, providing options for researchers who wish to have maximal comparability in food insecurity estimates across households with and without children.

Implications for HUD-HIM

The USDA-FSM provides valuable insight for developing an accessible measure of HI. As long as selected item-specific cut points are well chosen to differentiate between secure and insecure households, the dichotomy-based sum score look-up table technique is transparent and easy to use and interpret. The look-up table approach appears robust to differences in measurement structure across groups and time. However, such a formulation may be too simplistic for some purposes. Finer-tuned distinctions among insecure households are difficult to make, and there is no avenue for tracking households that show vulnerabilities to insecurity.

Ultimately, the success of the Rasch-based scaling technique hinges on the degree to which the underlying measurement model of unidimensionality and strict item sequencing holds. While these strong assumptions hold well for the USDA-FSM, the study team does not expect the same structure in the HUD-HIM. The items in the USDA-FSM were intentionally limited to those that reflect a Rasch structure, while the explicit intent for the HUD-HIM is to assess multidimensional HI. Households experiencing HI may also more readily use tradeoff coping strategies to mitigate the impact on household members. It may be possible to capitalize on a simple Rasch structure to develop individual dimensions of HI. It is also possible to explore complexities in dimensionality that might result from combining data from renters and homeowners through bifactor modeling. However, constructing a multidimensional scale and classification system will likely require a different approach.

[51] Three of the 18 items were removed prior to fitting the bifactor model due to local dependencies, which resulted in negative tetrachoric correlations with other indicators.

Multidimensional Poverty Index

To guide measurement efforts with respect to complex multidimensionality, the study team turns to a body of literature seeking to identify individuals who might be considered poor by multiple indicators, namely the field of multidimensional poverty. These multidimensional indices can be constructed so that they are decomposable with respect to dimensions to compare the relative contribution of "deprivations" (indicators of resource poverty) to the total score. Further, indices can be constructed to reflect inequality with which deprivations are distributed among the poor. For example, an increase in deprivation may have a greater impact among those who are acutely deprived than the non-deprived (non-monotonicity); if a poor person becomes newly deprived in an additional dimension, the overall poverty index should increase. Conversely, indices should be insensitive to the level of achievement in non-deprived individuals; if a non-poor person increases in resource access, the overall poverty index should not increase.

Different ways of aggregating information across HI dimensions are worth exploring in the HIM measurement development effort. There may be multiple scoring algorithms that can be recommended for different purposes. For this review, the study team outlines the development of the Oxford Poverty and Human Development Initiative's MPI, commonly referred to as the global MPI (Alkire and Jahan, 2018). This measure, developed in collaboration with the United Nations Development Programme in 2010, uses 10 indicators assessing three dimensions of achievement that are taken from the Human Development Index: 2 for health (nutrition and child mortality), 2 for education (years of schooling among individuals 10 and older and school attendance among school-aged children), and 6 for living standards (cooking fuel type, sanitation quality, drinking water access, presence of electricity, adequate housing construction materials, and presence of valued assets such as radio/TV, refrigerator, or vehicle). These indicators are aggregated and placed on a standardized metric that can be used to compare nations and regions within nations. The aggregation approach used for this measure is flexible and can accommodate different numbers and types of dimensions included and accommodate relative weights and relationships among dimensions.

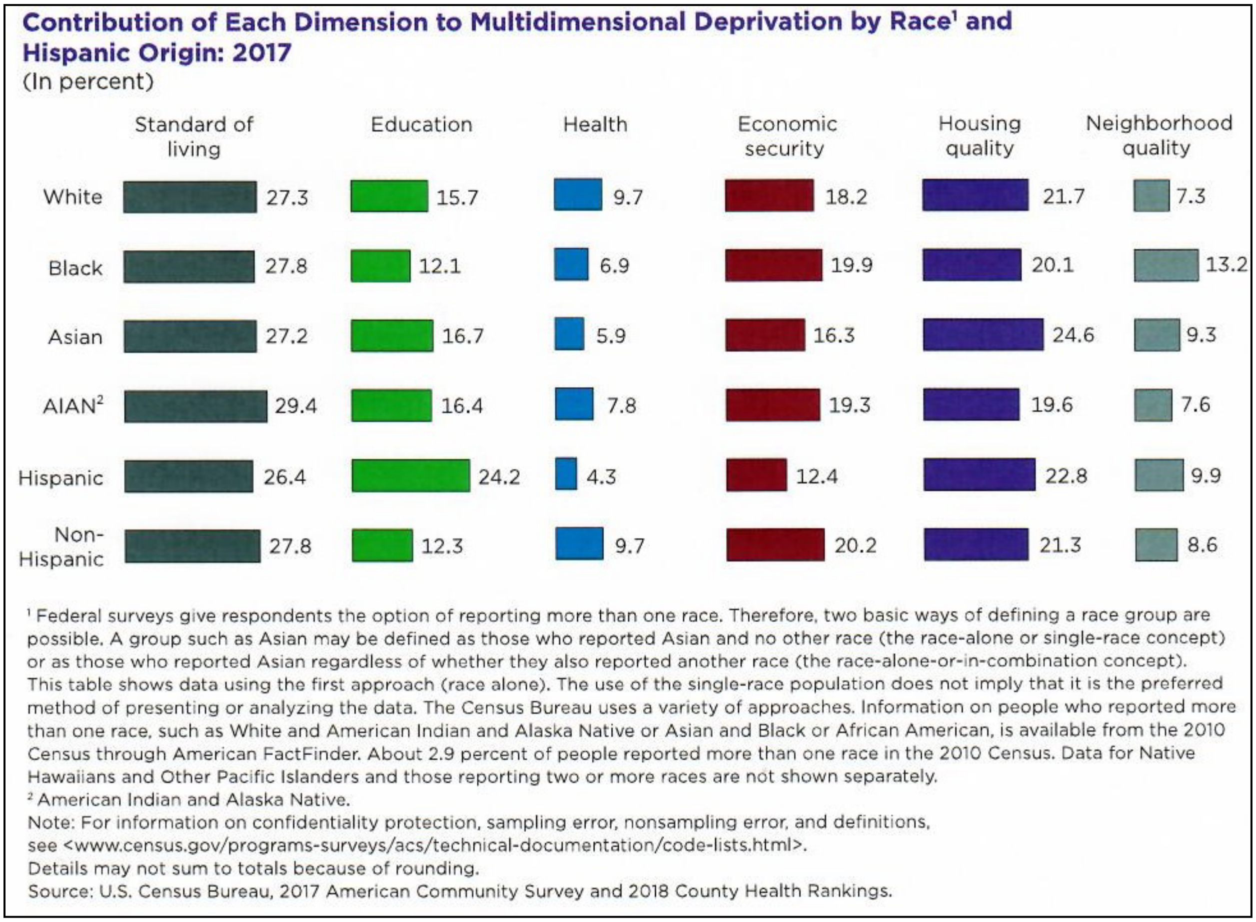
A straightforward headcount ratio approach (in other words, the number of identified poor relative to the population size) is limited; headcounts cannot be broken down to determine how much each dimension contributes to poverty. Alkire and Foster (2011) emphasized the need to create poverty indices that reflect the range, depth (severity), and prevalence of deprivations. The MPI utilizes an approach called the "dual cutoff." For each indicator, a cut point value is identified that distinguishes between those who are "deprived" versus those who are not (deprivation cutoff). To aggregate, available indicators are summed with equal weights within the dimension, and then the three dimensions are summed, also with equal weights.

When a second cut point is applied to the aggregate, a cut point that identifies the "multidimensionally poor" (poverty cutoff), one can obtain a headcount ratio by dividing by the population size. To obtain a more nuanced measure, one can multiply the headcount by an adjustment component that captures the intensity of poverty (similar to the intensity level of HI), namely the average deprivation score of those individuals identified as being multidimensionally poor. This measure is called a censored deprivation score because deprivation scores for those not flagged as multidimensionally poor are replaced by zero and are not considered in the censored headcounts. This method is poverty-focused (in other words, an increase in an achievement level in nondeprived persons leaves the value unchanged), and it is deprivation-focused (in other words, an increase in any non-deprived achievement leaves the value unchanged). Changes in the MPI over time reflect changes in the incidence of those who are multidimensionally poor, changes in the intensity of deprivation indicators, or the interaction between the two. Therefore, "the MPI provides an incentive to bring someone out of poverty—to reduce the headcount. It also provides an incentive to reduce the intensity of poor people's poverty—even if they remain MPI poor" (Alkire et al., 2011: 10).

For the MPI and the HIM, the selection of cut points should result in absolute classifications that are insensitive to inconsequential differences in culture and population characteristics over time, and they should also be open to periodic scrutiny and adjustment to recognize and adapt measurement characteristics for consequential changes in the number, type, or relative impact of indicators of deprivation. A cut point might reflect specific priorities and policy goals, such as identifying the lowest decile in a given assessment period or a specific number of individuals that can be supported within budgetary constraints. The authors of the index urge conducting robustness checks to assess the impacts of various dimension weighting schemes and cut points (see Dhongde and Haveman, 2019 for an example of these sensitivity checks).

A useful feature of the MPI, which may be valuable for the HIM, is that the resulting score can be disaggregated to reveal the dimensional deprivations contributing most to poverty. MPI scores can also be directly compared across subpopulations. Exhibit F.9 (taken from Glassman, 2019: 14) shows how the results of an MPI assessment in the United States have been displayed, decomposed by race and Hispanic ethnicity and dimension of deprivation. The decomposability of the MPI can be utilized to evaluate the impact of changes in the weighting scheme or the distribution of the achievements in the population. Not surprisingly, changes in the weighting scheme produce substantial differences in poverty assessment in terms of headcount and adjusted headcount ratios (Cavapozzi, Han, and Miniaci, 2015). It is important to assess the robustness of the chosen set of weights.

Exhibit F.9 | Example of How MPI Results Can Be Displayed



Source: Glassman (2019: 14)

One of the main advantages of the dual cut point approach is that it is generally open to an unlimited number of indicators. The dual cut point approach is also less sensitive to misclassifications and mismeasurement. It enables politicians to focus on the simultaneously deprived. However, it ignores the inequality of deprivations among the poor. The conceptually equivalent imbalance in HI dimensions is framed as differences in tradeoff strategies for coping with moderately severe housing stresses. It may be important to consider how these tradeoff strategies can be captured in the HIM.

One method for assessing tradeoffs is the first order dominance (FOD) technique (Permanyer and Hussain, 2018). FOD is a technique that allows for the comparison of alternative specifications for constructing scores from multidimensional ordinal data. Evaluation of FOD is strictly comparative across two populations and is determined as follows: Distribution *A* dominates Distribution *B* if the distribution of *B* can be obtained from *A* by shifting responses within A from preferred to less preferred outcomes. Conceptualized as a complement to the MPI, FOD does not rely on many assumptions that the MPI requires, such as the functional form of the index, the weights that are applied to each dimension, and the ways the indicators are chosen and normalized. However, it is sensitive to tradeoffs across dimensions (Dotter and Klasen, 2017). Differences between the MPI and FOD approaches might highlight the nature of these tradeoffs.

If dimensions are perfect substitutes, policymakers in a given region can improve easy dimensions to improve overall well-being, which can lead to unbalanced development composition.

Pinar (2019) offers a different option for incorporating tradeoff effects in the MPI: a generalized aggregation method that is flexible enough to consider different degrees of complementarity between well-being dimensions. The geometric mean penalizes both low and uneven achievements across dimensions. During aggregation of standardized deprivation scores, a "beta" parameter is chosen that expresses the degree of substitution or complementarity between dimensions (tradeoffs):

$$WI_{ti} = \left(\sum_{j=1}^{d} w_j \times (z_{tij})^{\beta} \right)^{\frac{1}{\beta}}$$

The weight (w_j) attached to dimension *j* is multiplied by z_{tij}, the normalized achievement level of an entity *i* in dimension *j* at time *t*. The beta parameter captures the value judgment of the decisionmaker concerning the degree of substitution or complementarity between dimensions. When beta is set to 1, lower achievement in one dimension can be compensated by a higher achievement in another. When beta decreases, it is increasingly difficult to compensate for a decrease in one dimension with an increase in another. When beta is set to -∞, multidimensional well-being is determined by the worst outcome in all dimensions; change in any other dimension does not affect the composite. Deprivation profiles with relatively balanced achievements across the subdimensions are less sensitive to the choice of the beta parameter, but there can be major rank reversals when different beta parameters are used on unbalanced profiles.

Missing multidimensional data can be somewhat problematic. While the USDA-FSM model rests on modal unidimensionality to structure recommendations for missing data, multidimensionality in the MPI and HIM requires a somewhat different approach. The MPI currently adjusts for the data gaps by reweighting the other components in the same dimension. This practice assumes that one component can proxy for another in the same dimension. When deprivation dimensions have different mean levels, reweighting biases the results systematically. Some households may not have an eligible member for a given indicator. For instance, households without school-age children will have missing values for a child education indicator. In the MPI, households without an eligible population are considered nondeprived on the respective indicator, which reduces the chances that the household is considered multidimensionally poor.

Exhibit F.10 | Approaches from Key Related Measures Can Inform HUD-HIM Development

Measure	Advantages	Disadvantages	Key Takeaways that Inform HUD-HIM Development
Household Food Security Module developed by USDA (USDA-FSM)	Simplicity enhances transferability. Easily administered. Low rate of item nonresponse.	Does not measure duration or persistence of food security. Maintains food security as a single dimension.	Recent recommendations for improvement suggest latent class approaches. Despite recommendations, USDA prioritized simplicity and transparency of the USDA-FSM.
Global Multidimensional Poverty Index (MPI)	Construct measure is decomposable, allowing assessment of the relative contribution of each dimension. Measure combines 10 indicators of 3 dimensions into a composite measure of a single construct.	Primarily used to create an aggregate measure for comparing nations/regions rather than households. Missing data can produce bias. Assumes that deprivation cut points in one dimension are independent of deprivation levels in other dimensions.	FOD test can increase understanding of tradeoffs between dimensions. Generalized aggregation method can allow the construct measure to incorporate complementarities and substitutions across dimensions.

FOD = first order dominance. HUD-HIM = HUD Housing Insecurity Measure. MPI = Multidimensional Poverty Index. USDA = U.S. Department of Agriculture.
Source: Authors' compilation based on a review of the HI literature

Dotter and Klasen (2017) list four approaches to addressing the missing MPI indicators:

1. Drop households with "too much" missing information and adjust the sample weights. This step has the undesirable effect of reducing the sample size, but if the sampling weight adjustment is successful, outcomes will be representative of the larger sample.
2. Substitute the missing indicator with an indicator from the same dimension. This action doubles the weight attached to that indicator. While decomposition by indicator will no longer be possible, one could still decompose by dimension.
3. Substitute indicators from a comparable household member. Equally relevant indicators for all household members are difficult to come by.
4. Adjust the poverty cut point for some indicators for households without an eligible member.

The authors demonstrate a hybrid approach, combining the second, third, and fourth options and maximizing the data. First, they substitute the missing indicators with available indicators from the same dimension. If the substitution indicator is not available for defined subpopulations (households without an eligible member for an indicator), it lowers the poverty cut point for that subpopulation. Without understanding the structural nature of HI dimensions, it is unclear whether these same approaches can be used in the HIM or whether other approaches may be more appropriate.

Advanced statistical models can be brought to bear on the problem of determining dimensional weights, tradeoff strategies, and missing data. Specifically, latent class analysis (LCA) appears suitable for determining policy-relevant deprivation cut points and assigning classification statuses to deprivation profiles. LCA models are specifically designed to empirically identify categorical latent variables (classifications) and account for measurement error in the assignment of response patterns to these classifications. LCA does not rely on conventional modeling assumptions, such as normality, linearity, and homogeneity, making the approach flexible and adaptable to various deprivation indicators. The LCA model-based approach was illustrated in a recent multidimensional poverty evaluation of Trinidad and Tobago (Moonansingh, Wallace, and Dialsingh, 2019), using the approach to describe typical patterns of poverty in these areas. While the study stopped short of using the class descriptions to inform scoring algorithms for the MPI, there may be opportunities to do so with the HIM.

Implications for HUD-HIM

The main strength of the MPI is that it captures the frequency and breadth of multidimensional poverty and can, with modifications, be sensitive to an imbalance in deprivations, as might occur when tradeoff strategies are utilized. It is also robust to changes in the achievement levels of nondeprived persons and nondeprived dimensions. Lastly, it can be adapted to reflect an appropriate set of dimension weights geared toward specific policy goals.

One limitation of this approach is that it assumes that deprivation cut points are independent. However, the meaning or the assignment of a deprived status might differ relative to the individual’s achievement on another dimension, signaling an ability to escape deprivation. At this time, the study team is unaware of a strategy to address this shortcoming.

Summary and Implications for Continued Measure Development

The past 5 years have seen an increase in the scope of high-quality studies examining HI alongside more rigorous attempts to improve measurement. Several themes essential to establishing a foundation for the development of a comprehensive HI measure have been identified: concerns for HI measure development, recommendations for constructs that, if measured alongside HI, could assist in validity assessment, and identification of helpful approaches to scale development.

Concerns for HUD Housing Insecurity Measure Development

Although HUD has significantly advanced the work in defining and assessing HI through deploying the HUD-HIRM, necessary work in this area remains. A comprehensive definition of HI must now be translated into cut points such that HI intensity can be assessed and interpreted. In addition, careful empirical work is necessary to inform how HI dimensions are assessed before inclusion in a composite measure. Notably, the HUD-HIRM was not created with the intent to include neighborhood quality as a fourth dimension of HI, but the HUD-HIRM does include some questions regarding neighborhood safety, and the core AHS includes additional indicators of neighborhood condition. It may be beneficial to empirically examine these indicators and assess the costs and benefits of including a neighborhood quality dimension in the HUD-HIM.

Recent longitudinal studies demonstrate the potential value of including HI measures in established longitudinal datasets in the United States, such as the Panel Study of Income Dynamics and the Survey of Income and Program Participation. The HUD-HIRM is embedded within the AHS and has a longitudinal structure based on housing units (rather than households). Current and future efforts to develop the HUD-HIM may be improved if this longitudinal structure can be leveraged using strategies to examine within-household changes in HI to better elucidate hardship tradeoff strategies, causal mechanisms, and temporal HI dynamics for improved characterization of HI intensity.

Relatedly, HUD-HIM development would benefit from consideration of the timing characteristics of critical events. Recency and chronicity of HI may be central to some policy-related outcomes and should be considered in addition to HI severity. Subjective aspects of HI may not coincide with objective aspects. For example, individuals within a household may continue to worry over affordability after a near eviction, even if they currently are up to date on paying rent. Careful thought should be given regarding how the HUD-HIM is interpreted temporally.

Individual risk factors for HI are embedded in structural risk factors, which often vary geographically. One obvious use of the HUD-HIM will be to learn more about the impacts of these geographically varying structural risk factors on HI. To accomplish this, the HUD-HIM must be carefully constructed so that HI is measured independently of the structural risk factors. Independence is jeopardized when individual item response is influenced or biased by existing structural factors. For example, the eviction process is governed by state laws; and landlords' use of eviction, the threat of eviction, or other measures to secure rent are likely to vary across cases due to state law. In one location, eviction threats could be used frequently to induce rent payment and could be only loosely correlated with actual eviction. In other locations, eviction threats could be less frequent and more highly related to the high risk of actual eviction. In addition, careful consideration should also be given to subjective measures of HI and how responses may be biased by varied structural factors and contexts created by those factors. For example, social comparison could cause variations in the reporting of worry about housing affordability among households living in a homogenous low-income community compared to otherwise similar households living in a diverse mixed-income community.

Tradeoffs between multiple forms of material hardship are another area of concern for HUD-HIM development. These tradeoff strategies are likely influenced by both observed and unobserved individual characteristics, as well as structural factors, and may vary temporally as changes occur in personal finance, health care, consumer protections, and safety net services. The HUD-HIM should be able to assess changes in HI that occur as a result of changes in tradeoff strategies between non-housing material hardships. For example, if households choose to forgo food to maintain stable housing, then the measure should indicate that HI is improved compared to a situation in which households choose to prioritize food over housing expenses. A key gap in the literature examining tradeoff strategies is a lack of mixed-methods studies that allow the evaluation of empirical measures against qualitative, nuanced individual accounts of experiences. HUD-HIM assessment could be bolstered by mixed-methods investigations aimed at validity assessment.

Finally, one recognized limitation of the current approach to the HUD-HIM (shared with similar measures such as USDA-FSM and MPI) is that the assessment is geared toward the entire household as the unit of analysis rather than individuals. It may be the case that there is considerable intra-household variability. For example, a housing secure individual or family unit might be doubled up with an otherwise homeless individual or family unit. Future development of the HUD-HIM measure may explore strategies for isolating homogeneous units within the household (individuals or groups of individuals with a shared housing experience) and anchoring survey responses to these units.

Recommendations for Validity Assessment

There is no existing gold standard measure of HI—not even a comprehensive consensus definition for HI. Hence, efforts to assess the construct validity of the HUD-HIM are challenging. Construct validity can be assessed by demonstrating both convergent validity (in other words, demonstration that indicators believed to be associated with the HUD-HIM are related) and discriminant validity (in other words, demonstrating that indicators believed to be unrelated to the HUD-HIM are unrelated).

A strategic approach to assessing convergent validity includes validating the HUD-HIM against common outcomes associated with HI in multiple studies. Several validated instruments from public health meet this criterion, including the general self-rated health questions and three instruments widely used to assess depression (GHQ-12, K6, and BRFSS self-report depression/mental health questions). These health questions are not currently part of the AHS, but their inclusion in future deployments would be helpful. Finally, in recent years, the AHS has included rigorous assessments of food security, housing affordability, overcrowding, and eviction. These key indicators can aid the assessment of convergent validity by testing the HUD-HIM's ability to replicate established correlations.

Strategies for assessing divergent validity are more difficult to obtain from a literature review because few studies set out to provide evidence that two indicators are unrelated. However, the discussion of structural risk factors here provides some clues. Geographically varying structural risk factors should be contemporaneously associated with HI. However, it may be possible to identify changes in structural risk factors that are theoretically unassociated with HI in prior periods. For example, a moratorium on mortgage foreclosure and eviction should be related to contemporaneous HI but unrelated to HI measured before the implementation of the policy.

Helpful Approaches to Scale Development

The review of current and recent HI measurement development work here leads to the conclusion that multiple indicators provide more stable estimates of HI dimensions that are less prone to random measurement error. However, combining the indicators into a single index can create issues with interpretability. Further, if the composite is a simple sum score of dichotomized indicators, the number of indicators influences the sensitivity of the index. In some cases, using too many items has resulted in overestimating the prevalence of HI, capturing households who report even one housing problem. In other cases, using too few items has resulted in underestimation, ignoring households experiencing problems that are not assessed. The review of the global MPI has highlighted how the weighting of indicators within and across housing dimensions can help minimize these issues. Including an adjustment to the aggregation equation that captures the imbalance of insecurity across dimensions can also provide useful distinctions when tradeoff strategies come into play. Further, by incorporating the intensity of housing problems among insecure households as an additional element in the estimation of prevalence, emphasis is placed on improving the conditions for the most severely affected households rather than on moving only moderately affected households enough to reduce the number of households identified as insecure.

From the review of the USDA-FSM, the study team concludes that a simple table that converts sum scores to empirically derived numeric insecurity scale scores and corresponding insecurity classification statuses can be valuable and can be an effective way to handle supplemental items that are relevant to a special population, such as renters or owners. However, the success of such a table depends on a strict modal structure of items and must reflect a single dimension.

Conclusion

HUD's HI module is well aligned with common themes and best practices noted in the literature regarding the measurement of HI. While challenges exist in the construction of the HUD-HIM, many challenges are described by recent literature—a helpful first step toward solutions. Recent longitudinal studies underscore mechanisms and risk factors for HI, and the MPI development utilizing the latent class approach provides a useful demonstration of multidimensional scale development. Finally, the construct validity of the HUD-HIM will surely benefit from the large body of literature highlighting correlates of HI. Development of the HUD-HIM is poised to be rooted in a rich foundation representing contributions from numerous fields that will surely enhance the usefulness of a multidimensional measure of HI in the United States.

Appendix G: Reduced HI Measures: Additional Analysis

This appendix provides detailed results from stepwise regressions and graded response models, which were the two methods used by the study team to identify reduced sets of items to use to measure the three dimensions of housing insecurity (HI): lack of affordability (HI 1), lack of stable occupancy (HI 2), and lack of safety and decency (HI 3). The stepwise regressions identified the variables that explained the most variation in the overall gold standard score of each dimension. Variables that were removed from the stepwise regression correspond to items that do not explain a significant amount of variation in the gold standard scores. The graded response models identified items with similar difficulty parameters. Items with similar difficulty parameters are potentially redundant because they likely capture similar segments of the distribution of the HI dimension. The study team describes graded response models in more detail in the methods section in the main body of the report.

The study team reports the findings by showing the boundary characteristic curves (BCCs) of the highest response option for each item. The BCCs the study team include are graphs that show the probability of selecting the highest response option for the items of each HI dimension at different levels of the dimension (referred to as "theta" in the graded response model). For lower values of theta, the probability of selecting the highest (most insecure) response option should be lower. The probability will increase as theta increases until ultimately reaching 1.

The study team identified items with similar difficulty parameters as potentially redundant and removed items with weaker discrimination from the reduced model. The graded response models were the primary method of data reduction used by the study team. The stepwise models were estimated for comparison purposes but did not directly guide the decisions the study team made in developing the reduced measures of HI.

Also important to note is that this appendix presents the process the study team followed to develop the short form version of the reduced measures. Before the development of the short form, the study team developed the long form measures using the same process and set of results. The only difference was that the team was less liberal in deciding to remove potentially redundant variables. Specifically, the study team included the following items in the long form measures but not in the short form:

1. For HI1, the study team included the extent of worry about mortgage/rent payments, current lapses in housing payments, frequency of difficulty in making housing cost payments, and perceived severe housing cost burden but removed them from the short form.
2. For HI 2, the study team included risk of eviction or foreclosure, current worry about forced move, and number of moves but removed them from the short form.
3. For HI 3, the study team included running water and number of subfamilies but removed them from the short form.

When the long form measures were complete, the study team realized that the reduced scores were still based on a large number of survey items. The study team thus returned to the results and attempted to reduce further, which resulted in the short form measures. Finally, as the last step, the study team developed the medium form measures to provide a third option between the short and long forms. The study team developed the medium form based on the following decisions:

1. For HI 1, the study team removed perceived housing cost burden from the long form measure to develop the medium form measure. Perceived housing cost burden has poor discrimination and was thus identified as a measure that could potentially be removed without too much loss of information.
2. For HI 2, the study team removed specific items in the risk of eviction or foreclosure variable related to prior evictions/foreclosures to develop a reduced eviction/foreclosure variable included in the medium form measure. The study team describe the reduced eviction/foreclosure variable in appendix B.
3. For HI 3, the study team reduced the structural deficiencies measure by removing some individual structural deficiencies that informed the variable. To identify which deficiencies to remove, the study team examined correlations between each deficiency and the overall structural deficiency variable and kept only those with the strongest correlation. The study team included the reduced structural deficiency variable in the medium form measure (it is also included in the short form).

Lack of Affordability (HI 1)

Exhibit G.1 shows the variables that explain the most variation in the gold standard score of HI 1. The partial *r*-square shows the estimated proportion of the overall variation in the gold standard score explained by adding the variable to the model. The model *r*-square shows the estimated proportion of the overall variation explained by all the variables included in the model at the specific step (for example, the model *r*-square for step 2 shows the variation explained by the variables included in steps 1 and 2). The table also shows Mallow's C(p), which is a measure of the relative fit of the model; a smaller value indicates a better fit to the data. Finally, the table includes results from an *F*-test that indicates whether the variable's partial *r*-square is statistically different from zero.

The model starts with the variable that explains the most variation on its own and then successively adds variables until it is not possible to significantly ($p < 0.05$) increase the variance explained. Findings show that frequency of worry about payments is the most important variable. Other variables that add to the overall variance explained include extent of difficulty making payments and extent of worry about making payments. Some variables add a very small (but statistically significant) amount of variance explained, including a recent lapse in payments, perceived severe housing cost burden, difficulty paying utilities, and housing cost burden. A reduced measure should probably include frequency of worry about payments since that is most important, and, potentially, extent of difficulty making payments and extent of worry about payment, as these also contribute to the variance explained (although the increase is small).

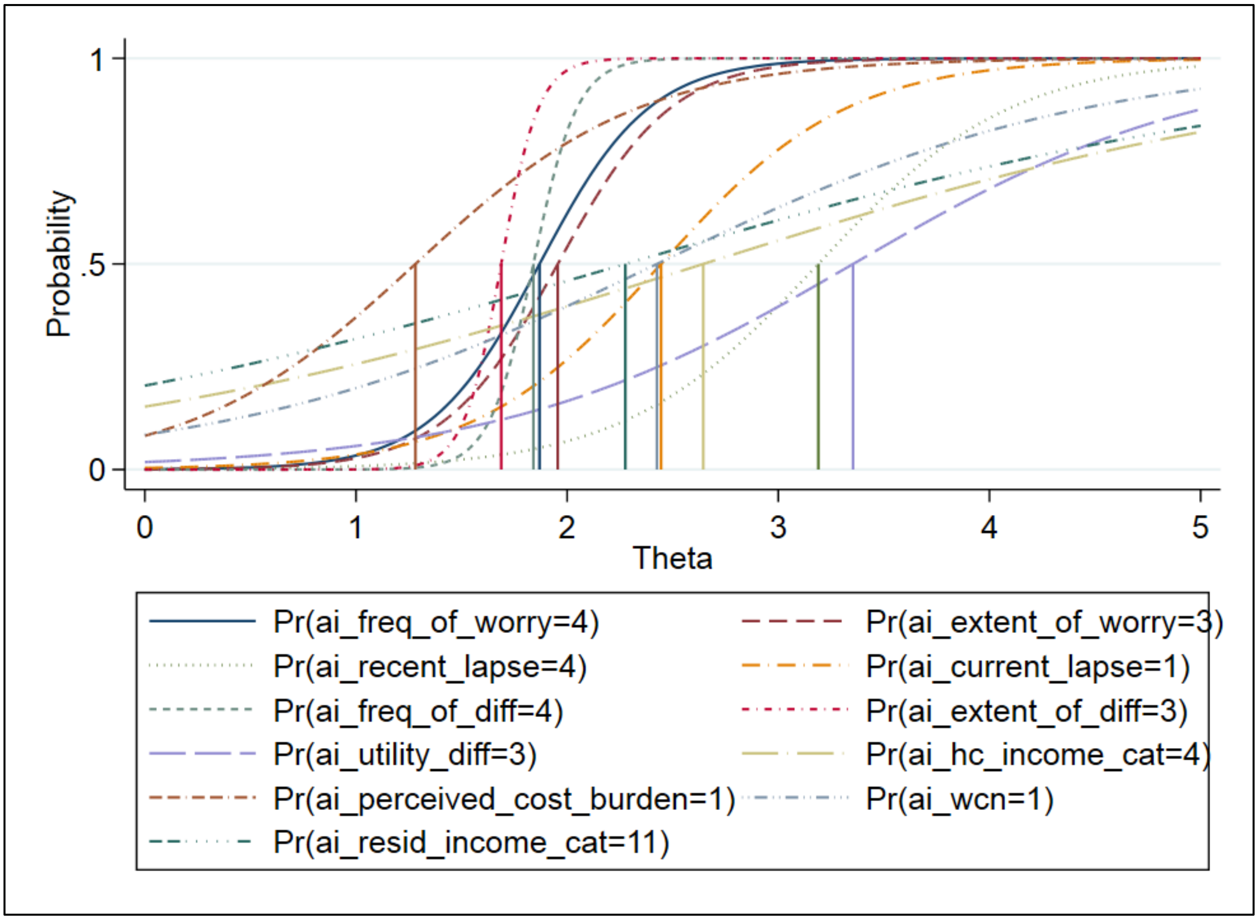
Exhibit G.1 | Stepwise Regression of Gold Standard on Lack of Affordability (HI 1) Indicators

Step	Variable Entered	Label	Partial *R*-Square	Model *R*-Square	C(p)	*F* Value	Pr > *F*
1	ai_freq_of_worry	Frequency of Worry About Mortgage/Rent Payment	0.786	0.786	561.24	9763	<.0001
2	ai_extent_of_diff	Extent of Difficulty Making Housing Payments (Mortgage/Rent)	0.0224	0.8084	226.7	310.4	<.0001
3	ai_extent_of_worry	Extent of Current Worry about Mortgage/Rent Payment	0.0076	0.816	114.1	110	<.0001
4	ai_perceived_cost_burden	Perceived Severe Housing Cost (Mortgage/Rent) Burden	0.0037	0.8198	59.73	55.23	<.0001
5	ai_recent_lapse	Recent Lapse in Mortgage/Rent Payment	0.0036	0.8233	8.097	53.59	<.0001
6	ai_freq_of_diff	Frequency of Difficulty Making Housing Payments (Mortgage/Rent)	0.0002	0.8235	6.95	3.15	0.0762
7	ai_utility_diff	Difficulty Paying Utilities	0.0002	0.8237	6.265	2.69	0.1013

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit G.2 provides BCCs that result from a graded response model (GRM) of HI 1. The *y*-axis of a BCC is the probability that a household answers the highest (most insecure) answer to the indicator. The *x*-axis is the value of the underlying dimension of HI 1 (small values more secure, large values more insecure). The underlying dimension is referred to as “theta” in item response theory models. The BCCs below show that items measuring frequency of worry about payments (blue) and frequency of difficulty making payments (light green) are similar in terms of item difficulty (the value of theta at which the probability of answering the highest response option is 0.5), but frequency of worry about payments has weaker discrimination. This finding is potentially evidence that frequency of worry about payments could be removed due to redundancy with frequency of difficulty in making payments, which discriminates better; however, frequency of worry about payments has the highest correlation with the gold standard and is the first item in the stepwise regression above (see exhibits 27 and G.1). The study team thus made no decisions about frequency of worry about payments based on the BCC.

Exhibit G.2 | Lack of Affordability (HI 1) Item Boundary Characteristic Curves

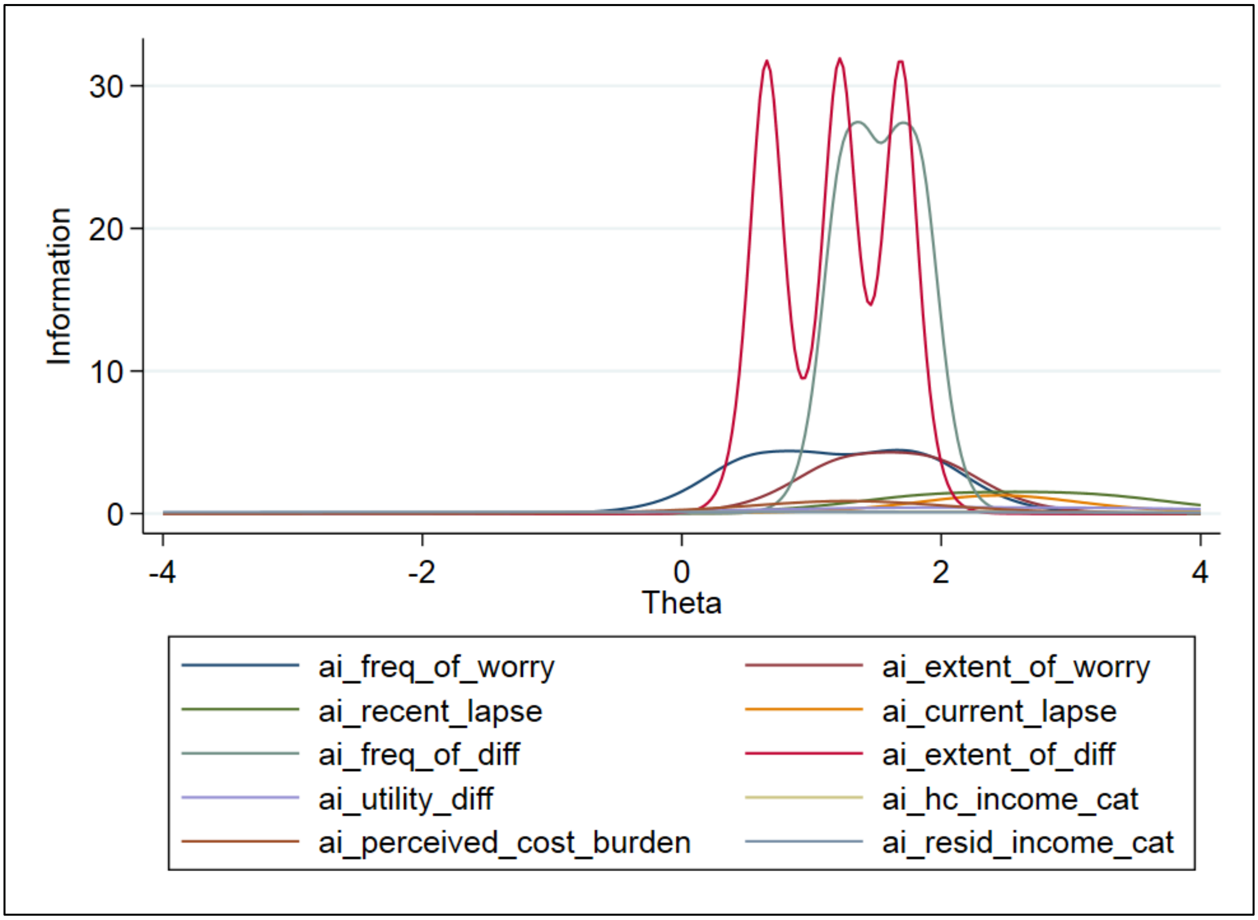


Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit G.2 also shows that current lapse in payments and worst case needs are very similar in terms of difficulty. Current lapse also has much better discrimination. The study team thus identified worst case needs as one variable to remove from the reduced measure of HI 1.

Exhibit G.3 displays item information functions (IIFs) that show how much information each item captures at different values of theta. In IIFs, the *y*-axis is now the amount of information captured by the item, which is akin to the variance explained. The extent of difficulty in making payments clearly captures the most information, followed by the frequency of difficulty in making payments. The IIFs for these variables are close together, and the IIF for extent of difficulty in making payments shows that the variable captures more information than frequency of difficulty in making payments. The study team thus identified frequency of difficulty in making payments as one variable to remove from the reduced measure of HI 1.

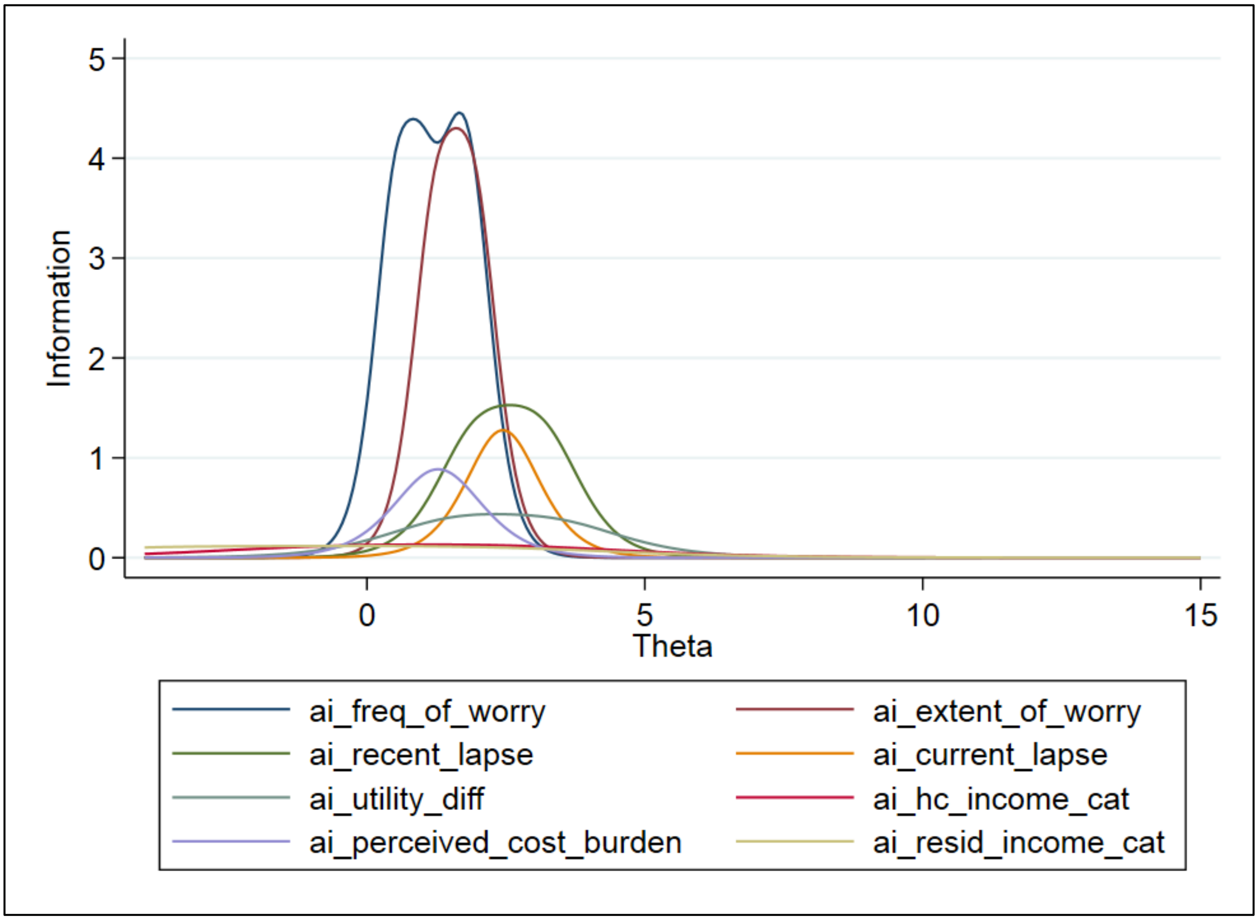
Exhibit G.3 | Lack of Affordability (HI 1) Item Information Functions



Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit G.4 shows the IIFs with the frequency and extent of difficulty in making payments variables removed. The IIFs for the remaining variables are now easier to compare. Frequency of worry and extent of worry about making payments capture similar amounts of information, although frequency of worry captures a little more. In addition, recent lapse in payment captures more information on the higher end of the distribution of theta. The study team thus identified all remaining items, except for frequency of worry about payments and recent lapse in payment, as variables to remove from the reduced measure.

Exhibit G.4 | Lack of Affordability (HI 1) Item Information Functions, Difficulty Making Payments Variables Removed



Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The variables that were removed from the short form reduced score of HI 1 included the following:

- Extent of worry about mortgage/rent payments.
- Current lapses in housing payments.
- Frequency of difficulty in making housing payments.
- Difficulty paying utilities.
- Housing cost burden.
- Worst case needs.
- Residual income.

The variables that were included in the short form reduced score of HI 1 included the following:

- Frequency of worry about mortgage/rent payments.
- Recent (in the last 12 months) lapses in housing payments.
- Extent of difficulty in making housing cost payments.

Lack of Stable Occupancy (HI 2)

Exhibit G.5, which shows the results from a stepwise regression, confirms that previous worry about a forced move explains the most variation in the gold standard score. The proportion of people living temporarily in the home because they have nowhere else to go, current worry about a forced move, the proportion of people living in the home due to financial difficulties, and forced moves also add to the variance explained. The number of moves adds a very small amount to the variation explained but remains statistically significant.

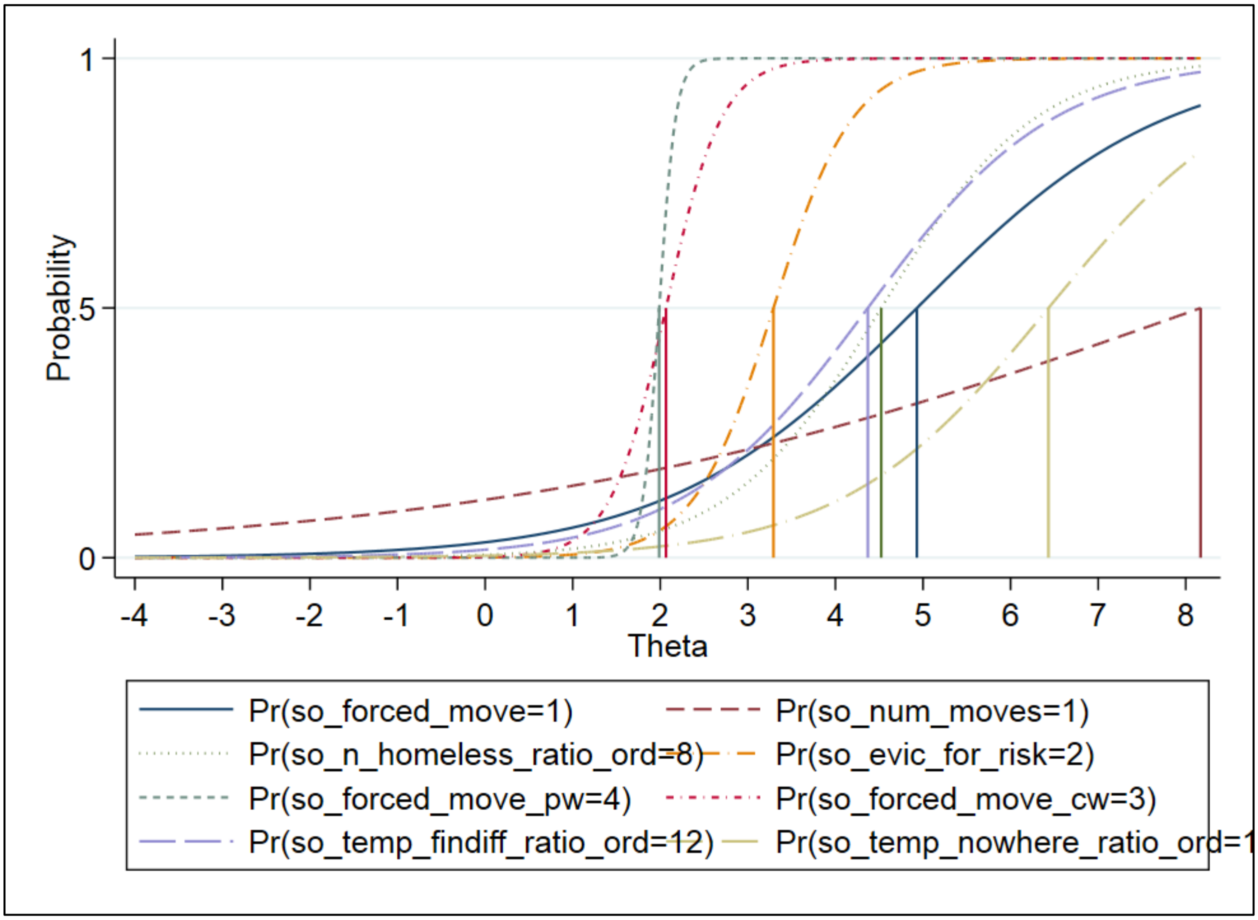
Exhibit G.5 | Stepwise Regression of Gold Standard on Lack of Stable Occupancy (HI 2) Indicators

Step	Variable Entered	Label	Partial *R*-Square	Model *R*-Square	C(p)	*F* Value	Pr > *F*
1	so_forced_move_pw	Previous worry about forced move	0.4126	0.4126	1466	1941	<.0001
2	so_forced_move_cw	Current worry about forced move	0.0744	0.487	933.1	400.7	<.0001
3	temp_nowhere_ratio	Proportion of persons who are living there temporarily because they have nowhere else to go	0.0454	0.5324	608.1	268.4	<.0001
4	so_forced_move	Forced move	0.0321	0.5645	379	203.5	<.0001
5	temp_findiff_ratio	Proportion of persons who are living there temporarily because of financial difficulties	0.0302	0.5947	163.3	206	<.0001
6	so_evic_for_risk	Risk of eviction or foreclosure	0.0133	0.608	69.74	93.4	<.0001
7	so_num_moves	Number of moves, 2 categories	0.0088	0.6168	8.611	63.12	<.0001

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit G.6 shows that previous worry about a forced move and current worry about a forced move have similar difficulty, but previous worry (worry in the past 12 months) has better discrimination than current worry about a forced move. The study team thus identified current worry about a forced move for removal from the reduced measure. The graph also shows that the proportion of people who experienced homelessness and proportion of people in the home temporarily staying due to financial difficulties have similar difficulty parameters, but the homelessness variable has slightly better discrimination. As a result, the study team dropped the proportion of people in the home staying due to financial difficulties from the reduced measure of HI 2.

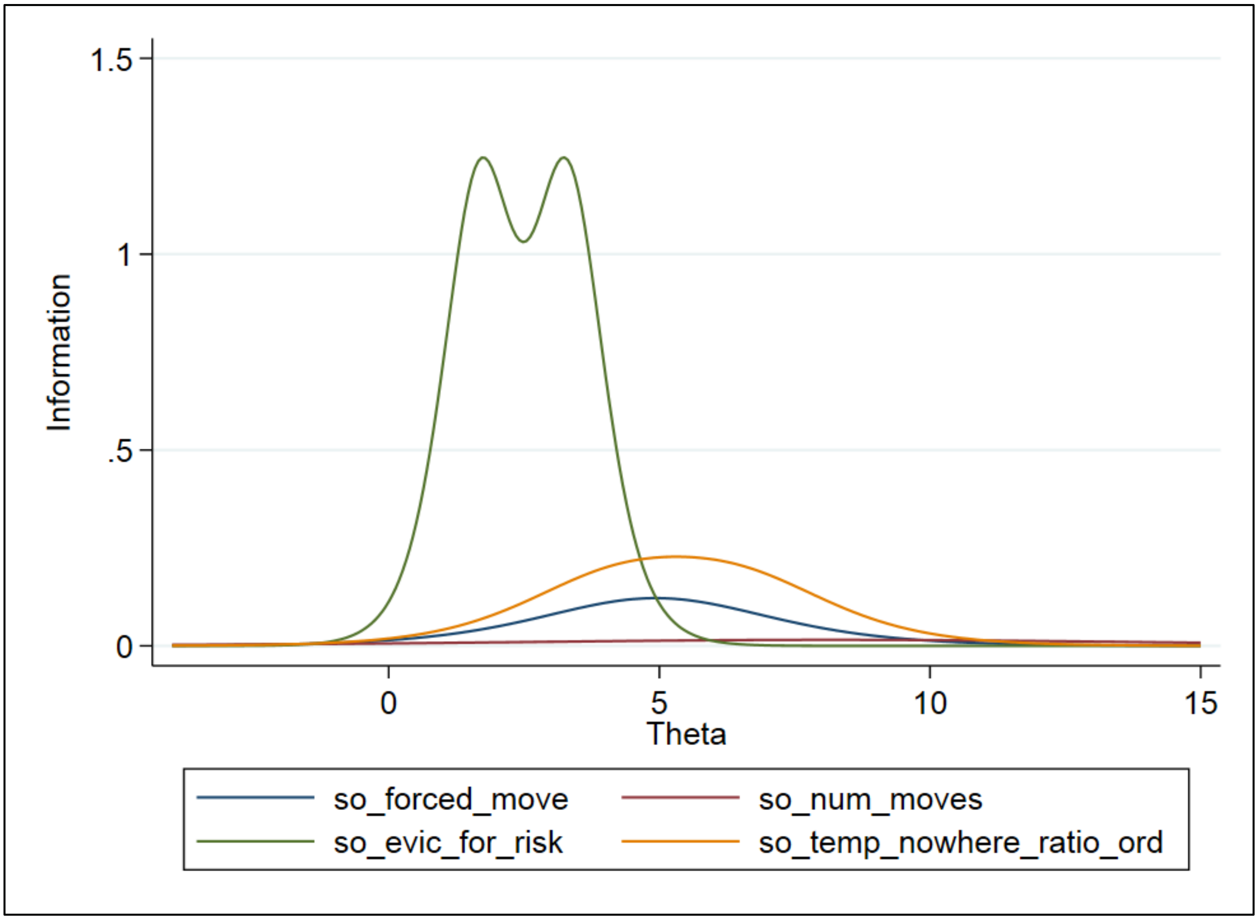
Exhibit G.6 | Lack of Stable Occupancy (HI 2) Item Boundary Characteristic Curves



Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit G.7 shows the IIFs for the rest of the HI 2 items. It is clear from the figure that risk of eviction or foreclosure captures the most information overall, and the proportion of people staying in the home because they have nowhere else to go captures the most information on the higher end of the distribution of theta. Risk of eviction or foreclosure, however, is a very complex variable based on nine items from the American Housing Survey (AHS) Core and Housing Insecurity Research Module (see appendix B for more information). The study team thus kept only the proportion of people staying in the home because they have nowhere else to go and dropped the rest of the variables in the reduced measure of HI 2.

Exhibit G.7 | Lack of Stable Occupancy (HI 2) Item Information Functions, Remaining Variables



Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The variables that were removed from the short form reduced score of HI 2 included the following:

- Risk of eviction or foreclosure.
- Current worry about forced move.
- Forced move.
- Number of moves.
- Proportion of persons in the household who are living there temporarily because of financial difficulties.

The variables that were included in the short form reduced score of HI 2 included the following:

- Previous worry about a forced move.
- Proportion of persons in the household who have experienced homelessness.
- Proportion of persons in the household temporarily staying because they have nowhere else to go.

Lack of Safety and Decency (HI 3)

Exhibit G.8 shows results from a stepwise regression of the HI 3 items with the gold standard factor score as the dependent variable. The results confirm that number of structural deficiencies also explains the most variation in the HI 3 gold standard. Other variables that also explain variation include feeling unsafe inside the home, heating breakdowns, plumbing breakdowns, feeling unsafe coming/leaving the home at night, persons per room, and sewage breakdowns. Importantly, because stepwise regression performs listwise deletion of missing data, the study team excluded unsafe_outside from this analysis (due to a large amount of missing data).

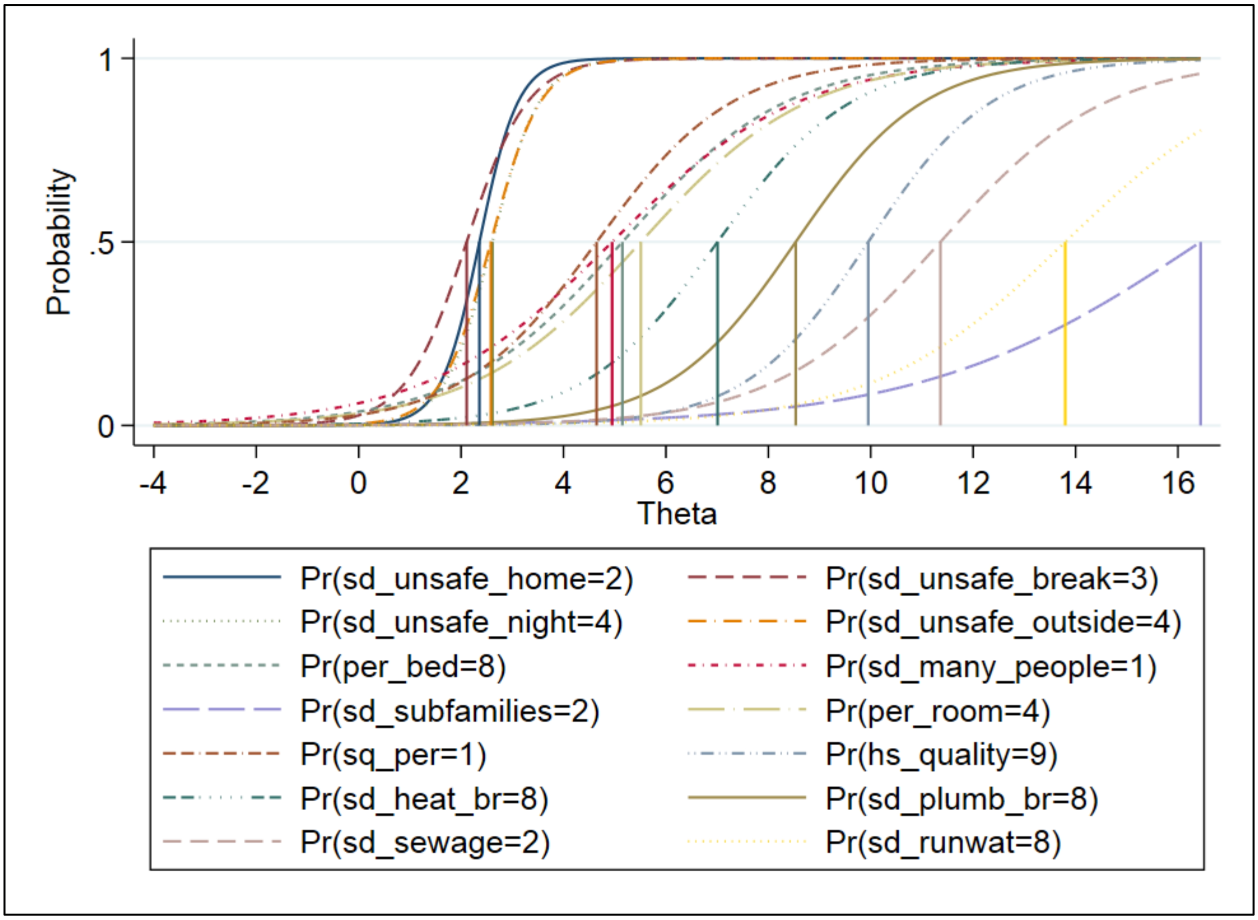
Exhibit G.8 | Stepwise Regression of Gold Standard on Lack of Safety and Decency (HI 3) Indicators

Step	Variable Entered	Label	Partial *R*-Square	Model *R*-Square	C(p)	*F* Value	Pr > *F*
1	hs_quality	Number of structural deficiencies	0.7659	0.7659	8388	8609	<.0001
2	sd_unsafe_home	Feeling unsafe inside home	0.0624	0.8283	5453	956.1	<.0001
3	sd_heat_br	Heating breakdowns	0.0307	0.8591	4009	573.1	<.0001
4	sd_plumb_br	Plumbing breakdowns: toilet	0.0277	0.8867	2709	641.4	<.0001
5	sd_unsafe_night	Unsafe coming/leaving home at night	0.0172	0.9039	1904	468.9	<.0001
6	per_room	Persons per room	0.0134	0.9173	1275	425	<.0001
7	sd_sewage	Sewage break	0.0133	0.9305	653.2	501.1	<.0001
8	sd_runwat	Running water	0.009	0.9395	232.2	389.9	<.0001
9	sd_unsafe_break	Unsafe against break-ins	0.0038	0.9433	55.64	175.5	<.0001
10	per_bed	Persons per bedroom	0.001	0.9443	10.31	47.34	<.0001

Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit G.9 shows the BCCs from the GRM of the HI 3 items. The BCCs indicate that the unsafe items share a similar difficulty and discrimination, as do square feet per person, too many people in the unit, persons per bedroom, and persons per room. The study team can likely select a reduced set of measures from these two groups. The remaining items are fairly spread out on the upper end of the distribution.

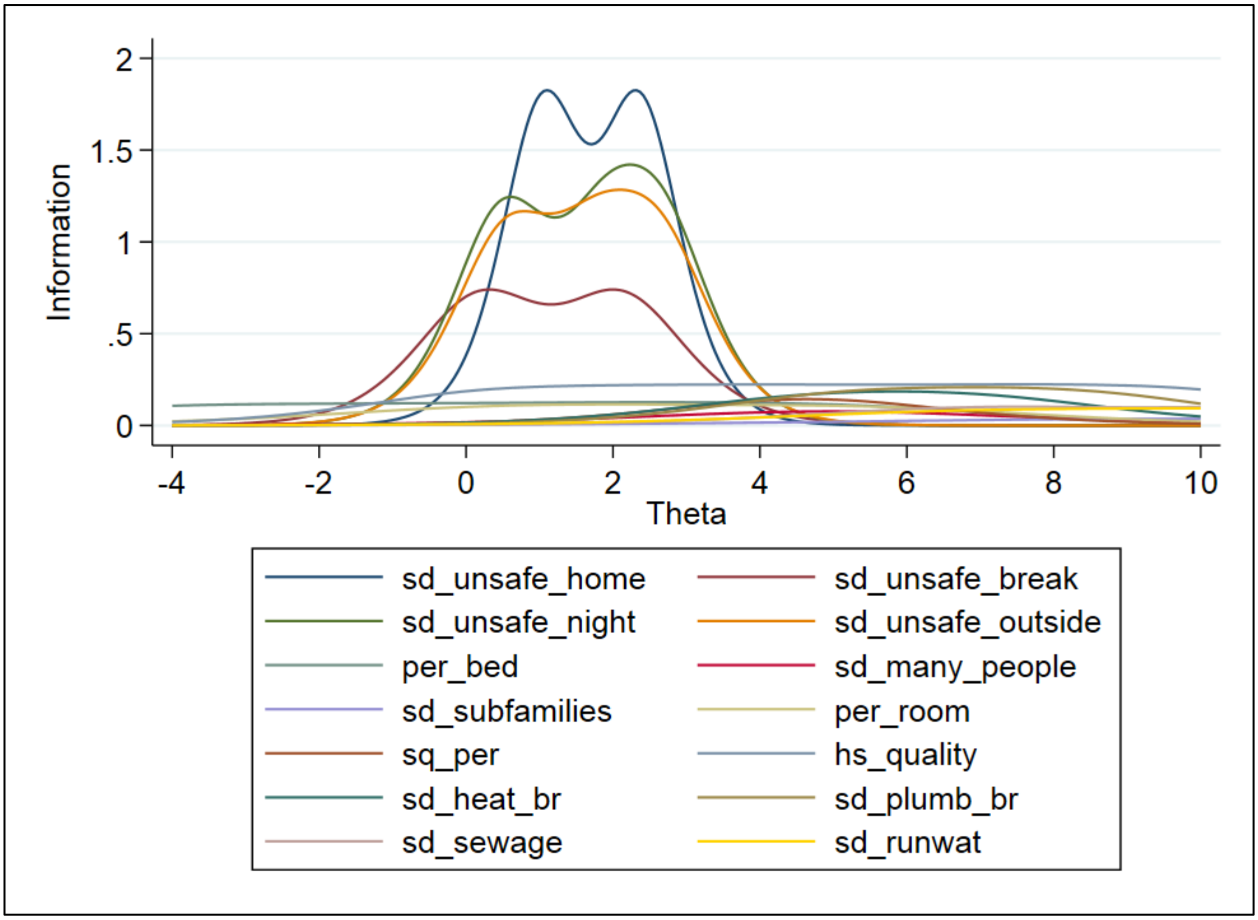
Exhibit G.9 | Lack of Safety and Decency (HI 3) Item Boundary Characteristic Curves



Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit G.10 shows the IIFs for each of the HI 3 items. The IIFs show that the unsafe variables clearly capture the most information in HI 3, especially in the range of theta between 0 and 4. Feeling unsafe inside the home explains the most, while feeling unsafe outside and unsafe coming/leaving the home at night are very similar in terms of information explained. Feeling unsafe against break-ins explains the least amount of information. The other variables seem to capture information on the higher end of the dimension, but they are hard to see in this graphic. The study team investigates these more below. Based on exhibit G.10, the study team decided to keep feeling unsafe inside the home and remove the other unsafe items from the reduced measures of HI 3.

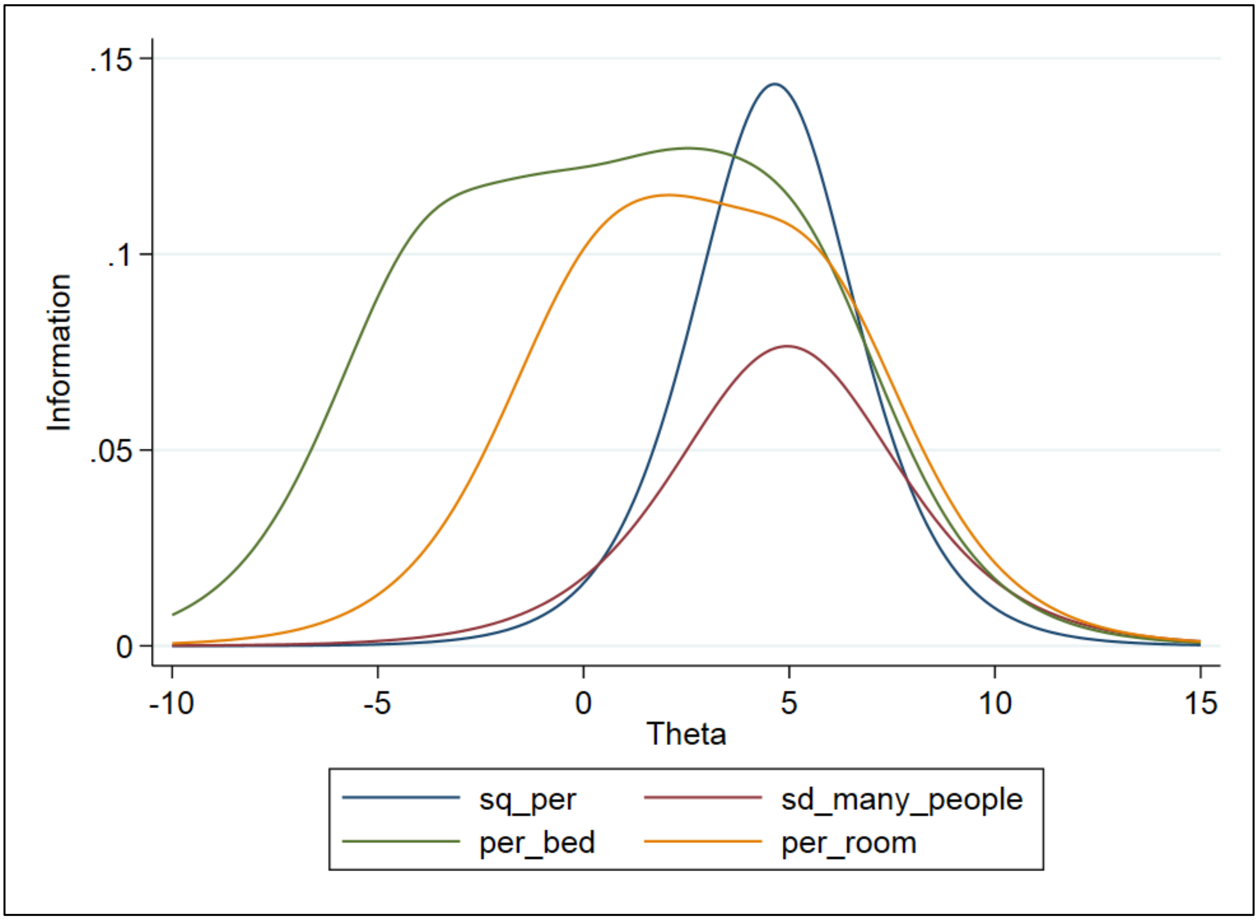
Exhibit G.10 | Lack of Safety and Decency (HI 3) Item Information Functions



Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit G.11 shows the IIFs for persons per bedroom, square feet per person, persons per room, and too many people in the unit. The IIFs show that persons per bedroom and square feet per person capture the most information. The study team thus removed the persons per room and too many people in the home variables from the reduced measure of HI 3.

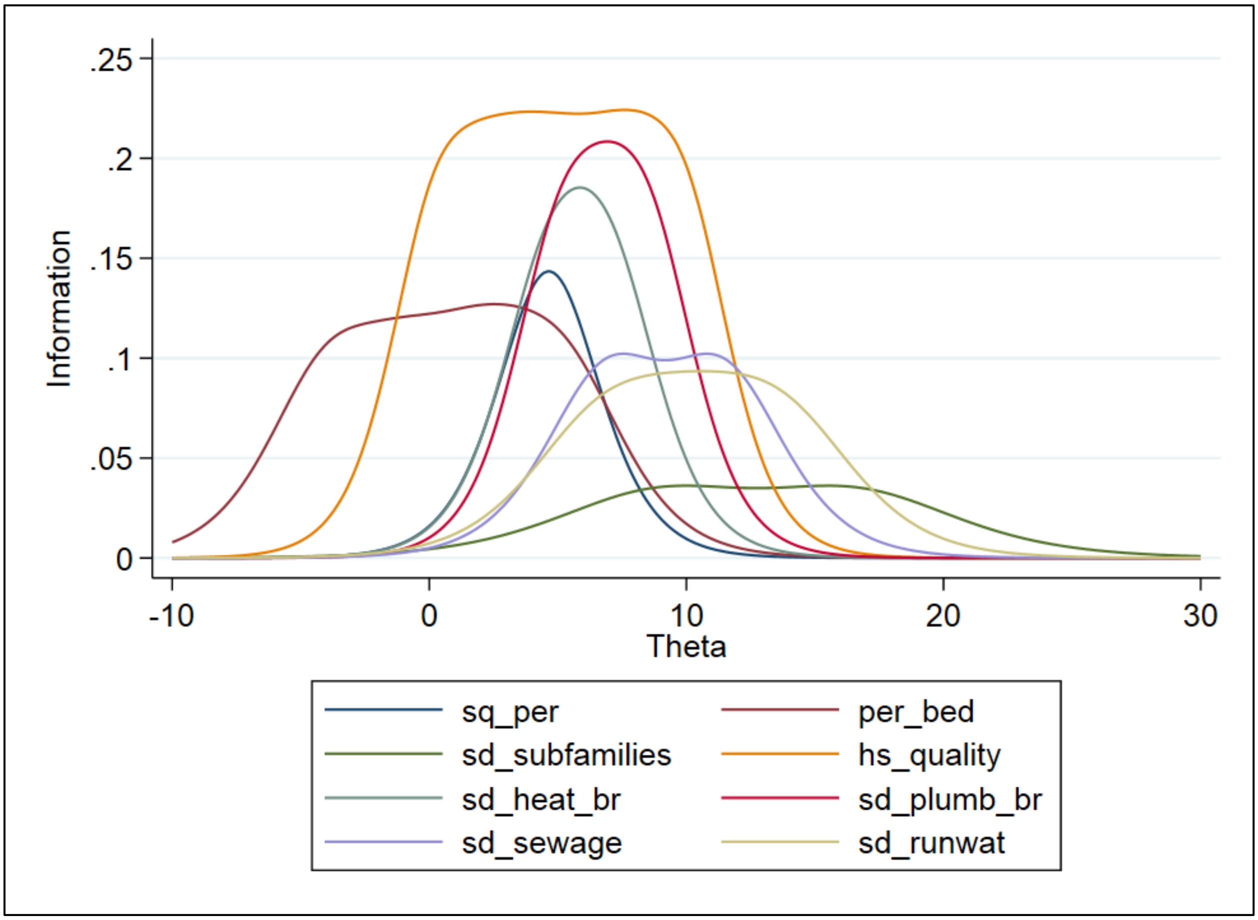
Exhibit G.11 | Item Information Functions for Persons Per Bedroom, Persons Per Room, Square Feet Per Person, and Too Many People in the Home



Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

Exhibit G.12 shows the IIFs for all HI 3 items except for the unsafe variables and the persons per room and too many people in the home variables, which the study team had already targeted for removal. The graphic shows that the number of structural deficiencies (hs_quality) explains the most information overall and that persons per bedroom explains more information on the lower end of the scale. Lack of running water and the number of subfamilies explain some information, but it is at the extreme end of the scale. Based on this graphic, the study team decided to remove all variables except persons per bedroom and the number of structural deficiencies. After internal discussion with HUD, the study team also retained the variable measuring plumbing breakdowns, which explains the most information (after number of structural deficiencies). The study team retained this variable because they plan to reduce the measure of structural deficiencies. Keeping plumbing breakdowns can offset some of the loss of information that may result from reducing the number of structural deficiencies variable. Currently, this variable is based on 13 items from the AHS. In Building a Reduced Lack of Safety and Decency (HI 3) Measure, the study team provides information on how this measure was reduced so that it is still possible to capture some of its information, but the variable is easier to measure and more transferable.

Exhibit G.12 | Item Information Functions for Lack of Safety and Decency (HI 3), Excluding Unsafe Variables, Persons Per Room, and Too Many People in the Home



Source: U.S. Census Bureau, 2019 American Housing Survey
Accuracy Statement: https://www2.census.gov/programs-surveys/ahs/2019/2019%20AHS%20National%20Sample%20Design,%20Weighting,%20and%20Error%20Estimation.pdf.

The variables that were removed from the short form reduced score of HI 3 included the following:

- Heating breakdowns.
- Running water.
- Sewage break.
- Too many people living in the unit.
- Number of subfamilies.
- Persons per room.
- Square feet per person.
- Unsafe for children to play outside.
- Unsafe against break-ins.

- Unsafe coming/leaving at night.

The variables that were included in the short form reduced score of HI 3 included the following:

- Number of structural deficiencies.
- Plumbing breakdowns: toilet.
- Persons per bedroom.
- Feeling unsafe inside the home.

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