Technical Appendix: 
The Cost of Eviction and Unpaid Bills of Financially Insecure Families for City Budgets

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Appendix

The financial health of cities depends on financially secure residents. Previous research has shown that families with even a small amount of readily available savings—from $250 to $749 in assets—are less likely to be evicted, miss a housing or utility payment, or receive public benefits when income disruptions occur (McKernan et al. 2016). But 36 percent of American families have less than $250 in nonretirement savings. Additionally, 30 percent of Americans have subprime credit scores, which limit access to credit during a crisis (Elliott, Ratcliffe, and Kalish 2016). Because many American families have low levels of savings and subprime credit scores, they are vulnerable to financial disruptions.

The precarious financial health of American families has spillover costs for cities. When families are evicted or cannot make housing or utility payments, cities lose revenue in missed property taxes and lost utility revenue and bear additional expenditures through providing services to the homeless. To quantify these links, we build upon this prior research to create 10 city-specific fact sheets (Chicago, Columbus, Dallas, Houston, Los Angeles, Miami, New Orleans, New York City, San Francisco, and Seattle) to show the cost of family financial insecurity to each city’s budget. This document presents the logic, assumptions, and data behind these fact sheets.

Logic, Assumptions, and Data

The logic models illustrate the steps involved to calculate the cost of household financial insecurity to cities, drawing upon national- and city-level data, including data from the US Census Bureau, the Bureau of Labor Statistics, and city budget estimates. We also generate household-level estimates of savings and of the risk of eviction and missed utility or mortgage payments among households with less than $2,000 in nonretirement savings. The following section describes each stage in the logic models, from establishing the base population of households with income or expense disruptions in each city, to determining the percentage of households in each city with assets below $2,000, to estimating the cost of eviction, unpaid utility bills, and missed property tax payments for each city. The costs to cities for each outcome (i.e., eviction, missed mortgage payments, and unpaid utility bills) are estimated through separate logic models and are then combined to produce a cost to the city government’s bottom line.
Establishing the Base Population

The first step in the logic model (stage 1), regardless of the household outcome being studied (i.e., eviction, missed mortgage payment, or unpaid utility bills) is to determine the number of households in each city likely to experience income or expense disruption. Based on Urban’s prior work using data from the 2008 panel of the Survey of Income and Program Participation (SIPP), 26 percent of households experience an income disruption each year because of an involuntary job loss, the onset of a health-related work limitation, or an income drop of 50 percent or more (McKernan et al. 2016). Other research finds that 60 percent of American households annually experience a financial shock—including income and expense disruptions—such as a car or home repair, illness or injury that included a hospital visit, or a loss of income from unemployment, a pay cut, or reduced hours (Pew 2015). We use 26 percent as a lower-bound estimate for income disruptions and 60 percent as an upper-bound estimate for experiencing a financial shock, which includes income and expense disruptions. Both the lower- and upper-bound percentages are multiplied by the 2015 US Census Bureau counts of households in each city from the American Community Survey, or ACS (appendix table A.1). The resulting counts are used to produce the range of households that would theoretically experience income or expense disruptions that year.

Finally, cities have different local economies, so the range of households affected by income or expense disruptions would be theoretically lower in cities with stronger economies (unemployment rates below the national rate) and higher in cities with weaker economies (unemployment rates above the national rate, which was 5.3 percent in 2015). The range of households affected by income and expense disruptions was multiplied by the ratio of the city-specific unemployment rate relative to the national rate, from 2015 Bureau of Labor Statistics (BLS) data (appendix table A.1). This produces a final unemployment rate–adjusted range of the percentage and number of households in each city that we estimate experience income or expense disruptions. These estimates are then used to calculate the cost to the city of households becoming evicted, missing mortgage payments, and not paying utility bills.
### APPENDIX TABLE A.1

City Estimates Used to Calculate Cost of Household Financial Insecurity

<table>
<thead>
<tr>
<th>Households</th>
<th>Owner-occupied housing units (%)</th>
<th>Unemployment rate (%)</th>
<th>Estimated share of households with less than $2,000 liquid savings (%)</th>
<th>Annual spending per homeless family ($)</th>
<th>Annual utilities revenue per household ($)</th>
<th>Annual median property taxes per homeowner household ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chicago</td>
<td>1,053,229</td>
<td>43.8</td>
<td>6.4</td>
<td>61.5</td>
<td>1,457</td>
<td>1,092</td>
</tr>
<tr>
<td>Columbus</td>
<td>344,839</td>
<td>44.5</td>
<td>4.1</td>
<td>56.9</td>
<td>3,828</td>
<td>1,530</td>
</tr>
<tr>
<td>Dallas</td>
<td>495,362</td>
<td>41.4</td>
<td>4.1</td>
<td>64.7</td>
<td>6,983</td>
<td>1,320</td>
</tr>
<tr>
<td>Houston</td>
<td>849,974</td>
<td>41.4</td>
<td>4.3</td>
<td>61.8</td>
<td>11,627</td>
<td>1,824</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>1,360,164</td>
<td>36.0</td>
<td>7.1</td>
<td>61.3</td>
<td>464</td>
<td>2,673</td>
</tr>
<tr>
<td>Miami</td>
<td>171,720</td>
<td>28.2</td>
<td>6.1</td>
<td>72.8</td>
<td>13,336</td>
<td>1,090</td>
</tr>
<tr>
<td>New Orleans</td>
<td>156,591</td>
<td>46.3</td>
<td>6.5</td>
<td>65.2</td>
<td>1,926</td>
<td>1,219</td>
</tr>
<tr>
<td>New York City</td>
<td>3,129,147</td>
<td>31.6</td>
<td>5.7</td>
<td>60.6</td>
<td>15,459</td>
<td>1,836</td>
</tr>
<tr>
<td>San Francisco</td>
<td>356,916</td>
<td>35.8</td>
<td>3.6</td>
<td>46.6</td>
<td>20,162</td>
<td>3,120</td>
</tr>
<tr>
<td>Seattle</td>
<td>311,038</td>
<td>46.6</td>
<td>4.1</td>
<td>46.2</td>
<td>4,704</td>
<td>4,411</td>
</tr>
</tbody>
</table>

**Sources:**
- 2015 ACS one-year data
- 2015 ACS one-year data
- BLS 2015
- Urban Institute model using data from 2013 SIPP and 2014 ACS
- Various sources (2014 and 2015)
- Various sources 2015
- 2015 ACS one-year data

**Note:** The various sources used to estimate annual homeless spending and utilities revenue in each city are described in the "City-Level Data" section.

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**Estimating the Share of Households in Each City with Nonretirement Savings below $2,000**

Fifty-two percent of households nationwide have less than $2,000 in nonretirement savings (McKernan et al. 2016). But some cities have residents who are more economically secure than those in other cities, suggesting that savings may vary, too. This study estimates the share of households that have less than $2,000 in nonretirement liquid assets for our 10 cities through a two-step data analysis using SIPP and ACS data (appendix table A.1). First, we use national-level SIPP data from the 2008 panel (specifically from data collected in 2011) to estimate with a logit regression model the relationship between whether a household has more or less than $2,000 in liquid assets and household demographic and economic factors. The model includes age, income, family composition, education level, immigration status, homeownership, race/ethnicity, employment status, and disability status. Then, we use the resulting national-level coefficients from the SIPP model and city-specific household-level ACS data from 2014 to predict the share of households in each city that have less than $2,000 in savings. The resulting percentages from the SIPP/ACS model are then used in each subsequent logic model (i.e.,...
Eviction, unpaid utility bills, and missed property tax payments) to calculate the number of households in each city with low levels of savings.

**Estimating the Cost of Eviction**

Eviction could be prevented if households had a better savings cushion to pay their rent during difficult financial times. When families are evicted, they may become homeless, and this presents a significant cost to cities. The logic model for eviction illustrates how the number of households who would have been evicted after an income or expense disruption because of low savings is estimated and what the cost to each city would be for these evictions.

As the logic model shows, there are three stages for estimating the cost to cities from evictions of financially insecure residents (appendix figure A.1). The model for evictions takes the percentage of households in the city that experience an income or expense disruption (calculated in stage 1), estimates how many households would have been evicted after an income disruption or financial shock because they lacked $2,000 in available savings (stage 2), then uses that number to calculate the cost to the city because of eviction-related homelessness (stage 3).

Stage 2 in the eviction model—calculating the number of households evicted because they lacked $2,000 in savings—has multiple steps. First, the share of households with savings below $2,000 with income or expense disruptions is calculated, first by multiplying the city’s household count by the percentage who had an income disruption (calculated in stage 1), and then by the percentage having liquid assets below $2,000 (calculated in the SIPP/ACS model). This produced a count of households in each city with assets above and below $2,000 for those with an income disruption (26 percent) at the lower bound and a financial shock (60 percent) at the upper bound.

The resulting household counts are then multiplied by eviction rates from the SIPP for households having less than $2,000 in savings (1.3 percent) and more than $2,000 in savings (0.09 percent). The difference of these two counts produced the number of households in each city who had less than $2,000 in liquid savings and were evicted because of their low savings when experiencing income disruptions (lower bound) or financial shocks (upper bound).

While stage 2 in the logic model is used to calculate the households evicted because of low savings, stage 3 calculates the cost to the city. The final cost estimate for each city is produced by multiplying the amount the city spends per homeless household by the lower- and upper-bound counts of households with less than $2,000 in savings who were evicted because of an income disruption or financial shock
(calculated in stage 2). The result is a range of estimates of the cost to cities of households having less than $2,000 in savings and therefore becoming evicted and using city homeless services. These estimates are later used, along with the cost of unpaid utility bills and missed mortgage payments, to produce a final cost to cities of residents’ financial insecurity (see “Estimating the Total Cost of Eviction, Unpaid Utility Bills, and Missed Property Tax Payments.”)
APPENDIX FIGURE A.1  
Cost to Cities of Eviction Logic Model

Output: Number of households in the city that experience a disruption
Stage 1: Establishing the base population

Stage 2: Financial security and eviction
Output: Number fewer households who would be evicted after disruption if they had assets above $2,000

Stage 3: Homelessness
Output: Cost to city per evicted household

Final output: Cost savings to city from reduction in evictions due to all households having savings above the threshold ($2,000)

Stage 1

1A. Share of households nationally with an income disruption (26%) or financial shock (60%) each year
1B. Number of households in the city
1C. Unemployment rate in the city relative to the national rate (to scale the share of households with income disruptions or financial shocks based on city economic conditions)

Stage 2

2A. Number of households in the city with liquid nonretirement assets above and below $2,000
2B. Difference between the share of households with a disruption who are evicted with assets above $2,000 and the share with assets below $2,000

Stage 3

3A. Cost to city per homeless household

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*a Stage 1 is calculated in the same way across all three logic models.

*b Only renters can become evicted, but all households are included in 2B. Therefore, all households are included in 1A and 1B.
Estimating the Cost of Unpaid Utility Bills

Unpaid utility bills reflect financial distress among households who do not have enough money to pay for basic needs each month. When households cannot pay their utility bills, public utilities may have difficulty covering their operating costs, which affects city budgets. Los Angeles and Chicago tax residential electricity usage, so when bills to the public electricity company are unpaid, the city loses revenue. The logic model for unpaid utility bills illustrates how the number of households who could not make payments after income or expense disruptions is estimated and how much that costs cities.

As the logic model shows, there are three stages for estimating the cost to cities from unpaid utility bills of financially insecure residents (appendix figure A.2). The model for unpaid utility bills takes the percentage of city households that experience a disruption (calculated in stage 1), estimates how many households could not pay utilities bills after an income disruption or financial shock because they lacked $2,000 in available savings (stage 2), then uses that number to calculate the cost to the city because of such unpaid bills (stage 3).

Stage 2 in the utilities model—calculating the number of households who missed utility payments because they lacked $2,000 in savings—has multiple steps. First, the number of households with savings below $2,000 with income or expense disruptions is calculated (see “Estimating the Cost of Eviction” for additional details). The resulting household counts are then multiplied by missed utility payment rates from the SIPP for households having less than $2,000 in savings (22.2 percent) and more than $2,000 in savings (7.1 percent). The difference of these two counts produces the number of households in each city who had less than $2,000 in liquid savings and missed utility payments because of their low savings when experiencing income disruptions (lower bound) or financial shocks (upper bound).

While stage 2 in the model describes how the households who missed utility payments because of low savings are calculated, stage 3 describes how the cost to the city is calculated. The final cost estimate for each city is produced by multiplying the yearly amount each household pays toward publicly operated utilities by the average number of months in a year that households who missed payments reported not paying (about six months) to produce a prorated annual amount left unpaid. This estimate is then multiplied by the lower- and upper-bound counts of households with less than $2,000 in savings who did not pay utility bills because of an income disruption or financial shock (calculated in stage 2) to produce a range of lost utility revenue for the city. For Los Angeles and Chicago, the only two cities profiled that tax their residents’ electricity usage, the average yearly utility tax revenue collected per household is also added to the calculations.
APPENDIX FIGURE A.2
Cost to Cities of Unpaid Utilities Bills Logic Model

Final output: Cost savings to city from reduction in unpaid utility bills due to all households having savings above the threshold ($2,000)

Stage 1: Establishing the base population\(^a\)
- 1A. Share of households nationally with an income disruption (26%) or financial shock (60%) each year
- 1B. Number of households in the city
- 1C. Unemployment rate in the city relative to the national rate (to scale the share of households with income disruptions or financial shocks based on city economic conditions)

Stage 2: Financial security and utilities
- 2A. Number of households in the city with liquid nonretirement assets above and below $2,000
- 2B. Difference between the share of households with a disruption who do not pay utility bills with assets above $2,000 and the share with assets below $2,000

Stage 3: City revenue\(^b\)
- 3A. Average household annual utility bill for city-owned utilities
- 3B. Adjustment for average number of times household did not pay utilities, among households that ever did not pay utility bills

Output: Number of households in the city that experience a disruption
Output: Number fewer households who would fail to pay utilities after disruption if they had assets above $2,000
Output: Cost to city per household that does not pay utility bill

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\(^a\) Stage 1 is calculated in the same way across all three logic models.

\(^b\) Not all cities receive revenue from the same utilities, though all cities studied have some public utilities.
Estimating the Cost of Missed Property Tax Payments

When homeowners have difficulty paying their property taxes, it typically reflects tremendous financial stress and puts homeowners at risk of losing their home. When households cannot pay their property taxes, city budgets are often affected because so much of city revenue comes from property taxes. The logic model for missed property tax payments is used to calculate the number of homeowners who could not pay their property taxes after an income or expense disruption and how much that costs cities.

The logic model for missed property taxes takes the percentage of households in each city that experience a disruption (calculated in stage 1), estimates how many homeowners with and without mortgages could not pay their property taxes after an income disruption or financial shock because they lacked $2,000 in available savings (stage 2), and then uses those numbers to calculate the cost to the city because homeowners did not pay property taxes (stage 3; see appendix figure A.3).

Stage 2 in the property taxes model—calculating the number of homeowner households who missed property tax payments because they lacked $2,000 in savings—has multiple steps. First, the share of homeowner households (mortgage and nonmortgage holders) with savings below $2,000 with income or expense disruptions is calculated (see “Estimating the Cost of Eviction” for additional details). The resulting household counts are then multiplied by the percentage of mortgage-paying homeowners who missed mortgage payments in the SIPP and had less than $2,000 in savings (21.3 percent) and more than $2,000 in savings (6.6 percent). In doing so, we derive estimates that assume all homeowners miss their property tax payments at the same rate at which mortgage holders miss their mortgage payments. Therefore, the difference of these two counts produces the number of households in each city who had less than $2,000 in liquid savings and missed property tax payments because of their low savings when experiencing income disruptions (lower bound) or financial shocks (upper bound).

While stage 2 in the model describes how the homeowner households in each city who missed mortgage (and property tax) payments because of low savings is calculated, stage 3 describes how the cost to the city is calculated. The final cost estimate for each city is produced by multiplying homeowners with low liquid savings who missed paying property taxes by the median yearly amount homeowners paid toward property taxes (from the 2015 ACS 1-year estimates, reported in appendix table A.1; medians were used here instead of averages to minimize skew from high-value homes). These estimates are produced for both the upper- and lower-bound estimates for income or expense disruptions (stage 2) to produce a range of the cost of lost property tax revenue for the city.
APPENDIX FIGURE A.3
Cost to Cities of Unpaid Property Taxes Logic Model

Final output: Cost savings to city from reduction in unpaid property taxes due to all households having savings above the threshold ($2,000)

Stage 1: Establishing the base population
1A. Share of households nationally with an income disruption (26%) or financial shock (60%) each year
1B. Number of households in the city
1C. Unemployment rate in the city relative to the national rate (to scale the share of households with income disruptions or financial shocks based on city economic conditions)

Stage 2: Financial security and homeowners
2A. Share of households that own their homes
2B. Number of homeowner households in the city with liquid nonretirement assets above and below $2,000
2C. Difference between the share of mortgage-holder households with a disruption who do not pay mortgage with assets above $2,000 and the share with assets below $2,000

Stage 3: City revenue
3A. Median property taxes paid per homeowner household

Output: Number of homeowner households in the city that experience a disruption
Output: Number fewer homeowner households who would fail to pay property taxes after disruption if they had assets above $2,000
Output: Cost to city per homeowner household that does not pay property taxes

THE COST OF EVICTION AND UNPAID BILLS OF FINANCIALY INSECURE FAMILIES

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a Stage 1 is calculated in the same way across all three logic models.
b Models include homeowners only; failure to pay rent is not hypothesized to affect property taxes at a meaningful magnitude.
c Includes mortgage holders only; homeowners who own their homes outright do not have monthly housing payments.
Estimating the Total Cost of Eviction, Unpaid Utility Bills, and Missed Property Tax Payments

Finally, to calculate a final cost to cities' budgets because of eviction, missed property taxes, and missed utility payments, all city subtotals are added together for both the lower- and upper-bound estimates. Thus, a range of costs is produced inclusive of the three factors (eviction, unpaid utility bills, and missed property tax payments) for each city.

City-Level Data

To derive final costs to cities of residents' financial insecurity, several data sources are used to produce the estimates of the cost of homelessness and the cost of missed utility bills. Property tax data are not described in this section because these estimates are all from the American Community Survey. The following describes the sources and assumptions behind the homelessness and utility bill estimates.

Homelessness Cost Estimates

To determine how much each city spent per homeless family in 2014–15, we use the number of homeless and the budget for homeless spending in the city. The following section describes the data sources and assumptions made for each city's estimate of the cost of caring for a homeless family.

Chicago. The count of homeless people in Chicago comes from the Annual Homeless Assessment Report (AHAR) to Congress and its point-in-time (PIT) estimates for 2015 (Henry et al. 2015). To approximate the number of households affected, the census count is converted from individuals to a household approximation. The 2015 PIT survey found that 64 percent of the homeless were single, so the remaining 36 percent of the individuals in the Chicago count are divided by two to approximate families. The number of homeless family units in Chicago is 82 percent of the number of homeless individuals.

Chicago budget data on homeless spending comes from the 2015 budget appropriations data portal and includes the line items for homeless services for youth and homeless services from the local budget. The resulting dollar amount from the budget is divided by the household count to approximate the money the city spent in 2014–15 per homeless household.
**Columbus.** The City of Columbus does not list homeless spending in its 2014–15 fiscal year budget. The estimate for the money it spent per temporarily homeless family came from Spellman and coauthors (2010, 5-3).

**Dallas.** The 2014–15 Dallas budget provides the calculated estimate of the money spent per homeless family in the fiscal year 2015 proposed budget book (City of Dallas 2014).

**Houston.** The City of Houston does not list homeless spending in its 2014–15 fiscal year budget. The estimate for the money it spent per temporarily homeless family came from Spellman and coauthors (2010, 5-11).

**Los Angeles.** The count of homeless in Los Angeles (i.e., the city and county) comes from the AHAR to Congress and its PIT estimates for 2015 (Henry et al. 2015). To approximate the number of households affected, the census count is converted from individuals to a household approximation. The 2015 PIT survey found that 64 percent of the homeless were single, so the remaining 36 percent of the individuals in the Los Angeles count are divided by two to approximate families. The number of homeless family units in Los Angeles is 82 percent of the number of homeless individuals.

Los Angeles budget data on homeless spending comes from the 2014–15 fiscal year adopted budget (City of Los Angeles 2014, 185 and 401). The dollar amount from the budget is divided by the household count to approximate the money spent in 2014–15 per homeless household.

**Miami.** The count of homeless in Miami (i.e., the city of Miami and Miami-Dade County) comes from the AHAR to Congress and its PIT estimates for 2015 (Henry et al. 2015). To approximate the number of households affected, the census count is converted from individuals to a household approximation. The 2015 PIT survey found that 64 percent of the homeless were single, so the remaining 36 percent of the individuals in the Miami count are divided by two to approximate families. The number of homeless family units in Miami is 82 percent of the number of homeless individuals.

Miami budget data on homeless spending comes from the 2014–15 adopted budget and includes all expenditures for the homeless trust listed on page 163, with the exception of the domestic violence board line item. 8

**New Orleans.** The count of homeless in New Orleans (specifically New Orleans and Jefferson Parish) comes from the AHAR to Congress and its PIT estimates for 2015 (Henry et al. 2015). To approximate the number of households affected, the census count is converted from individuals to a household approximation. The 2015 PIT survey found that 64 percent of the homeless were single, so the remaining 36 percent of the individuals in the New Orleans count are divided by two to approximate
families. The number of homeless family units in New Orleans is 82 percent of the number of homeless individuals.

New Orleans budget data on homeless spending comes from the 2015 budget and includes expenses for homeless health care services from the operating budget book (City of New Orleans 2014, 264).

**New York City.** The count of homeless in New York City comes from the AHAR to Congress and its PIT estimates for 2015 (Henry et al. 2015). To approximate the number of households affected, the census count is converted from individuals to a household approximation. The 2015 PIT survey found that 64 percent of the homeless were single, so the remaining 36 percent of the individuals in the New York City count are divided by two to approximate families. The number of homeless family units in New York City is 82 percent of the number of homeless individuals.

New York City budget data on homeless spending came from the 2015 adopted budget (Council of the City of New York 2015, 2).

**San Francisco.** The count of homeless in San Francisco comes from the AHAR to Congress and its PIT estimates for 2015 (Henry et al. 2015). To approximate the number of households affected, the census count is converted from individuals to a household approximation. The 2015 PIT survey found that 64 percent of the homeless were single, so the remaining 36 percent of the individuals in the San Francisco count are divided by two to approximate families. The number of homeless family units in San Francisco is 82 percent of the number of homeless individuals.

San Francisco budget data on homeless spending comes from the 2014–15 adopted budget (City and County of San Francisco 2014, 161).

**Seattle.** The count of homeless in Seattle (i.e., the city of Seattle and King County) comes from the AHAR to Congress and its PIT estimates for 2015 (Henry et al. 2015). To approximate the number of households affected, the census count is converted from individuals to a household approximation. The 2015 PIT survey found that 64 percent of the homeless were single, so the remaining 36 percent of the individuals in the Seattle count are divided by two to approximate families. The number of homeless family units in Seattle is 82 percent of the number of homeless individuals.

Seattle budget data on homeless spending comes from the 2015 adopted budget information for emergency and transitional services (City of Seattle 2015, 197).
Utility Payment Estimates

To determine how much money each city might lose in utility revenue in 2015, we collect data about the public utilities in each city. The following section describes the data sources and assumptions we make for each city’s estimate of lost revenue because of missed payments for water and electric utility bills.

**Chicago.** Annual water usage estimates for 2015 are based upon calculations from the average monthly bill across 30 cities, which finds that households of four would pay to use 100 gallons of water per person per day for water, sewage, and storm water services. These usage estimates are then combined with city-specific rate information to estimate an average household cost.

Chicago does not have a public electric company, but charges its residents a utility tax on its usage of 0.628 cents for the first 2,000 kilowatt hours (kwh) per month. The average monthly residential electricity usage in Illinois in 2015 was 719 kwh, and the bill was $89.91, so the municipal tax paid each year is calculated based on these data points.

**Columbus.** Annual water usage estimates for 2015 are based upon calculations from the average monthly bill across 30 cities, which finds that households of four would pay to use 100 gallons of water per person per day for water, sewage, and storm water services. These usage estimates are then combined with city-specific rate information to estimate an average household cost.

Columbus has a small public electric company that serves approximately 14,000 residential customers. The average monthly residential electricity usage in Ohio in 2015 was 877 kwh, and residential public utility customers in Columbus are charged $.0873/kwh with a $10.70 billing fee. The electricity estimate for Columbus is calculated for the 14,000 public electricity users, rather than the whole population.

**Dallas.** Annual water usage estimates for 2015 are based upon calculations from the average monthly bill across 30 cities, which finds that households of four would pay to use 100 gallons of water per person per day for water, sewage, and storm water services. These usage estimates are then combined with city-specific rate information to estimate an average household cost. Dallas has no public electric company.

**Houston.** Annual water usage estimates for 2015 are based upon calculations from the average monthly bill across 30 cities, which finds that households of four would pay to use 100 gallons of water per person per day for water, sewage, and storm water services. These usage estimates are then combined with city-specific rate information to estimate an average household cost. Houston has no public electric company.
Los Angeles. Annual water usage estimates for 2015 are based upon calculations from the average monthly bill across 30 cities, which finds that households of four would pay to use 100 gallons of water per person per day for water, sewage, and storm water services. These usage estimates are then combined with city-specific rate information to estimate an average household cost.

Los Angeles does not have a public electric company, but does charge a utility tax of 10 percent on its usage among residents. The average California residential customer used 577 kwh per month in 2015. The average public electricity bill paid in Los Angeles for a 500 kwh customer in October 2014 ($78.88), as published in the *Los Angeles Times*, is used to calculate the annual utility users tax paid per household.

Miami. Annual water usage estimates for 2015 are made comparable to the other cities by calculating rates for a residential customer who uses 12,000 gallons of water a month (the amount a household was estimated to have used in other cities). The average monthly bill published by the Miami-Dade Water and Sewer Department is $51.11 for 6,750 gallons per month. The monthly bill is then adjusted to reflect 12,000 gallons of monthly usage. Miami has no public electric company.

New Orleans. Annual estimates for water and sewer bills are compiled from the Sewerage and Water Board of New Orleans rates. To be consistent with the other cities, estimates are based upon a household of four people using 100 gallons of water per day in a month (or 12,000 gallons of water a month, the amount a household was estimated to have used in other cities). The charges for water service and quantity, sewage service and volume, and the annual safe drinking water administrative fee are compiled into one annual charge for such a household. New Orleans has no public electric company.

New York City. Annual water usage estimates for 2015 are based upon calculations from the average monthly bill across 30 cities, which finds that households of four would pay to use 100 gallons of water per person per day for water, sewage, and storm water services. These usage estimates are then combined with city-specific rate information to estimate an average household cost. New York City has no public electric company.

San Francisco. Annual water usage estimates for 2015 are based upon calculations of the average monthly bill across 30 cities, which finds that households of four would pay to use 100 gallons of water per person per day for water, sewage, and storm water services. These usage estimates are then combined with city-specific rate information to estimate an average household cost. San Francisco has no public electric company.
Seattle. Annual water usage estimates for 2015 are based upon calculations from the average monthly bill across 30 cities, which finds that households of four would pay to use 100 gallons of water per person per day for water, sewage, and storm water services. These usage estimates are then combined with city-specific rate information to estimate an average household cost.

Seattle's public electric company, Seattle City Light, published its average residential power bill for 2015 in its annual report (Seattle City Light 2015, 77).

The Urban Institute’s Collaboration with JPMorgan Chase
The Urban Institute is collaborating with JPMorgan Chase over five years to inform and assess JPMorgan Chase’s philanthropic investments in key initiatives. One of these is financial capability, a multipronged effort to improve household and community financial health by identifying, supporting, and scaling innovative solutions that help low- and moderate-income families increase savings, improve credit, and build assets. The goals of the collaboration include using data and evidence to inform JPMorgan Chase’s philanthropic investments, assessing whether its programs are achieving desired outcomes, and informing the larger fields of policy, philanthropy, and practice. This project highlights the impact financial insecurity has on city budgets and on families.
Notes


3. The eviction model assumes that all the people evicted in our model use city homeless services. This assumption helps compensate for low and uncertain measurement of the evicted population in available data sources. We make this assumption for two reasons. First, the Survey of Income and Program Participation's estimate of evictions is much lower than other survey estimates (e.g., Matthew Desmond in his book Evicted: Poverty and Profit in the American City estimates with his survey that 16 percent of households encounter eviction in a year). SIPP estimates are unusually low because households who face housing disruptions from eviction are also those most likely to leave the SIPP sample. Second, while there are numerous surveys of homeless individuals, including the point-in-time surveys conducted every year across the nation on the same night and reported to the US Department of Housing and Urban Development, no national survey records evicted households. We have no national estimate of how many evicted households become homeless.

4. This average is based on authors' calculations from Mills and coauthors (2016).

5. Because of data limitations, this analysis uses rates of missed mortgage payments as a proxy for missed property tax payments. We use the SIPP to estimate how income disruptions relate to different financial hardship outcomes (e.g., eviction, missed utility bills, and missed mortgage payments) for households with different levels of savings. But the SIPP does not ask if property tax payments were missed. Because property tax payments for many homeowners are bundled via escrow with mortgage payments, this is a reasonable proxy.

6. All property tax data come from "Mortgage Status by Median Real Estate Taxes Paid (Dollars): Universe: Owner-Occupied Housing Units, 2011–2015 American Community Survey 5-Year Estimates," US Census Bureau, American Fact Finder, accessed January 10, 2017, https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_15_5YR_B25103&prodType=table. The American Community Survey may overestimate the property taxes that households pay, especially within municipalities that offer tax breaks to low-income households. A 2016 Lincoln Institute of Land Policy report finds that the real property tax rate for a $150,000 home for the 10 cities studied is often lower than that paid on a $300,000 home (Lincoln and Minnesota 2016). Many states and municipalities also provide tax breaks to elderly residents and long-term homeowners, which can substantially lower individual tax bills. The ACS provides the same benchmark for measurement across the 10 cities studied, but is based on self-reported household data that may not take into account the tax breaks households receive.


15. Ibid.

16. Ibid.


22. Ibid.

23. Ibid.
References


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For more information on this project, see Elliott and Kalish 2017 Chicago, Columbus, Dallas, Houston, Los Angeles, Miami, New Orleans, New York, San Francisco, Seattle.