Do the Poor Pay More for Housing? Exploitation, Profit, and Risk in Rental Markets[1]

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This article examines tenant exploitation and landlord profit margins within residential rental markets. Defining exploitation as being overcharged relative to the market value of a property, the authors find exploitation of tenants to be highest in poor neighborhoods. Landlords in poor neighborhoods also extract higher profits from housing units. Property values and tax burdens are considerably lower in depressed residential areas, but rents are not. Because landlords operating in poor communities face more risks, they hedge their position by raising rents on all tenants, carrying the weight of social structure into price. Since losses are rare, landlords typically realize the surplus risk charge as higher profits. Promoting a relational approach to the analysis of inequality, this study demonstrates how the market strategies of landlords contribute to high rent burdens in low-income neighborhoods.

BEYOND BENIGN INEQUALITY

Nearly 45 years ago in the pages of *Science*, Arthur Stinchcombe (1972) reviewed the book *Inequality* by Christopher Jencks and coauthors. "There

[1] We thank Jeff Blossom, Geoff Boeing, Shawn Bucholtz, Ann Carpenter, Tamara Cole, James Davis, Deborah De Laurell, Michael Goldman, John LaFave, Jacob Rugh,

0002-9602/2019/12404-0003$10.00

are two broad approaches to studying inequality," Stinchcombe began. The first explains social differences on the basis of "individual conditions," such as race, gender, and age. Those who adhere to this perspective offer a "picture of American society [that] is curiously benign." In this accounting, there are no staunch defenders of the status quo; no one is actively profiting from the poverty of others. Instead, income inequality is explained by differences in educational background or test scores. The second approach, however, "usually is associated with a theory that people at the top *try* to keep people at the bottom unequal, for their own advantage." Those who ascribe to this perspective view inequality not as an accident but as a plan. As Stinchcombe put it, "The higher the power of the rich, the higher the rate of exploitation; that is, the higher the deliberately maintained distance between pairs of individuals" (p. 603).[2]

Inequality (Jencks et al. 1972) adopted the first approach, with significant rigor and originality, and much of sociology followed suit. Status attainment models of mobility (Blau and Duncan 1967), aided by the acceleration of computational computing power, gained prominence by explaining inequality as the result of average individual differences (Tomaskovic-Devey and Avent-Holt 2016). Social disparities came to be understood as the result of variation in individual characteristics without much reference to relationships between people, collectives, or organizations. Thus a father's occupational status was reinterpreted as an attribute belonging to the son, whose success in the labor market had less to do with the behavior of employers than with his own attributes (Stinchcombe 1978). "By the middle of the twentieth century," observe Shanahan and Tuma (1994, p. 745), "social scientists had almost completely switched their gaze from inter*group* distributions to inter*individual* distributions."[3]

Another body of work offered an alternative approach to the study of inequality, one that referenced large-scale social and economic dislocations

Yajuan Si, Christina Tapiero, and Simone Zhang for feedback, data guidance, and research assistance. This research was supported by the Ford Foundation. Direct correspondence to Matthew Desmond, Department of Sociology, Princeton University, 153 Wallace Hall, Princeton, New Jersey 08544. E-mail: matthew.desmond@princeton.edu

[2] These two theories of inequality can be traced back to the class concepts of Weber (who emphasized life chances) and Marx (who emphasized exploitation) (Sayer 1991; Wright 1992).

[3] Jencks et al. (1972, p. 14) plainly state, "We are primarily concerned with inequality between individuals, not inequality between groups." Although this approach does not deny the importance of social structure, it necessarily deemphasizes one group benefiting at the expense of another by explaining inequality based on individual attributes. For example, both Blau and Duncan (1967, p. 239) and Jencks et al. (1972, p. 217) explain black-white inequality by referencing not historical and modern-day racism, where white advantage is tied to black disadvantage, but the outcomes of that racism, such as blacks' lower return on educational attainment in the form of income or occupational prestige.

(e.g., Dahrendorf 1959; Giddens 1973). Among these, William Julius Wilson's *The Truly Disadvantaged* (1987) was the most influential in steering the American poverty debate. To Wilson, concentrated poverty among African-Americans in urban centers was the result of increasing male joblessness owing to deindustrialization and the decriminalization of racial residential integration, which spurred the exodus of middle-class black families from the ghetto. Wilson's theory of inequality was addressed, not to individual attributes, but to social structures that were the result of historical legacies of racial discrimination and fundamental transformations of the American economy. This perspective resulted in an outpouring of empirical investigations into the reproduction of urban poverty (e.g., Small and Newman 2001; Sampson 2012). Structural theories of inequality differ from individualistic accounts in their orienting level of analysis, but they are no less benign. To Wright (1994, p. 36), Wilson's perspective understands "poverty as a by-product of social causes." "No one intended this calamity," he writes, "and no one really benefits from it."

Both individualistic and structural models of inequality focus on studying poor people and poor places. A long tradition of sociological thought, however, promotes an alternative approach, a relational theory of inequality trained on connections between the financially secure and insecure. As Tilly argues in *Durable Inequality* (1998, p. 33), a touchstone for this perspective, the crucial causal mechanisms driving inequality do not consist of individual attributes or structural legacies of historical arrangements but "social relations among persons." Accordingly, "we have no choice but to undertake relational analyses of inequality." Tilly (2005, pp. 100, 107) further clarifies that "in a relational view, inequality emerges from asymmetrical social interactions in which advantages accumulate on one side or the other. . . . Explanation of inequality and its changes must therefore concentrate on identifying combinations and sequences of causal mechanisms—notably exploitation, opportunity hoarding, emulation, and adaptation—within episodes of social interaction."

A relational approach to inequality posits that a comprehensive theory of poverty must look beyond poor people and places to examine the broader context of inequality involving objective connections between advantaged and disadvantaged populations (Desmond 2014). "Markets are not invisible hands but rather network structures, relationships between actors embedded in institutional space," writes Tomaskovic-Devey (2014, p. 56). When researchers have trained their focus on that institutional space—namely, firms—they have produced accounts of inequality based on unequal resource flows between different actors (Baron and Bielby 1980; Sakamoto and Kim 2010). In this view, inequality is not benign; someone profits from it. Thus, a relational perspective sees exploitation as the foundational mechanism of inequality. As Brady, Biradavolu, and Blankenship (2015, p. 1127) recently put it, “Rather than simply saying [the poor] are oppressed or disadvantaged, exploitation means there is an identifiable actor receiving disproportionate rewards.”

This article applies a relational approach to the study of rental housing markets. Across the United States, the decline of affordable housing has transformed the lives of the poor. Most poor renting families today receive no housing assistance and reside in the private rental market, where over half spend at least 50% of their income on housing costs and a quarter spend over 70% on them (Eggers and Moumen 2010). Increasing rent burden among low-income families directly contributes to their economic scarcity and hardship and is a source of residential insecurity, eviction, and homelessness (Newman and Holupka 2014; Desmond 2016). Yet sociologists have yet to identify the basic sources of the affordable housing crisis or to fully articulate the inner workings of rental markets. Conspicuously absent from most accounts of neighborhood dynamics or inequality are landlords,[4] who play a vitally important role in the lives of low-income families, dictating where they live, setting their rents, overseeing the quality of their dwellings, and preventing or initiating their evictions.

We explore how tenant exploitation (overcharging renters relative to the market value of their home) and landlord profit margins vary across neighborhood contexts, specifically investigating the degree to which renters living in low-income neighborhoods are “exploited consumers” (Caplovitz 1967). Analyzing novel data from a restricted-use, nationally representative survey of landlords, conducted by the U.S. Census Bureau, and a recent survey of property owners in Milwaukee, Wisconsin, we find higher levels of renter exploitation in poor neighborhoods. Landlords operating in those neighborhoods also enjoy higher profits, owing to significantly lower mortgage and tax burdens but not significantly lower rents. These findings demonstrate how the market strategies of landlords contribute to high rent burdens in low-income neighborhoods.

Exploitation of Labor and Land

There is a robust sociological debate about the precise meaning of exploitation. Working in the Marxist tradition, Wright (1997) observes that exploitation occurs when one group excludes another from some productive resource (e.g., land, factory machines) to enrich themselves at the other group’s expense by appropriating the latter’s labor effort. “Exploitation, therefore, does not merely define a set of *statuses* of social actors but a pattern of ongoing *interactions* structured by a set of social relations, relations which mu-

[4] Important exceptions include Sternlieb (1969), Logan and Molotch (1987), and Rosen (2014).

tually bind the exploiter and the exploited together" (p. 11). Sørensen (2000, p. 1532) prefers to "restrict exploitation to inequality generated by ownership or possession of *rent-producing assets* . . . where the advantage to the owner is obtained at the expense of nonowners" (see also Tilly 1998, p. 10). Sakamoto and Liu (2006) argue that Wright's strong version, which emphasizes the mutual dependence of exploiters and the exploited, and Sørensen's narrower version are compatible, while underscoring the importance of establishing a definition of exploitation that can be empirically measured.

To that end, a parsimonious definition of exploitation in the labor market is being underpaid relative to the observed market value of what one produces (Sakamoto and Kim 2010; Brady et al. 2015). A small number of recent studies have empirically examined exploitation. These include analyses of how brokers contribute to the exploitation of female sex workers in India (Brady et al. 2015); how wage inequality is produced by workers marshaling privileged categories to hoard opportunities (Avent-Holt and Tomaskovic-Devey 2010); how heightened exploitation increases inequality (Sakamoto and Kim 2010); and how women and blue-collar workers are underpaid relative to their productivity (Liu, Sakamoto, and Su 2010). These studies are important contributions to the sociology of stratification. But they all focus exclusively on exploitation in the labor market, while similar dynamics may also be at work in the housing market. As Caplovitz demonstrated in *The Poor Pay More* (1967), exploitation can occur not only in production but also in consumption.

The focus on wages and work in prior research has led to the notion that the very poor, particularly those who are jobless, are not exploitable as much as expendable (Wright 1994, p. 49). This may be true when it comes to labor but not when it comes to land, for there exists a long history of slum exploitation in America.[5] As Mumford observes (1961, p. 417), "What the steamship companies discovered in the nineteenth century in their exploitation of steerage passengers, the ground landlords discovered long before: maximum profits came, not from providing first class accommodations for those who could well afford them at a handsome fee, but from crowded slum accommodations, for those whose pennies were scarcer than the rich man's pounds."

During America's rapid period of urbanization, colonial proprietors adopted the institutions and strategies of England's landed gentry, and American land and housing law borrowed extensively from English codes,

[5] If Wilson's (1987) theory is innocent of exploitation in the labor force, the reason is that it focuses on shuttered factories and the systematic exclusion of the urban poor from gainful employment. Poverty is caused not by unfair work conditions but by no work at all. But the labor market is not the only site for potential exploitation. The housing market harbors that potential as well. Employers may have fled the inner city, but landlords remained.

including the doctrine of absolute liability for rent, which held tenants unequivocally responsible for rent even if their homes were destroyed by fire or flood. As more people flocked to cities throughout the late 18th and early 19th centuries, urban land values soared, and landlords began subdividing their properties to make room for more renters (Mumford 1938, pp. 82–86). The Panic of 1837 accelerated the process. Cellars, attics, and storage sheds were fashioned into single-room apartments, and poor families proved to be a profitable market even through a depression. "The crowding of old housing stock made tenant houses profitable not only through the first conversion to multitenant occupancy but through subsequent subdivisions that increased gross rents," Blackmar (1989, p. 199) observes about New York City during the Panic. "The reduced maintenance expenses and tax assessments that accompanied deterioration further increased landlords' net rents." When tenements began appearing in New York City in the mid-1800s, their rent was 30% higher than that of better apartments uptown (Riis [1890] 1997, p. 11).

The institutionalization of the black ghetto at the beginning of the 20th century increased the exploitative possibilities of landed capital. As the black population in northern cities grew, real estate developers saw an opportunity to make handsome profits by buying up properties on the edges of the ghetto and slicing them into flats. Legal segregation meant that ghetto landlords had a captive tenant base and "had nothing to gain by improving [their] old houses" (Spear 1967, p. 148). The rise of the dual housing market (one white, one black) allowed landlords to charge blacks higher rents for worse housing. In postwar Chicago, blacks paid 15%–50% more in rent than whites living in similar accommodations (Hirsch 1983, p. 29). As late as 1960, the median monthly rent in Detroit was higher for blacks than for whites (Sugrue [1996] 2005, p. 54). Before the modern ghetto collapsed in the postindustrial economy, real estate brokers developed a new technique of exploitation, one focused on selling black families houses "on contract," often for double or triple their assessed value. "The reason for the decline of so many black urban neighborhoods into slums," writes Satter (2009, p. 5), "was not the absence of resources but rather the *riches* that could be drawn from the seemingly poor vein of aged and decrepit housing."

Measuring Tenant Exploitation and Landlord Profit

The slum has never been a by-product of the modern city, a sad accident of industrialization and urbanization. Rather, the slum has historically been a prime moneymaker for those who saw in land scarcity, housing dilapidation, and racial segregation the opportunity to maximize their rate of return (Mumford 1961, p. 418). If labor exploitation is understood to be getting paid less than the market value of what one produces (Sakamoto and Kim

2010), then we can extend this definition to the housing market by operationalizing exploitation as being overcharged relative to the market value of what one purchases, paying more for less.[6] Thus, renter exploitation (y) can be measured as the ratio of annual rents from all rental units (r) over property value (v):

$$y = \frac{r}{v}.$$

Neighborhoods in which rents amount to a higher proportion of property value are characterized by higher exploitation. Here, overpayment is not defined in terms of economic rents and does not presuppose barriers to entry that limit competition among landlords (e.g., collusion, monopoly). Rather, overpayment is relative to the costs of purchasing a housing unit and therefore rests on credit constraint among renters. A renter is exploited relative to the counterfactual of property ownership. We expect the difference in rents between poor and nonpoor neighborhoods to be relatively smaller than the difference in property values between poor and nonpoor neighborhoods (Boeing and Waddell 2016; Desmond 2016), thus producing higher renter exploitation in lower-income communities.

It is important to recognize, however, that evidence of heightened exploitation of tenants in poor neighborhoods does not necessarily mean that landlords in those neighborhoods reap higher profits. Landlords renting to low-income families may face steep maintenance costs, owing to aging housing stock or overcrowding, as well as frequent missed payments and higher turnover rates (O'Flaherty 1996; Desmond 2016). If rents appear inflated in poor neighborhoods, relative to housing values, that may simply reflect the cost of doing business, as rents in distressed communities are upwardly adjusted to account for higher levels of landlord risk. Accordingly, we use an accounting framework to estimate monthly profits earned by each housing unit, observing variation across properties located in poor and nonpoor neighborhoods. To calculate monthly profits per unit, we deduct expenses from revenue (rent). As discussed further below, we report three definitions of profit, based on the inclusion of different types of expenses: predictable, regular expenses; light maintenance; and irregular costs. Doing so approximates meaningful measures of financial gain for landlords facing different levels of risk and focuses on different time horizons for assessing rates of return.

DATA AND METHODS

This study required data that included detailed information on property values, rental revenues, and landlord expenses, along with geographic iden-

[6] Along with a housing unit, renters also purchase services provided by landlords (e.g., repairs, maintenance), the costs of which are captured in our analysis of landlord profit margins. We return to this point below.

tifiers of rental units that allowed us to observe potential variation in exploitation and profit rates across neighborhood contexts. To implement our analyses, we gained access to a restricted version of the U.S. Rental Housing Finance Survey (2012): a geocoded, nationally representative survey of landlords' revenues and expenses. This is the first study to examine the restricted-use version of these data. We supplement analyses of nationally representative data with a detailed case study of Milwaukee, drawing on the Milwaukee Area Renters Study (2009–11), an original survey of tenants, and the Milwaukee Rental Property Owners Survey (2015), a new survey of landlords—augmenting both data sets with several administrative data sources. The national data establish broad patterns with respect to renter exploitation and landlord profits, but they also reveal substantial heterogeneity across housing markets. The Milwaukee case study offers an in-depth examination of these dynamics in a slack market and provides insight into possible mechanisms driving variation in renter exploitation and landlord profits across poor and nonpoor neighborhoods.

U.S. Rental Housing Finance Survey

The U.S. Rental Housing Finance Survey (RHFS) is the only recent, nationally representative survey of property owners. Sponsored by the U.S. Department of Housing and Urban Development, the Census Bureau conducted the RHFS in 2012, relying on a stratified random-selection procedure to construct its sample. First, two strata were created with respect to geographic size: one being all large cities (with more than 100,000 housing units) and the other including a random selection of smaller cities and rural areas. Second, four strata were created with respect to building size: properties with 2–4 units, those with 5–24 units, those with 25–49 units, and those with over 50 units.[7] Multiunit rental property addresses (those with at least 80% rental units as of the 2010 census) were identified from the Census Master Address File and randomly selected from each of the eight strata. This procedure produced a representative survey of multifamily rental properties across the United States. Census-trained field agents interviewed property owners and managers in person, generating a 65% response rate. After data collection, sampling weights were constructed to promote representativeness and ad-

[7] The RHFS excluded prefabricated homes, mobile homes, public housing, and single-unit rental properties. According to the American Community Survey, in 2016 single-unit properties accounted for nearly 35% of occupied rental housing units (U.S. Census Bureau 2016). According to the American Housing Survey, higher costs incurred by landlords of single-unit properties, owing to the lack of economy-of-scale returns, are generally offset by higher rents charged for these units (U.S. Census Bureau 2015). Although single-unit properties constitute a significant a share of the rental market, we do not have strong reason to believe that their exclusion from the RHFS affected our main results.

dress nonresponse bias (U.S. Census Bureau 2014). We draw on a restricted-use, geocoded version of RHFS microdata, accessed through the Federal Statistical Research Data Center, to assess the relationships between renter exploitation, landlord profits, and neighborhood poverty rates. Geocoding was conducted by the Census Bureau using latitude and longitude identifiers associated with building addresses.

The RHFS posed a battery of questions about housing finance, property values, expenses, and revenue. Regarding mortgages, it collected information on formal mortgages issued by banks and other lending institutions, mortgages from private individuals, and other loans or purchasing agreements. Nationwide, only 1% of mortgages were loans issued by private individuals, and only 3% consisted of loans other than mortgages, lines of credit, and purchase agreements.[8] With respect to landlord expenses, the RHFS collected information on property taxes, insurance payments, utilities, property manager and professional fees, maintenance, and security costs, as well as an extensive list of major repairs and improvements to roofs, furnaces or heating appliances, plumbing, exterior upkeep, windows, doors, floors, electrical wiring, kitchens, bathrooms, security systems, swimming pools, playgrounds, and handicap-access installations. The RHFS also asked property owners about potential rent revenues (what they could have netted with no vacancies and missed payments) and actual rent revenues.

In the RHFS, the units of analysis are buildings, not individual units. However, because the data include the number of rental units in each property, our outcomes can be calculated as averages across units in a property. Importantly, the RHFS bases property values—the denominator in our exploitation equation—on property owners' responses, which could introduce measurement error.[9] The Milwaukee data (discussed below) avoid these

[8] If informal and formal mortgages are differentially allocated across poor and nonpoor neighborhoods, our results could be biased if informal mortgages are insufficiently recorded. As such, we also collaborated with the Atlanta Federal Reserve Bank to estimate the prevalence of informal mortgages on rental properties across the United States (Carpenter and Desmond 2017). Drawing on the restricted CoreLogic Deeds data set, we found that of the 3.96 million multifamily deed records between 2000 and 2016, only 148,318 (4%) involved a private lender, such as a family member, friend, business partner, or other individual financer. A separate analysis found that in census block groups with at least one multifamily property between 2012 and 2016, 0.6% of deed transactions in nonpoor neighborhoods (with a poverty rate below 27%) and 1.4% of deed transactions in poor neighborhoods involved a private lender. Although informal mortgages in the multifamily rental market are more common in poor neighborhoods, they remain rare across all neighborhoods nationwide.

[9] If property owners in different neighborhoods had nonrandom error in their estimates of property value, bias could result. Specifically, if landlords in poor neighborhoods were more likely to underestimate their property value than landlords in nonpoor neighborhoods, that could induce a spurious correlation between exploitation and neighborhood poverty. The RHFS asks about the basis on which landlords provide their property value estimates. Landlords in poor neighborhoods are less likely to rely on property price and

limitations by drawing on a sample of rental units and incorporating administrative data on property values. They are also free from limiting disclosure requirements that accompany restricted-use census data.

Milwaukee Area Renters Study

To calculate tenant exploitation in Milwaukee, we used geocoded monthly rent data from the Milwaukee Area Renters Study (MARS). MARS is a representative survey of 1,086 tenants in Milwaukee's private rental sector, designed to collect data on housing, residential mobility, eviction, and urban poverty. To bolster response rate and data quality, surveys were administered in person in English and Spanish by professional interviewers at tenants' place of residence. For each household, interviewers surveyed an adult leaseholder or an adult knowledgeable about household financial matters. MARS has a response rate of 83%. Interviews were conducted from 2009 to 2011. Households were selected through multistage stratified sampling, with saturated sampling within selected block groups (for detailed explanation, see Desmond, Gershenson, and Kiviat [2015]). After data collection, custom design weights were calculated to reflect the inverse of selection probability, facilitated by a Lahiri (1951) procedure, based on the demographic characteristics of Milwaukee's rental population and adjusted to MARS's sample size. We use these custom weights throughout our analyses to facilitate estimates generalizable to Milwaukee's rental population.

To collect data on property values, we matched MARS respondents' property (by address and year) to the Milwaukee Master Property Record (MPROP) and the Milwaukee Treasurer's Tax Records (MTTR), administrative data that include the number of housing units and each building's assessed value.[10] This process achieved a 99% match rate. (Unmatched ad-

appraisals for their estimates (31% and 14%, respectively)—compared to landlords in middle-class (49% and 30%) and affluent (36% and 23%) neighborhoods—and are more likely to report using tax assessments: 55% for those in poor neighborhoods, 41% for those in affluent neighborhoods, and 21% for those in middle-class neighborhoods. The biggest reporting differences, however, are between landlords in middle-class neighborhoods and those in poor and affluent neighborhoods. Although we cannot rule out nonclassical measurement error in property value reporting, the basis of landlords' estimates does not vary linearly with neighborhood poverty.

[10] Specifically, we used the assessed value of Milwaukee properties in 2010 as the indicator of their market value (to match the MARS sampling period of 2009–11). To evaluate the degree to which assessed values reflected the market values of residential properties in Milwaukee, we compared assessed values in 2010 to the sale price of all such properties sold that same year. Using the unique tax key of each property, we merged sale records reported by the City of Milwaukee with assessment records, obtaining a 96% match rate. We found that the median property sold for $7,050 below its assessed value or 6.3% of the median assessed value of those properties ($111,400), reflecting the depressed housing

dresses were excluded from our analysis.) MARS's data on monthly rent, provided by tenants, coupled with MPROP and MTTR data, allow us to calculate exploitation rates as the annualized amount of each tenant's rent, scaled by the number of units in a property and divided by the property's value.

Milwaukee Rental Property Owners Survey

Accurately measuring Milwaukee landlords' profit margins requires substantial information on their expenses, similar to that available in the RHFS. Accordingly, in 2015 we fielded a survey of landlords in Milwaukee: the Milwaukee Rental Property Owners Survey (MRPOS). We relied on the MARS sample frame to draw a survey of the landlords renting to a representative sample of Milwaukee tenants. The Milwaukee Master Property Record included ownership and owner address data that allowed us to identify the landlords of rental properties represented in the MARS sample. By surveying these property owners, MRPOS provides information on expenses and profits representative of Milwaukee rental units.

The MRPOS survey asks property owners about specific housing units sampled in MARS. Of the identified property owners, 417 owned one sampled property and 249 owned more than one (reflecting MARS's clustered design). To avoid respondent fatigue, for the latter group we administered surveys focused on two randomly selected MARS-sampled units. The MRPOS survey included questions about expenses pertaining to the building and the specific housing unit sampled in MARS. Building-specific questions inquired about monthly mortgage payments, property insurance, utilities, and repairs to the roof, furnace, water heater, plumbing, major painting, and regular maintenance and repair. Unit-specific questions inquired about expenses related to new tenants, rent and rent nonpayment, and the number of bedrooms in a specified apartment. We also asked landlords to report the number of housing units they owned, how much time they spent each week on property management, any charges paid to building managers or property manage-

market. In contrast, when we compared assessed values to sale prices in 2013, after the recession ended, among the 2,704 residential properties sold in Milwaukee in 2013, the median property sold for $300 above its assessed value or 0.002% of the median assessed value of those properties ($121,950). Although the same cannot be said for all markets and all years, in 2013 the assessed values of Milwaukee residential properties were tightly coupled with their sale prices. As such, in a robustness test, we reran the Milwaukee exploitation analysis using 2013 assessed values. Results were very similar to those using the 2010 data. Additionally, we evaluated the stability of assessed values by observing the share of properties in Milwaukee that received multiple assessments between 1984 and 2016, likely triggered by property owners' appeals. Of the 5.2 million property records, only 267 (0.00005%) had multiple assessments in the same year, indicating that assessed values in Milwaukee are remarkably stable from year to year.

ment companies, and how they set rents. To generate estimates of profits per rental unit, we adjusted building-level expenses by dividing them by the number of units in the building. We similarly adjusted expenses measured at the level of all properties owned by a landlord (property management fees) or recorded on a yearly or quarterly basis (property taxes, repairs, new tenant costs, water bill). These items are comparable to those in the RHFS.

The survey was implemented in three mailings beginning in January 2015 and ending in September 2015. The final sample includes responses from 207 landlords (response rate = 32%), covering 292 housing units or 27% of MARS-sampled housing units. Nonresponse could introduce selection bias into our estimates if the landlords who responded to the survey differed significantly from those who did not. To assess this possibility, we gathered administrative data on items also recorded in MRPOS, comparing responders and nonresponders. First, we drew on the MPROP and MTTR, examining information on the number of housing units, property values, and tax payments for each listed building. Second, we obtained data on Milwaukee water bills from 2008 to 2010. Third, we compiled mortgage data through the Milwaukee Register of Deeds. We supplement these administrative data with census block group-level estimates of poverty and racial composition from the American Community Survey and decennial census. Table A1 (in the appendix) presents descriptive statistics for the housing units of responding and nonresponding landlords. Overall, these comparisons indicate that our results are not substantially biased by nonresponse.[11] Expenses, critical for estimating profits, are consistent across responders and nonresponders. Nonetheless, in light of the differences in neighborhood composition between responders and nonresponders—housing units owned by MRPOS respondents tend to be located in neighborhoods with slightly lower poverty rates and a lower proportion of black residents—we employ weights (described below) to correct for dissimilarities that could arise from differential response across observable characteristics.

In addition to assessing nonresponse bias, the administrative data allow us to assess the validity of several items collected through MRPOS. Water expenses in MRPOS align with those recorded in administrative data. Mortgage coverage rates are slightly lower in MRPOS, which likely reflects paid-off mortgages being preserved in administrative data. Finally, the number of housing units reported by MRPOS respondents is slightly lower compared to property records. This discrepancy matters for calculating landlord profit margins, as all building-level expenses are divided by the number

[11] Responders and nonresponders have very similar values for water bills and mortgage prevalence; these differences are not statistically significant. Responders have fewer units within a building than nonresponders, but again, the difference was not statistically significant. On average, responders own more valuable buildings and have higher property taxes; however, the confidence intervals on these figures are large and overlapping.

of rental units in each building. Building-unit discrepancies between data sources affected 80 addresses; we randomly selected 20 to be inspected by a fieldworker who recorded a visual count of housing units. The field investigation revealed the administrative data to be more accurate, with discrepant addresses tending to be duplexes with two units counted in the administrative data and one reported by landlords. Accordingly, we rely on administrative data to measure the number of housing units per building.[12]

We developed custom weights for this new survey. To begin, we relied on weights calculated for MARS, which allow the data to be representative of Milwaukee's renter population.[13] Next, we multiplied MARS weights by the inverse of the square root of the probability of selection into the MRPOS sample. To adjust for nonresponse, we took advantage of a unique opportunity to modify the weights with data collected in the MARS survey. We estimated propensity scores predicting MRPOS survey response by the following variables reported by tenants represented in MARS: residential tenure, monthly rent, receipt of a government rent subsidy, strategies of locating housing, eviction history, income, enrollment in the Supplemental Nutrition Assistance Program, education, race and ethnicity, citizenship status, criminal record, gender, social ties, and family size. We then multiplied by the inverse of these propensity scores to up-weight landlords who were less likely to respond.

Median Regression Models

To improve model fit and reduce the influence of outliers, we employ median regression models. We predict potential exploitation at the median quantile ($\tau = 0.5$) conditional on covariates:

$$Q_{0.5}(y_{ic}|x_c, w'_{ic}) = \beta_0 + \beta_1 x_c + \boldsymbol{\beta_2 w'_{ic}} + e_{ic}, \tag{1}$$

[12] MRPOS landlords failed to report rent for 33 units represented in our survey, by either skipping the item or reporting no rent revenue. We exclude these units from our sample because they likely represent deals for building managers (e.g., free rent in exchange for maintenance), units no longer on the market, or vacant units. The MRPOS did not ask if a housing unit was vacant or for how long. The RHFS directly addresses this limitation by asking property owners about potential and actual rents received, the difference reflecting revenue lost from vacancies and nonpayment. Thus, our estimates based on national data fully address revenue losses from vacancies, while our estimates based on Milwaukee data account only for lost rental income, tenant-turnover expenses, and nonpayment. Moreover, because Milwaukee units' missing rent data are evenly split between properties in poor and nonpoor neighborhoods, including them does not affect our results as they pertain to differences between these types of neighborhoods.

[13] Instead of pursuing a weighting strategy to represent Milwaukee landlords—which would have involved down-weighting owners with many housing units—applying the MARS weights enables us to estimate profits earned off housing units occupied by the average Milwaukee renter.

where y_{ic} is defined initially as the potential exploitation for housing unit i in neighborhood c. We predict exploitation using the poverty rate and percentage of black residents in a census block group (our neighborhood metric), along with $\boldsymbol{w}'_{ic}$, a vector of control variables. We rely on minimal controls describing building characteristics because they are already reflected in property values, which serve as the denominator in our measure of exploitation. The control vector includes measures for the number of bedrooms in the unit and the number of units in the building, to capture variation in returns to scale of property management.[14] Next, we replace y_{ic} with measures of profit margins that indicate landlords' realized returns. In these models, to adjust for opportunity costs, we add an additional control for the number of hours landlords report spending on property management.

The estimates from these models indicate median, rather than mean, associations between neighborhood poverty and tenant exploitation or landlord profit margins. For the profit margin models in particular, we believe that large cost outliers affecting mean profits make the median a better summary of the patterns affecting most landlords. But in an additional analysis and discussion below, we also consider how differential exposure to rare, large costs—deemphasized in the median regression framework—shapes the risks and returns landlords face.

RESULTS

Do the Poor Pay More for Housing?

Figure 1 shows the bivariate correlation between neighborhood poverty and exploitation found in the MARS/MPROP/MTTR merged data.[15] Rental units in neighborhoods with less than 15% poverty rates have exploitation rates around 10%. There, rents sum to the value of property in around 10 years. But in high-poverty neighborhoods, those with 50%–60% poverty rates, exploitation more than doubles as annual rents amount to 25% of property values. A substantial shift also appears between black and nonblack neighborhoods: a 10%–15% median exploitation rate in minority-black neighborhoods compared to a 20%–25% rate in majority-black neighborhoods.

Table 1 presents the median regression results for these Milwaukee data and the nationally representative RHFS data. The models report strong as-

[14] In additional analysis, we also condition on building age and length of landlord ownership. These controls do not affect our results. Because building age can affect property values and length of ownership can affect mortgages, we exclude these variables in the main models.

[15] We are unable to display national patterns in this figure owing to RHFS disclosure restrictions.

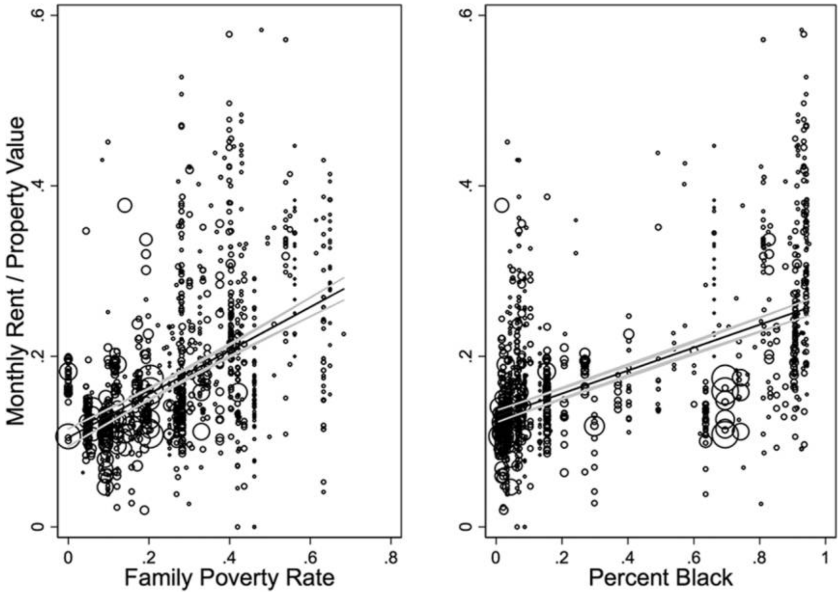

FIG. 1.—Renter exploitation and neighborhood characteristics (Milwaukee). Observations are scaled by survey weights. Fitted values are from bivariate median regressions. Data are from the Milwaukee Area Renters Study (2009–11), Milwaukee Master Property Record (2013), Milwaukee Treasurer's Tax Record (2013), and the American Community Survey (2013).

sociations between exploitation and neighborhood poverty rates in both the Milwaukee and national samples. In Milwaukee, model 1 shows that a 10 percentage point increase in neighborhood poverty increases predicted median renter exploitation by 2.2 percentage points. Model 2 shows similar results for the share of black residents in a neighborhood: a 10-point increase in the percentage of black residents in a neighborhood increases predicted median renter exploitation by 0.8 percentage points.[16]

These patterns replicate in the national data. Models applied to the RHFS show that a 10 percentage point increase in neighborhood poverty increases median potential exploitation by around 0.8 percentage points, a third of the association found in Milwaukee. And nationwide, a 10-point increase in the percentage of black residents in a neighborhood also increases median potential exploitation by around 0.8 percentage points. Renters in poor and predominantly black neighborhoods do pay more for housing, relative to its

[16] We also fit these models using both mean ordinary least squares regression and unconditional quantile regression, using the recentered influence function approach (Firpo, Fortin, and Lemieux 2009). Results are robust across different specifications.

TABLE 1
Renter Exploitation Rates by Neighborhood Characteristics

	Milwaukee		National	
	(1)	(2)	(3)	(4)
Family poverty rate	.22***		.08***	
	(.01)		(.02)	
Number of units in building	.01***	.01***	.00***	.00***
	(.00)	(.00)	(.00)	(.00)
Bedrooms	−.00	−.00	−.00	.00
	(.00)	(.00)	(.00)	(.00)
Percent black		.08***		.08***
		(.00)		(.00)
Constant	.09***	.08***	.10***	.11***
	(.01)	(.00)	(.01)	(.00)
Pseudo-R^2	.17	.18	.01	.01
Observations	923	923	1,900	1,900

Note.—Findings from weighted median regression models reported. SEs are indicated in parentheses. The numbers of national sample observations are rounded to the nearest hundred because of disclosure limitations. Models 1 and 2 are estimated on data from the Milwaukee Area Renters Study (2009–11), the Milwaukee Treasurer's Tax Records (2010), and the Milwaukee Master Property Record (2010). Models 3 and 4 are estimated on data from the Rental Housing Finance Survey (2012).

* $P < .05$.
** $P < .01$.
*** $P < .001$.

property value. Poverty has a particularly large association with exploitation in Milwaukee, but the same general pattern holds nationally.[17]

Are Landlord Profits Higher in Poor Neighborhoods?

If the poor pay more for housing relative to property values, do landlords in poor neighborhoods incur more expenses, offsetting this exploitation advantage? Table 2 lists profits and expenses of rental housing units across poor and nonpoor neighborhoods. We consider a neighborhood to be "poor" if it has a poverty rate at or above the median poverty rate in the MRPOS sample (27%). Because Milwaukee is a relatively poor city, its median poverty rate is higher than the rate in RHFS's nationally representative sample of buildings. Accordingly, we divide neighborhoods in the RHFS sample into three categories: a "poor" category that aligns with the threshold we used for Milwaukee (27% poverty rate or higher), a "middle-class" group of neighborhoods with poverty rates above the median of the remaining national sample (8%–26% poverty rate), and an "affluent" category of the remaining properties located in low-poverty neighborhoods (less than 8% poverty rate).

[17] All models are weighted. Unweighted models produced consistent findings.

TABLE 2
RENTAL UNITS' MEDIAN PROFITS AND EXPENSES PER MONTH: POOR AND NONPOOR NEIGHBORHOODS

	Milwaukee			National			
	Overall	Nonpoor	Poor	Overall	Affluent	Middle-Class	Poor
Monthly rent	650	650	600	625	735	674	511
Mortgage payments	188	219	0	80	87	201	0
Property taxes	138	153	103	69	120	79	40
Insurance payments	30	30	37	25	38	24	23
Utilities	42	42	45	35	36	50	25
Property manager fees[a]	0	0	0	0	4	0	0
Regular profits	231	174	319	250	250	225	298
Maintenance[b]	0	0	0	0	8	0	0
Profits with light maintenance	151	141	318	236	216	191	288
Large repairs[c]	52	54	44	83	83	71	127
Tenant turnover[d]	0	0	0	37	14	35	38
Profits with irregular costs	35	21	151	45	49	3	98
Total hours spent per month	9	9	35				
Hours spent per unit per month[e]	2.2	2.2	2.6	1	1	1	1
Percent of total income from rent	20	20	23				
Number of units in building	2	2	2	3	3	3	2
Bedrooms	2	2	2				
Units landlord owns	4	4	12				
Observations	259	130	129	1,900	700	700	500

NOTE.—In the Milwaukee data, neighborhoods are considered "poor" if they have a poverty rate at or above the citywide median (27%) and "nonpoor" if they have a lower poverty rate. In the national data, neighborhoods are considered "poor" if they have a poverty rate of at least 27%, "middle-class" if they have a poverty rate between 8% and 26%, and "affluent" if they have a poverty rate below 8%. Because entries are median values, rents minus expenses need not sum to profits. Weighted data are from the Milwaukee Rental Property Owners Survey (2015), Milwaukee Master Property Record (2013), and the Rental Housing Finance Survey (2012). The numbers of national sample observations are rounded to the nearest hundred because of disclosure limitations.

[a] Property manager fees explicitly include professional expenses (legal and accounting) exclusively in the national data.

[b] Maintenance includes security expenses exclusively in the national data.

[c] In the Milwaukee data, large repairs include improvements to roofs, furnaces or heating systems, water heaters, plumbing systems, painting jobs, and other major repairs. In the national data, large repairs include improvements to roofs, furnaces or heating systems, plumbing systems, exteriors, other capital improvements, windows, doors, floors, electrical systems, kitchens, bathrooms, security systems, swimming pools, playgrounds, and handicap-access installations.

[d] In the Milwaukee data, tenant turnover includes expenses from nonpayment of rent and cost of new tenants. In the national data, tenant turnover is the difference between actual and potential rent (vacancies), reported by landlords.

[e] In the Milwaukee data, hours spent per month are an average for all of a landlord's properties. In the national data, they include only the surveyed property.

Table 2 shows that in Milwaukee, median monthly rent in poor neighborhoods ($600) is not significantly different from that in nonpoor neighborhoods ($650). This finding aligns with recent nationally representative research, showing a compressed distribution of rents in cities with slack housing markets (Boeing and Waddell 2016). By contrast, the national sample—which includes properties located in a wide variety of housing markets: high- and low-cost areas alike—shows larger differences in rents across poor and nonpoor neighborhoods. Nationally, the difference between median rent in poor and middle-class neighborhoods ($511 vs. $674) is three times that of Milwaukee's rent gap between poor and nonpoor neighborhoods.

Expenses can also vary by neighborhood characteristics. First, we consider expenses that landlords face with regularity. Regular expenses include mortgage payments, property taxes, property insurance, utilities, and property management fees. These ongoing, predictable costs account for the bulk of expenses landlords face. Across both the national and Milwaukee samples, these regular expenses are considerably higher in nonpoor neighborhoods. Most important, in Milwaukee the majority of rental properties in poor neighborhoods (60%) do not have mortgages—low housing prices in distressed communities allow many landlords to purchase properties outright—but the majority of properties in nonpoor neighborhoods (77%) do. Both in Milwaukee and nationwide, the median monthly mortgage payment for rental properties located in poor neighborhoods is $0, compared to $219 in nonpoor Milwaukee neighborhoods and $201 in middle-class neighborhoods in the national sample. Property taxes and housing values steadily increase as poverty diminishes. Nationally, landlords in nonpoor neighborhoods pay two to three times more in property taxes than those in poor neighborhoods.

Owing to these factors, rental properties located in poor neighborhoods command higher regular profits. Nationally, the median rental unit in a poor neighborhood yields $298 after regular expenses are deducted from rents, compared to $225 in a middle-class neighborhood and $250 in an affluent neighborhood. In Milwaukee, the median rental unit in a poor neighborhood makes $319 per month, compared to $174 a month for a property located in a nonpoor neighborhood. In Milwaukee, the gap in regular monthly profits between poor and nonpoor neighborhoods is larger than what we observe in the national sample owing to compressed rents across Milwaukee neighborhoods.

Landlords also face additional maintenance and repair expenses that cut into regular monthly profits. In Milwaukee, most rental housing units (70%) do not require ongoing monthly maintenance, such as landscaping or snow removal. In fact, in both poor and nonpoor neighborhoods, the median rental unit incurs no ongoing maintenance costs. Among units with monthly maintenance costs, median costs in poor neighborhoods are $50 and median costs in nonpoor neighborhoods are $58 (though at the mean, maintenance costs are higher in poor neighborhoods). After accounting for ongoing maintenance, the median rental unit in a poor Milwaukee neighborhood yields a monthly profit of $318, compared to $141 for properties in nonpoor neighborhoods, a twofold difference. Nationally, maintenance cost patterns are similar, if less stark. Maintenance costs lower median profits by $34 in affluent and middle-class neighborhoods but only by $10 in poor neighborhoods.

Sometimes, landlords face infrequent but consequential expenses that can undermine profitability. In Milwaukee, sizable repair costs are infrequent: the median rental unit required no expenses on most major repairs in the last year, and no single large repair, aside from paint jobs, was experienced by more than 20% of the sample. Citywide, these costs are comparable across poor and nonpoor neighborhoods at the median (and the means), but repair costs are more concentrated among landlords in poor neighborhoods: a smaller proportion report repair costs, but those costs tend to be bigger. In the national sample, the median property located in a poor neighborhood had $127 in monthly large repairs, compared to $71 and $83 for properties located in middle-class and affluent areas, respectively. Finally, across several measures, tenant turnover, nonpayment of rent, and vacancies are more common in poor neighborhoods, both in Milwaukee and nationwide. All of these periodic expenses partially offset the lower regular expenses enjoyed by landlords in these neighborhoods.[18]

After accounting for all expenses, nationwide the median rental unit located in a poor neighborhood yields $98 in profits, compared to only $3 in middle-class neighborhoods and $49 in affluent neighborhoods. Across the United States, landlords operating in poor neighborhoods enjoy median profits double those of landlords operating in affluent neighborhoods. In Milwaukee the median rental unit located in a poor neighborhood produces a monthly profit of $151, after all expenses, while those in nonpoor neighborhoods, owing to large mortgage payments, make $21.

In Milwaukee, landlords in poor neighborhoods also spend more time managing their properties: typically 35 hours a month, compared to nine hours a month for landlords in nonpoor areas. This pattern was not replicated in the national data, however, which shows no differences in landlord time commitments across neighborhood contexts. This discrepancy likely reflects the fact that in the nationally representative RHFS data, information about hours spent on property management pertains only to the surveyed property, whereas in the Milwaukee-based MPROP data, it pertains

[18] Our profit measures build on each other. Our estimate of "profits with light maintenance" also includes all expenses used to calculate "regular profits," and our measure of "profits with irregular costs" also includes all expenses used to calculate "regular profits" and "profits with light maintenance."

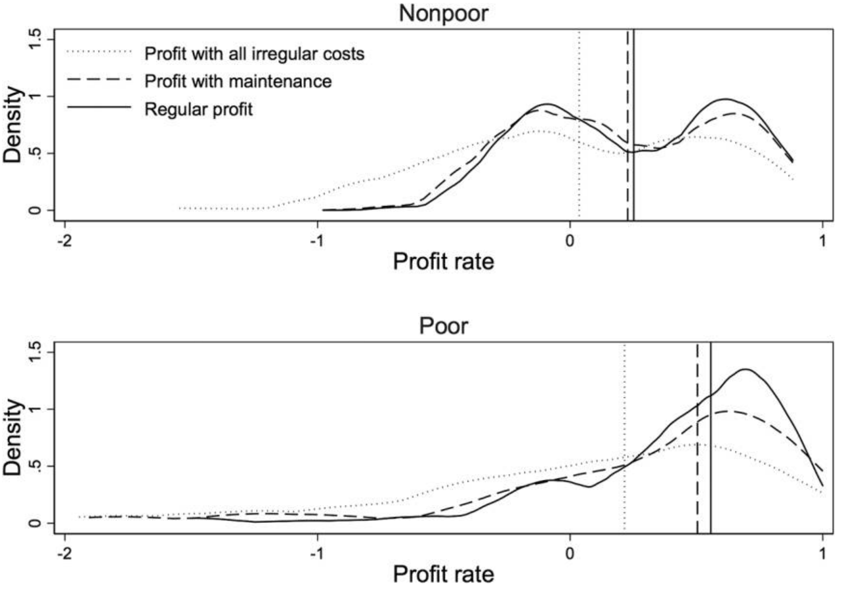

FIG. 2.—Distributions of profit rates for nonpoor and poor neighborhoods (Milwaukee). Vertical lines indicate weighted median values. Neighborhoods are considered "poor" if they have a poverty rate at or above the citywide median (27%) and "nonpoor" if they have a lower poverty rate. Data come from the Milwaukee Property Owners Survey (2015), Milwaukee Master Property Record (2013), and American Community Survey (2013).

to all properties. The typical landlord operating in poor Milwaukee neighborhoods has a larger portfolio than those in nonpoor areas, owning 12 properties versus four, information that was not recorded in RHFS. In Milwaukee, then, we observe landlords in poor neighborhoods devoting more time to their work simply because they own more properties. In Milwaukee, the typical landlord spends 2.6 hours per month on each unit in poor neighborhoods and 2.2 hours per month on each unit in nonpoor neighborhoods, a fairly trivial difference.[19]

Next, we examine in more detail the distribution of profit margins by dividing the dollar value of profits by monthly rent. Figure 2 displays the weighted distributions of different housing unit profit rates (as opposed to profit amounts, as displayed in table 2) in poor and nonpoor neighborhoods

[19] Our data do not allow us to assess the nature of those hours, whether they were especially easy or difficult, or the quality of services provided. Conducting rent shakedowns, flipping properties, and distributing eviction notices can take as much time as working with tenants and bringing properties up to code. The hours landlords devote to managing properties, particularly in low-income communities, may reflect either work that benefits tenants and the preservation of affordable housing stock or strategies that facilitate tenant exploitation and the erosion of affordable housing stock.

in Milwaukee.[20] The figure's vertical lines depict median profit margins across the three definitions of profits discussed above. In poor Milwaukee neighborhoods, profit margins more or less reflect a unimodal distribution. In nonpoor neighborhoods, however, the distribution is bimodal—with a peak of positive profit margins similar to those in poor neighborhoods, coupled with a peak of losses (of around 10% of revenue)—reflecting a gap in profit rates between properties owned free and clear and those still carrying mortgages.

In both poor and nonpoor neighborhoods, profit rate distributions are left skewed, with long tails below zero. This pattern reflects compressed rent revenues coupled with variable expenses. Eighty percent of housing units in the Milwaukee sample rent for between $500 and $900, but expenses are highly inconsistent across rental units. A large mortgage payment or sizable plumbing job can bite into a landlord's bottom line. These added expenses, particularly irregular costs, displayed by the dotted line, increase the variance of profit margins and reflect the rarity but significance of large expenses to a subset of rental properties.

Modeling Landlord Profits across Poor and Nonpoor Neighborhoods

We formally test these patterns with median regression models estimating landlord profit margins by neighborhood poverty rates (table 3). These models control for the number of units in each building, the number of bedrooms per unit, and the number of hours spent by the landlord on property management. In both the Milwaukee and national data, we observe a strong positive relationship between neighborhood poverty rates and landlord profit margins for regular monthly profit margins and profit margins with light maintenance. In Milwaukee, model 5 reports a clear linear relationship between median landlord profits and neighborhood poverty rate: a 10% increase in neighborhood poverty is predicted to increase landlord profitability by 13 percentage points. Nationally, the pattern holds, but the magnitude of the association is smaller by almost a half, with a 10% increase in neighborhood poverty expected to increase landlord profitability by 7 percentage points. Slightly smaller associations hold for profits after accounting for light maintenance expenses (models 6 and 9) in both the Milwaukee and national samples.[21] Controlling for the time landlords spent managing property did not affect our main findings in either data set.

[20] As with fig. 1, we are unable to display national profit margin distributions owing to RHFS disclosure restrictions.

[21] In both the Milwaukee and national data, rental properties located in predominantly black neighborhoods also yield higher profits than those in nonblack neighborhoods, a pattern that aligns with a long and troubled history of extracting excess profits from African-American communities (Sugrue 2005; Satter 2009).

TABLE 3
LANDLORD PROFIT RATES AND NEIGHBORHOOD CHARACTERISTICS

	MILWAUKEE			NATIONAL		
	Regular Profits (5)	Profits with Light Maintenance (6)	Profits with Irregular Costs (7)	Regular Profits (8)	Profits with Light Maintenance (9)	Profits with Irregular Costs (10)
Family poverty rate	1.34**	1.30***	1.30***	.71***	.58***	.36
	(.50)	(.34)	(.36)	(.08)	(.10)	(.42)
Number of units in building	.01*	.01***	.02***	.00	−.00	−.00
	(.01)	(.00)	(.00)	(.00)	(.00)	(.00)
Bedrooms	−.10	−.03	−.07	−.02	−.06*	−.10
	(.07)	(.05)	(.05)	(.02)	(.03)	(.07)
Hours spent	.00	.01*	.01**	−.01***	−.00*	−.01
	(.00)	(.00)	(.00)	(.01)	(.00)	(.00)
Constant	.19	.01	−.16	.37***	.42***	.20
	(.22)	(.13)	(.15)	(.05)	(.06)	(.13)
Pseudo-R^2	.11	.09	.07	.02	.02	.01
Observations	259	259	259	1,900	1,900	1,900

NOTE.—SEs are indicated in parentheses. The numbers of national sample observations are rounded to the nearest hundred because of disclosure limitations. Weighted data are from the Milwaukee Property Owners Survey (2015), the Milwaukee Master Property Record (2013), and the Rental Housing Finance Survey (2012).
* $P < .05$.
** $P < .01$.
*** $P < .001$.

Table 3 also shows results modeling profit rates that account for irregular costs. In Milwaukee, model 7 shows the association between neighborhood poverty and profit rates to be strong and statistically significant, even after accounting for all observable landlord expenses.[22] However, in the national data, the association shrinks and loses statistical significance. Furthermore, landlord profit models that draw on the RHFS are sensitive to weighting. In the national data, without weights, the association between neighborhood poverty rates and landlord profit margins turns negative. This suggests that in some markets, profits are higher in poor neighborhoods (areas up-weighted by the RHFS sample weights); in others markets, they are lower. On the basis

[22] Unlike models 5 and 6, model 7 is sensitive to weighting. Without weights, the association of profits with irregular costs and neighborhood poverty rates remains positive but loses statistical significance, owing to considerable variation in large repairs among Milwaukee landlords. Large outliers drive expenses from irregular repairs. In Milwaukee, the mean for all repairs is $119, while the median is $52. This is particularly the case for expenses associated with tenant turnover and nonpayment. While only 17% of rental units lost money owing to these factors, some reported substantial losses. We explore this issue in more depth below.

of the exploitation results reported above (which are not sensitive to weighting), we expect that housing values could moderate the association between neighborhood poverty and landlord profits. In high-cost housing markets, rising property values, high rents, and gentrification might offset benefits from cheap mortgages and low property taxes, factors that drive higher profits in poor neighborhoods in low-cost housing markets like Milwaukee.

To test this line of thought, figure 3 shows profit values predicted by model 9 of table 3 but with an interaction term for median metropolitan statistical area housing value. The results show that in relatively low-cost housing markets (those with housing values in the 10th percentile of the distribution), landlord profit margins increase at a steep rate with neighborhood poverty rates. The same pattern is found in medium-cost housing markets (those with median housing values), although the upward slope has a shallower incline. However, in high-cost housing markets (those with housing values in the 90th percentile), landlord profits decline with neighborhood poverty. Because the RHFS is not representative at subnational levels, these patterns should be interpreted as preliminary and suggestive. Nonetheless, they suggest a plausible interpretation of heterogeneity in the profit-poverty relationship: in high-cost, majority-renting cities such as New York and San Francisco, which command exorbitantly high rents, landlords operating in low-poverty neighborhoods reap higher returns; however, in low-cost areas of the country such as Milwaukee and Cleveland, where property values vary

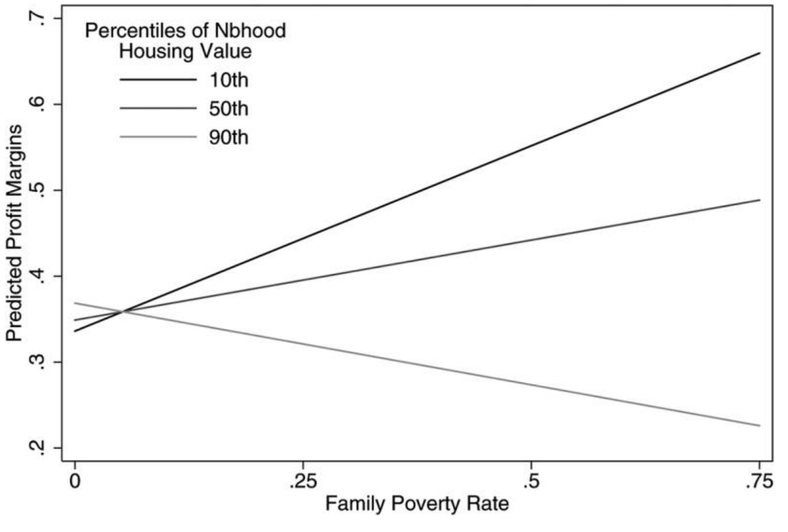

FIG. 3.—Neighborhood poverty and landlord profits by median neighborhood housing value, Rental Housing Finance Survey (2012) (weighted).

considerably across neighborhood contexts but rental prices do not, the opposite is true.

DISCUSSION

To examine exploitation and profit seeking in rental housing markets, this study combines novel data from a nationally representative survey of landlords with multiple survey and administrative data pertaining to landlords and tenants in Milwaukee. First, we find tenant exploitation—being overcharged relative to the market value of a property—to be higher in poor neighborhoods and those with a large concentration of African-Americans. These neighborhoods have lower property values and property taxes, but rents do not diminish with neighborhood disadvantage as quickly as property values do. This enables landlords operating in those neighborhoods to extract high rents relative to the value of their properties. However, heightened exploitation does not necessarily produce higher profits for landlords, as the cost of doing business (e.g., turnover, vacancies) could be higher in disadvantaged communities. Accordingly, we also employ an accounting framework to estimate monthly profits earned by rental units. Estimating three definitions of profits that capture regular and irregular expenses, we show that median landlord profit margins are higher in neighborhoods with higher poverty rates, even after accounting for a wide array of expenses. We now examine potential explanations of these patterns with supplementary analyses that focus on different time horizons, risk exposures, and stigma for landlords operating in poor and nonpoor neighborhoods.

Our findings reflect two distinct profit strategies among landlords, depending on the kinds of neighborhoods in which they operate. The typical landlord operating in nonpoor neighborhoods has rather thin profit margins after regular expenses and maintenance costs are subtracted from the rent. This implies a long-term investment strategy, where capital is housed in property and expected to appreciate. Our findings imply that rents in nonpoor neighborhoods cannot be lowered by a significant amount if landlords hope to make modest profits. Indeed, those who incur irregular costs to their rental units more or less break even. Nor, we suspect, can rents be significantly raised in soft housing markets like Milwaukee, where the distribution of rents is much more compressed than in high-cost cities (Boeing and Waddell 2016). Landlords who have invested in a nonpoor neighborhood are not betting on today but on tomorrow. In poor neighborhoods, however, landlords are betting on today. These landlords see much higher monthly profit margins per housing unit. This short-term investment strategy does not rely on future equity, a risky proposition in distressed communities, but on the simple fact that in poor neighborhoods mortgage and property tax payments are significantly lower than in nonpoor neighborhoods but rents are not.

To test this line of thought, we draw on historical administrative records from Milwaukee and chart property appreciation between 1984 and 2016. We compare appreciation for properties in poor and nonpoor neighborhoods for the buildings in the MRPOS sample. Specifically, we predict changes in assessed property value per unit with the number of years a surveyed MRPOS landlord has owned a building. We include property fixed effects to focus on changing value within each sampled property. Figure 4 charts the property values per unit predicted by this model. Buildings in Milwaukee's nonpoor neighborhoods have appreciated quicker, on average, than buildings in poor neighborhoods. However, this difference in appreciation rates, and indeed any appreciation at all, appears only for buildings owned for 10 years or more, likely reflecting the slow growth in property values since the Great Recession. Nonetheless, these results provide some suggestive historical evidence that landlords in nonpoor neighborhoods can ex-

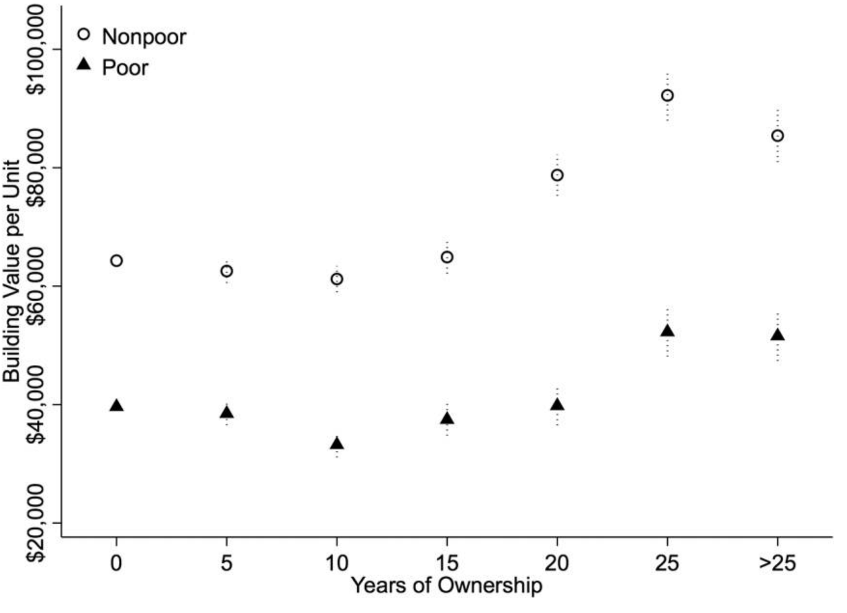

FIG. 4.—Fixed-effects regressions estimating appreciation in value per housing unit (Milwaukee). Neighborhoods are considered "poor" if they have a poverty rate at or above the citywide median (27%) and "nonpoor" if they have a lower poverty rate. The models predict building value with years of ownership, conditional on fixed effects for housing units. Results can be interpreted as average housing unit value appreciation for landlords in poor and nonpoor neighborhoods. Data come from the Milwaukee Property Owners Survey (2015), Milwaukee Master Property Records (1984–2016), and American Community Survey (2013).

pect to benefit more from building value appreciation than those operating in poor neighborhoods, particularly for long-term owners.

Yet combining these appreciation estimates with the profit differences calculated above (table 2) suggests that landlords in poor neighborhoods come out ahead in both the short and long run. Median landlords in poor neighborhoods make $130 more per unit, per month, than median landlords in nonpoor neighborhoods, or $1,560 more each year. In nonpoor Milwaukee neighborhoods, appreciation increased housing values only by around $3,000 after 10 years and $15,000 after 20 years. Assuming stable profit margins and no appreciation in poor neighborhoods over time, the profits of landlords in poor neighborhoods are still more than double those of landlords in nonpoor neighborhoods, even after the latter have enjoyed 20 years of appreciation. Bearing in mind that these estimates focus on a single, slack housing market still reeling from the Great Recession, our findings indicate that appreciation rates in nonpoor neighborhoods do not overtake the extra profits extracted by landlords in poor areas, even after an extended period of time.[23]

If exploitation relies on the exclusion of a disadvantaged group from a productive resource (Wright 1997), in our case, that resource is housing lo-

[23] Because our data do not include initial money invested by landlords, we cannot measure potential capital opportunity costs by comparing returns from rental properties with alternative investment strategies. However, we can estimate these costs under different assumed investment scenarios. Focusing on the Milwaukee sample, we assume that the capital bound up in a property owned outright is 100% of the property's value. For mortgaged properties, we expect capital investment of at least 20% as a down payment, while also considering different assumptions (30%, 40%, 50%, and 60% of the property's value) that approximate how much of the mortgage has been paid down. For both mortgaged and nonmortgaged properties, we then estimate the monthly opportunity costs of invested capital by assuming a 5.71% return (the average rate of return for the Standard and Poor's 500 between 2000 and 2015) distributed over 12 months and all rental units in a building. We then add these capital costs to our most stringent measure of profits, which accounts for regular and irregular expenses. At the weighted median, monthly per-unit rental profits in nonpoor neighborhoods are $94 less than estimated returns from alternative investments and $22 less in poor neighborhoods. The capitalization rate of rental properties (annual per-unit income/capital invested in each rental unit) is 1.5% in nonpoor neighborhoods and 4.9% in poor neighborhoods, using our measure of profits remaining after all expenses. Median regression models indicate that returns on capital invested in rental properties are higher in poor neighborhoods. This finding is qualitatively consistent across the three profit definitions and across all mortgage assumptions but loses statistical significance for the profits with irregular costs when mortgaged capital investment is assumed to be below 40% of the property's value. Properties are more expensive in nonpoor neighborhoods; this expense is not offset by increased use and availability of mortgages. To more accurately compare returns from rental properties with other investment strategies, one would need to account for depreciation and appreciation of property values, the mortgage interest deduction, the liquidity advantage of rental income, and other factors. However, our coarse estimates indicate that the rental profit advantage identified in poor neighborhoods is not nullified when considering potential returns lost by forgoing alternative investment strategies.

cated outside of poor neighborhoods. Renters in poor neighborhoods are excluded from both home ownership and apartments in middle-class communities on account of their poverty, poor credit, eviction or conviction history, or race (through discrimination) (Massey and Lundy 2001; Desmond 2016). These renters are exposed to exploitation on account of their reliance on housing and their lack of options for securing it. However, exploitative outcomes can be brought about by the prudence of market actors just as much as by their greed, especially when they take above-average risks. We found that, compared to their peers in affluent communities, landlords in high-poverty neighborhoods face more risks in the form of rent nonpayment and vacancies and are exposed to repair costs that are either higher (in the national data) or at least more concentrated (in the Milwaukee sample). Landlords anticipating potential risk may price up their housing units, just as landlords who have themselves incurred losses may recoup by asking future renters to pay for the misfortunes of past tenants, thereby generating widespread exploitation by socializing risk. “The idea of risk,” writes Ewald (1991, p. 203), “assumes that all individuals who compose a population are on the same footing: each person is a factor of risk, each person is exposed to degrees of risk. The risk defines the whole.” (Caplovitz [1967] used “poor consumers” and “risks” interchangeably.) Because landlords operating in poor communities cannot know with certainty whether a new tenant will cost them money, they may attempt to mitigate that risk by raising the rents of all their tenants, carrying the weight of social structure into price.[24] Poor renters pay double—purchasing the good and the risk—but because losses remain infrequent in absolute terms, landlords typically realize the surplus “risk charge” as higher profits.

To observe this proposed risk structure directly, we estimated model 7 with the Milwaukee sample at several quantiles other than the median. If some landlords experience uncommon but large expenses associated with operating in poor neighborhoods, then the typical profit advantage for landlords in high-poverty communities should be nullified or reversed by those who suffered the largest losses. The results are presented in figure 5. While profits are found to be higher in poor neighborhoods across most of the distribution, this relationship reverses for the landlords in the 10th percentile. In other words, for the Milwaukee landlords who reaped the lowest profits (including those reporting negative returns), the association between neighborhood poverty rate and landlord profit rate is negative. The opposite is true, however, for the typical Milwaukee landlord as well as those who enjoyed the largest profits in the sample. In the national data, evidence for this pattern was inconclusive as estimates at the bottom tail of the landlord profit distribution were statistically insignificant; however, models applied to the

[24] We thank a reviewer for raising this point.

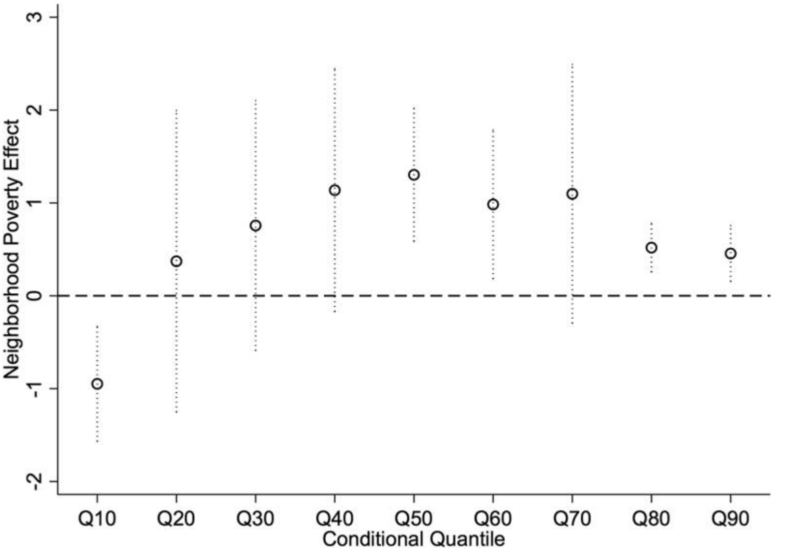

FIG. 5.—Neighborhood poverty and landlord profits across the profit distribution (Milwaukee). Coefficients are conditional quantile regression estimates drawn from models that use the same variables as in model 7 in table 3. Data come from the Milwaukee Property Owners Survey (2015), Milwaukee Master Property Record (2013), and American Community Survey (2013).

Milwaukee data indicate that landlords in poor neighborhoods incur bigger losses than their peers in nonpoor neighborhoods.

Perceived market risk and consumer exploitation have long gone hand in hand. When the Federal Housing Administration redlined black neighborhoods, creating a dual housing market that enabled significant exploitation within these neighborhoods, it justified this decision by claiming that insuring mortgages in black communities was too risky (Sugrue 2005; Satter 2009). Beyond the housing market, a similar pattern can be observed today in pawnshops, check cashing stations, payday lenders, and rent-to-own businesses that cater to low-income consumers and explain high-interest charges on account of anticipated risk (Baradaran 2015). In short, consumer exploitation is made possible when a disadvantaged group is deemed risky and forced to pay a social price. As Caplovitz (1967, p. 180) observed, the poor "are shunted to a special class of merchants who are ready to accept great risk. . . . Society now virtually presents the very poor risks with twin options: of foregoing major purchases or of being exploited."

However, market-based reactions aimed at reducing risk can often bring about the opposite result. When landlords in poor neighborhoods raise the rent to protect themselves from potential loss, they increase their risk of nonpayment driven by cost burden (Desmond 2016). In fact, we find that the losses incurred by landlords in poor neighborhoods are more often the result of nonpayment and vacancies than repairs and maintenance costs. As when risk-mitigation strategies undertaken by one lender increase the risk of another—for example, when lenders approve a high-interest payday loan, they significantly increase the borrowers' risk of credit card delinquency (Agarwal, Skiba, and Tobacman 2009)—landlords who raise rents in anticipation of losses help to invite those losses by overburdening their consumer base.

The perceived risk that may help drive higher profits in poor neighborhoods may also help ensure they remain high by preventing investors from flocking to this market segment. Typically, when there are higher profits to be had in a marketplace with low barriers to entry, entrepreneurs find their way to it; with time, this can erase the lucrative advantage on which they originally sought to capitalize (Smith [1776] 1976, pp. 67–69). However, it may be the case that new entrants to the rental market, and even experienced investors operating in nonpoor sectors of the city, are generally unaware of the higher profits that can be extracted from tenants in disadvantaged communities. Conventional wisdom about renting in poor communities may emphasize the risk and not the reward (e.g., Gans 1995), a misrepresentation that those profiting most from the situation have no incentive to correct.[25] We also recognize that poor neighborhoods possess strong profit-making capacity precisely because they lack amenity value. Even if investors sense the opportunity, many have no desire to participate in this challenging and morally ambiguous business. As one real estate investor bluntly put it, "Yes, you can make money in a bad neighborhood, but you also can face some problems no civilized person should have to face. You're better off looking for the worst house in the best neighborhood" (Sheets 1998, p. 232). The market advantage that accompanies renting in poor neighborhoods requires landlords to confront the realities of concentrated disadvantage and accept possible reputational costs of being labeled a "slumlord." Just as there is a stigma associated with living in a low-income neighborhood, there is also a stigma of landlording in one. All these reasons, which require further empirical study, imply that the benefits that accrue to landlords operating in poor neighborhoods are not temporary, as are many unique advantages in a free market, but durable.

IMPLICATIONS FOR THEORY AND POLICY

Our study demonstrates that to fully understand the root causes of the affordable housing crisis, researchers will need to synthesize sociological

[25] Travis (2019) identifies a consistent concern about risk, liability, and catastrophic loss in an analysis of the 45 most popular landlord guidebooks published between 1995 and 2015.

and economic perspectives. Economic theorists have long observed that housing is a peculiar commodity, emphasizing that rents and property values cannot be fully understood by appealing to conventional norms of economic exchange (Wolf 1981; Evans 1991). Yet since economic research on real estate markets far outpaces sociological efforts, analysts tend to answer critically important questions about housing dynamics by appealing to the neoclassical model. Empirical analyses that employ a sociological perspective, however, can produce surprising and policy-relevant findings that complicate and challenge theoretical models grounded in the laws of supply and demand (Logan and Molotch 1987). Contributing to this effort, our study revealed that neighborhood context exerts influence on the distribution of rents and landlord profit margins, even conditional on standard economic indicators (e.g., housing size, hours a landlord worked). More sociological research is needed to paint a comprehensive picture of the inner workings of rental markets, where the vast majority of low-income families reside.

Although the study of housing traditionally has occupied a prominent place in the sociology of poverty and urban life, today many sociologists of inequality overlook its importance. This is a consequential oversight, since the lack of stable, affordable housing is a wellspring for a constellation of social problems: from educational inequality and health disparities to community instability and increased material hardship (Desmond 2016). Our study has shown that market actors in general—and landlords, in particular—should be seen as central players in theories of neighborhood selection and community life (Gilderbloom and Appelbaum 1987). Neighborhoods are markets; a full explication of their dynamics would focus not only on the people who live in them but also on the people who own them.

This research agenda needs significantly more work, including studies that go beyond the limitations of our own. For one, our findings suggest that there may be considerable heterogeneity in market dynamics across housing markets. In low- and medium-cost housing markets, landlord profit margins are higher in poor neighborhoods; however, in the country's most expensive housing markets, cities with comparatively high rents and a high proportion of renters, owning rental property in affluent communities may be more lucrative. The RHFS data are representative only at the national level, preventing us from providing reliable descriptive estimates of landlord profit margins across cities or states. New data and further research are needed to systematically identify and explain the dynamics of different housing markets, contributing to a nuanced and complex sociology of housing that could replace one-size-fits-all theories and policy prescriptions. Second, more research is needed to uncover the root causes of the lack of affordable housing across America and to plumb the motivations and behaviors of different types of landlords. At the least, we need a collective effort dedicated to developing a systematic typology of the structures and dynamics of different housing markets as well as a corresponding typology of different market actors found within each market type. Finally, our study's findings indicate that rental property can generate healthy profit rates, particularly in poor neighborhoods, but rare and costly expenses make those returns far from guaranteed. This raises a number of policy-relevant questions. Should policy makers focus on decreasing property owners' risk (e.g., through state-sponsored insurance), with the hope that doing so would deflate rents in low-income communities? Or should they place limits on landlords' profit-seeking behaviors (e.g., through rent stabilization or rent control measures)? Much more research trained at such questions is necessary to inform policies and regulations aimed at addressing the affordable housing crisis.

Finally, this study has contributed to the empirical study of exploitation. While most research in this developing subfield has focused on labor (e.g., Sakamoto and Kim 2010; Brady et al. 2015), we extend this line of work into housing markets. Doing so invites future research that examines how housing dynamics are governed by relations between multiple actors implicated in the reproduction of inequality, these together constituting a thick web of rich and poor, exploiters and exploited alike. This relational perspective recognizes that exploitation long has helped to create "the slum" and its inhabitants; that money made slums because slums made money. To study exploitation, then, is not simply to reacquaint the sociology of stratification with a long-neglected concept; it is also to study poverty without taking as one's fundamental object of analysis poor people or their communities. A comprehensive theory of inequality will not only account for historical and structural dislocations and the social psychology of disadvantaged individuals; it will also document unequal relations of disparity and opportunity, identifying the social conditions that give rise to exploitative practices and how those practices deepen inequality in America.

By providing empirical evidence on the profit margins of landlords, our study holds significant legislative and policy implications. The law binds together housing policy and landlord profit. Legal scholars and courts have concluded that city regulations, including rent stabilization and just-cause eviction requirements, are permissible only if they "provide landlords with a just and reasonable return on their property" (Westray 1988, pp. 336–37). The profit margins of landlords have heretofore avoided empirical investigation. Accordingly, many policy analysts have simply assumed that extending tenant protections would automatically drive up rents, an assumption based on the presumption that landlords with thin profit margins would be forced to pass on additional costs to tenants (Schill 1993).

If landlords operating in low-income communities were found to have small profit margins, then tenant protections or housing regulations, from enforcing lead abatement to providing legal representation to tenants facing eviction, could result in property owners increasing rents, passing on additional costs to break even. However, we found the profit margins of landlords in poor neighborhoods to be higher than those of landlords operating in more affluent communities. As future research assesses competing explanations for high profits in poor neighborhoods—further distinguishing between different investment strategies, risk premiums, compensating differentials, and other market failures—it may leave less reason to worry that programs designed to improve housing quality or prevent eviction would automatically drive housing costs above rents, particularly if those programs were implemented in poor neighborhoods.

Evidence of heightened profits in poor communities also implies that the lack of affordable housing in those communities is driven not only by supply levels or regulatory barriers (e.g., Quigley and Raphael 2004; Glaeser, Gyourko, and Saks 2005) but also by the market dynamics of landlords. Three important implications flow from this finding. First, initiatives to promote home ownership in distressed communities could go a long way toward decreasing families' housing cost burden, since in those communities rents are considerably higher than mortgage payments. Because relatively high rents in low-income communities are not necessary to meet all expenses, opportunities to expand home ownership programs in distressed neighborhoods appear promising. Second, if landlords in poor neighborhoods are up-pricing their rental units to adjust for possible risk, then policies or products could be designed to mitigate that risk and lower housing costs. For example, renters could buy into subsidized insurance pools to cover landlord losses and prevent eviction, ensuring that risk among poor renters is shared but not felt as acutely. Third, initiatives designed to expand affordable housing that do not directly confront profit seeking among landlords may prove ineffective. For example, studies have shown that landlords in low-income neighborhoods overcharge housing voucher holders, making the program less cost-effective and therefore limiting its reach (Desmond and Perkins 2016). Public policies aimed at easing families' rent burdens should be grounded in a firm understanding of property owners' business practices.

APPENDIX

TABLE A1
Nonresponse Bias Assessment

	Responders	Nonresponders	*P*-Value
Building value	$205,992	$159,144	.24
Number of units in building	5	7	.13
Percent black	.34	.40	.02
Family poverty rate	.27	.30	.01

TABLE A1 (*Continued*)

	Responders	Nonresponders	*P*-Value
Water bill	348	362	.50
Percent with mortgage	.64	.63	.77
Property taxes	$6,344	$5,274	.37

NOTE.—All sampled landlords were owners of record for a property represented in the Milwaukee Area Renters Study (2009–11). Responders answered the Milwaukee Property Owners Survey (2015). Values are based on unweighted data. Administrative data sources were drawn from the City of Milwaukee—Master Property Record (2013), Treasurers Office (2013), Water Works (2010), Register of Deeds (2014)—as well as the U.S. Census (2010) and American Community Survey (2013).

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