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Housing and Employment Insecurity among the Working Poor

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ABSTRACT

While social scientists have documented severe consequences of job loss, scant research investigates why workers lose their jobs. We explore the role of housing insecurity in actuating employment insecurity, investigating if workers who involuntarily lose their homes subsequently involuntarily lose their jobs. Analyzing novel survey data of predominately low-income working renters, we find the likelihood of being laid off to be between 11 and 22 percentage points higher for workers who experienced a preceding forced move, compared to observationally identical workers who did not. Our findings suggest that initiatives promoting housing stability could promote employment stability.

KEYWORDS: job loss; eviction; displacement; unemployment; inequality; working poor.

The average month in 2012 saw 1.7 million workers laid off or discharged (Bureau of Labor Statistics 2013). Between 1981 and 2003, at least 30 million full-time workers lost their jobs (Uchitelle 2006). Those most likely to be laid off are members of the working poor. In particular, less educated and minority workers have the greatest chance of losing their jobs and, once unemployed, often have difficulties finding new ones (Keys and Danzinger 2008). Because of the severe consequences of job loss, understanding why low-income workers lose their jobs is critical for advancing the social science of unemployment and poverty as well as to developing effective policy interventions to prevent displacement.

Yet scant research investigates why workers lose their jobs. "We know very little about the fundamental causes of why displacement occurs," Lori Kletzer (1998:130) observes. "The nearly exclusive focus on consequences rather than causes is understandable, but unfortunate." Economists have developed theoretical models that explain firings as the result of firms' eventually learning about the skills and fit of workers (attributes unknown previous to hiring) and laying off the incompetent or mismatched (Jovanovic 1979). However sensible, this model lacks empirical verification. Sociologists have produced a handful of studies showing that African Americans are more likely to be fired from public sector jobs (Zwerling and Silver 1992) and elite occupations (Wilson and McBrier 2005). These studies indicate that discrimination may be affecting employers' decisions about whom to let go, but they do not address job loss among those at heightened risk of it: the working poor.

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To better understand why low-income workers lose their jobs, we investigate the relationship between employment and housing insecurity. Since 1970, the United States has witnessed the rise not only of precarious work but also of precarious housing. The new job market is characterized by a turn from security to insecurity (Kalleberg 2011). The new housing market is characterized by a drastic increase in rents, a decrease in new households receiving federal assistance, and low-income workers having to dedicate a large percentage of their income to housing costs (Schwartz 2010). The condition of working poverty today, then, is one of *double precarity* marked by insecure employment and insecure housing. Scholars speak of the "age of layoffs" (Uchitelle 2006:124) and the commonplace of evictions in distressed neighborhoods (Desmond 2012b:120). Could these events be connected?

This study investigates if low-income workers who were involuntarily removed from their homes—by eviction, landlord foreclosure, or housing condemnation—subsequently experienced an involuntary dismissal from their jobs. Applying matching techniques as well as discrete hazard models to novel survey data of low-income Milwaukee renters, we find forced removal to be a strong and robust predictor of job loss. Matching models show the likelihood of experiencing job loss to be between 11 and 22 percentage points higher for workers who experienced a preceding forced move. By showing that housing loss substantially increases the likelihood of job loss, this study identifies housing insecurity as an important source of employment insecurity among low-income workers. It is the first study to do so and is among the first efforts to document the effects of forced removal.[1]

THE COSTS OF LOSING A JOB

What are the costs of losing a job beyond the immediate and drastic loss of income? First, because prospective employers presume terminated workers to be unproductive or irresponsible, laid off workers commonly experience long stretches of unemployment (Gibbons and Katz 1991). This is especially true for less-educated workers seeking low-wage work (Kletzer 1998). Long spells of unemployment themselves can serve as a barrier to reentering the job market.

Job loss, additionally, brings about sizeable and durable earnings losses. Displaced workers who find new jobs on average earn roughly 17 percent less than they would have had they been continuously employed (Farber 2005; Ruhm 1991). More disconcerting is growing evidence that earnings losses of laid off workers are stubbornly resilient, persisting for as long as 20 years post displacement (Couch and Placzek 2010; Gangl 2006).

Job loss can foil attempts at asset building—especially if families drain their savings to survive unemployment spells (Mortensen 1986)—and can damage workers' mental and physical health and well-being (Linn, Sandifer, and Stein 1985; Paul and Moser 2009; Young 2012). Daniel Sullivan and Till von Wachter (2009) even link job loss to mortality, estimating a 10 to 15 percent increase in annual death hazards 20 years post displacement. If this increase is indefinitely sustained, it implies a 12- to 18-month loss of life for a worker let go at age 40.

DOUBLE PRECARITY

As the service sector has come to eclipse manufacturing, the United States has witnessed an increase in "bad jobs" offering low pay, no benefits, and little certainty (Herzenberg, Alic, and Wial 1998). Although no sector of the economy is untouched by precarious work, these "bad jobs" are disproportionately staffed by the working poor, whose numbers have been increasing since 1980 (Kalleberg 2011; Newman 1999). The precariousness of employment is due in part to the "financialization of the economy" (Davis 2009; Jung 2015), which has led to permanent terminations becoming "a basic component of employers' restructuring strategies" (Kalleberg 2008:5). The concurrent decline in

1 Important research documenting the effects of foreclosure on families and communities now is beginning to appear (e.g., Burgard, Seefeldt, and Johnson 2012; Currie and Tekin 2011), but very little is known about the consequences of eviction and other forms of involuntary displacement disproportionately experienced by low-income families.

union strength has only exacerbated this trend (Fantasia and Voss 2004). Yet these theories cannot fully address why employment instability has increased among certain members of the labor force: namely young men, the less educated, and African Americans (Neumark 2000). By one estimate, between 2001 and 2003, roughly 17 percent of workers with less than 12 years of schooling lost a job, compared to roughly 10 percent of those with at least 16 years of schooling (Farber 2005). And qualitative studies have described the jobs of the working poor as characterized by instability and high levels of churning (Ehrenreich 2010; Newman 1999).

But why are some low-wage workers fired while others are not? A recent review of the literature on employment instability calls for researchers to move beyond documenting the trend toward greater instability and to begin to study possible causes (Hollister 2011). We propose a novel factor contributing to the increased employment instability of low-wage workers. To address these questions, we examine dynamics taking place not within the low-wage labor market but within the low-income housing market.

Housing insecurity has risen in relative lockstep with employment insecurity. In the private rental market, where most low-income families live, affordable housing has shrunk dramatically. Median asking monthly rent increased by 70 percent from 1990 to 2006 (Downs 2008), years that saw far more modest gains in incomes at the bottom of the wage distribution. Meanwhile, the number of new households receiving federal subsidies plummeted to fewer than 3,000 in an average year between 1995 and 2007, compared to 161,000 in an average year between 1981 and 1986 (Schwartz 2010). Today, only 25 percent of households that qualify for housing assistance benefit from it (Rice and Sar 2009). As a result of these changes, rent burden among low-income households has surged. In 2013, the majority of poor renting families spent at least half of their income on housing costs, with almost a quarter dedicating over 70 percent to it (Desmond 2015). Alex Schwartz (2010:29) estimates that half of all American renters in the bottom quartile of the income distribution spend at least half of their income on housing costs.[2]

Many low-income workers dedicate most of their paychecks to rent and utilities. According to one study (Brennan and Lipman 2007), between 1997 and 2005 the number of low- to moderate-income working families who dedicated more than half of their income to housing costs increased by 87 percent. In 2010, one in four working renters spent more than half their income on housing costs (Williams 2012).

The concurrent escalation of both employment and housing insecurity means that many low-income workers today find themselves in a situation of double precarity: the job and the home are both on shaky ground. Worker protections have been rolled back since the 1970s, alongside tenant protections. Federal income-targeted housing subsidy programs have been reduced or eliminated, subsidized units have been lost without replacement, and rent control has been widely repealed (Bratt, Stone, and Hartman 2006; Marcuse and Keating 2006). And if layoffs have become a normal feature of precarious work, evictions have become a normal feature of precarious housing (Hartman and Robinson 2003).

In most American municipalities, landlords can evict tenants for any number of reasons (e.g., property damage, disturbing the peace), including a desire to use the property for other purposes (a "no fault" displacement). When landlords wish to begin formal eviction proceedings, they sue the tenant for the property and arrears in civil court; in most cities landlords may initiate the eviction process days after tenants have missed payments or otherwise violated the lease agreement. Indigent

2 The problem is not America's alone. Urban housing costs have risen around the globe, especially in "superstar cities" whose real-estate markets have experienced an influx of global capital, driving housing prices upward and crowding out low-income residents (Gyourko, Mayer, Sinai 2013). In London, the cost of an average house requires 20 years of the average British salary. In Lagos, Africa's largest city, 60 percent of all residents dedicate 50 to 70 percent of their monthly income to rent, even as the majority of the city's residents live in one-room dwellings. A recent report estimated that the global housing affordability gap amounts to $650 billion or 1 percent of the global GDP. Roughly 330 million urban households worldwide live in substandard or unaffordable housing demanding over 30 percent of their income (McKinsey Global Institute 2014).

tenants in the United States have no right to legal counsel in civil court. In some housing courts, then, most landlords have lawyers and most tenants do not, an imbalance that likely explains why in several cities the majority of tenants do not attend their court hearing and receive default eviction judgments (Engler 2010). When tenants receive an eviction judgment, they are ordered from their home by a set date. Many tenants move before the allotted date. If they do not, landlords may have the tenants removed by law enforcement officers, often accompanied by a moving crew who piles the tenants' belongings on the sidewalk or takes them to a storage facility. The entire process, from first eviction notice to removal by law enforcement officers, often takes a month, although in some cities it takes longer. For this reason, many landlords prefer to remove tenants themselves, executing "informal evictions" that take place outside the court. A recent study found that in Milwaukee there are two informal evictions for every formal one (Desmond and Shollenberger 2015).

Milwaukee sees 16 court-ordered evictions a day. One in 29 renter-occupied households in the city is evicted annually; in the predominately black inner city, that ratio jumps to 1 in 14 (Desmond 2012b). Milwaukee is no outlier. For example, in 2012, New York City courts hosted almost 80 nonpayment evictions a day. That same year, 1 in 9 occupied rental households in Cleveland, and 1 in 14 in Chicago, were summoned to eviction court (Desmond 2015).[3]

HOUSING LOSS AND JOB LOSS

Fully grasping the challenges faced by the working poor involves not only recognizing the coexistence of employment and housing instability but also examining their interrelationship. To further understand the double precarity of the working poor, this study investigates a possible link between arguably the two most consequential shocks related to employment and housing instability: involuntary housing loss and involuntary job loss.

Although forced moves may affect homeowners through foreclosure, in this article we focus on renters, who are at much higher risk of involuntary displacement.[4] Specifically, we examine if eviction and other involuntary moves from rented homes lead to job loss. Given the affordable housing crisis, many more families are in arrears than actually are evicted (Desmond 2012b). For families dedicating the majority of their income to housing costs, falling behind in rent does not require a major life event, like the death of a family member. Pedestrian expenses—a reduction in work hours, car repairs—can cause families to come up short with the rent. When this happens, landlords show considerable discretion over whom to spare and whom to evict (Lempert and Ikeda 1970), and extra-financial considerations, such as the presence of children in the household, can influence their decision (Desmond et al. 2013). These considerations, coupled with the frequency of eviction in low-income neighborhoods, reveal that many forced moves are not solely the result of tenants' behavior. And irrespective of its underlying cause, an involuntary move itself can be a consequential event. Forced removal has been linked to homelessness and material hardship (Burt 2001; Desmond and Kimbro 2015) as well as substandard housing and increased residential instability (Desmond, Gershenson, and Kiviat 2015).

Why might forced removal from housing lead to job loss? We propose that eviction temporarily diminishes the ability of many low-wage workers to perform at their jobs. Before we elaborate, let us stress two important contextual points. First, as noted above, many low-wage workers staff jobs that

3 Other countries have adopted landlord-tenant laws similar to those found in the United States, but the eviction process is markedly different. For example, with the Housing Act of 1988, the United Kingdom erased several eviction protections that stood for over a decade, but landlords are still required to give two-months notice, as opposed to the five-day notice required of landlords in many American cities. In France, landlords who wish to evict a tenant must hire *huissiers*, housing specialists who manage the process, which can stretch on for months through multiple court appearances and appeals. Crucially, too, in many countries outside the United States tenants facing eviction have the right to counsel (Lidman 2006). When tenants are represented, their chances of avoiding eviction increase significantly, regardless of the merits of their case (Pattanayak, Greiner, and Hennessy 2013; Seron et al. 2001).

4 According to the Department of City Development, approximately 16,000 Milwaukee property owners received foreclosure notices between 2008 and 2010. During that timespan, 36,434 eviction cases were filed against Milwaukee renter households. Even at the height of the foreclosure crisis, then, over two eviction cases were filed for every foreclosure notification.

do not offer paid leave, advanced scheduling notice, or many protections from termination (Kalleberg 2011). Such working conditions make it difficult to respond to life disruptions in a way that does not affect workplace performance. A more privileged worker might use a paid sick day to attend eviction court, but this option is not available to many low-wage workers. Second, involuntary displacement from housing often is a drawn-out process involving several trying events that take place before the actual moment of removal (e.g., multiple court appearances) and after it (e.g., homelessness, temporary shelter). The process of removal itself, from first eviction notice to relocating to a new apartment, can stretch over months (Desmond and Shollenberger 2015), during which time workers will be expected to perform adequately at their already tasking jobs that offer little room for error.

The period before the forced move—which may be characterized by conflicts with a landlord or lengthy encounters with the judicial system—can lead to workers making mistakes due to their preoccupation with non-work matters. After the forced move, workers may have to miss work to search for new housing. Owing to the stigma of an eviction, they may have increased search times. Many will ultimately settle for subpar housing and within a year will have moved again (Desmond et al. 2015). Forced moves can result in workers' relocating to less convenient locations, which may increase their likelihood of tardiness and absenteeism. If the renter has children, he or she may need to find childcare arrangements and acclimate their children to new schools. In the worst cases, forced moves lead to homelessness, the dissolution of families, and the loss of possessions (Burt 2001). These conditions could also impair job performance. The accumulated stress of all of these factors—beginning in the period before the eviction and persisting even after workers have found new lodgings—compromises workers' mental and emotional capacities. Indeed, research has shown that after eviction, renters report significantly higher rates of depression and parenting stress (Desmond and Kimbro 2015); and some studies have even linked eviction to suicide (Fowler et al. 2015). Each renter may experience a forced move differently, but all of these paths have the potential to lead to decreased job performance and, in some cases, job loss.

DATA

This article draws on the *Milwaukee Area Renters Study* (MARS), an original survey of 1,086 tenants in Milwaukee's private housing sector. MARS was designed (and later weighted) to facilitate estimates generalizable to Milwaukee's rental population. The sample was limited to people who were living in rental housing and who had not owned a home in the two years prior to being interviewed. English and Spanish surveys were administered in-person at tenants' places of residence between 2009 and 2011.[5] Households were selected through multi-stage stratified probability sampling. Drawing on Census data, Milwaukee block groups were sorted into three strata based on racial composition. Block groups were classified as white, black, or Hispanic if at least two-thirds of their residents identified as such. Then, each of these strata was subdivided into high- and moderate-poverty census blocks based on the overall income distribution of each racial or ethnic group in Milwaukee. Blocks were randomly selected from each of these six strata. Interviewers visited every household in selected blocks, saturating target areas. MARS has a response rate of 83.4 percent.[6]

5 Since this study took place in the wake of the foreclosure crisis and Great Recession, one may wonder if we observed more forced moves and layoffs than we would have in more prosperous times. With respect to forced moves, although foreclosures of rental property increased during the crisis (Been and Glashausser 2009), formal evictions in Milwaukee actually declined slightly after 2006 (Desmond 2012b). These opposing trends may somewhat cancel out one another. With respect to job loss, it is quite likely that some dismissals captured in the MARS survey may not have been observed in boom times. But layoffs and firings since the 1970s increasingly have become a routinized part of doing business, in good times and bad (Farber 2010; Kalleberg 2011). Low-income workers regularly lost their homes and jobs before the Great Recession, and they will face these hardships well after it. Nevertheless, the volatility of both the housing and labor markets during our study period is an important factor to bear in mind when interpreting our results.

6 For more information on MARS, see Desmond et al. 2015.

The median annual household income among MARS respondents was $25,003, considerably lower than that of the Milwaukee population ($35,851). Forty-four percent of MARS respondents were employed full time at the time of their interview; 20 percent were employed part time. The median annual income was $22,000 for full-time workers and $13,200 for part-time workers. The modal worker represented in the MARS data, then, is a member of the working poor.[7]

MARS collected a complete two-year retrospective residential history for each respondent. To prime memory, respondents were shown a two-year calendar and asked to provide their birthday and to name "two or three things that have happened in the past two years that really stand out." Then, going back two years, interviewers asked respondents to list "all the places [they had] lived or stayed for at least a month." Respondents were asked several questions about each residence, including why they moved from one place to another.

Measuring reasons for moving is not simple. When asked why they moved, tenants may respond in a way that maximizes their own volition or social desirability (Shepperd, Malone, and Sweeny 2008). As the first author learned while conducting fieldwork among low-income tenants (Desmond 2012a, 2012b), someone who was, say, evicted from a run-down apartment was more likely to explain that she moved "because the landlord wouldn't fix anything" than because she was forced out. Accordingly, to collect reliable data about the motivations for moving, interviewers asked each respondent a series of ordered yes/no questions, beginning with involuntary removals and ending with voluntary moves:

> An eviction is when your landlord forces you to move when you don't want to. Were you, or a person you were staying with, evicted?
>
> Did you, or a person you were staying with, [leave after receiving] an eviction notice?
>
> Did you move away from this place because your landlord told you, or a person you were staying with, to leave?
>
> Did you move away from this place because you, or a person you were staying with, missed a rent payment and thought that if you didn't move you would be evicted?
>
> Did you move away from this place because the city condemned the property and forced you to leave?
>
> Did you move away from this place because (a) the landlord raised the rent; (b) the neighborhood was dangerous; (c) the landlord wouldn't fix anything and your place was getting run down; (d) the landlord went into foreclosure?

If a respondent answered no to all of these questions, she or he finally was asked, "I see that none of these reasons fit your case. Why did you move away from this place?" We believe this approach minimized recall bias and allowed us to collect accurate data on the motivations for moves.

We consider a move to be "forced" if it was initiated by landlords or city officials (e.g., code inspectors) and involved situations in which tenants had no choice other than to relocate (or thought as much). Forced moves include formal evictions (which are processed through the court), informal evictions (which are not), landlord foreclosures, and housing being condemned.

Later in the survey, interviewers instructed respondents to again consider the two-year calendar, asking, "In the last two years, have you ever been laid off or fired from a job?" If respondents answered in the affirmative, they were asked how many times they had been laid off or fired and to provide the month and year of each instance. The phrasing of this question may have resulted in our collecting some instances of job loss attributed to the business cycle (as any alternative phrasing likely would have), but the bias is likely conservative and minor. It is conservative because if some proportion of the job loss we observed is attributed to market swings beyond the individual, then it is merely

7 All MARS figures in this paragraph are unweighted. Statistics about the entire Milwaukee population come from the 2010 U.S. Census.

introducing into our model variance that is unexplainable by our individual-level variable *forced move*. It is therefore likely minor because, were it not, we would not have consistently observed housing loss to be a statistically significant predictor of job loss.

Carefully collected retrospective data have been shown to be considerably accurate even for lengthy recall periods (Berney and Blane 1997; Haas 2007). Retrospective data are most reliable when they involve salient life events (Mathiowetz and Duncan 1988), are limited to a recent recall period (Beckett et al. 2001), and are collected with the aid of a memory prop (Sayles, Belli, and Serrano 2010). The retrospective data in our study meet these criteria. They focus on the memorable shocks of involuntary moves and job dismissals, are restricted to a two-year recall period, and were collected with a recent history calendar designed to prime memory. Accordingly, we believe our retrospective data to be of high quality.

METHODS

To estimate the effect of forced removal on job loss, we employed methods that reduce estimation bias caused by omitted variables, treatment selection, and effect heterogeneity. By collecting housing and employment data on a two-year retrospective timeline, we were able to observe the temporal ordering of job loss and forced removal and avoid the problem of reverse causality. Our data also allowed us to estimate the effects of involuntary job loss on forced moves. As we later discuss, these analyses help allay concern that our findings are spurious. We also employed two matching techniques that inform doubly robust regression models. As a final specification test, we used discrete hazard models with and without fixed effects to account for right censoring and omitted variable bias.

Because MARS is comprised of tenants who lived in non-owner-occupied housing in the two years prior to being interviewed, everyone in the sample was at risk of experiencing eviction, landlord foreclosure, or property condemnation during our timeframe. We restricted our analysis to respondents who were at risk of job loss (e.g., the employed) by including only those who indicated that they were working at some point in the previous year. This reduced the sample to 689 respondents.

Matching

To promote causal inference, we used two matching techniques. Matching improves balance through pruning observations for which there are no good comparisons and weighting those that remain, reducing estimation bias due to effect heterogeneity and model dependence in subsequent analyses on matched data (Ho et al. 2007; Morgan and Winship 2007). The first matching technique is nearest-neighbor matching (with replacement) on propensity scores.[8] Propensity scores are the estimated probabilities that each renter will experience a forced move. If treatment selection depends on the covariates used to estimate the propensity score, then samples balanced on propensity scores allow unbiased estimates of the average treatment effect for the treated (ATT) in expectation (Rosenbaum and Rubin 1983). The second technique is coarsened exact matching (CEM) (Blackwell et al. 2009; Iacus, King, and Porro 2012). Ideally, every treatment case would be matched with control cases with identical covariates; however, exact matching is near impossible when matching on multiple continuous covariates. CEM compromises by performing exact matches on *coarsened* covariates.[9] Weights were produced so that the sample is perfectly balanced in terms of these coarsened variables. In this study, we coarsened household structure and residential tenure before matching, choosing sample quartiles as cut points. We performed exact matches on all other variables mentioned below.

8 We used four nearest-neighbor matching because it produced the best sample balance statistics. However, our findings also are robust to specifications of (at least) one-, two-, three-, and five nearest-neighbor matching. Findings are also robust to the use of other distance metrics, as in Mahalanobi's nearest-neighbor matching.

9 For example, "residential tenure" could be coarsened into the response categories "1 to 6 months in current residence," "7 to 12 months," etc.

Because we wish to determine if forced removal predicts job loss, we first observed whether respondents experienced a forced move during the two-year retrospective calendar, placing those who did in the treatment group. Next, respondents who experienced job loss in the year-long period following that forced move were assigned a 1 on the job loss variable. We assigned respondents who did not experience a forced move to the control group. We assigned those members of the control-group who experienced job loss in the year preceding the interview a 1 on the job loss variable.[10]

We relied on previous research to select variables for matching. Because family structure is an important predictor of eviction (Desmond 2012b), we matched on respondent's gender, marital status, whether the respondent has children, and the number of other adults in the household from which the respondent was (or could have been) involuntarily removed. To account for possible racial discrimination in the housing and job markets (Massey and Lundy 2001; Zwerling and Silver 1992), we matched on respondents' race and ethnicity (African American, Hispanic, and other). We also matched on variables indicating a criminal record—one indicator for felonies and another for any criminal record—which can influence one's housing and job prospects (Pager 2007; Western 2006). To account for socioeconomic status, we matched on variables indicating whether the respondent has less than a high school degree, a high school degree, or some college education. We also matched on an integer variable measuring the number of months respondents lived in the residence from which they were (or could have been) involuntarily removed.[11]

We matched on two "shocks" that could lead to eviction and job loss. If the longer one works at a job, the less likely one will be involuntarily dismissed from it (Farber 1999), then a worker laid off from a previous job may be more likely to be laid off from a subsequent one. Job loss, then, may cause forced removal and subsequent job loss. Accordingly, we matched on *previous* job loss so as not to misattribute the effect of past dismissals to housing loss instead. Similarly, because job loss and a forced move might be brought about by relationship dissolution (Gorman 1999), we observed if respondents experienced the end of a (self-defined) "serious relationship." We observed previous job loss and relationship dissolution through variables that respectively take the value of 1 if a respondent lost a job or exited a relationship in the year preceding the first forced move observed in the retrospective calendar. If no forced move was observed, these variables respectively take the value of 1 if the respondent was laid off or exited a relationship in the first year of the retrospective calendar (between 13 and 24 months prior to being interviewed). Finally, we matched on age, as the elderly are at heightened risk of job loss (Chan and Stevens 2001).[12]

We estimated the average treatment effect for the treated (ATT) through "doubly robust regression," which uses weights produced by the matching techniques to further reduce estimation bias within a regression framework (Iacus et al. 2012:5). Doubly robust regression allows adjustment for imperfect covariate imbalance post matching. Our estimates are doubly robust in the sense that they will be unbiased if either the propensity score model or the outcome model is correctly specified (Stuart 2010). The consistency of our results across all estimates of the ATT demonstrates that our findings are robust to multiple modeling decisions.

We fit three regression models informed by propensity scores. These control for the same set of variables that were used to estimate the propensity score with two exceptions: tenure and number of adults in the residence from which the respondent was (or could have been) evicted. We also add a quadratic term for age. The first model conditions on the propensity score as a regressor, while the second model reweights observations with the inverse of the propensity score (Busso, DiNardo, and McCrary 2014). The third model is fit on all treatment cases and "matched" control cases; control

10 Using as a control group those who undertook voluntary moves, rather than those who *did not* experience a forced move, did not alter our findings. This indicates that it is *involuntary* mobility, not residential mobility per se, that leads to job loss.

11 If respondents did not experience a forced move, this variable measures how long they have lived in their current residence. An uninterrupted housing spell indicates that the respondent has a low latent propensity for forced removal.

12 We conditioned on age rather than restricting our sample to prime working-age adults (25 to 63). However, our models are robust to such a restriction.

cases are weighted to account for possible resampling (Leuven and Sianesi 2003). In the CEM doubly robust regressions, we regress job loss on the full set of matched variables, as this helps control for any remaining imbalance on the uncoarsened variables (Ho et al. 2007). CEM prunes control *and* treatment cases for which there are no good matches, ensuring that subsequent models are fit on samples sharing common support (Blackwell et al. 2009; Iacus et al. 2012). Because CEM prunes treatment cases, these regressions are fit on smaller samples than the other models reported below.

In the Appendix, we display summary statistics of our key variables (Table A1), the logistic regression model used to estimate propensity scores (Table A2), and balance statistics for variables included in the propensity score analysis (Tables A3 and A4). As displayed in Tables A3 and A4, bias was reduced substantially after matching on propensity scores. Figures A1 and A2 show substantial overlap in the distribution of propensity scores across treatment and control groups for the samples in Table 2. The degree of overlap is an important determinant of the relative performance of the reported estimators of the ATT (Busso et al. 2014).

Discrete Hazard Models

As a robustness check, we complemented matching analyses with discrete hazard models that allow for multiple "failures" (job losses) per respondent. Discrete hazard models enable us to account for unobserved heterogeneity among respondents through fixed-effects logistic regression models (Chamberlain 1980). In these models, the unit of observation is person-months, clustered within respondents, and our risk set is comprised of renters who either report current employment or who have been laid off within the previous two years. Respondents reenter the risk set after each job loss, unless they report no new job after the final layoff.

Our explanatory variable is having experienced a forced move in the year before the month of observation.[13] These models control for whether respondents experienced job loss or exited a serious relationship in the year before the month of observation. Additionally, models control for the number of months since the respondent was previously laid off. In order for the latter quantity to be knowable, respondents must have been fired at least once in the two years prior to being surveyed. Accordingly, we excluded from these models both the long-term employed and those with no work experience prior to their current job. As a sensitivity analysis, we also estimated a discrete hazard model with the time-invariant covariates included in our matching estimates and regressions in lieu of fixed effects, allowing us to retain a larger sample of the newly employed.[14]

These discrete hazard models were fit on smaller samples than were the regression models described above. Also, the respondents in these samples are the "newly employed," and so represent an even less stable population than that targeted by the full models. As such, we advise caution when interpreting findings from our hazard models. Nonetheless, we present these models to demonstrate the robustness of our findings to various modeling decisions.

RESULTS

Almost 20 percent of our full weighted sample experienced job loss at least once in the two years prior to being interviewed. Among those, 15 percent had been laid off or fired two or more times during this time period. Roughly 19 percent of our full weighted sample experienced at least one forced move in the two years prior to being interviewed. Among those, 35 percent experienced two or more

13 A 12-month observation window has the advantage of netting out any seasonal fluctuations in housing and labor markets, e.g., evictions spike in the summer (Desmond 2012b) and job loss among low-wage workers is more common in the winter, when construction jobs disappear and retail slows down after the holiday rush. Our findings are robust to other time windows as well.

14 We examined whether our findings were sensitive to assumptions about time-to-reentry (after job loss) for the risk set. We tested this by dropping observations from one to four months after the respondent experienced job loss (thereby increasing the chances that the respondent was working again). The forced move coefficient remained significant when dropping from 1 to 4 months. These tests suggest that our findings are not an artifact of our sample.

forced moves. The most common type of forced move in our sample (42 percent) was court-ordered formal eviction, followed by informal evictions (28 percent) (landlord-initiated but not court-ordered involuntary removals) and foreclosures of rental property (22 percent). Seven percent of forced moves were housing condemnations, and 2 percent involved a family missing a rent payment and moving in anticipation of eviction.

Both involuntary job loss and housing loss were found to be common events in the lives of Milwaukee working renters. Roughly 42 percent of those who lost a job in the two years prior to being interviewed also experienced a forced move. We now report evidence suggesting that housing loss regularly leads to job loss.

Doubly Robust Regressions

Table 1 displays three logistic regression models. The first includes the propensity scores as a covariate while the second reweights observations using the inverse propensity score. In these models—which were fit on the full sample—involuntary housing loss is a statistically significant predictor of job loss, even after accounting for the propensity for forced removal from housing. These findings were reproduced in Model 3, which displays the doubly robust logistic regression performed on a sample matched by propensity scores. Because of the matching process in Model 3, only the forced move coefficient is substantively meaningful.

For ease of interpretation, we estimated the average marginal effect of forced removal on job loss. This quantity was calculated using the observed values of covariates and the estimated coefficients from the logistic regression models. The probability of job loss was calculated twice for each respondent: once while assuming she has experienced a forced move, and again while assuming she has not. The difference between these two estimates is the individual-level "marginal effect" of housing loss on job loss (Bartus 2005). We calculated the average marginal effect by averaging this quantity across all respondents. For Model 1, the average increase in probability of job loss given housing loss is .11; for Model 2 it is .13; and for Model 3 it is .15. These estimates are similar to the matching estimator of the ATT, which is the difference in means between treatment and control groups (ATT = .140; $p = .022$). In other words, forced removal increases low-income workers' chances of experiencing job loss by 11 to 15 percentage points. We show the robustness of these findings to alternate matching algorithms in Table 2, which displays regression models estimated on data matched by CEM.[15]

Our CEM regressions affirm the robustness of our finding that forced removal is a significant predictor of job loss. The average marginal effect of housing loss on job loss probabilities is .22. That is, we expect a forced move to increase the chances that a typical respondent loses his job within a year by around 22 percentage points. In our matched sample, workers who did not experience a forced move had about a 1 in 6 chance of losing their job; those who did had nearly a 1 in 3 chance.

Sensitivity Analysis: Discrete Hazard Models

To account for possible unobserved heterogeneity across respondents, we employed fixed-effect discrete hazard models with repeat failures. We also estimated a discrete hazard model on a larger sample while controlling for the time-invariant controls used in the matching analyses.

Table 3 displays three discrete hazard models. Model 1 documents a substantively large and statistically significant effect of housing loss on job loss. Model 2 includes two other time-variant shock variables: prior job loss and relationship dissolution. Here, the coefficient for forced removal retains its size and significance, while the other two shocks exert no statistically significant effects on job loss.

15 Multivariate balance was measured by the L1 statistic (using the Scott method for breaks) with lower values representing greater multivariate balance (Blackwell et al. 2009). The unmatched data have an L1 of .874. We tried multiple CEM specifications, and report results in Table 3 from a doubly robust regression fit on a sample with an L1 of .439. This was among the lowest L1 statistics that we were able to achieve without undue loss of observations; this indicates that the matched sample has substantially better balance than the original sample. This is not surprising, since CEM achieves exact matches on all non-continuous variables.

Table 1. Logistic Regression Predicting Job Loss with Propensity Score Matching

	Model 1		*Model 2*		*Model 3*	
	Coef.	*SE*	*Coef.*	*SE*	*Coef.*	*SE*
Forced move	.725*	.284	.821*	.321	1.018**	.357
Previous job loss	.398	.410	.464	.456	2.430**	.753
Relationship dissolution	.134	.348	−.061	.436	−.527	.854
Female	.163	.247	.260	.288	.634	.487
Married	−.208	.336	−.242	.370	.118	.604
Children	1.153***	.352	1.615***	.399	2.423*	1.167
Black renter	−.310	.295	−.438	.348	−.472	.561
Hispanic renter	−.255	.338	−.264	.421	−.374	.612
Other ethnicity renter	1.186*	.475	1.003	.556	.059	.837
Criminal record	−.254	.496	−.084	.511	−.142	.707
Felony record	.974	.554	.875	.601	.322	.814
Less than high school	.180	.515	−.380	.527	.569	.837
High school/GED	.455	.418	−.072	.460	1.031	.806
Some college	.420	.406	.034	.442	.278	.778
Age	−.030	.072	−.043	.085	−.071	.149
Age squared	.000	.001	.000	.001	.001	.002
Propensity for forced move	−.505	1.760				
Constant	−2.090***	1.324	−1.797*	1.579	−3.928*	2.630
N	624		624		271	
Pseudo R^2	.074		.081		.165	

Notes: Model 1 includes propensity score as a regressor. Model 2 reweights observations with the inverse propensity score. Model 3 is fit only on nearest-neighbor matched sets. SE = robust standard errors.
*$p < .05$ ** $p < .01$ *** $p < .001$ (two-tailed tests)

These fixed-effect discrete hazard models indicate that our finding identifying forced removal from housing as a robust predictor of job loss is not due to respondents' unobserved time-invariant characteristics.

To ensure the findings of our discrete hazard models are not an artifact of sample selection, we estimated the discrete hazard model with a full set of time-invariant covariates. We received a nearly identical estimate for the coefficient of forced removal (Model 3).[16] Comparing the results of these discrete hazard models to those of the doubly robust regressions, we see a remarkably stable estimate of the effect of housing loss on job loss.

Does Job Loss Cause Housing Loss?

We also ran our models in reverse to investigate the effects of job loss on housing loss. After employing analyses similar to those reported above, we found some evidence that job loss brings about forced removal from housing. For example, in discrete hazard models predicting job loss with controls similar to those in Model 3 of Table 3, the effect of job loss on housing loss is statistically significant, but only a tenth of the estimated size of the effect of housing loss on job loss. The weight of the evidence suggests that the disruptive effects of housing loss on job loss are considerably greater than the reverse.

16 Findings in this section were robust to estimation using fixed-effects linear probability models (see Klaassen and Magnus 2001).

Table 2. Logistic Regression Predicting Job Loss with Coarsened Exact Matching (CEM)

	Coef.	*SE*
Forced move	1.667***	.521
Previous job loss	.507	1.509
Relationship dissolution	−.110	1.045
Female	−1.287	.835
Married	.636	1.534
Children	.473	1.357
Black renter	2.518	1.780
Hispanic renter	2.203	1.948
Other ethnicity renter	1.200	2.141
Criminal record	.089	1.091
Felony record		
Number of other adults	−.543	.436
Less than high school	14.394***	2.088
High school/GED	14.426***	1.863
Some college	14.338***	1.796
Age	−.375	.222
Age squared	.006	.003
Months since move	.005	.007
Constant	−12.333**	4.157
N	136	
Pseudo R^2	.196	

Notes: Felony record was dropped due to multicollinearity. The model displayed here is estimated on a model that did not match on age, as this resulted in a smaller sample ($n = 78$). Nonetheless, our estimate of the effect of forced moves is robust to matching on age ($b = 1.548$; $p = .029$). SE = robust standard errors.
$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$ (two-tailed tests)

Examining the reasons renters experienced a forced move helps to reveal why this is the case. Almost half of forced moves we captured had little to do with tenants' incomes being too low or their rent being too high. They were attributed, rather, to landlords either exerting control over their property—by removing tenants for nonmonetary reasons or allowing their property to fall into disrepair—or losing control of their building to a lending institution via foreclosure. In many of these cases, tenant poverty or unemployment was not the decisive factor.

Moreover, respondents did not frequently identify job loss as the reason for their missing payments that result in their being involuntarily forced from housing. Roughly half of forced moves resulting from missed payments were attributed to income losses. Some respondents mentioned being laid off or having their work hours reduced, but more commonly they observed that their housing situation was financially unsustainable from the start, as with extremely rent-burdened households. An additional quarter of forced moves resulting from missed payments involved tenants purposefully withholding rent because the landlord would not address housing problems or to save money for another apartment. Nine percent were due to rent hikes, and another 7 percent involved renters incurring unexpected expenses (e.g., funeral, medical bills).

These findings increase our confidence that our main finding is not spurious. Even after considering our methods—which address effect heterogeneity, reverse causality, unobserved heterogeneity, and account for several life shocks—one may still wonder if what we have observed is not a causal relationship between housing loss and job loss but the clustering of negative events owing to some unobserved event or based on the presumption that the kind of people who lose their jobs are the

Table 3. Discrete Hazard Models of Job Loss

	Model 1		*Model 2*		*Model 3*	
	Coef.	*SE*	*Coef.*	*SE*	*Coef.*	*SE*
Forced move	.970***	.273	.995**	.305	1.597***	.427
Previous job loss			−.118	.371	.962	.522
Relationship dissolution			−.456	.920	.666	.734
Female					1.014	.732
Married					.660	.678
Children					.568	.697
Black renter					−.420	.847
Hispanic renter					.026	1.024
Other ethnicity renter					−.140	1.133
Criminal record					1.192	.703
Felony record					−.670	.711
Number of other adults					.378	.286
Less than high school					−1.181	.869
High school/GED					−1.379*	.607
Some college					−1.170	.781
Age					−.042	.208
Age squared					.001	.003
Months since job loss					−.012	.043
Constant					−4.585	3.492
N	466		466		1,306	
N (groups)	36		36		111	
Pseudo R^2	.300		.301		.113	

Notes: Models 1 and 2 use conditional (fixed-effects) logistic regression models.
$^*p < .05$ $^{**}p < .01$ $^{***}p < .001$ (two-tailed tests)

kind that lose their homes. Yet we found strong effects in one direction but weak to null effects in the opposite direction. The ordering of events matters, indicating that we have observed something more than the clustering of negative events owing to unobserved events or renters' latent behavioral traits.

DISCUSSION

Poverty researchers interested in labor market dynamics primarily have focused on two major problems: unemployment and underpaid employment. To address chronic joblessness in disadvantaged neighborhoods, researchers have proposed various strategies for bringing jobs back to the inner city (Porter 1995; Wilson 1996). To address insecurity and poor labor conditions, researchers have proposed increasing the minimum wage, strengthening wage subsidies, and helping low-wage workers unionize (Shulman 2007; Uchitelle 2006).

Much less attention, however, has been dedicated to developing effective policies designed to help those who have a job keep it. Job loss can lead to prolonged unemployment (Kletzer 1998), push workers into insecure jobs (Farber 2005), result in long-term earnings losses (Couch and Placzek 2010), and compromise physical and mental health (Paul and Moser 2009). Accordingly, fostering conditions that would facilitate continual employment would promote economic stability and well-being among low-income working families. Identifying the causes of job loss is a necessary prerequisite to developing effective policy solutions; yet social scientists have dedicated scant attention to documenting why low-income workers lose their jobs.

This study addresses this lacuna by investigating if involuntary housing loss brings about job loss. Undergoing a forced move can consume renters' time and cause them to miss work; consume their thoughts and cause them to make mistakes on the job; overwhelm them with stress and cause them to act unprofessionally in the office; result in their relocating farther away from their worksite and increase their likelihood of tardiness and absenteeism; and lead to homelessness, relationship dissolution, and other severe consequences. These conditions can impair the job performance of low-wage workers already staffing precarious positions with little security or protections.

We find, first, both job loss and forced removal from housing to be common events in the lives of low-income working renters in Milwaukee. We calculated that roughly one in five working renters involuntarily lost a job two years prior to being interviewed; in the same timespan, roughly one in five also involuntarily lost a home. Applying a variety of statistical techniques on novel retrospective data of working renters in Milwaukee, this study provides evidence that housing loss leads to a substantial increase in the probability of job loss. We estimate the likelihood of experiencing job loss to be between 11 and 22 percentage points higher for workers who experienced a preceding forced move, compared to observationally identical workers who did not. When we examined the effects of forced removal for respondents with relatively stable work histories and those with unstable employment, we found forced removal to be an actuator of job loss for both groups.[17] This suggests, troublingly, that forced removal leads to job loss even among stably employed workers and that double precarity is not a condition restricted only to already unstable, short-term employees. Furthermore, fixed-effect discrete hazard models show our results to be robust to omitted variable bias. And our finding that job loss is a weaker predictor of housing loss than vice versa further supports our conclusions. Because sequence matters, we are more confident that the observed relationship between housing loss and job loss is not spurious.

Before discussing the implications of our results, let us mention this study's context and some limitations. First, this study took place in Milwaukee. In its socioeconomic profile, Milwaukee is a fairly typical Midwestern city, one marked by a steady erosion of economic prosperity since the 1970s, owing to the flight of manufacturing jobs from the central city and the rise of racially segregated neighborhoods (Trotter 2007). Milwaukee's racial composition, population, median rent, and unemployment rate is similar to those of many other midsize American cities (Department of Housing and Urban Development 2009; Pager 2007). Renters occupy 52 percent of Milwaukee's housing units; many cities—e.g., Chicago, Houston, Baltimore—have similar proportions of renter-occupied households (National Multi Housing Council 2009). Housing and eviction laws vary widely from city to city. Cities with a stalwart tradition of tenant unionizing as well as those with an economically diverse rental population, like New York, tend to boast of toothier tenant protections than those, like Milwaukee, in which most middle-class households own their homes. We suspect most cities' renter protections resemble Milwaukee's more than New York's. Nevertheless, the extent to which these findings apply to settings beyond Milwaukee must be judged by future research.

Another consideration has to do with unobserved life shocks. The MARS data allow us to account for multiple disruptive events (e.g., previous job loss, relationship dissolution), but they do not record all possible consequential shocks. Particularly, the data do not allow us to control for pre-treatment "health shocks" potentially associated with housing loss, job loss, or both. A pair of considerations, however, suggests that our findings are not attributed to unobserved health shocks. First, if unobserved health shocks were the root cause of our findings, we would expect respondents' health status to alter our results. But when we controlled for health status with measures of current physical health, mental health history, and cancer history—included both in our doubly robust regressions and in our propensity score matching algorithm—we arrived at similar results (available upon request). Second, as mentioned above, forced moves are a much stronger predictor of involuntary job loss than vice

17 The discrete hazard models were restricted to renters with *unstable* employment histories, while Table A3 shows that the doubly robust regressions primarily featured renters with relatively *stable* pre-treatment employment histories.

versa. If the link between housing and job loss were in fact attributable to unobserved health shocks—or any unobserved life shock, for that matter—we would not have found the temporal ordering of events to be so crucial.[18]

We believe our study holds important implications for social science and policy. This study is the first to present evidence showing that low-wage workers who involuntarily lose their housing are much more likely subsequently to lose their jobs. In so doing, it contributes to the neglected work of identifying the consequences of eviction and other forms of forced displacement disproportionately experienced by low-income families. As severe housing burden among low-income households continues to rise, involuntary removal is likely to increase. If eviction is becoming a common moment in the life course of the urban poor (Desmond 2012b; Hartman and Robinson 2003), social scientists must rigorously identify its ramifications. Understanding how forced removal affects the life chances of low-income households—investigating its effects on families, children, and neighborhoods—would deepen our knowledge of the mechanisms of health and economic disparities and would help to reveal the lived experienced of American poverty today.

This study identifies involuntary displacement as a previously overlooked mechanism of social stratification. Forced removal from housing may serve as a crucial turning point in the lives of poor working families, with eviction leading to job loss, which in turn can result in durable earnings losses and nontrivial negative health outcomes. The outlook is particularly troubling for African Americans, who not only are disproportionately evicted (Desmond 2012b) but who also face considerable discrimination in both the labor and housing markets (Pager and Shepherd 2008). In other words, previous research would lead us to suspect that the group with comparatively high rates of involuntary displacement from housing is likely also the group for whom the effects of displacement are most acute, manifest in elongated search times to secure new housing and, should job loss follow eviction, new employment.

Our findings indicate that to fully understand the trajectories of low-income workers, we not only should examine dynamics related to neighborhoods (Wilson 1996) and precarious work (Kalleberg 2011), but also those related to *housing*, eviction and other forced moves being among the most consequential of them. This article, then, emphasizes the need for social scientists to more thoroughly examine the relationship between employment and housing insecurity. The perspective of double precarity holds three broad implications for students of inequality. First, important sources of social disadvantage in one realm (e.g., the labor market) may often be found in another (e.g., the housing market). Second, a comprehensive analysis of poverty cannot focus narrowly on income, as is the convention; it must also account for the expenses of low-income families, housing often taking the largest piece of the pie. This raises a third implication: the need to pull housing—and the private rental market in particular—back to the center of the poverty debate.

Our findings suggest that for those low-income workers in Milwaukee who are experiencing housing instability, poor performance on the job may have less to do with inherent ineptitude than with the temporary disruption caused by their living situation. This means layoffs owing to involuntary moves are inefficient from an employer's perspective—and hence costly. When employers dismiss those who recently experienced a forced move, they often unnecessarily lose their investment in those workers and must expend more resources hiring and training new employees. Businesses with high turnover rates increase their likelihood of failure and decrease the quality of their labor force (Lane 2000). When employers repeatedly dismiss not characteristically bad workers but temporarily bad workers who recently experienced the trauma of a forced move, they may contribute to destabilizing and deskilling their labor force, thereby potentially locking both capital and labor into a suboptimal equilibrium.

18 Similarly, we examined two other potentially consequential events—becoming homeless and first conviction—but they were too rare to be controlled for in our models. Instead, we replicated our models on a sample that excluded renters who had experienced either of these events ($n = 13$). Doing so did not substantially alter our findings.

Policy makers looking to expand opportunity for working Americans often overlook housing, choosing instead to focus on expanding access to education or raising wages. But if housing instability begets employment instability, then policy makers seeking to increase job security should focus on ways to promote housing stability. Our findings suggest that such initiatives would be most effective if they not only controlled costs but also provided families more influence over their living arrangements. These might include programs designed to expand access to homeownership for working families or to incentivize landlords to offer long-term, fixed-rent leases. Such initiatives are worth pursuing because providing decent, affordable, and stable housing is a human capital investment analogous to education or job training, one that could strengthen and steady the American workforce.

APPENDIX

Table A1. Descriptive Statistics for the At-Risk Subsample

Variable	*Mean*	*SD*	*Min.*	*Max.*	*Obs.*
Job loss	.181		0	1	679
Forced move	.144		0	1	688
Previous job loss	.069		0	1	679
Relationship dissolution	.125		0	1	673
Female	.590		0	1	687
Married	.155		0	1	683
Children	.651		0	1	688
Black renter	.429		0	1	687
Hispanic renter	.183		0	1	687
Other ethnicity renter	.042		0	1	687
Criminal record	.159		0	1	686
Felony record	.081		0	1	682
Number of other adults	.693	.835	0	5	674
Less than high school	.158		0	1	683
High school/GED	.341		0	1	683
Some college	.332		0	1	683
Age	35.303	11.200	15	70	683
Months since move	40.007	57.606	0	635	675

Notes: In this table, the variable for job loss represents having experienced job loss in the year following a forced move or (if respondents did not experience a forced move) in the second year of the retrospective calendar. These statistics are unweighted, and should be viewed as descriptive of our estimation sample, not of Milwaukee's renter population. The estimation sample contains all MARS respondents who were determined to have been employed during the year prior to the interview.

Table A2. Logistic Regression Predicting Propensity for Forced Removal

	Coef.	*SE*
Previous job loss	−.483	.570
Relationship dissolution	−.345	.417
Female	.191	.290
Children	.554	.355
Married	−.529	.413
Black renter	.144	.339
Hispanic renter	.115	.416
Other ethnicity renter	.210	.690
Criminal record	.982*	.440
Felony	−.726	.568
Number of other adults	.090	.156
Less than high school	1.068†	.568
High school/GED	.797	.518
Some college	.547	.515
Age	.131	.090
Age squared	−.002	.001
Months since move	−.020***	.006
Constant	−5.066***	1.682
N	624	
Pseudo R^2	.095	

†$p < .10$ *$p < .05$ **$p < .01$ ***$p < .001$ (two-tailed tests)

Table A3. Covariate Balancing in Unmatched and Matched Samples from Propensity Score Matching

Variable	*Sample*	*Treated*	*Control*	*Bias (percent)*	*Reduced (percent)*	T	P
Previous job loss	Unmatched	.052	.075	−9.4		−.73	.466
	Matched	.052	.045	2.7	71.8	.19	.853
Relationship dissolution	Unmatched	.104	.130	−8.0		−.64	.523
	Matched	.104	.091	4.0	49.9	.27	.787
Female	Unmatched	.649	.585	13.2		1.08	.283
	Matched	.649	.614	7.3	44.5	.46	.649
Married	Unmatched	.117	.161	−12.7		−1.00	.319
	Matched	.117	.117	.0	100	.00	1.000
Children	Unmatched	.792	.627	36.9		2.85	.004
	Matched	.792	.799	−1.5	96.1	−.10	.921
Black renter	Unmatched	.506	.411	19.1		1.58	.114
	Matched	.506	.513	−1.3	93.2	−.08	.936
Hispanic renter	Unmatched	.208	.177	7.7		.65	.517
	Matched	.208	.192	4.1	46.7	.25	.803
Other ethnicity	Unmatched	.039	.044	−2.5		−.20	.843
	Matched	.039	.032	3.2	−32.1	.22	.829
Criminal record	Unmatched	.234	.143	23.4		2.08	.038

(continued)

Table A3. Continued

Variable	*Sample*	*Treated*	*Control*	*Bias (percent)*	*Reduced (percent)*	T	P
	Matched	.234	.201	8.3	64.4	.49	.628
Felony record	Unmatched	.117	.080	12.2		1.07	.284
	Matched	.117	.107	3.3	73.3	.19	.849
Number of other adults	Unmatched	.753	.698	5.5		.54	.590
	Matched	.753	.753	.0	100	.00	1.000
Less than high school	Unmatched	.234	.146	22.4		1.98	.048
	Matched	.234	.201	8.3	62.9	.49	.628
High school/GED	Unmatched	.377	.333	9.2		.76	.447
	Matched	.377	.445	−14.2	−55.3	−.86	.393
Some college	Unmatched	.312	.335	−4.9		−.40	.690
	Matched	.312	.279	6.9	−42.0	.44	.661
Age	Unmatched	34.844	35.356	−4.8		−.38	.708
	Matched	34.844	35.214	−3.5	27.8	−.23	.815
Months since move	Unmatched	21.636	43.430	−48.4		−3.11	.002
	Matched	21.636	20.971	1.5	96.9	.20	.840

Table A4. Overall Covariate Balancing in Matched and Unmatched Samples from Propensity Score Matching

Sample	*Pseudo* R^2	*LR Chi*^{2}	$p >$ *Chi*^{2}	*Mean Bias*	*Median Bias*
Unmatched	.090	42.01	.000	15.0	10.8
Matched	.009	1.85	1.000	4.4	3.4

Notes: The pseudo R^2, LR Chi^2, and $p >$ Chi^2 statistics refer to a logistic regression model containing all of the variables in Table A3 and fit on matched and unmatched samples. The LR Chi^2 and $p >$ Chi^2 are test statistics for the global null hypothesis that the coefficients for these variables are all simultaneously equal to 0 (Leuven and Sianesi 2003). Accordingly, the low pseudo R^2 indicates that control variables have nearly no ability to predict treatment assignment in the matched sample. The low Chi^2 test statistic indicates the improbability of rejecting the global null hypothesis for the matched sample. Thus, the statistics in this table indicate a well-balanced sample with only insubstantial bias remaining. (The term "bias" refers to standardized differences in the means of conditioning variables.)

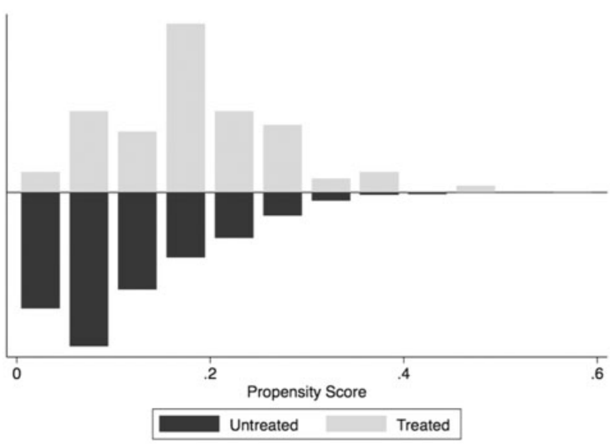

Figure A1. Frequency of Observations in Treatment and Control Groups across Estimated Propensity Score, Full At-Risk Sample

Notes: This figure shows a sufficient amount of common support between treatment and control groups in the full sample. Common support is an important determinant of the performance of estimators of the ATT (Busso et al. 2014).

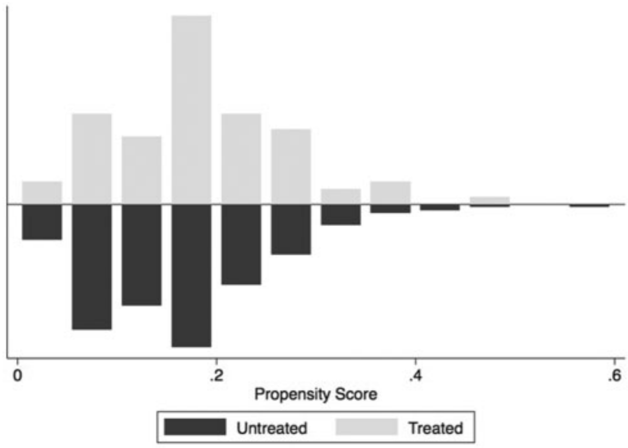

Figure A2. Frequency of Observations in Treatment and Control Groups across Estimated Propensity Score, Matched Sample

Notes: This figure shows a sufficient amount of common support between treatment and control groups in the full sample. Common support is an important determinant of the performance of estimators of the ATT (Busso et al. 2014).

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