Housing Voucher Take-Up and Labor Market Impacts

Eric Chyn
Joshua Hyman
Max Kapustin

Abstract

Low participation rates in government assistance programs are a major policy concern in the United States. This paper studies take-up of Section 8 housing vouchers, a program in which take-up rates are quite low among interested and eligible households. We link 18,109 households in Chicago that were offered vouchers through a lottery to administrative data and study how baseline employment, earnings, public assistance, arrests, residential location, and children's academic performance predict take-up. Our analysis finds mixed evidence of whether the most disadvantaged or distressed households face the largest barriers to program participation. We also study the causal impact of peer behavior on take-up by exploiting idiosyncratic variation in the timing of voucher offers. We find that the probability of lease-up increases with the number of neighbors who recently received voucher offers. Finally, we explore the policy implications of increasing housing voucher take-up by applying reweighting methods to existing causal impact estimates of voucher receipt. This analysis suggests that greater utilization of vouchers may lead to larger reductions in labor market activity. Differences in take-up rates across settings may be important to consider when assessing the external validity of studies identifying the effects of public assistance programs.

INTRODUCTION

Low participation rates in government assistance and benefit programs are a major policy concern in the United States (Currie, 2006). Estimates suggest that the take-up rate is 8 to 14 percent for the State Children's Health Insurance Program (LoSasso & Buchmueller, 2004), 69 percent for Food Stamps (Currie, 2006), and 75 to 85 percent for the Earned Income Tax Credit (EITC) (Bhargava & Manoli, 2015; IRS, 2002; Scholz, 1994). Low take-up can undermine the effectiveness of government policies by decreasing the likelihood that benefits reach certain types of eligible households.

One large social program with historically low rates of take-up is tenant-based rental housing assistance, commonly referred to as the Section 8 housing voucher program. In 2011, the federal government provided two million families with Section 8 assistance at a cost of over \$18 billion, approximately equal to expenditures on Temporary Assistance for Needy Families (TANF) (Falk, 2012; NCSHA, 2011). Despite the prevalence of this program, voucher take-up tends to be low, particularly in large cities where the lease-up rate is often near 50 percent (Finkel & Buron, 2001; Mills et al., 2006; Sanbonmatsu, 2011).

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This low take-up rate is surprising for two reasons. First, housing assistance is among the most generous U.S. social programs. In 2013, the average annual gross income of a family receiving a voucher was just over $13,000, while the average annual housing subsidy was worth almost $8,000, and as much as $12,000 in higher cost-of-living cities (Collinson, Ellen, & Ludwig, 2016). Second, unlike many other means-tested social programs, housing assistance is not an entitlement. Hence, the low take-up rate for Section 8 is among those eligible families who are aware of and sufficiently motivated to apply for assistance. One reason the low take-up rate may not be surprising is that successful voucher take-up requires landlord participation. In this way, participation in Section 8 is unlike the decision to take up other social benefit programs such as TANF or EITC.

In this paper, we answer two research questions. First, what are the predictors of successful lease-up when a household is offered a housing voucher? The answer is of practical importance to the Department of Housing and Urban Development (HUD) and local Public Housing Authorities (PHAs). Housing authorities often allocate vouchers through lotteries, suggesting policymakers prefer that all eligible households have an equal chance of receiving assistance. Yet, if the families that successfully lease up are the most advantaged of those offered a voucher, then the program may not be reaching those households that could benefit most from assistance. Identifying factors that predict lease-up can help eliminate impediments to their participation.

Our second research question relates to a literature seeking to understand the representativeness of experimental treatment effect estimates (Allcott, 2015; Andrews & Oster, 2017; Bisbee et al., 2017; Chyn, 2018). We ask: How would the labor market effects of housing assistance change if voucher take-up rates increased? Mills et al. (2006) and Jacob and Ludwig (2012) measure the effects of housing assistance on labor supply in settings where households were randomly chosen to receive a voucher offer. However, their estimates provide the causal effect of vouchers only among families in their sample who "comply" by successfully leasing up if offered a voucher (Angrist, Imbens, & Rubin, 1996). If the effects on labor supply among complier households differ from those that would occur among non-complier households, potential efforts to bolster take-up may either exacerbate or diminish the average impact of vouchers. We extend the analysis of voucher effects from Jacob and Ludwig (2012) by providing new estimates using weights based on observed compliance patterns. Our approach scales up the treatment effects for compliers who are observationally similar to non-compliers so that our estimates represent the effect of vouchers on the entire population of voucher-seeking households.

To address these two questions, we study take-up in the context of a housing lottery in Chicago where authorities offered Section 8 vouchers to 18,109 households from 1997 to 2003. This setting provides several advantages relative to previous studies of voucher take-up (Finkel & Buron, 2001; Mills et al., 2006; Shroder, 2002). One advantage is that our sample is considerably larger than in prior studies.[1] Hence, we may be able to detect effects with greater statistical precision. Next, we are able to link household members to administrative data on income, arrests, public assistance usage, residential location, and children's academic performance. This allows us to examine lease-up behavior in greater detail. Finally, a distinguishing feature of our work is that our sample primarily lived in private housing at baseline. By contrast, Shroder (2002) studied individuals living in public housing who received a voucher through the Moving to

[1] For example, the sample sizes in Finkel and Buron (2001), Mills et al. (2006), and Shroder (2002) are 2,609, 4,650, and N = 1,308, respectively.

Opportunity (MTO) voucher experiment. The distinction is meaningful for two reasons: one, the value of a housing voucher varies based on whether the family is living in private or public housing; and two, the experience of Chicago, where the overwhelming majority of families applying for housing vouchers live in private housing, is increasingly the norm. Nevertheless, we acknowledge that the evidence presented here is from one major city during a short period of time, limiting its generalizability.

Our analysis of the predictors of housing voucher take-up provides mixed evidence on whether the most disadvantaged households are the least likely to use a voucher. On the one hand, household head employment prior to receipt of a voucher is extremely predictive in our sample: those who worked are 24 percentage points more likely to lease up after controlling for other observed characteristics. We also find that household heads arrested within the two years prior to receiving a voucher offer are nearly 7 percentage points less likely to lease up. On the other hand, among the approximately 60 percent of the sample who are employed prior to voucher offer, those with higher earnings are less likely to lease up, possibly because they face both larger time costs of search and a lower subsidy dollar value. We also find that families whose children are performing worse in school are more likely to lease up. In addition to these findings, we also observe that lease-up varies non-trivially by season, such that offering vouchers only during high lease-up months of the year could increase overall take-up rates by 5 percent. In our sample, the predictors of lease-up are very similar between the households living in private and public housing at baseline.

We also estimate impacts of neighborhood peer behavior on lease-up. Specifically, we test whether an individual is more likely to lease up if their Census block group neighbors recently received housing voucher offers. We interpret the results from this analysis as causal estimates since the timing and location of voucher offers is random after conditioning on the number of nearby voucher applicants. Our results show that households that had one additional neighbor who recently leased up were nearly 3 percent more likely to lease up themselves. These estimates add to recent evidence that social interactions with neighbors may influence where voucher users choose to live (Ellen, Suher, & Torrats-Espinosa, 2018), and complement a broader literature that shows peers affect program take-up (Aizer & Currie, 2004; Dahl, Loken, & Mogstad, 2014; Duflo & Saez, 2003; Figlio, Hamersma, & Roth, 2015).

Finally, with regard to our second research question, we find that increasing voucher take-up would not result in larger reductions in employment or increased reliance on public assistance relative to the estimates in Jacob and Ludwig (2012). However, our results provide suggestive evidence that increased take-up might result in larger negative effects on earnings. This analysis relies on several strong assumptions, but nonetheless suggests that increasing take-up rates could result in larger intensive margin reductions in labor market activity among voucher recipients. These results highlight that variation in take-up rates may be an important aspect to consider when evaluating external validity. Causal impacts estimated in settings of low take-up may not generalize to situations where take-up is higher, and whether results generalize may differ based on the outcome of interest.

This paper is organized as follows. The next section presents details on the Section 8 housing voucher program and reviews the related literature. The third section describes our data and presents summary statistics. The fourth section presents a simple theoretical model of lease-up. The fifth section presents our results for predictors of take-up. The sixth section details our empirical approach to, and results of, re-weighting the labor supply effects of increased take-up. The seventh section concludes.

BACKGROUND

Program Details

The Section 8 Housing Choice Voucher Program is a federally-funded housing assistance program for low-income families, administered by local Public Housing Authorities (PHAs). Vouchers subsidize low-income families to rent private, market-rate housing.[2] A household using a voucher must contribute 30 percent of its adjusted income toward rent, with the voucher making up the difference between the family's contribution and the lesser of the Fair Market Rent (FMR) or the unit rent.[3] The FMR varies based on the size of a unit and is determined annually by HUD for each metropolitan area.[4] In Chicago from 1997 to 2003, the FMR was set at approximately the 45th percentile of the metropolitan area rent distribution.

A family offered a voucher has a limited amount of time to find and lease a unit, which in our setting is 60 days.[5] If a household fails to do so, it loses the opportunity to receive housing assistance, and the PHA offers the voucher to another family. To successfully lease up with a voucher, a landlord must first be willing to have Section 8 participants as tenants.[6] Further, the desired unit must meet minimum housing quality standards; have one bedroom for every two persons; and, during our sample period, required school-aged children of the opposite sex to have separate bedrooms (HUD 1993; HUD 2001). This last rule implies that a household with two teenage boys would be entitled to a smaller FMR than a similar household with one boy and one girl.[7] As part of the process, a family must file a Request for Lease Approval with the PHA, await inspection, and sign a lease after receiving approval.

Prior to voucher issuance, the PHA briefs families about the housing voucher program. As part of this briefing, the PHA distributes packets with information on the voucher's term, policies regarding extensions of time to find a unit, and a list of landlords or real estate agents who can assist families in finding a unit. Although HUD's voucher guidebook mentions several ways that PHAs can assist families in their search (e.g., providing transportation, counseling, childcare, or a list of available units), it does not require them to provide any of these.[8] For additional details about housing voucher rules, see HUD (2001) and Olsen (2003).

It is important to note that the take-up rate in the Section 8 voucher program is conceptually distinct from other assistance programs for three reasons. First,

[2] Since 1987, families can use vouchers offered by one PHA to live in the jurisdiction of another PHA ("porting out"), though most do not.
[3] Adjusted income reflects dependents ($480 deduction per child), disability ($400 deduction per disabled household member), childcare expenses, and medical care expenses exceeding 3 percent of annual income. Although some forms of public assistance, such as Temporary Assistance for Needy Families (TANF), are considered income, the Earned Income Tax Credit (EITC) and the value of in-kind benefits, such as Food Stamps (Supplemental Nutrition Assistance Program [SNAP]) and Medicaid, are not.
[4] For example, the 2016 FMR schedule in Cook County (Chicago) was $1,001 for a one-bedroom, $1,176 for a two-bedroom, $1,494 for a three-bedroom, and $1,780 for a four-bedroom.
[5] Extensions of an additional 60 days could be granted for families in need of large units or who have documented medical problems.
[6] While it is illegal for landlords to discriminate on the basis of income in Chicago and other large cities, income discrimination and discrimination explicitly against voucher users has been demonstrated in past research (Phillips, 2017; Popkin & Cunningham, 1999).
[7] This is because the household with a boy and a girl needed to obtain an apartment with separate bedrooms for each of the two children whereas a household with two teenage boys would only be entitled to an apartment that has a bedroom for both children to share.
[8] Unfortunately, we have been unable to determine which if any of these were provided in the setting studied here.

take-up rates for other programs are often measured as the fraction of all eligible households who participate. In contrast, because housing assistance is not an entitlement and eligible families may not receive a voucher due to supply limitations, take-up rates are measured as the fraction of all voucher-receiving households—rather than all those eligible—who successfully lease up. Second, the costs of using a housing voucher, including search and moving, are often much higher than the costs of using other social programs. Finally, using a housing voucher requires the participation of a third party, the landlord, which differs from programs that feature direct provision of benefits by the government. While this requirement is similar to other in-kind benefit programs such as SNAP (Supplemental Nutrition Assistance Program) and WIC (food and nutrition service for Women, Infants, and Children) that rely on retailers to accept these non-cash payments, there may be more room for landlords to discriminate against voucher-holders in comparison to food retailers serving SNAP and WIC recipients. For all of these reasons, an important caveat to our analysis is that our analysis of program take-up may not generalize to other public assistance programs.

Previous Literature

What we know about housing voucher lease-up rates and the characteristics of households that successfully lease up comes from a series of HUD-commissioned reports (Finkel & Buron, 2001; Kennedy & Finkel, 1994; Leger & Kennedy, 1990; Mills et al., 2006) and work by HUD economist Mark Shroder (2002). While the older HUD reports offer context and historical information, the studies by Finkel and Buron (2001), Mills et al. (2006), and Shroder (2002) are the most relevant to this paper since they focus on a similar time period. Table 1 summarizes results from these papers.

Finkel and Buron (2001) examine the success rate and predictors of lease-up for 2,609 households in 48 large PHAs across the country.[9] The authors find several characteristics to be associated with lease-up. Elderly-headed households, households with five or more members, those with no children, and those with relatively high or zero household income were all less likely to lease up with a voucher. Households with a disabled household head were more likely to lease up. Metropolitan area-level vacancy rates also had a positive effect on leasing, while success rates did not differ by the household head's race, gender, or source of income.

Mills et al. (2006) study a Welfare-to-Work (WtW) program across six PHAs providing vouchers to 4,650 households. Among the authors' findings are that higher earnings and participation in job training were both positive predictors of lease-up. Having been previously employed, having dependent children, receiving TANF, and not receiving supplemental security income (SSI) were also positively associated with lease-up.

Shroder (2002) examines data from the MTO experiment, in which 1,308 households living in public housing in Baltimore, Boston, Chicago, Los Angeles, and New York were randomly offered standard Section 8 vouchers.[10] Shroder finds

[9] Seventy percent of the sample was offered vouchers in May and June.

[10] An additional 1,740 households in MTO received "experimental" vouchers, which they could only use if they moved to Census tracts in which fewer than 10 percent of households were poor. Shroder finds that the predictors of successful lease-up differ among households offered vouchers with the location constraint relative to those offered unconstrained vouchers, the group most similar to our study. For a summary of the MTO experiment and its results, as well as a discussion about the benefits of growing up in a disadvantaged neighborhood and documentation of the low mobility rate of voucher recipients, see Sard and Rice (2014).

Table 1. Past research on predictors of housing voucher lease-up.

	Finkel & Buron (2001) (1)	Mills et al. (2006) (2)	Shroder (2002) (3)
Voucher lease-up rates			
Overall	69%	71%	61%
Chicago	82%	n/a	67%
HH demographics & employment			
Black		+	
Elderly HHH	−	n/a	n/a
Household size	−	n/a	−
Has dependent children	+	+	n/a
Number of preschool-age children	n/a	n/a	+
Relatively high income	−	+	
Zero income	−	n/a	n/a
Source of income (SSI, welfare, etc.)			−
Disabled HHH	+	n/a	
Other characteristics			
Metropolitan area vacancy rates	+	n/a	+
Metropolitan area unemployment rate	n/a	+	n/a
HHH's subjective prob. of searching successfully	n/a	n/a	+
HHH's dissatisfaction w/ current nbhd.	n/a	n/a	+
HHH's comfort with change	n/a	n/a	+
Belonging to a church nearby	n/a	n/a	−
Having many friends in neighborhood	n/a	n/a	−
Current housing condition	n/a	n/a	−
Years living in metropolitan area	n/a	n/a	−
N (Households)	2,609	4,650	1,308
N (Chicago only)	85	n/a	199

Notes: Finkel and Buron (2001) examine 2,609 households in 48 PHAs that were offered vouchers during the spring and summer of 2000. Mills et al. (2006) examine 4,650 households in six PHAs that were offered vouchers from 2000 to 2001. Shroder (2002) examines 1,308 households in five PHAs that were offered vouchers from 1994 to 1998. Chicago sample sizes in Finkel and Buron (2001) and Shroder (2002) are 85 and 199 households, respectively. + indicates a positive relationship, − indicates negative, an empty cell indicates no relationship, and n/a indicates that this characteristic is not available in this study. HH = household; HHH = household head.

that metropolitan area vacancy rates and the number of preschool-aged children in the household are positively associated with the voucher success rate. Household size is negatively related to take-up, as is receiving SSI/SSDI/SS Survivor benefits. Additionally, several variables from the baseline survey in the MTO experiment predicted lease-up. For example, the household head's subjective probability of having a successful search, dissatisfaction with current neighborhood, and self-reported level of comfort with change are all positively associated with successful lease-up. Belonging to a church nearby, having many friends in the neighborhood, current housing condition, and years living in the metropolitan area are negatively related to successfully leasing up with a voucher.

As shown in Table 1, Finkel and Buron (2001), Mills et al. (2006) and Shroder (2002) report average voucher lease-up rates that exceed the 50 percent lease-up rate in our sample. There are several points to keep in mind about this contrast. First, Finkel and Buron (2001) use data from a wide-range of public housing authorities across the U.S. and find that take-up is around 69 percent on average. Chicago, like other large cities in the U.S., has lower lease-up rates.[11,12] Second, Shroder (2002) studied public housing households. We show in our data that such households have a higher probability of leasing up (Table 3, column 1). Finally, Mills et al. (2006) studied households in the WtW program, which only provided vouchers to TANF recipients. In our data, we also find that households receiving public assistance are substantially more likely to lease up (Table 3, column 1).

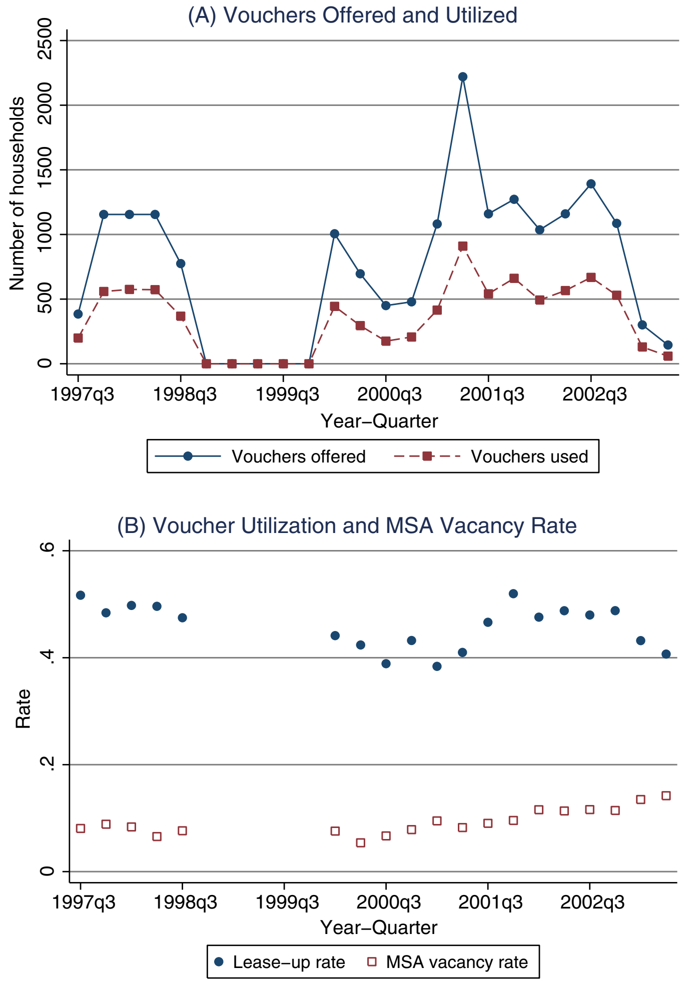
In addition to Shroder (2002) and the HUD-affiliated reports, there is also a literature that provides evidence that landlord preferences are a barrier to voucher take-up (Desmond, 2016; Phillips, 2017). Focus group research provides further insights on difficulties in the lease-up process. For example, Popkin and Cunningham (1999) interviewed individuals who failed to lease up and found that almost 90 percent did not submit a single Request for Lease Approval. This implies that finding a willing landlord or suitable unit poses a greater challenge to applicants than passing an inspection.[13]

DATA

The Chicago Housing Authority Corporation (CHAC), a private entity tasked by HUD to administer Chicago's Section 8 program, reopened the city's voucher wait list in July 1997 for the first time in over a decade. A total of 82,607 income-eligible household heads applied before the list was closed just a few weeks after it opened. In August 1997, CHAC randomly assigned each applicant a lottery number from one to 82,607 and informed those families with the 35,000 best (lowest) lottery numbers of their position and told them that they would receive a voucher within three years. CHAC told the remaining families (numbers 35,001 to 82,607) that they would not receive a voucher. CHAC then began to offer vouchers to households beginning with the lowest lottery numbers.[14] By May 2003, 18,109 families from the wait list had been offered housing vouchers. At this point, CHAC was "over-leased" and stopped offering new vouchers.

We focus on the 18,109 families that were offered a voucher by May 2003. Figure 1a displays the number of these families that were offered vouchers by CHAC each quarter from 1997:III to 2003:II, as well as the number that used them. As shown in the bottom panel, the take-up rate fluctuated in a narrow range, averaging 50.4 percent across the sample period. Quarterly rental vacancy rates for the Chicago metropolitan area during this period are included in Figure 1b.[15] There is no apparent relationship between vacancy rates and lease-up, nor between time on the wait list and lease-up.

[11] For example, Finkel and Buron (2001) report lease-up rates of 47 percent for Los Angeles and 56 percent for New York City.
[12] The lease-up rate in our sample is also lower than the reported lease-up statistic reported for Chicago in Finkel and Buron (2001). One reason for this discrepancy could be the fact that the take-up rate for Chicago in Finkel and Buron (2001) is calculated from a sample of only 85 households.
[13] Other qualitative studies, such as DeLuca, Garboden, and Rosenblatt (2013), find that even among those households that lease up, limited search time, poor understanding of program rules, and limited housing options in low-poverty neighborhoods lead households to settle for subpar apartments in high-poverty neighborhoods.
[14] Service of the wait list was interrupted from August 1998 until early 2000 so that vouchers could be distributed to a set of Latino families in response to a discrimination lawsuit against the City.
[15] Annual rental vacancy rates for Chicago are available during this period from the Census Bureau's Housing and Vacancy Survey, as are quarterly rates since 2005. We impute quarterly rates during our period by running four separate regressions in which we first regress the quarter one vacancy rate on the annual rate during 2005 to 2014 (10 observations) and then predict out-of-sample to each of the years in our data. We then repeat for the remaining three quarters.



Notes: Figure 1A reports the number of CHAC vouchers issued to, and the number subsequently used by, families on the waiting list from 1997:III to 2003:II. No vouchers were issued from September 1998 until January 2000 in response to a discrimination lawsuit against the City of Chicago. Figure 1B reports the fraction of voucher offers made each quarter that were subsequently used (lease-up rate) and the annual, MSA-level vacancy rate.

Figure 1. Voucher Offers, Utilization, and MSA Vacancy Rate. [Color figure can be viewed at wileyonlinelibrary.com]

The data on these 18,109 households are an extension of the data used in Jacob and Ludwig (2012). We obtain baseline address information, lottery number, basic household demographics, and information for the household head and spouse from the CHAC wait list application forms. These forms do not include identifying information for other members of the household, so we determine who else was living with the household head at baseline using data from the Illinois Department of Human Services (IDHS). This means we have information on those household members living with the household head only at the time of the lottery, and so we cannot capture changes to household size and composition between the time of the lottery and voucher offer. We obtain voucher usage from

HUD 50058 records, which families must complete annually to verify program eligibility.

We use data from the 2000 Census to determine tract-level characteristics of households' baseline neighborhoods, and we calculate annual local crime rates from beat-level Chicago Police Department data. We have access to Illinois Unemployment Insurance (UI) data that provide quarterly employment and earnings information; IDHS records that provide quarterly indicators of TANF, Food Stamps, and Medicaid usage; Illinois State Police arrest records for juveniles and adults; and Chicago Public Schools data for children's test scores. For approximately half of the households in our sample, we also have data on residential location at the time they received a voucher offer, obtained from their public assistance records. We use these address data to calculate the distances between a household's baseline address and local amenities, as well as to determine whether a household recently moved to a new address. For more data details, please see the Appendix.[16]

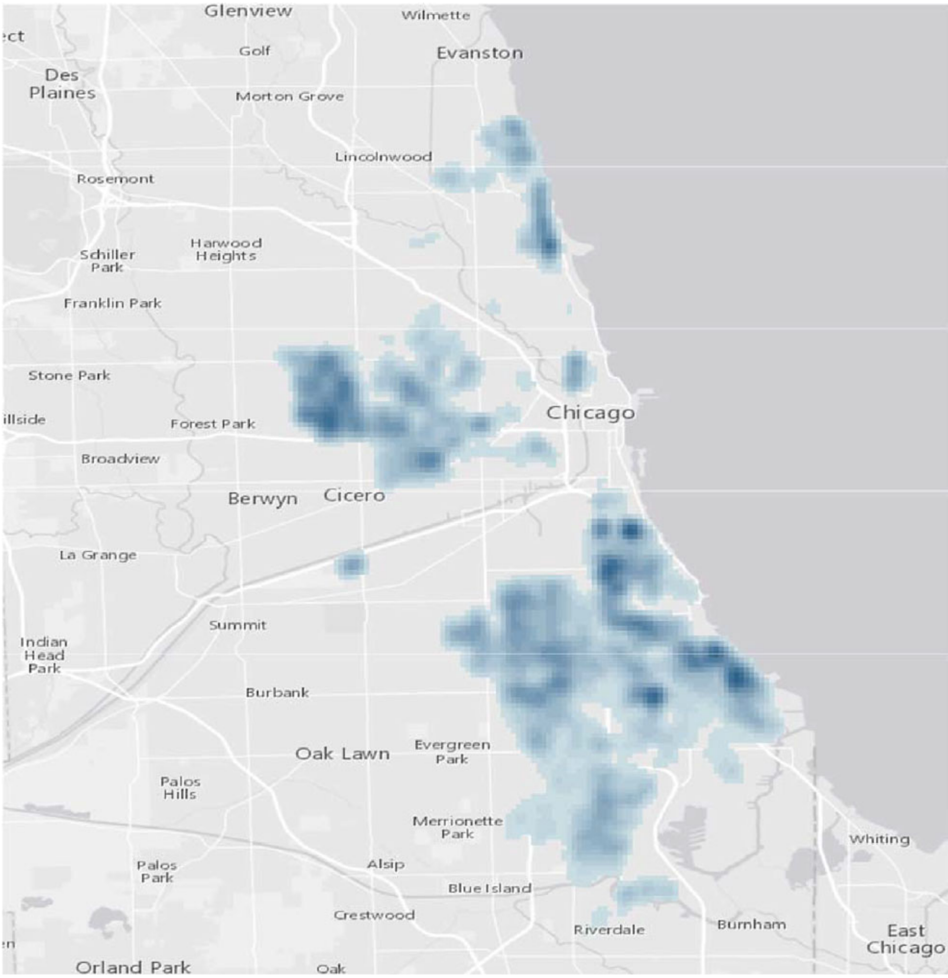
Figure 2 displays the locations of households in our sample at the time they applied to the lottery. Households are concentrated in the historically low-income South and West sides of Chicago. Figure 3 shows the variation in voucher take-up rates across Census tracts in Chicago. Darker areas represent neighborhoods with the highest rates. Take-up rates do not vary considerably across tracts. The interquartile range for the fraction of a baseline tract's households that lease up is 43 to 58 percent.

Table 2 provides sample means by baseline housing status. Among the 89 percent of the sample living in private housing at baseline (column 1), the average age at voucher offer of the household head was 39, with the majority being unmarried African-American women. Among the 49 percent of households with children at the time of voucher offer, the average number of children was two and the average child's age was 10.5. Nearly 60 percent of household heads were employed during the year prior to voucher offer, earning on average $17,700 annually, and nearly the same percentage received TANF, Food Stamps, or Medicaid. During the two years prior to voucher offer, about 10 percent of household heads and children were arrested at least once.

The 11 percent of households living in public housing at baseline (column 5) were even more likely to be headed by an unmarried African-American woman with children. The household head was slightly less likely to be employed, earned substantially less conditional on working ($13,800 annually), and was considerably more likely to receive public assistance. The likelihood of the household head or children having been recently arrested was also greater among the public housing sample, particularly so for children.

Table 2 also displays differences in characteristics between households that successfully lease up with their voucher and those that do not. The raw differences in means presented in columns 4 and 8 suggest that household heads who lease up are more likely to be black, female, unmarried, younger, employed, have children, use public assistance, and live in more impoverished, racially homogenous neighborhoods with higher violent crime rates than their counterparts who do not lease up. Nearly all of these differences are the same sign among the households living in public housing at baseline, although there are some differences in magnitude.

[16] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

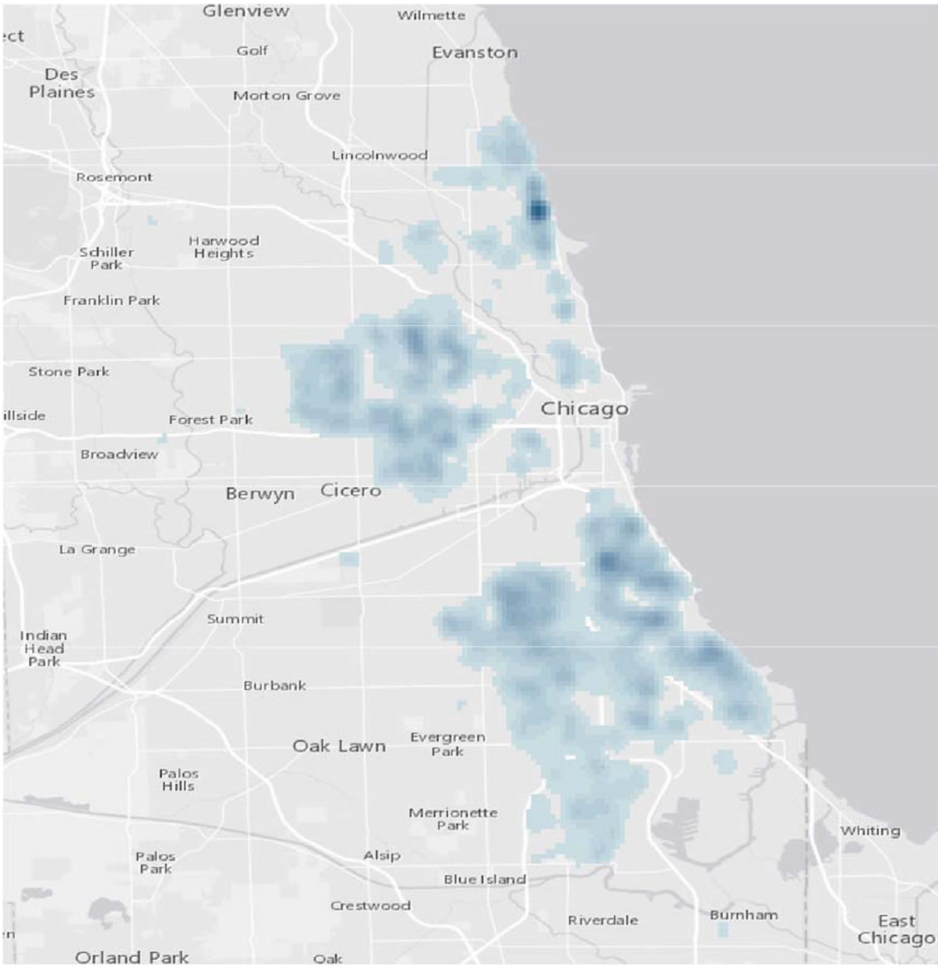


Notes: Map displays the density of sample households throughout the Chicago area based on their baseline address. The highest concentrations of households, represented by the dark blue regions, are located in the historically low-income South and West sides of the city.

Figure 2. Household Locations at Time of Voucher Lottery (July 1997). [Color figure can be viewed at wileyonlinelibrary.com]

Appendix Table A1 further documents lease-up patterns by household size and composition.[17] We split our sample by all combinations of whether the household head is single and female, single and male, or married; working-aged or elderly; able-bodied or disabled; and whether there are zero, one, two, or more than two children in the household. Elderly households and working-age, married, childless households have the lowest lease-up rates, between a quarter and a third. Working-aged, single, female-headed households with three or more children have the highest lease-up rates, approaching two-thirds. Across all of these groups, disabled household heads are slightly more likely than able-bodied household heads to lease up.

[17] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.



Notes: Map displays variation in voucher lease-up rates across Census tracts in the Chicago area with voucher recipients, based on their baseline address. Higher rates of voucher use are shaded dark blue.

Figure 3. Heat Map of Voucher Lease-Up. [Color figure can be viewed at wileyonlinelibrary.com]

MODEL

To motivate our empirical analysis, we consider a simple, one-period model of the lease-up process.[18] As discussed previously, program rules dictate that a voucher recipient must find a rental unit within 60 days that meets minimum housing standards (verified by inspection).[19]

With this in mind, a household receiving a voucher offer must undertake a search for suitable housing. Let V represent the net benefit of living in the next rental

[18] Our discussion is similar in spirit to Shroder (2002).
[19] Note that this design does not preclude households from attempting to apply their voucher offer to their pre-program residence. In our sample, this happens infrequently, with only 6.8 percent of households that use the voucher deciding to initially "lease in place." One explanation for this low rate can be found in Popkin and Cunningham (1999), in which several of the focus group participants explained that they attempted to lease in place, but their landlords refused to accept the Section 8 voucher.

Table 2. Descriptive statistics of households, by baseline housing status.

	Private Housing at Baseline				Public Housing at Baseline			
	All (1)	Leased Up (2)	Did Not Lease Up (3)	Difference (4)	All (5)	Leased Up (6)	Did Not Lease Up (7)	Difference (8)
Demographics (household head)								
Male	0.164	0.117	0.211	−0.095***	0.125	0.072	0.193	−0.121***
Black	0.912	0.935	0.886	0.049***	0.942	0.971	0.903	0.069***
Hispanic	0.033	0.028	0.040	−0.012***	0.007	0.004	0.011	−0.008*
Age[1]	38.540	36.630	40.436	−3.806***	39.742	36.711	43.608	−6.897***
Disabled	0.258	0.261	0.255	0.006***	0.278	0.237	0.329	−0.092***
Has spouse	0.104	0.075	0.134	−0.059***	0.077	0.058	0.100	−0.041***
Household composition								
Number of adults (including HHH)[1]	1.462	1.438	1.486	−0.048***	1.540	1.566	1.506	0.060***
Has children[1]	0.494	0.565	0.424	0.141***	0.537	0.612	0.442	0.170***
Number of children[1]	2.031	2.079	1.968	0.111***	2.389	2.455	2.274	0.181**
Average age of children[1]	10.510	10.260	10.840	−0.579***	10.881	10.660	11.268	−0.608**
Average composite test scores of children[2,3]	−0.172	−0.196	−0.135	−0.061***	−0.294	−0.295	−0.292	−0.003***
Employment and public assistance usage (HHH)[4]								
Employed	0.585	0.663	0.508	0.155***	0.541	0.624	0.436	0.188***
Annual earnings (thousands of 2013 $)	17.712	14.547	21.795	−7.249***	13.802	12.422	16.307	−3.885***
Recently began employment	0.074	0.090	0.057	0.033***	0.084	0.095	0.071	0.024*
Recently ended employment	0.146	0.174	0.118	0.056***	0.131	0.158	0.098	0.060***
Received public assistance	0.582	0.724	0.442	0.282***	0.737	0.809	0.645	0.164***
Received Food Stamps	0.501	0.646	0.358	0.288***	0.659	0.742	0.552	0.190***
Received TANF	0.265	0.349	0.181	0.168***	0.391	0.459	0.306	0.153***
Received Medicaid	0.512	0.642	0.383	0.259***	0.660	0.731	0.570	0.161***

Table 2. Continued.

	Private Housing at Baseline				Public Housing at Baseline			
	All (1)	Leased Up (2)	Did Not Lease Up (3)	Difference (4)	All (5)	Leased Up (6)	Did Not Lease Up (7)	Difference (8)
Criminal activity[2]								
Household head arrested	0.096	0.092	0.100	−0.008*	0.111	0.091	0.137	−0.047***
Household children arrested[5]	0.102	0.101	0.103	−0.002***	0.135	0.133	0.137	−0.003***
Baseline neighborhood characteristics in 1997								
Poverty rate	0.283	0.295	0.270	0.025***	0.584	0.613	0.547	0.067***
Fraction black	0.791	0.826	0.756	0.070***	0.857	0.888	0.818	0.070***
Property crime rate (per 1,000)	74.458	74.850	74.048	0.802***	115.949	120.256	110.439	9.818**
Violent crime rate (per 1,000)	36.298	37.667	34.866	2.801***	61.498	66.079	55.636	10.443***
Distance to nearest:								
School	0.398	0.353	0.482	−0.130***	0.224	0.209	0.248	−0.039**
Hospital	1.373	1.314	1.483	−0.169***	1.207	1.175	1.261	−0.086***
Train or bus station	0.244	0.218	0.292	−0.075***	0.110	0.106	0.118	−0.012***
N (Households)	16,179	8,042	8,137		1,930	1,079	851	

Notes: The sample is households that applied for and received Section 8 vouchers during 1997 to 2003. See text for details. HHH = household head. 1 = At voucher offer. 2 = During two years prior to voucher offer. 3 = Conditional on having at least one child tested in Chicago Public schools during pre-offer period. 4 = During year prior to voucher offer. 5 = Conditional on having at least one child during pre-offer period. ***Significant at the 1 percent level; **5 percent level; *10 percent level.

property that the household considers. Denote the probability that this particular unit can be successfully leased—that is, pass inspection and gain the landlord's approval—as *P*. Finally, let *C* represent the costs (monetary or otherwise) associated with finding and applying for this particular unit. In this case, the household will continue searching for housing as long as:

$$PV - C > 0$$

That is, households search as long as the expected benefit outweighs the cost. Households will fail to lease if costs are high, expected value is low, or their perceived probability of finding a suitable unit is low.

We can relate many of the variables in our data to the probability of finding a unit, the expected benefits of leasing, and the costs associated with search. The probability of finding a unit is related to the supply of suitable units, the number of landlords willing to lease to housing voucher recipients, and the family's search strategy, which may be informed by those in its social network (Ellen, Suher, & Torrats-Espinosa, 2018). Variables in our data that may relate to the probability of finding a unit include the number of adults and children in the household, because larger units may be more difficult to find within the allotted search time (Popkin & Cunningham, 1999).[20] Others include the metropolitan vacancy rate because the greater the overall supply of rental units, the more likely it is that a household will find one to lease using a voucher, and offer timing, because rental markets are seasonal and it may be difficult to find an apartment when the market is less active.

The net benefit of leasing up can vary substantially across individuals depending on their financial status, family's current and recent life circumstances, and current neighborhood quality. For example, a new unit in a high-quality neighborhood may not offset the loss of proximity to existing social connections for one household, while for another family that loss of proximity could itself be seen as an additional benefit of moving. Variables in our data that may relate to the net benefit of lease-up include the FMR, which partially determines the magnitude of the subsidy, as well as measures of current neighborhood quality. Individuals currently living in worse neighborhoods, which we measure in our data using crime and poverty rates, and distance to amenities such as schools and hospitals, should value vouchers more than individuals living in better neighborhoods. Other variables in our data related to the net benefit of leasing up include children's recent academic performance and criminal activity. Families with children whose academic or social performance has suffered prior to voucher receipt may place a higher value on moving to a new school or neighborhood.

Finally, searching for a unit is a costly endeavor for many applicants, and variables in our data that relate to the cost associated with search include household head age and disability status because elderly or disabled household heads may find it difficult to search for housing. Similarly, household heads with young children that require childcare may find it harder to search for housing.

Of course, some variables may relate to lease-up through multiple channels. For example, while the presence of young children may increase the cost of searching for an apartment, it may also increase the net benefit of relocating to a higher quality unit or neighborhood relative to households with older or no children. Or, while elderly household heads may find housing search more difficult, landlords may prefer to lease to them, as elderly voucher holders are often considered to be good tenants.

[20] While a greater household size means eligibility for a larger FMR, and therefore, a larger subsidy, we directly control for FMR separately in our analysis.

PREDICTING VOUCHER USE

Our empirical strategy is to predict whether a household leases up, y, using a rich set of household-level covariates, X. To do this, we estimate the following linear probability model for households offered a voucher through the lottery:[21]

$$y = \alpha + X\beta + M + Y + \varepsilon, \tag{1}$$

where our estimates of the coefficients in the β vector reveal which characteristics are predictive of lease-up. We include month-of-year fixed effects, M, and year fixed effects, Y. We report heteroskedasticity-robust standard errors. While many of the household characteristics in X are endogenous, the goal of this analysis is to determine which of them are predictive of take-up, and not to estimate their causal impact on lease-up.

Basic Demographics

Table 3 presents the main results for our entire sample, including households living in private and public housing at baseline. Even after controlling for covariates, column 3 shows that basic household head demographics are important and statistically significant predictors of lease-up. When offered a voucher, male household heads are 6 percentage points less likely than women, and non-married household heads are 7 percentage points more likely than those who have a spouse, to lease up. Black household heads are 5.4 percentage points more likely than whites to lease up, a result that is counter to a long literature demonstrating racial discrimination in rental markets (e.g., Desmond, 2016) but consistent with results from one of the studies most similar to our own (Mills et al., 2006). This may also reflect the possibility that, because Chicago is a city with a high degree of racial segregation where most voucher recipients are black, black households are more readily able to tap into social networks that facilitate their housing search than non-black households (Ellen, Suher, & Torrats-Espinosa, 2018).

Probability of Finding a Unit

The next variables that we examine provide insight into whether supply-side constraints (such as the availability of suitable units) matter. Column 3 shows zero association between lease-up and the number of adults in the household, and a negative relationship between the number of children in the household and lease-up. The result for number of children is consistent with prior evidence that household size is negatively associated with lease-up, likely due to the reported difficulty in finding larger rental units (Finkel & Buron, 2001; Shroder, 2002).

The estimate for our only direct measure of the supply of housing, the metropolitan area vacancy rate, has the predicted sign: lease-up rates increase when the vacancy rate is higher. Note that this relationship exists after controlling for other covariates even though there is no apparent visual relationship between vacancy and lease-up rates in Figure 1b. Our estimates imply that a one percentage point increase in the vacancy rate is associated with a two percentage point increase in the likelihood of leasing up.

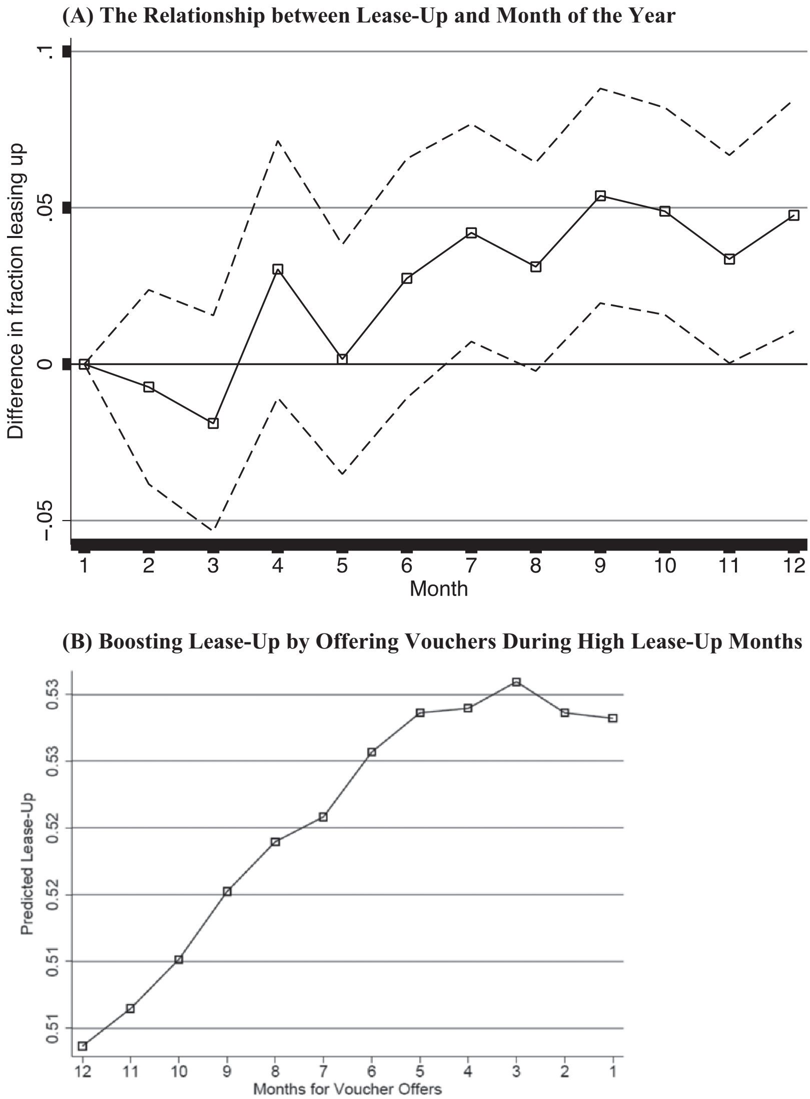
Finally, Figure 4a explores lease-up and the timing of vouchers by plotting the coefficients for the month fixed effects from equation (1). These results show that

[21] Estimating this model using logit does not substantively alter any of our findings. See Appendix Tables A2 and A3. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

Table 3. Predictors of lease-up.

	Bivariate		Multivariate	
	Coefficient (1)	Std. Error (2)	Coefficient (3)	Std. Error (4)
Demographics (household head)				
Male	−0.183***	(0.010)	−0.060***	(0.010)
Black	0.154***	(0.013)	0.054***	(0.017)
Hispanic	−0.104***	(0.021)	0.023	(0.025)
Has spouse	−0.158***	(0.012)	−0.070***	(0.013)
Probability of finding and leasing suitable unit[1]				
Number of adults (including household head)	−0.012***	(0.004)	−0.005	(0.006)
Number of children	0.049***	(0.003)	−0.012**	(0.006)
MSA vacancy rate	0.007***	(0.002)	0.018*	(0.010)
Expected net benefit of a voucher				
FMR of voucher offer (thousands of 2013 $)	0.181***	(0.012)	0.045*	(0.024)
Recently moved[2]	0.021*	(0.011)	−0.013	(0.010)
Average composite test scores of children[3]	−0.065***	(0.009)	−0.016*	(0.009)
Household children arrested[3]	0.068***	(0.016)	−0.013	(0.017)
Poverty rate[4]	0.279***	(0.020)	0.043	(0.029)
Fraction black[4]	0.184***	(0.012)	0.073***	(0.015)
Property crime rate (per 1,000)[4]	0.000***	(0.000)	0.000	(0.000)
Violent crime rate (per 1,000)[4]	0.002***	(0.000)	0.000	(0.000)
Distance to nearest school (miles)[1]	−0.044***	(0.007)	−0.075***	(0.019)
Distance to nearest hospital (miles)[1]	−0.024***	(0.004)	−0.017**	(0.007)
Public housing residency (baseline)	0.062***	(0.012)	−0.024*	(0.014)
Cost of finding a unit				
Disabled	−0.005	(0.008)	0.033***	(0.009)
Difficult to categorize				
Household head is middle-aged (40–64)	−0.079***	(0.008)	−0.033***	(0.008)
Household head is elderly (65+)	−0.213***	(0.016)	−0.094***	(0.017)
Received Food Stamps[2]	0.282***	(0.007)	0.099***	(0.014)
Received TANF[2]	0.210***	(0.008)	0.025**	(0.011)
Received Medicaid[2]	0.252***	(0.007)	0.008	(0.015)
Has children	0.145***	(0.007)	0.063***	(0.018)
Average age of children	0.009***	(0.001)	−0.004***	(0.001)
Distance to nearest rail or bus stop (miles)[1]	0.039***	(0.008)	0.079***	(0.021)
Household head arrested[3]	−0.033***	(0.012)	−0.076***	(0.012)
Recently ended employment[2]	0.113***	(0.010)	−0.021*	(0.011)
Recently began employment[2]	0.117***	(0.014)	−0.108***	(0.015)
Employed[2]	0.161***	(0.007)	0.238***	(0.011)
Annual earnings (thousands of 2013 $)[2]	−0.002***	(0.000)	−0.005***	(0.000)
R-squared			0.17	

Notes: The sample is all Chicago households offered a housing voucher between 1997 and 2003 (N = 18,109). Each point estimate and standard error are from a single Linear Probability Model regression of an indicator equal to one if the household leased up on the covariates. The regression also includes offer year and offer month fixed effects and indicators for missing values. Standard errors are heteroskedasticity-robust. FMR = Fair Market Rent. 1 = At voucher offer. 2 = During year prior to voucher offer. 3 = During two years prior to voucher offer. 4 = At baseline (July 1997). ***Significant at the 1 percent level; **5 percent level; *10 percent level.



Notes: Estimates in Figure 4A come from equation (1) in the text. Point estimates and 95 percent confidence intervals represent the difference in the probability of successful lease-up associated with each month relative to January (the omitted group). All regressions include controls for demographics, household composition, baseline neighborhood characteristics, MSA vacancy rate, year of voucher arrival, distances to local amenities, and missing indicators. Figure 4B calculates the predicted lease-up rate if vouchers were only offered during the X highest lease-up months of the year, where X is on the x-axis. For example, the first point, at X = 12, is the current lease-up rate, because vouchers are offered during all 12 months. The next point, at X = 11, is the lease-up rate if vouchers were only offered in the 11 months of the year with the highest lease-up rates based on Figure 4A. The final point, at X = 1, is the predicted lease-up rate if vouchers were only offered during the single highest lease-up month of the year, i.e., September.

Figure 4. Seasonality of Lease-Up.

the season is important, with offers in the summer and fall months resulting in higher lease-up rates relative to those in the spring and winter months.[22] These results are consistent with the seasonality of the rental market in Chicago, which is heaviest in the summer and lightest in the winter.

We conduct back-of-the-envelope calculations to demonstrate how much lease-up rates would improve if housing authorities issued vouchers only in months that experience higher lease-up rates.[23] For example, if housing authorities did not issue vouchers during the three months of the year with lowest lease-up (offering them only during the nine months with highest lease-up rates), the lease-up rate would increase from 50.4 percent to 51.5 percent, a 2.2 percent increase. Figure 4b extends on this exercise by plotting predicted lease-up rates from 11 additional permutations. We start with a scenario where housing authorities provide vouchers in the 11 highest months and end with a scenario where vouchers are offered only during the single highest month. The first point on the figure, at month 12, is the current lease-up rate in the sample. The predicted lease-up rate peaks at 53.1 percent (a 5.4 percent increase) when vouchers are offered during the three months of the year with highest lease-up rates.[24] While it may be infeasible for housing authorities to issue all vouchers in just a single month or two each year, this exercise illustrates that simply changing which half of the year vouchers are offered, a policy that seems low-cost and feasible, could raise lease-up rates by 4.6 percent.

Net Benefit of Lease-Up

Now, we examine variables that measure the net benefit of leasing up with a voucher. As expected, we find that the FMR for which a household is eligible has a positive relationship with lease-up. The FMR varies by year and household size, both of which we control for here; the remaining variation is due to differences in the gender composition of school-aged children in the household.[25] Before conditioning on other variables, we find that a $1,000 increase in the FMR is associated with an 18.1 percentage point increase in lease-up probability. However, after controlling for other factors, the estimate drops to 4.5 percentage points.

[22] We explore whether this relationship is different for households with school-aged children relative to households without school-aged children. Parents may wish to avoid moving their children from school during the school year; however, search may be costlier during the summer for parents with childcare needs. We find no evidence of a difference, suggesting that these two channels may offset one another.

[23] To perform this calculation, we create a dummy variable that is equal to one for the months of the year with high take-up, estimate our main model including that dummy, and then estimate the counterfactual lease-up rate if all households were offered vouchers in these months. This effectively scales the difference in lease-up rates between high and low months by the fraction of the sample offered vouchers in low lease-up months. For example, if the observed lease-up rate in our sample is 50.4 percent, the coefficient on the six-month dummy is 4.2 percentage points, and the fraction of the sample offered vouchers in the low months is 54 percent, then the increase is $0.54 * 4.2 = 2.3$ percentage points.

[24] The reason that the difference in predicted lease-up is greatest during three months of the year relative to the other nine, rather than in a single month relative to the other 11, is that those three months exhibit similarly high lease-up rates, substantially higher than the next highest month. Comparing lease-up rates in the single highest month relative to the remaining 11 months therefore yields a smaller difference between the two groups than is found when comparing lease-up rates in the three highest months to the remaining nine months.

[25] As mentioned earlier, and as noted by Currie and Yelowitz (2000), HUD rules during our sample period specified that "persons of opposite sex, other than husband and wife or very young children, shall not be required to occupy the same bedroom" (HUD 1993, p. 188). Therefore, a household with two teenage boys would be entitled to a significantly smaller FMR than a similar household with one boy and one girl. Subsequently, HUD and PHAs moved away from this policy and toward a "two heartbeats per room" rule, requiring that two people share a bedroom regardless of age or gender. Due to this rule, a household with two teenage boys would be entitled to a smaller rental unit (and lower value of FMR) than a similar household with one boy and one girl.

The perceived benefit of a voucher may be greater if households are unhappy with the current neighborhood and educational situation for their children. We find evidence of this being the case. Households are more likely to lease up if their children's recent academic performance is lower, with a standard deviation lower average test score associated with a 1.6 percentage point higher lease-up rate.[26,27] We find no statistically significant relationship between lease-up and whether a household's children were recently arrested. This is surprising given that household heads participating in the MTO demonstration listed moving away from gangs and drugs as the first or second most important reason for participating in the program (Sanbonmatsu et al., 2011). However, their concern may have primarily reflected the fear of their children being victims of crime, and only secondarily that their children would be involved in it.

Finally, we find mixed evidence that individuals living in more disadvantaged neighborhoods are more likely to use a voucher. Once we control for other factors, rates of crime in an individual's baseline neighborhood do not predict lease-up. Living closer to a school and to a hospital is predictive of *more* voucher take-up, suggesting that the areas surrounding them may be otherwise undesirable along unobserved dimensions. Interestingly, an increase of one standard deviation in the percentage of an individual's baseline neighborhood that is black is associated with a 7.3 percentage point increase in the probability of take-up. Similar to the finding that black household heads are more likely to lease up, this finding may reflect stronger social networks among voucher users for black households in Chicago. Households living in public housing at baseline, while more likely to lease up without controlling for other household or neighborhood characteristics, are 2.4 percentage points *less* likely to lease up after controlling for observed characteristics. This result likely reflects the smaller net financial gain for these households relative to households living in private housing for whom leasing-up provides a new and generous housing subsidy.

Costs Associated with Search

We next examine measures of the cost of searching for a unit. Disabled household heads are 3.3 percentage points more likely to lease up, counter to our expectation based on search costs, but similar to results from prior work.[28]

Variables Potentially Related to Lease-Up through Multiple Channels

Many characteristics may relate to lease-up through multiple channels. As found in prior work, the household head's age at the time of voucher offer is negatively predictive of lease-up. Household heads who are middle-aged (between 40 and 64) are 3.3 percentage points less likely to lease up than younger household heads (less than 40 years old), and elderly household heads are 9.4 percentage points less likely. These results suggest that younger households have an easier time looking

[26] We define children's average test scores as the average across subjects of scores standardized to have a mean of zero and a standard deviation of one. We assess test scores and being arrested during the two years prior to voucher offer.

[27] Recent research suggests that voucher recipients typically move to neighborhoods with better schools only in specific situations when school quality is salient, such as when their child is entering kindergarten, or when there are affordable rental units near good schools (Ellen, Horn, & Schwartz, 2016; Horn, Ellen, & Schwartz, 2014).

[28] While additional search services provided by CHAC would be an intuitive explanation for this positive result, such services do not appear to have been offered by CHAC during this period (Popkin & Cunningham, 1999).

for housing, and that this phenomenon swamps any greater preference of landlords for older tenants.

Consistent with both Finkel and Buron (2001) and Mill et al. (2006), households with children are 6.3 percentage points more likely to lease up than households without children. This result suggests that the benefit of vouchers for parents outweighs any difficulty in finding an apartment either because landlords prefer households with no children or because the search process is most costly for households with children. Note that because we control for the FMR, the size of the voucher subsidy is not at play in this comparison.

Families with older children have a lower probability of lease-up: having children who are, on average, 10 years or older reduces the probability of successful lease-up by 4 percentage points. This may suggest that landlords prefer to lease to families with relatively younger children, that the perceived benefit to leasing-up is inversely related to the number of years a family's children will be able to benefit from the housing, or that moving is more disruptive once children are older. Any of these possibilities suggest that the probability of lease-up and net benefit channels outweigh the role of higher housing search costs for households with younger children.

Interestingly, we find that receipt of Food Stamps and TANF positively predicts lease-up, but that Medicaid receipt has no relationship. This pattern does not correspond with HUD rules governing which social program benefits count toward income (TANF) and which do not (Food Stamps and Medicaid).

Distance between baseline address and a rail or bus stop has a positive relationship with lease-up. Living one mile farther away from a transit stop is associated with a 7.9 percentage point larger probability of lease-up. This suggests that the amenity value of the transit stop (i.e., higher net benefit if the household currently lives further from public transit) outweighs the search cost channel (i.e., costlier to search for housing if there is little access to public transit).

The household head having been arrested in the two years prior to receiving a voucher offer is associated with a 7.6 percentage point reduction in voucher use, suggesting either increased search costs due to incarceration or a reduced probability of lease-up due to disapproving landlords. To help shed light on which mechanism may be at play, we estimate whether the relationship between arrest and lease-up changes depending on how recent the arrest was prior to voucher offer. We find that within the two years prior to offer, the effect is stable across quarters.[29] The lack of a dynamic relationship for household head arrest suggests that the arrest penalty for lease-up is primarily due to landlord preferences as opposed to household head incarceration, which would produce an increasing penalty as the arrest occurs closer to the offer quarter.[30] This explanation is consistent with recent qualitative evidence showing that landlords prefer not to rent to tenants with certain attributes, such as a criminal history, and that landlords demand a rent premium from such applicants (Desmond, 2016). The Section 8 voucher program makes it more difficult for such landlords to demand this premium. This may lead landlords to rent to voucher holders at lower rates.

There is a positive relationship between lease-up and whether a household head recently ended employment, without controlling for other factors. Interestingly, after

[29] We similarly estimate the dynamic relationship between lease-up and employment, public assistance usage, and children's arrests, and find no differences in the relationships by how recent the quarter was to voucher offer.

[30] Further, the large majority of arrests in our data are for relatively minor offenses such as drug or property crimes, as opposed to violent crimes. We have no measure of what fraction of the arrests lead to convictions, and what fraction of convictions lead to incarceration, but given the nature of these crimes and the likelihood of them resulting in conviction, it seems plausible that most of the difference in lease-up is not due to household heads being incarcerated.

controlling for other factors, the point estimate switches sign, such that household heads who recently ended employment are 2.1 percentage points *less* likely to lease up (relative to a household head who had been unemployed at voucher offer for some time). Household heads who recently began employment are 10.8 percentage points less likely to lease up.[31]

Finally, employment for the household head is an important, positive predictor of lease-up, possibly suggesting that individuals who are able to secure work are more appealing as tenants and prove more capable at navigating the lease-up process.[32] Employed household heads are 16.1 percentage points more likely to lease up in the bivariate specification, and 23.8 percentage points more likely controlling for other variables. However, conditional on being employed, those with higher earnings are less likely to lease up. Relatively higher earning households face a smaller subsidy and have a higher time-value of search.[33] A one standard deviation increase in an individual's earnings, for example, is associated with a 6.8 percentage point decrease in their probability of using a voucher. These results suggest an inverted U-shaped relationship between advantage and lease-up: those households who are the least advantaged struggle to lease up in spite of having the lowest time-cost of search and largest potential subsidy. Those households that can secure employment, but earn relatively little, have a relatively low time-cost of search, are still eligible for a large subsidy, and either face more approving landlords or can successfully navigate the search process. The most advantaged individuals face a high time-cost of search and a low potential subsidy and lease up at a lower rate likely due to these factors.

Heterogeneity by Baseline Housing Status

Given that one of the most important previous works to examine lease-up in the Section 8 voucher program relied on a sample of households living in public housing at baseline (Shroder, 2002), we examine whether our results are heterogeneous by baseline housing status. While only 11 percent of our sample lived in public housing at baseline, examining whether the predictors of lease-up are different for this group can speak to the external validity of Shroder (2002). Columns 1 and 2 of Table 4 present the main results estimated for the 16,179 households living in private housing at baseline, and columns 3 and 4 present results for the 1,930 households living in public housing. Columns 5 and 6 present the difference between the estimates from the two samples and the p-value from the statistical test that they are equal.

The point estimates for the private housing sample (column 2) in Table 4 are nearly identical to the main results (column 3) in Table 3, which is unsurprising given that nearly 90 percent of the sample lived in private housing at baseline. Due to the smaller size of the public housing sample, our estimates for this group reveal fewer statistically significant predictors of successful lease-up. However, the signs of the significant point estimates match nearly uniformly those for the private sample,

[31] We define recently beginning employment as starting an employment spell during the four quarters prior to voucher offer after a spell of non-employment lasting at least one year. Recently ending employment is defined in an analogous manner.

[32] Employment is defined as having positive earnings during at least one of the four quarters prior to voucher offer. This result is robust to alternative definitions of employment, such as having earnings in excess of $100 during one of the preceding four quarters.

[33] An alternative explanation for the negative relationship between earnings and the likelihood of leasing up is that some household heads meet the voucher income criteria at the time they apply but exceed the criteria when an offer is made. Excluding household heads whose nominal earnings in the year prior to an offer exceed HUD's income limits does not materially change this relationship.

Table 4. Predictors of lease-up, by baseline housing status.

	In Private Housing at Baseline		In Public Housing at Baseline		Difference by Baseline Housing Status	
	Coefficient (1)	Std. Error (2)	Coefficient (3)	Std. Error (4)	Difference (5)	p-value (6)
Demographics (household head)						
Male	−0.053***	(0.011)	−0.115***	(0.036)	0.061	0.098
Black	0.048***	(0.017)	0.090	(0.055)	−0.041	0.472
Hispanic	0.023	(0.025)	−0.097	(0.126)	0.120	0.343
Has spouse	−0.074***	(0.013)	−0.020	(0.043)	−0.054	0.229
Probability of finding and leasing suitable unit[1]						
Number of adults (including household head)	−0.009	(0.006)	0.024	(0.016)	−0.033	0.053
Number of children	−0.014**	(0.006)	0.001	(0.015)	−0.015	0.358
MSA vacancy rate	0.017	(0.011)	0.020	(0.031)	−0.003	0.934
Expected net benefit of a voucher						
FMR of voucher offer (thousands of 2013 $)	0.051*	(0.026)	−0.008	(0.060)	0.059	0.363
Recently moved[2]	−0.022**	(0.011)	0.040	(0.029)	−0.061	0.044
Average composite test scores of children[3]	−0.019**	(0.009)	0.005	(0.028)	−0.024	0.406
Household children arrested[3]	−0.017	(0.018)	0.002	(0.045)	−0.019	0.691
Poverty rate[4]	0.023	(0.032)	0.135*	(0.080)	−0.112	0.190
Fraction black[4]	0.078***	(0.016)	0.015	(0.059)	0.063	0.289
Property crime rate (per 1,000)[4]	−0.000	(0.000)	0.000	(0.000)	−0.000	0.337
Violent crime rate (per 1,000)[4]	0.000	(0.000)	0.000	(0.000)	0.000	0.970
Distance to nearest school (miles)[1]	−0.080***	(0.020)	−0.088	(0.079)	0.008	0.920
Distance to nearest hospital (miles)[1]	−0.015*	(0.007)	−0.022	(0.018)	0.008	0.696

Table 4. Continued.

	In Private Housing at Baseline		In Public Housing at Baseline		Difference by Baseline Housing Status	
	Coefficient (1)	Std. Error (2)	Coefficient (3)	Std. Error (4)	Difference (5)	p-value (6)
Cost of finding a unit						
Disabled	0.037***	(0.009)	−0.011	(0.026)	0.048	0.084
Difficult to categorize						
Household head is middle-aged (40–64)	−0.028***	(0.009)	−0.080***	(0.028)	0.052	0.073
Household head is elderly (65+)	−0.073***	(0.018)	−0.253***	(0.048)	0.180	0.000
Received Food Stamps[2]	0.103***	(0.014)	0.055	(0.044)	0.047	0.301
Received TANF[2]	0.023**	(0.011)	0.045	(0.030)	−0.022	0.489
Received Medicaid[2]	0.008	(0.016)	0.032	(0.045)	−0.024	0.602
Has children	0.062***	(0.019)	0.062	(0.058)	−0.001	0.991
Average age of children	−0.004***	(0.001)	−0.007	(0.004)	0.003	0.517
Distance to nearest rail or bus stop (miles)[1]	0.080***	(0.021)	0.055	(0.104)	0.025	0.810
Household head arrested[3]	−0.067***	(0.013)	−0.148***	(0.036)	0.080	0.032
Recently ended employment[2]	−0.019	(0.012)	−0.026	(0.036)	0.006	0.866
Recently began employment[2]	−0.109***	(0.016)	−0.101**	(0.044)	−0.008	0.864
Employed[2]	0.242***	(0.012)	0.183***	(0.035)	0.060	0.106
Annual earnings (thousands of 2013 $)[2]	−0.005***	(0.000)	−0.003**	(0.002)	−0.002	0.226
N (Households)	16,179		1,930			
R-squared	0.172		0.176			

Notes: The sample is all Chicago households offered a housing voucher between 1997 and 2003. Each point estimate and standard error are from a single Linear Probability Model regression of an indicator equal to one if the household leased up on the covariates. The regression also includes offer year and offer month fixed effects and indicators for missing values. Standard errors are heteroskedasticity-robust. FMR = Fair Market Rent. 1 = At voucher offer. 2 = During year prior to voucher offer. 3 = During two years prior to voucher offer. 4 = At baseline (July 1997). ***Significant at the 1 percent level; **5 percent level; *10 percent level.

Table 5. Peer effects in housing voucher take-up.

	(1)	X Var. Mean (2)	X Var. Std. Dev. (3)	Effect Size (4)
Panel A. Reduced Form				
Number of HHs Offered Voucher During:				
Most Recent Quarter	0.008*** (0.003)	1.077	1.654	0.013
Next Quarter (Falsification)	0.003 (0.003)	1.077	1.647	
Panel B. Two Stage Lease Squares				
Number of HHs Leased-Up During:				
Most Recent Quarter	0.015*** (0.005)	0.590	1.096	0.016
Next Quarter (Falsification)	0.005 (0.005)	0.605	1.106	

Notes: The sample is all Chicago households (HHs) offered a housing voucher between 1997 and 2003 (N = 18,109). In panel A, each point estimate is from a separate Linear Probability Model regression of an indicator equal to one if the HH leased up on all of the covariates included in Table 3, an additional variable measuring the number of voucher applicants in the HH's census block group, and the number of voucher offers received by HHs in the block group in the prior quarter (row 1) or next quarter (row 2). Panel B replaces the nearby offer variables with the number of HHs nearby who leased up, and instruments for those variables with the nearby offer variables. ***Significant at the 1 percent level; **5 percent level; *10 percent level.

suggesting that the predictors of successful lease-up are similar between households living in private and public housing at baseline.[34]

Peer Effects in Housing Voucher Take-Up

Previous studies have found important evidence of peer effects in program participation (Aizer & Currie, 2004; Dahl, Loken, & Mogstad, 2014; Duflo & Saez, 2003; Figlio, Hamersma, & Roth, 2015). We exploit the randomized nature of the voucher lottery in our study to provide the first examination of whether peer effects exist in housing voucher take-up. Specifically, for each of the 18,109 households offered a voucher in our sample, we create a measure of the number of neighboring (within the same Census block group) households that received a housing voucher offer in the quarter prior to the focal household's own voucher offer. We add this measure as an independent variable in our main equation (1). Importantly, we control for the number of voucher applicants in a household's Census block group since this is potentially endogenous and will be correlated with the number of neighbors who receive voucher offers. Hence, our identifying assumption is that the timing and location of the voucher offers are random after conditioning on the number of households applying for a voucher in the block group.

We find small, but statistically significant evidence of peer effects, as reported in panel A of Table 5. Having one additional neighbor offered a voucher during the past quarter increases the probability of lease-up by 0.8 percentage points, or 1.6 percent. Scaling this effect reveals that a one standard deviation (1.65) increase in the number of neighbors with recent offers leads to a 1.3 percentage point, or

[34] The few exceptions where there are statistically significant differences across the samples are the following: the number of adults and recently moving are more positively related to lease-up in the public sample; disability status is less positively related; and household head age and recently having been arrested are even more negatively related.

2.6 percent, increase in take-up.[35,36] Note that the estimates in Table 5 are conditional on the household characteristics included in equation (1). When we estimate a model that omits these controls, we obtain nearly identical point estimates (see Appendix Table A4).[37] The robustness of the estimates to the inclusion of controls is consistent with the assumption that the timing and location of voucher offers are random after conditioning on total applications within a given neighborhood.

One hypothesis is the number of neighbors who *successfully* use their voucher affects a household's own lease-up probability. With this in mind, we provide 2SLS estimates of the impact of peer lease-up where the first stage uses the number of neighbors recently offered a voucher as an instrument for the number of recent neighbors who leased up. The 2SLS estimates in panel B of Table 5 show that one additional neighboring household recently leasing-up increases the probability of own lease-up by 1.5 percentage points, or 3 percent. Scaling by a one standard deviation increase in recent neighboring lease-up, we find an effect of 1.6 percentage points or a 3.2 percent increase in take-up.

Finally, we also provide results from a falsification test to support our interpretation of our analysis of peer effects. Specifically, we test whether the number of neighbors who receive vouchers in the *next* quarter has an impact on lease-up. In line with our expectation, Table 5 shows there is no evidence of an impact of neighbors who receive vouchers after the focal household has already received their offer.

REVISITING THE LABOR MARKET EFFECTS OF HOUSING ASSISTANCE

Methodology: Reweighting the Effects of Voucher Use

We next consider the role of compliance in estimating the impact of voucher assistance on household behavior. Jacob and Ludwig (2012) (henceforth JL) exploit the exogenous variation in housing assistance created by the CHAC 1997 lottery to estimate the effect of means-tested housing benefits on labor supply and public assistance usage. They find that voucher receipt reduces employment and earnings while increasing participation in social programs. Their estimates represent local average treatment effects (LATEs) that are valid for the set of housing voucher compliers, i.e., the approximately half of households that would lease up if offered a voucher, and not lease up if not offered a voucher (Angrist, Imbens, & Rubin, 1996; Imbens & Angrist, 1994). Although the estimate of the LATE is credibly identified through the lottery design, it is widely acknowledged in the applied literature that the LATE may differ from another parameter of interest: the average treatment effect (ATE).[38] The latter would be useful for evaluating what would occur if compliance rates increased (e.g., if additional search assistance was provided). Estimating the ATE requires moving beyond the purely experimental framework provided by the housing voucher lottery.

We revisit the impact of housing assistance on labor supply and public assistance usage by estimating ATEs using inverse compliance score weighting based on the

[35] When we consider nearby offers during the prior two quarters instead of only the prior quarter, the effect is attenuated and only marginally statistically significant. There is zero detectable peer effect looking further back beyond two quarters prior.
[36] When we estimate the peer effect models separately by baseline housing status, we find no evidence of heterogeneity by private versus public housing.
[37] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.
[38] A large literature discusses the distinction between LATE and ATE estimates. A general overview is provided by DiNardo and Lee (2011).

extrapolation framework provided by Angrist and Fernandez-Val (2010) and Aronow and Carnegie (2013). Specifically, we weight each member of our sample by the inverse of his or her lease-up compliance score, which is the predicted probability of being a complier based on observed characteristics. This has the effect of re-weighting the complier sample to reflect the covariate distribution in the entire population selected for treatment.

Intuitively, the thought experiment behind our approach is as follows: How would the effects of vouchers change if take-up were improved? The difficulty in answering this question stems from the fact that some types of households may be underrepresented among the group that leases up with a voucher. The weighting procedure solves this problem by scaling up the labor market impacts for complying households that are less likely to lease up.[39] These low-probability compliers represent the type of household head that will be affected if voucher take-up is improved.

We implement the estimation procedure in two steps.[40] First, we estimate the predicted probability of a household being a "complier" using the covariates specified in equation (1). This probability, referred to as a compliance score, reflects the likelihood that a household uses a voucher when offered one through the lottery.[41] Then, the inverse of this compliance score serves as the weight for each household in a weighted IV estimation, as outlined in JL:

$$Lease\ d_{it} = \alpha + \theta_1 PostOffer_{it} + \theta_2 PreOffer_{it} + X\Gamma + \gamma_t + \epsilon_{it} \tag{2}$$

$$y_{it} = \alpha + \pi_1 Leased_{it} + X\Gamma + \gamma_t + \epsilon_{it} \tag{3}$$

For the first stage equation in (2), the outcome is an indicator for whether household i uses a housing voucher by period t. Here, a family that stops using its voucher does not become "untreated." The variable $PostOffer_{it}$ equals 1 if household i is offered a voucher in any period prior to (and including) t and is 0 otherwise. $PreOffer_{it}$ equals 1 if household i will eventually receive a voucher offer but has not yet as of period t. The vector γ_t controls for calendar-year effects. Finally, we include X in the regression to control for baseline characteristics, where X is the set of covariates from Jacob and Ludwig (2012), which is slightly different from those we use in the present paper (see Appendix A for a description of the JL covariates). Standard errors are clustered by household (Bertrand, Duflo, & Mullainathan 2004). In addition, we bootstrap the entire estimation process to account for variance due to estimation of the compliance score.

[39] Consider the following simplified example based on Aronow and Carnegie (2013) to see how re-weighting the sample recovers the average treatment effect (ATE). Suppose that gender is the only determinant of compliance and that 50 and 25 percent of men and women comply with treatment, respectively. Assume that the treatment effect is always 0 for men and 2 for women. In this case, the average treatment effect is 1 assuming men and women have equal proportion in the experiment. However, the LATE is equal to the ratio of the ITT and the compliance rate in the treatment group. In this case, the LATE is equal to 2/3 since the ITT is equal to 1/4 (=0.5*0.05*0 + 0.5*0.25*2), and the average compliance rate is 0.375.

[40] Appendix A discusses the implementation in detail and provides a simple numerical example illustrating the above intuition. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

[41] The compliance score is calculated by subtracting the likelihood of take-up if assigned to the control group, obtained from a probit model estimated on control group households, from the likelihood of take-up if assigned to the treatment group, obtained from a separate probit model estimated on treatment group households. See Appendix A for details.

As discussed in Angrist and Fernandez-Val (2010) and Aronow and Carnegie (2013), this weighting method consistently estimates the ATE under three assumptions. First, the ATE for all individuals with a given set of characteristics must equal the ATE for all compliers with the same covariate profile. This is similar to the selection-on-observables assumption used in matching estimators. As in matching, this assumption is more plausible given a rich set of covariates with which to estimate the model, which we use in the present analysis.[42]

The second assumption is that we have specified the compliance score estimator properly, a concern we attempt to address by flexibly parameterizing our covariates and testing the sensitivity of the estimates to different functional forms. We test whether our results are sensitive to including either a quadratic or cubic in all of our continuous covariates, and find that our results are unchanged. The third assumption is that there must be non-zero compliance in *every* covariate profile. Intuitively, this assumption requires that the compliance score is strictly above zero (i.e., each unit has a non-zero probability of being a complier). Figure A1 in Appendix A shows the density of compliance scores. Less than 1 percent of the sample has a compliance score of 0.05 or smaller.[43]

In addition to these three assumptions necessary for the weighting procedure to estimate the ATE, there are two additional context-specific assumptions we make for this exercise. First, we assume that any new policies to increase take-up do not dramatically change the pool of households applying for a housing voucher in a way that directly affects labor supply. Possible changes to the voucher program, such as reducing the labor supply distortion implicit in the program design, could increase lease-up rates, but would also induce households with stronger labor market earnings potential to apply for a voucher. Other policies housing authorities could use to increase take-up might include increasing the search period beyond 60 days, providing child care or transportation to ease housing search, or offering vouchers only during months when rental markets are more active and lease-up rates are higher. We believe these types of policies could improve take-up, but would be less likely to affect the applicant pool in a way that mechanically alters the effects of housing assistance on labor supply.

Second, the validity of this exercise relies on the assumption that the groups currently with the lowest take-up rates would be those most likely to see increases in their take-up. This assumption seems sensible given that these groups have the largest numbers to contribute to the increased take-up. On the other hand, these groups may be the hardest to get to take up the voucher, given that there must be some reason they did not lease up in the first place. Both of these assumptions point to the theoretical nature of this exercise—that lease-up has somehow increased to 100 percent, a situation in which all households, even those struggling most to lease up successfully, manage to do so. Put differently, while the ATE we identify may be valid for a situation with a 100 percent lease-up rate, we cannot identify whether the LATE changes linearly toward the ATE as lease-up increases from 50 to 100 percent.

Improved Housing Assistance Take-Up and Labor Supply

In this section, we use our analysis of the predictors of lease-up to examine whether policies to increase take-up would affect our understanding of the effect of vouchers on labor supply. We begin our analysis by replicating the LATE estimates reported

[42] It is worth noting that despite the rich set of covariates that we use to predict take-up, the R-squared for that regression is still only 0.17.

[43] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

Table 6. Effects of housing vouchers on labor supply and public assistance receipt (LATE vs. ATE).

		LATE (Replicating Jacob and Ludwig 2012)			ATE	
	CM (1)	IV (2)	CCM (3)	Obs. (4)	IV (5)	Obs. (6)
HHH Employed	0.592	−0.036** (0.009)	0.605	42,358	−0.032** (0.015)	42,025
HHH Earnings	3291.02	−328.949** (74.560)	3113.90	42,358	−471.420*** (137.952)	42,025
HHH Earnings>$3220 (FT@$8/hr)	0.404	−0.045** (0.009)	0.403	42,358	−0.056*** (0.015)	42,025
HHH Earnings conditional on working	5557.98	−227.544** (80.221)	5128.37	38,628	−435.003*** (144.568)	38,362
HHH Log earnings conditional on working	8.279	−0.073** (0.018)	8.220	38,628	−0.117*** (0.029)	38,362
HHH Received public assistance	0.46	0.067** (0.009)	0.552	42,358	0.075*** (0.012)	42,025
HHH Received TANF	0.146	0.017** (0.004)	0.110	42,358	0.018*** (0.005)	42,025
HHH Received Medicaid	0.4	0.058** (0.009)	0.484	42,358	0.062*** (0.012)	42,025
HHH Received Food Stamps	0.375	0.076** (0.008)	0.449	42,358	0.084*** (0.011)	42,025

Notes: Columns 2 through 4 replicate the results from Table 3 of Jacob and Ludwig (2012). Column 5 presents re-weighted estimates, weighting by the inverse of the predicted compliance probability. The difference in sample size between columns 4 and 6 is because we trim observations with less than a 5 percent predicted compliance probability. HHH = household head. CM = control mean. IV = instrumental variables. CCM = control complier mean. See text for discussion of these estimates. We construct standard errors (clustered at the household level) by bootstrapping (N = 200) the entire estimation process to account for variance in the estimated compliance score. All earnings measured in 2007 dollars. ***Significant at the 1 percent level; **5 percent level; *10 percent level.

in JL in columns 2 through 4 of Table 6, using their sample of 42,358 families headed by a working-aged (younger than 65), able-bodied adult at the time they applied to the CHAC wait list. We maintain their presentation by also reporting the control group mean (CM) in column 1 and the control complier mean (CCM) in column 3, which is the average outcome for the controls who would have used vouchers had they been assigned to the treatment group (Katz, Kling, & Liebman, 2001).[44]

Our replication of JL produces results that are identical to those in their paper: Voucher use reduced quarterly employment by 3.6 percentage points and quarterly earnings by $329, declines of 6 and 11 percent, respectively, relative to the CCM. Further, vouchers increased participation in social assistance programs by 6.7 percentage points (12 percent), with most of the increase concentrated in Medicaid and Food Stamps.

We report the ATE in column 5. Both sets of ATE estimates drop observations with estimated compliance scores less than 5 percent, per the recommendation of

[44] In practice, the CCM is calculated by subtracting the LATE estimate of π_1 from the mean outcome of housing voucher participants.

Aronow and Carnegie (2013).[45] The ATE of voucher use on the probability of being employed (row 1) is nearly identical to the LATE in JL of 3.5 percentage points. This suggests that if the lease-up rate improved, the new individuals leasing up would experience employment effects similar to those individuals currently leasing up.

In contrast, the ATE results for earnings consistently suggest that the negative impact of voucher use will be magnified if take-up is increased. For example, using our inverse compliance score weights, we find that voucher use reduces logged quarterly earnings conditional on working by 11.7 percent. These effects are notably larger than the 7.3 percent LATE estimated in JL, though given the statistical imprecision of the estimates, the p-value from the statistical test of equality across the two coefficients is 0.19. We find a similar pattern of results for the other dependent variables measuring household head earnings.[46] These results, while statistically imprecise, suggest that the earnings of those individuals who are less likely to lease up are more sensitive to voucher receipt than the earnings of individuals currently leasing up.

To document this finding more explicitly, Figure 5 splits the JL sample into thirds based on the lease-up compliance score and provides the LATE for each subsample. Figures 5a and 5b show the effects of voucher receipt on earnings conditional on working and log earnings, respectively.[47] For both, the LATE is near zero for voucher recipients with the highest likelihood of lease-up and only somewhat lower for individuals in the middle third of the distribution. Most interestingly, the group with the lowest predicted probability of lease-up experiences negative effects that are the largest in magnitude and statistically different from those of the highest group.[48] This previously undocumented heterogeneity is consistent with and more statistically precise than the ATE analysis. Taken together, these findings suggest that increasing take-up for households with a relatively low predicted probability of take-up may increase the magnitude of the (negative) average effect of vouchers on earnings for a given voucher population.

Finally, for public assistance receipt, the ATE (7.5 percentage points) is larger than the LATE (6.7 percentage points), but the magnitude of the difference is small. There are similarly small or near zero differences for whether the household head received TANF, Medicaid, or Food Stamps when examined individually. In summary, the LATE estimates from Jacob and Ludwig (2012) appear to be a good approximation of the effects on employment and public assistance receipt for a broader population.

CONCLUSION

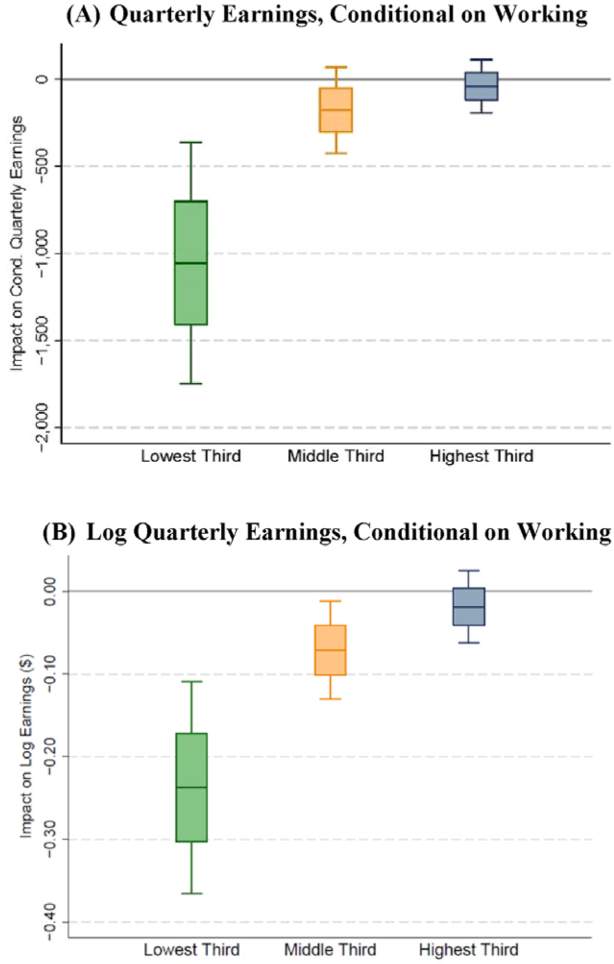
This paper, in the context of housing policy, examines two important and current issues in social policy and program evaluation: understanding low take-up rates of public assistance programs, and understanding factors that affect external validity of experimental and quasi-experimental LATEs. For the first question, we document housing voucher lease-up patterns in a large administrative dataset of voucher

[45] Including these observations can skew the results because the inverse weighting method assigns any observation with a low compliance score an extremely large weight. We argue that it is sensible to leave aside these individuals because it is unlikely that any policy or intervention would induce these individuals to lease up.

[46] These are: a) household head quarterly earnings; b) a dummy for whether the household head earns more than $3,220, which is equivalent to working full time at $8/hour; and c) household head earnings (in levels) conditional on working. The p-values from the tests of equality for these outcomes are 0.31, 0.45, and 0.22, respectively.

[47] The middle of each box shows the point estimate for each group, the edge of the box shows the standard error, and the whisker shows the 95 percent confidence interval.

[48] For both sets of results in Figure 5 (panels A and B), we can reject the null hypothesis that there is no difference between the estimates for the bottom and top tercile at the one percent significance level.



Notes: These figures show box and whisker plots based on estimates of the LATE of vouchers on quarterly earnings (Figure 5A) and log quarterly earnings (Figure 5B), conditional on working. The center of the box is a point estimate obtained through 2SLS (see equations (2) and (3) in the text). The top and bottom of each box outline the range of estimates that fall within one standard error of the point estimate. The top and bottom whiskers are the range identified for the 95-percent confidence interval. Each of the three estimates pertains to a compliance score subgroup, which is based on the predicted probability of lease-up (compliance). All earnings measured in 2007 dollars.

Figure 5. LATE Effect of Vouchers on Earnings, by Compliance Score Subgroups. [Color figure can be viewed at wileyonlinelibrary.com]

recipients in Chicago. We find extensive heterogeneity in lease-up rates by household size and composition. Elderly households and working-age, married, childless households have lease-up rates between a quarter and a third. Single women who are working age and have three or more children lease up about two-thirds of the time. In terms of economic status, we find that employment prior to receipt of a voucher offer is extremely predictive of leasing up in our sample. However, among the approximately 60 percent of the sample who were employed, those with higher earnings were less likely to lease up.

We also identify a number of additional factors predictive of voucher take-up that suggest a family's perceived benefit from a voucher could strongly influence lease-up. For example, poor recent academic performance by children in the household, and living further from amenities such as a public transit stop, are both associated with greater lease-up. Other estimates suggest landlord preferences may be important. For example, household heads who have an arrest within the two years prior to receiving a voucher offer are 7 percentage points less likely to lease successfully. Finally, we provide novel evidence that peer effects matter in housing voucher take-up: an individual is more likely to take up a voucher if they have neighbors who have recently leased up themselves.

For our second research question, we apply a reweighting method to estimates of the effect of housing vouchers from Jacob and Ludwig (2012) and find that increasing voucher take-up would not substantially change average impacts on employment or public assistance receipt. At the same time, there is suggestive evidence that higher take-up may exacerbate the (negative) effects on earnings. Supporting this finding, we document statistically larger reductions in earnings among households with a low probability of being a complier than those households with a high probability of being a complier—the former group comprising those to whom any increase in take-up rates is likeliest to accrue.

While our administrative data allow us to examine and document lease-up behavior in more detail than previously possible, we acknowledge that the data are limited to one major city during a relatively short time period. This prevents us from measuring how lease-up might vary with changes in the voucher program parameters. Further, many unanswered questions remain about *why* lease-up varies with many of the factors that we identify.

In spite of these limitations, our work identifying factors predicting successful lease-up has several important policy implications. First, in spite of the intention of many housing authorities, the heterogeneity in lease-up patterns that we uncover demonstrates that the characteristics of households who use Section 8 housing vouchers differ from those who fail to use them. Policymakers hoping to give all eligible households an equal chance of successfully using a voucher should consider offering search assistance or making other adjustments to help certain groups, such as elderly households, that we identify as struggling to lease up.

Second, several of our results point to specific policies to increase take-up. Specifically, our results show that vacancy rates and the season of the year matter for leasing. This implies that housing authorities may want to take the timing of voucher disbursement into account. Housing authorities could either restrict voucher offers to occur during months of the year with high predicted lease-up, or adjust the search period length for those offered vouchers during times we predict to have a lower success rate. Our findings on neighborhood quality and children's recent academic performance suggest that a household head's perceptions of the non-financial value of the voucher are important. Housing authorities could capitalize on this by emphasizing to households at the time of the offer the various ways that vouchers can improve their lives outside of the monetary value of the rent subsidy. Our results showing a large lease-up penalty for household heads who are unemployed or have been recently arrested are consistent with recent research suggesting landlord preferences matter (Desmond, 2016; Phillips, 2017). Policies aimed at reducing landlord discrimination could go a long way toward increasing lease-up for these groups. Finally, given the peer effects that we detect, housing authorities could improve lease-up rates at little cost by clustering voucher offers within neighborhoods such that a few neighborhoods at a time receive a large number of vouchers, rather than offering smaller numbers of vouchers across neighborhoods citywide.

Third, while Mills et al. (2006) and Jacob and Ludwig (2012) offer the best evidence to date about the effects of housing assistance on labor supply, their findings are specific to those in their samples who "comply" by leasing up with a voucher. With access to the same data used by Jacob and Ludwig (2012), we examine the representativeness of their estimates by using a reweighting approach to estimate effects for a broader population. Our results suggest that efforts to increase lease-up may come at some cost of reducing self-sufficiency for beneficiaries. Moving beyond the context of housing assistance, recent important work demonstrates that one key consideration for the external validity of experimental estimates is selection into the experiment (Andrews & Oster, 2017; Chyn, 2018). We show that variation in take-up rates may be another important consideration for external validity of experimental and quasi-experimental estimates of the effects of public assistance programs on household behavior.

ERIC CHYN is an Assistant Professor in the Department of Economics at the University of Virginia, P.O. Box 400182, Charlottesville, VA 22904-4182 (e-mail: ericchyn@virginia.edu).

JOSHUA HYMAN is an Assistant Professor in the Department of Public Policy at the University of Connecticut, 10 Front Street, 4th Floor, Hartford, Connecticut 06103 (e-mail: joshua.hyman@uconn.edu).

MAX KAPUSTIN is Research Director at the University of Chicago Crime Lab, 33 N. LaSalle Street, Suite 1600, Chicago, Illinois 60602 (e-mail: kapustin@uchicago.edu).

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APPENDIX A

Details on Estimating Inverse Compliance Score Weights

As discussed in the article, we use a weighting approach to generalize the local average treatment effect (LATE) estimates presented in Jacob and Ludwig (2012). Our weighting procedure follows the general framework discussed in Angrist and Fernandez-Val (2010) and Aronow and Carnegie (2013). Specifically, the compliance score c_i that we estimate is:

$$c_i\,(X) = \boldsymbol{E}\,(D|Z = 1, X) - \boldsymbol{E}(D|Z = 0, X)$$

where D is an indicator for ever using a housing voucher, Z is a dummy variable instrument indicative of winning a voucher offer, and X is a set of covariates. In other words, the compliance score is the strength of the first stage conditional on observed covariates. Note that in the language of the potential outcomes framework of Angrist et al. (1996), this is the predicted probability of being a complier. Recall that a complier is an individual who accepts an experimental treatment when assigned to the treatment group but does not obtain the treatment if assigned to the control group.

When no members of the control group are able to obtain the treatment, the second term in the above expression is always zero and the probability of being a complier is just the likelihood of accepting the treatment given that the individual is a member of the treatment group.[49] In our case, we face "two-sided non-compliance" because a small fraction of CHAC 1997 lottery applicants are able to obtain a housing voucher through other means. Hence, the second term in the expression above is non-zero and we must model take-up in the control group. Note that in the language of the potential outcomes framework of Angrist et al. (1996), these control group individuals who obtain the treatment are called always-takers.

In our setting of two-sided non-compliance, we estimate the compliance score in two steps. First, we use the sample of treated households and estimate a probit model of leasing-up given the characteristics X. Using the parameters from this model, we predict $\boldsymbol{E}(D|Z = 1, X)$ for both treated and control units. Second, we use the sample of control households and estimate a probit model of leasing-up given the characteristics X. Using the parameters from this model, we predict $\boldsymbol{E}(D|Z = 0, X)$ for both treated and control units. Having calculated $\widehat{c_i}(X)$, we define our weights for each individual as $\widehat{w}_i(X) = 1/\widehat{c_i}(X)$ and use these in our 2SLS estimates of the impact of voucher use on labor supply. For the interested reader, Figure A1 shows the density $\widehat{c_i}(X)$ for the sample.

[49] The case in which there are no always-takers but some members of the treatment group do not receive the treatment is referred to as "one-sided non-compliance." For an example of weighting in this context of one-sided compliance, see Follmann (2000).

Table A1. Lease-up rates by household size and composition.

	Lease-Up Rate				Sample Size			
	No Children (1)	One Child (2)	Two Children (3)	Three+ Children (4)	No Children (5)	One Child (6)	Two Children (7)	Three+ Children (8)
Single Female Household Head								
Working-Age, Non-Disabled	0.48	0.57	0.59	0.61	3941	2878	2063	1843
Working-Age, Disabled	0.51	0.60	0.59	0.66	1551	465	346	506
Elderly, Non-Disabled	0.29				251	7	5	4
Elderly, Disabled	0.32				261	9	4	2
Single Male Household Head								
Working-Age, Non-Disabled	0.34	0.32	0.29	0.40	1017	88	35	30
Working-Age, Disabled	0.43	0.56			793	25	10	13
Elderly, Non-Disabled	0.22				55	0	0	0
Elderly, Disabled	0.33				70	2	0	0
Married Household Head								
Working-Age, Non-Disabled	0.25	0.35	0.46	0.52	557	204	158	147
Working-Age, Disabled	0.37	0.65	0.48	0.56	355	71	44	59
Elderly, Non-Disabled	0.28				107	3	1	0
Elderly, Disabled	0.32				126	1	0	2

Notes: The sample is Chicago households living in private market or public housing at baseline (July 1997) and offered a housing voucher between 1997 and 2003. N = 18,109. We omit lease-up rates for cells with fewer than 25 households.

Table A2. Logit estimation of lease-up for households in private housing at baseline.

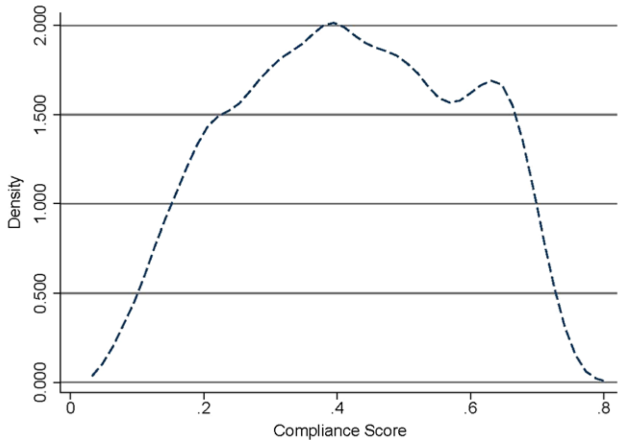
	Coefficient (1)	Std. Error (2)	Marginal Effect[5] (3)	Std. Error (4)
Demographics (household head)				
Male	−0.258***	(0.053)	−0.065***	(0.013)
Black	0.236***	(0.088)	0.059***	(0.022)
Hispanic	0.121	(0.126)	0.030	(0.031)
Has spouse	−0.373***	(0.066)	−0.093***	(0.016)
Probability of finding and leasing suitable unit[1]				
Number of adults (including household head)	−0.042	(0.028)	−0.011	(0.007)
Number of children	−0.065**	(0.030)	−0.016**	(0.007)
MSA vacancy rate	0.079	(0.053)	0.020	(0.013)
Expected net benefit of a voucher				
FMR of voucher offer (thousands of 2013 $)	0.244*	(0.126)	0.061*	(0.032)
Recently moved[2]	−0.108**	(0.053)	−0.027**	(0.013)
Average composite test scores of children[3]	−0.089**	(0.045)	−0.022**	(0.011)
Household children arrested[3]	−0.086	(0.086)	−0.022	(0.021)
Poverty rate[4]	0.133	(0.152)	0.033	(0.038)
Fraction black[4]	0.385***	(0.076)	0.096***	(0.019)
Property crime rate (per 1,000)[4]	−0.000	(0.001)	−0.000	(0.000)
Violent crime rate (per 1,000)[4]	0.000	(0.001)	0.000	(0.000)
Distance to nearest school (miles)[1]	−0.369***	(0.098)	−0.092***	(0.025)
Distance to nearest hospital (miles)[1]	−0.074**	(0.035)	−0.018**	(0.009)
Cost of finding a unit				
Disabled	0.184***	(0.044)	0.046***	(0.011)
Difficult to categorize				
Household head is middle-aged (40–64)	−0.135***	(0.042)	−0.034***	(0.010)
Household head is elderly (65+)	−0.349***	(0.095)	−0.087***	(0.024)
Received Food Stamps[2]	0.463***	(0.065)	0.116***	(0.016)
Received TANF[2]	0.118**	(0.055)	0.029**	(0.014)
Received Medicaid[2]	0.038	(0.073)	0.009	(0.018)
Has children	0.285***	(0.091)	0.071***	(0.023)
Average age of children	−0.018***	(0.007)	−0.004***	(0.002)
Distance to nearest rail or bus stop (miles)[1]	0.381***	(0.109)	0.095***	(0.027)
Household head arrested[3]	−0.321***	(0.062)	−0.080***	(0.016)
Recently ended employment[2]	−0.103*	(0.058)	−0.026*	(0.014)
Recently began employment[2]	−0.537***	(0.078)	−0.134***	(0.019)
Employed[2]	1.150***	(0.059)	0.287***	(0.015)
Annual earnings (thousands of 2013 $)[2]	−0.025***	(0.002)	−0.006***	(0.000)
N (Households)	16,179		16,179	

Notes: The sample is Chicago households living in private market housing at baseline (July 1997) and offered a housing voucher between 1997 and 2003. Each point estimate and standard error are from a logit regression of an indicator equal to one if the household leased up on the covariates. The regression also includes offer year fixed effects and indicators for missing values. Standard errors are heteroskedasticity-robust. FMR = Fair Market Rent. 1 = At voucher offer. 2 = During year prior to voucher offer. 3 = During two years prior to voucher offer. 4 = At baseline (July 1997). 5 = Marginal effects calculated at the means of all covariates included in the model. ***Significant at the 1 percent level; **5 percent level; *10 percent level.

Table A3. Logit estimation of lease-up for households in public housing at baseline.

	Coefficient (1)	Std. Error (2)	Marginal Effect[5] (3)	Std. Error (4)
Demographics (household head)				
Male	−0.544***	(0.175)	−0.134***	(0.043)
Black	0.429	(0.278)	0.106	(0.069)
Hispanic	−0.423	(0.656)	−0.104	(0.162)
Has spouse	−0.105	(0.212)	−0.026	(0.052)
Probability of finding and leasing suitable unit[1]				
Number of adults (including household head)	0.113	(0.080)	0.028	(0.020)
Number of children	0.002	(0.076)	0.000	(0.019)
MSA vacancy rate	0.090	(0.149)	0.022	(0.037)
Expected net benefit of a voucher				
FMR of voucher offer (thousands of 2013 $)	−0.033	(0.305)	−0.008	(0.075)
Recently moved[2]	0.200	(0.150)	0.049	(0.037)
Average composite test scores of children[3]	0.030	(0.133)	0.007	(0.033)
Household children arrested[3]	0.003	(0.218)	0.001	(0.054)
Poverty rate[4]	0.668*	(0.386)	0.165*	(0.095)
Fraction black[4]	0.091	(0.278)	0.022	(0.068)
Property crime rate (per 1,000)[4]	0.001	(0.001)	0.000	(0.000)
Violent crime rate (per 1,000)[4]	0.000	(0.002)	0.000	(0.000)
Distance to nearest school (miles)[1]	−0.444	(0.418)	−0.109	(0.103)
Distance to nearest hospital (miles)[1]	−0.115	(0.086)	−0.028	(0.021)
Cost of finding a unit				
Disabled	−0.031	(0.129)	−0.008	(0.032)
Difficult to categorize				
Household head is middle-aged (40–64)	−0.381***	(0.130)	−0.094***	(0.032)
Household head is elderly (65+)	−1.268***	(0.265)	−0.313***	(0.066)
Received Food Stamps[2]	0.239	(0.202)	0.059	(0.050)
Received TANF[2]	0.246	(0.152)	0.061	(0.037)
Received Medicaid[2]	0.150	(0.211)	0.037	(0.052)
Has children	0.270	(0.282)	0.067	(0.069)
Average age of children	−0.030	(0.020)	−0.007	(0.005)
Distance to nearest rail or bus stop (miles)[1]	0.257	(0.539)	0.063	(0.133)
Household head arrested[3]	−0.702***	(0.166)	−0.173***	(0.041)
Recently ended employment[2]	−0.123	(0.184)	−0.030	(0.045)
Recently began employment[2]	−0.514**	(0.218)	−0.127**	(0.054)
Employed[2]	0.893***	(0.176)	0.220***	(0.043)
Annual earnings (thousands of 2013 $)[2]	−0.016**	(0.007)	−0.004**	(0.002)
N (Households)	1,930		1,930	

Notes: The sample is Chicago households living in public housing at baseline (July 1997) and offered a housing voucher between 1997 and 2003. Each point estimate and standard error are from a logit regression of an indicator equal to one if the household leased up on the covariates. The regression also includes offer year fixed effects and indicators for missing values. Standard errors are heteroskedasticity-robust. FMR = Fair Market Rent. 1 = At voucher offer. 2 = During year prior to voucher offer. 3 = During two years prior to voucher offer. 4 = At baseline (July 1997). 5 = Marginal effects calculated at the means of all covariates included in the model. ***Significant at the 1 percent level; **5 percent level; *10 percent level.



Notes: The figure shows the kernel density estimate of the compliance scores estimated for our sample of 16,179 working-aged, able-bodied, CHAC 1997 lottery applicants living in private market housing. Details on estimation of this score are provided above.

Figure A1. Compliance Score Density. [Color figure can be viewed at wileyonlinelibrary.com]

Table A4. Peer effects sensitivity test.

	No HH Controls (1)	Main Specification (With HH Controls) (2)	X Var. Mean (3)	X Var. Std. Dev. (4)
Panel A. Reduced Form				
Number of HHs Offered Voucher During:				
Most Recent Quarter	0.008***	0.008***	1.077	1.654
	(0.003)	(0.003)		
Next Quarter (Falsification)	0.004	0.003	1.077	1.647
	(0.003)	(0.003)		
Panel B. Two Stage Lease Squares				
Number of HHs Leased-Up During:				
Most Recent Quarter	0.016***	0.015***	0.590	1.096
	(0.006)	(0.005)		
Next Quarter (Falsification)	0.009	0.005	0.605	1.106
	(0.005)	(0.005)		

Notes: The sample is all Chicago households (HHs) offered a housing voucher between 1997 and 2003 (N = 18,109). Each point estimate comes from an augmented version of the model provided in equation (1). Specifically, we add measures of the number of voucher applicants in the HH's census block group, and the number of voucher offers received by HHs in the block group in the prior quarter (row 1) or next quarter (row 2). Estimates with and without household level characteristics are reported in columns 1 and 2, respectively.

APPENDIX B

Data Appendix (Reproduced from Jacob and Ludwig, 2012)

Baseline information on the 82,607 adults and nearly 8,700 spouses that applied to CHAC for a housing voucher in 1997 comes from the lottery application forms. These files include information on address, lottery number, and household demographics, such as the number and gender of other children and adults in the household, as well as identifying information (names, date of birth, and social security number) for the household heads and spouses. We impute certain demographic variables that are either incomplete or not included on the application forms using information from the Illinois Department of Human Services (IDHS) Client Data Base (CDB). For example, household head gender is not included on the CHAC application form, so we use gender from the CDB and then impute missing values based on name. These imputations are made by comparing the first name of the household head with lists of names of known gender using four data sources: Census data, Social Security Administration data, two websites with lists of names; and, finally, using a gender-assigning algorithm. For spouses with missing gender, we assign them the opposite gender of the household head.

Similarly, to determine race, we start with the CDB race variable and then impute missing values using the less complete lottery application information. For those observations that are missing, we check to see whether "multiple races" is checked on the CHAC application. To determine the coding of these multiple races, we create an empirical link by looking at those individuals with multiple races on the CHAC application forms who also have race information in the CDB. For each combination of multiple races, we choose the modal race that is indicated by the CDB. For example, if those who are listed as both white and Hispanic on the CHAC forms are listed most often as Hispanic in the CDB, then we assume that all people marked both white and Hispanic on the CHAC forms are Hispanic.

To create and clean our age variables, we use information from both the CHAC application forms and the IDHS client data base. The age variables we create indicate age during 1997 when the CHAC lottery application takes place. They include two household invariant variables—household head age and spouse age—and one person invariant age variable for the person in question. For the household heads, if the CHAC age is missing but we have CDB age, then we use CDB age. If he or she indicates age as less than 16 years old on the application form and we have no CDB information, then we set the age as equal to missing. If the CHAC age is less than 18 or greater than 70, and the difference between that age and the CDB age is greater than one, then we use the CDB age. For spouse age, we use date of birth information, if available, and, when missing, we use CDB age as long as it is a reasonable value (i.e., not less than 16). For kids and other household members, we first check for members age 0 to 18 who are a household head or spouse somewhere else in the sample (e.g., a 17-year-old who applied as a head and is also the child of a parent who applied separately as a head). For all those that we find, we make sure their age is consistently reported across observations. There are a small number of observations that have an age greater than 100 and we set these as equal to missing.

There are several seemingly infeasible outliers in the CHAC information on household composition. We take the following steps to clean this information: for number of male children and female children we set values ranging from 20 to 29 equal to 2, and values from 10 to 19 equal to 1. Similarly, for number of adult females and adult males, we set values of 10, 11, and one instance of 81, all equal to 1. We set negative values equal to 0. When there are zero adults listed, we impute one adult, male or female, based on household head gender. We then create total household, total adult, and total child categories by summing the cleaned household composition variables. We confirm that these cleanings have no impact on our randomization checks or any other results.

Data on voucher utilization comes from HUD 50058 records, which families must complete at least once a year to verify eligibility and also when they exit or enter housing programs or if household composition or income changes. These HUD 50058 forms provide complete longitudinal information on housing assistance administered by CHAC (i.e., all tenant-based rental assistance such as Section 8 vouchers and certificates, but excluding public housing), including when the household started and stopped receiving assistance and the different addresses where the households lived while on a Section 8 voucher. We merge the application data to CHAC files on voucher utilization using CHAC tenant identification numbers coupled with name, social security number, and date of birth. We use a probabilistic match that is robust to misspellings, typos, and other minor inconsistencies across data sets. These files also provide information on the type of apartment leased and the number of members in the household.

To track residential locations for both the treatment and control groups, we rely on passive tracking sources such as the National Change of Address (NCOA) registry and national credit bureau checks. Because of resource constraints, we tracked a random 10 percent subsample of all CHAC applicants. We have confirmed that this subset matches the overall applicant pool on a variety of baseline characteristics, and that the impact estimates on labor supply for this 10 percent subsample are virtually identical to the impact estimates for the full sample. We are also able to verify (at least partially) the accuracy of the passive tracking techniques using the subset of families who received housing vouchers. In the vast majority of these cases, the location information obtained through passive tracking matches the information found in the administrative 50058 records. Using these addresses along with 2000 census data, we are able to characterize each household's residential neighborhood down to the block group level.

We determine whether a family was living in public housing or project-based Section 8 housing at the time of the lottery by merging baseline addresses from the CHAC application files to lists of subsidized units maintained by the Chicago Housing Authority and HUD. We use baseline housing status because housing arrangements may be influenced by the outcome of the voucher lottery. This means that the group identified as living in a housing project at baseline may include some families who are in private-market housing by the time they are actually offered a housing voucher by CHAC. This occurs in part because of the natural transition of families out of project-based housing units over time, and in part because the city of Chicago was demolishing thousands of units of public housing during the course of the 1990s (see Jacob, 2004).

To measure labor market participation and earnings, we have obtained quarterly earnings data from the Illinois unemployment insurance (UI) program, maintained by the Illinois Department of Employment Security (IDES). If an individual works for more than one employer in a given calendar quarter, we aggregate up earnings from all employers. People in our sample are counted as working in a given quarter if they report having any earnings at all in the UI data in a quarter. Household-level employment is defined as having anyone in the CHAC baseline household show any earnings in a given quarter. We set to missing those person-quarter observations where quarterly earnings are reported to be less than $5 in nominal terms. We set equal to the 99th percentile of the distribution those drop outlier observations at the top end, defined as those greater than in the 99th percentile of the distribution. Earnings figures are then converted into constant 2007 dollars.

We obtain our welfare information from the IDHS administrative data bases. They provide us with start and end dates of ACDF/TANF, Food Stamp, and Medicaid spells for every household member of those households that we match to the CDB. From these start and end dates, we then create for each of the welfare programs a variable indicating the number of days during the current quarter that a person was receiving assistance and separate binary indicators for whether the person received assistance during the current quarter, the first quarter of 1997, and second quarter of 1997. We also create binary indicators for whether the household head received assistance of any type during the current quarter, the first quarter of 1997, and the second quarter of 1997.