How Do Changes in Housing Voucher Design Affect Rent and Neighborhood Quality?

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Online Appendix

Appendix A

We build a model to understand how changes in voucher generosity may accrue to landlords or tenants. The model contains two key features. First, landlords post prices, and may adjust their posted price based on the government-set rent ceiling. In particular, they may post a price equal to the rent ceiling and actively recruit voucher holders; together, these activities act as a means of price discrimination. Second, it is harder for a new voucher holder to find a unit in a high-quality neighborhood than in a low-quality neighborhood.

The assumption that voucher holders face a trade-off between finding a unit in a high-quality neighborhood and finding a unit at all is motivated by three features of the institutional context. First, because vouchers typically pay a flat amount across a metro area, a voucher can cover the cost of 68% of units in the lowest-rent neighborhoods but only 15% of units in higher-rent neighborhoods, as shown empirically in Figure 2 (top panel). Second, once a tenant is issued a voucher, she has 60-90 days to "use or lose it". These challenges are exacerbated for reasons unique to housing voucher holders such as discrimination, high transportation costs, and steering to specific units.[29] Given these constraints, it is not surprising that roughly one-in-three families issued a voucher are unable to lease a unit under the program in the allotted time (Abt Associates 2001).

Two lessons emerge from the model's comparative statics. Historically, HUD has attempted to improve neighborhood quality using uniform increases in voucher generosity (U.S. Department of Housing and Urban Development 2000). The model's first lesson is that theory does *not* provide a clear prediction whether a uniform increase in voucher generosity will accrue to landlords or tenants. Tenants will benefit if the probability of matching is already high such that they use the more generous vouchers to move to better neighborhoods. On the other hand, landlords will benefit if they can raise their rents without tenants moving to quality.

[29] Audit studies have found that landlords discriminate, refusing to rent to people with a voucher (Lawyers Committee for Better Housing Inc 2002; Perry 2009). Voucher recipients also seem to have high transportation costs; participants with cars in the Moving to Opportunity experiment moved to and stayed in higher-quality neighborhoods in terms of crime and school quality (Pendall et al. 2014). Voucher holders are often steered towards a short list of units by housing authority recommendations (Abt Associates 2001).

The second lesson is that tilting the rent ceiling is a cost-effective way to raise neighborhood quality. A policy lever which HUD has piloted in recent years is tilting the rent ceiling so that it is higher in high-quality neighborhoods and lower in low-quality neighborhoods. Intuitively, this policy reduces the penalty for searching in high-quality neighborhoods which is implicit in the status quo policy. This policy is cost-effective because it changes the incentives voucher holders face when searching, without increasing the opportunity for price discrimination by raising the average rent ceiling.

1. Environment

There is a continuum of neighborhoods with heterogeneous quality q where q is an observable, dollar-denominated index with positive measure for all $q \geq q_{min}$ and zero measure for $q < q_{min}$. Our model focuses on differences in neighborhood quality because improving neighborhood quality is the explicit objective of the rent ceiling policies we study (U.S. Department of Housing and Urban Development 2000). However, our empirical analysis also estimates improvements in unit quality because this is one way that increases in voucher generosity can accrue to tenants rather than landlords.

Housing Demand . — In each neighborhood q, there are private nonvoucher (NV) tenants whose demand is decreasing in rental price r. Their housing demand gives rise to a reduced-form demand curve $D_{NV}(r;q)$. Because the focus of this paper is the neighborhood choices of voucher recipients, we take the demand of nonvoucher recipients as exogenous.[30] Voucher holders demand is not price sensitive, and they will lease any unit at or below the government-set voucher rent ceiling of $\bar{r}$. Voucher demand is given by

$$D_V(r,q) = \begin{cases} 0 & r > \bar{r} \text{ or } q \neq q^* \\ \alpha \tilde{D}_V & r = \bar{r} \text{ and } q = q^* \\ \tilde{D}_V & r < \bar{r} \text{ and } q = q^* \end{cases}$$

where q^* is the neighborhood that voucher holders rent in (the optimal choice of q^* is described in Section A.1), and $\tilde{D}_V$ is the endogenously-set share of units leased to voucher holders with $r < \bar{r}$.[31] In Section A.1, we explain that landlords making an active choice to set their rent at the rent ceiling also engage in recruiting activity which results in additional voucher holder demand, reflected in the

[30]In practice, it seems likely that any re-optimization by nonvoucher recipients in response to housing voucher policy changes will be small because voucher holders are only 6% of U.S. renters.

[31]A small fraction of voucher recipients choose to rent a unit priced above the rent ceiling and pay more out-of-pocket, as discussed in Section I. This could be incorporated into the model by allowing for modest unit demand in the case when $r > \bar{r}$. Because few voucher recipients rent units above the ceiling and those that do will be price-sensitive, incorporating these tenants into the model would have little impact on the landlord's incentives in setting pricing.

exogenous parameter $\alpha > 1$. The total occupancy rate of units in q renting at price r is

$$D(r;q) = D_{NV}(r;q) + D_V(r,q).$$

and is assumed to be between 0 and 1.

LANDLORD'S PROBLEM. — There is a unit mass of landlords indexed by i in each neighborhood q. For simplicity, we suppress the q argument in this subsection. Landlords each own one unit of housing, and landlords may choose one of two rents: $\{r_i, \bar{r}\}$:

1) r_i is the landlord's reservation rent if they were renting only to private tenants. As with private nonvoucher tenant demand, landlord r_i is set outside the model. The variable $x = r_i - q$ embodies the markup or discount charged by the landlord relative to the quality in the neighborhood. We assume x has univariate distribution F in all neighborhoods q. As a regularity condition, assume that F is twice-differentiable with $\frac{df(x)}{dx} < 0$. Later in our analysis, we use this assumption to generate a trade-off between the probability of finding a unit and neighborhood quality, which ensures a unique solution to the voucher holder's problem.

2) The landlord may also set rent at $\bar{r}$, which is the voucher rent ceiling.[32] Landlords who choose this rent also engage in activities to recruit voucher holders and ensure that their unit would pass the inspection for Housing Quality Standards mandated by the voucher program.[33] Recruiting activity increases demand from voucher holders $\tilde{D}_V$ to $\alpha\tilde{D}_V$ where $\alpha > 1$ is an exogenous parameter. However, this activity has effort cost e_i. As a regularity condition, we assume that $e_i > \bar{r}(\alpha\tilde{D}_V + D_{NV}(\bar{r})) - r_i D_{NV}(r_i)$. The intuition for this assumption is that recruiting activities are sufficiently costly that a landlord whose reservation rent r_i is greater than $\bar{r}$ will not lower her rent in order to attract voucher holders. These assumptions are consistent with qualitative evidence that some landlords in low-quality neighborhoods specialize in recruiting voucher holders (Rosen 2014, Turner 2003).

Landlord profits $\Pi(r)$ are rent times the occupancy rate minus any recruiting costs. The landlord chooses rent to maximize profits:

$$\begin{aligned} \Pi(r) &\equiv rD(r) - e_i\mathbf{1}(r = \bar{r}) \\ r^* &= \max_{r\in\{r_i,\bar{r}\}} \Pi(r). \end{aligned} \tag{A1}$$

[32] Housing authorities are required to verify that the rent on the unit is reasonable as described in Section I. This could be modeled as the housing authority rejecting voucher leases among some units which the landlord priced at $\bar{r}$. The housing authority would be most likely to reject when the distance between r_i and $\bar{r}$ is large.

[33] In principle, the decision to set rent at the rent ceiling and the decision to actively recruit voucher holders are separable. However, separating these decisions complicates the algebra and our simpler model contains sufficient conditions for price discrimination.

Conditional on revenue, landlords are indifferent between leasing to a voucher tenant or a private tenant. Note that in neighborhoods without any voucher holders, $D_V = 0$ and so it is always the case that $r_i^* = r_i$.

VOUCHER HOLDER'S PROBLEM. — There is a representative agent for voucher holders. Recall that the agent is not price sensitive, so she will rent any unit which costs less than or equal to the rent ceiling. The probability of finding a unit is $\mathbb{P}(\bar{r}, q)$ in the neighborhood she choses to search in. The probability is increasing in $\bar{r}$ and decreasing in q. Let $V(q)$ (with $V'(q) > 0$ and $V''(q) < 0$) denote the relative utility gain from finding a unit with quality q over remaining unmatched. The agent chooses to search in a neighborhood of a quality level q to maximize utility:

$$
\begin{aligned}
q^* &= \max_q U(\mathbb{P}, q) \\
&= \max_q \quad \underbrace{\mathbb{P}(\bar{r}, q)}_{\text{Match Probability}} \quad \underbrace{V(q)}_{\text{Utility if Matched}} \quad .
\end{aligned} \tag{A2}
$$

The utility function as defined above yields a trade-off between match probability and neighborhood quality. Higher-quality neighborhoods q are more attractive to voucher holders, but it is harder to find a unit in those neighborhoods. Define $F^*(x)$ as the distribution of optimal rents in q^* with $x = r^* - q^*$. The voucher holder's probability of finding a unit is:

$$
\mathbb{P}(\bar{r}, q) \equiv \begin{cases} F^*(\bar{r} - q) & \text{if } q = q^* \\ F(\bar{r} - q) & \text{if } q \neq q^* \end{cases} .
$$

It will be convenient to define the joint distribution (e_i, r^*) as G. There are measure $\bar{V}$ of voucher holders who successfully lease a unit. This is the sum of voucher holders renting units priced at the ceiling and voucher holders renting units priced below the ceiling:

$$
\alpha \left(F^*(\bar{r} - q^*) - F(\bar{r} - q)\right) \tilde{D}_V + F(\bar{r} - q)\tilde{D}_V = \bar{V}. \tag{A3}
$$

POLICY PARAMETERS. — Assume that the rent ceiling has a linear structure $\bar{r}(q) = r_{base} + cq$ with $c \in [0, 1)$. Historically, HUD has used a single rent ceiling r_{base} across an entire metro area, with $c = 0$. However, this formulation is useful because in Section IV, we analyze a recent HUD policy innovation that tilted the rent ceiling to lower r_{base} and make c positive.

2. Equilibrium Definition and Solution

Equilibrium Definition - Given occupancy rates, a measure of vouchers, a distribution of effort costs and landlord reservation rents, recruiting technology, and voucher holder utility $\{D(r;q), \bar{V}, \{e_i, r_i\}, \alpha, V(.)\}$, an equilibrium is defined by three conditions:

1) Landlords price optimally using equation A1.

2) Voucher holders choose neighborhoods optimally using equation A2.

3) The market for vouchers clears using equation A3.

Solution – We show that each of the three conditions holds so an equilibrium exists. To show that the first condition is satisfied, note that landlords can only choose two possible rent levels in equation A1, so a landlord will choose $\bar{r}$ if

$$\Pi(\bar{r}) > \Pi(r_i) \Rightarrow$$
$$\bar{r}\alpha D_V + \bar{r} D_{NV}(\bar{r}) - e_i > r_i D_V + r_i D_{NV}(r_i) \Rightarrow$$

(A4)
$$\underbrace{(\bar{r} - r_i)}_{\text{higher rent}} \left(\tilde{D}_V + D_{NV}(\bar{r})\right) + \underbrace{\bar{r}(\alpha - 1)\tilde{D}_V - e_i}_{\text{gain from recruiting vouchers}} > r_i \underbrace{(D_{NV}(r_i) - D_{NV}(\bar{r}))}_{\text{lower occupancy rate}}$$

The first term on each side of the inequality in equation A4 reflects the classic price versus quantity trade-off for a monopolistic supplier. Raising the posted price raises revenue conditional on occupancy, but reduces the occupancy rate. The second term on the left-hand side of the inequality reflects benefits and costs unique to the voucher market.

By charging $\bar{r}$ and actively recruiting voucher holders, our model effectively allows landlords to price discriminate. Comparative advantage dictates that only some landlords price discriminate. Specifically, by setting $\Pi(\bar{r}) = \Pi(r_i)$, it is possible to trace out a frontier of effort costs and reservation rents $(\hat{e}, \hat{r})$ where the landlord is indifferent about which price to choose. Landlords with (e_i, r_i) below this frontier, meaning that they have a combination of low recruiting effort costs and/or low reservation rents in the private market, will optimally set rents at the rent ceiling.

The second equilibrium condition is that voucher holders choose their preferred neighborhood. It is convenient to make two algebraic substitutions in the tenant's problem in equation A2: $\bar{r}(q) = r_{base} + cq$ and $\mathbb{P}(\bar{r}, q) = F(\bar{r} - q)$. The first substitution comes from the definition of the rent ceiling in Section A.1. For the second, recall from Section A.1 that $\mathbb{P} = F(\bar{r} - q)$ for all q except q^*, where it is $F^*(\bar{r} - q^*)$. However, because of the regularity assumption on e_i in the landlord's problem, only landlords with $r_i < \bar{r}$ will consider raising their prices to $\bar{r}$ and no landlords with $r_i > \bar{r}$ will lower their price to $\bar{r}$. This implies that

$F^*(\bar{r}-q^*) = F(\bar{r}-q)$. Next, differentiate the voucher holder utility function with respect to q. The unique solution of optimal neighborhood choice $q = q^*$ is implicitly defined by[34]

(A5)
$$\underbrace{(1-c)}_{\text{Penalty for Better Neighborhood}} \times \underbrace{f(r_{base}+cq-q)V(q)}_{\text{Increased Matching Probability}} = \underbrace{F(r_{base}+cq-q)V'(q).}_{\text{Increased Neighborhood Quality}}$$

Equation A5 reveals that tenants choose a neighborhood q^* by trading off the left-hand side – which is the increased probability of finding a unit from choosing a lower q^* – with the right-hand side, which is additional utility from living in a higher-quality neighborhood.

The third equilibrium condition, which is the market-clearing condition for vouchers, is given by equation A3. $\bar{V}$ and α are fixed exogenously, and $(F^*(\bar{r}-q^*) - F(\bar{r}-q))$ is set by equation A3. The market-clearing equation can be solved by setting the free parameter $\tilde{D}_V$ as $\bar{V}/[\alpha\left(F^*(\bar{r}-q^*) - F(\bar{r}-q)\right) + F(\bar{r}-q^*)]$. This equilibrium $\left(\left(F^*(\bar{r}-q^*) - F(\bar{r}-q)\right), \tilde{D}_V\right)$ is unique.[35]

Remark – Recall that G is the joint distribution of optimal rents and effort costs (e_i, r^*). The average rent paid on voucher units is

$$\text{(A6)} \qquad \mathbb{E}_G r^* \equiv \int_{-\infty}^{\bar{r}-q}\int_{e_{min}}^{\hat{e}} \left[1+\alpha\mathbf{1}(x=\bar{r}-q^*)\right](x+q^*)dG(e_i, r^*).$$

3. Comparative Statics

We first characterize how an increase in housing voucher generosity affects average voucher rents.

Proposition 1 *Raising the rent ceiling increases the average rent paid on voucher units.*

$$\frac{\partial \mathbb{E}_G(r^*;q)}{\partial \bar{r}} = \underbrace{\alpha f^*(\bar{r}-q)}_{\text{units at rent ceiling}} + \underbrace{(\bar{r} - E\left[r|(e_i,r_i)=(\hat{e},\hat{r})\right])}_{\text{gap in rents relative to ceiling}} \underbrace{g(\hat{e},\hat{r})}_{\text{units re-pricing to rent ceiling}}$$

Proof: Differentiate equation A6 with respect to $\bar{r}$.

[34]Proof: Differentiate equation A2 twice with respect to q. The second-order condition in the maximand $U(\mathbb{P},q)$ is negative: $U_{qq} = (-1+c)^2\frac{df(\cdot)}{dq}V(\cdot) + 2f(\cdot)V'(\cdot)(-1+c) + F(.)V''(\cdot) < 0\forall q$. The first term is negative because $\frac{df(\cdot)}{dq}$ is negative by assumption, the second term is negative because $c<1$ and the third term is negative because $V''<0$ by assumption.

[35]The equilibrium is unique because landlord price discrimination $f^*(\bar{r}-q^*)$ is strictly increasing in $\tilde{D}_V$ and the market-clearing condition implies that $f^*(\bar{r}-q^*)$ is strictly decreasing in $\tilde{D}_V$. For the first clause, note that increased $\tilde{D}_V$ increases the incentive to price discriminate, thereby raising $f^*(\bar{r}-q^*)$. For the second clause, totally differentiate the market clearing condition with respect to f^* and solve for $\frac{d\tilde{D}_V}{df^*}$. This yields $\frac{d\tilde{D}_V}{df^*} = \frac{(1-\alpha)-f^*\tilde{D}_V}{(\alpha-1)f^*+F^*}$, which is negative because the numerator is negative and the denominator is positive.

This proposition applies to every neighborhood q. However, the expression collapses to zero in a neighborhood with no voucher holders. Proposition 1 shows that average rents rise most when there are already many units priced at the rent ceiling which will increase their rents, and when there are many landlords who re-price their units from the prior rent r_i to the new ceiling $\bar{r}$.

Next, we consider how two changes to the schedule of rent ceilings across a metro area affect optimal neighborhood quality chosen by voucher holders. Recall that the rent ceiling can be expressed as a constant r_{base} and a linear slope c: $\bar{r}(q) = r_{base} + cq$. We analyze the impact on quality of raising r_{base} and the impact of raising c.

Proposition 2 *Starting from a constant rent ceiling ($c = 0$), the impact on neighborhood quality of raising the rent ceiling r_{base} or raising it by c is*

$$\frac{\partial q^*}{\partial r_{base}} = \frac{\overbrace{\frac{\partial f(.)}{\partial x} V(\cdot)}^{U_{\mathbb{PP}}} - \overbrace{f(\cdot)V'(\cdot)}^{U_{\mathbb{P}q}}}{SOC} > 0$$

$$\frac{\partial q^*}{\partial c} = \frac{\frac{\partial f(.)}{\partial x} V(\cdot)q^* - f(\cdot)V'(\cdot)q^* - \overbrace{f(\cdot)V(\cdot)}^{U_{\mathbb{P}}}}{SOC} > 0$$

where second-order condition $SOC \equiv \frac{\partial f(.)}{\partial x} V(\cdot) - 2f(\cdot)V'(\cdot) + FV''(\cdot) < 0$.

Proof: Differentiate equation A5 with respect to r_{base} and with respect to c.

When the rent ceiling increases uniformly ($\frac{\partial q^*}{\partial r_{base}}$), absent any behavioral change, the probability of finding a unit rises in every potential neighborhood. Two forces lead the voucher holder to substitute to a higher-quality neighborhood. The first term in the numerator, $U_{\mathbb{PP}}$, leads to increased quality because as the probability of finding a unit approaches 1, additional increases in the probability of matching do little to increase utility. The second term in the numerator, $U_{\mathbb{P}q}$, leads to increased quality since an additional unit of quality is more valuable when the probability of successfully leasing is higher. However, if tenants put little value on improving neighborhood quality and the policy change substantially increases the probability of finding a unit, then raising r_{base} will have little impact on neighborhood quality.

When the rent ceiling tilts toward higher-quality neighborhoods ($\frac{\partial q^*}{\partial c}$), the neighborhood quality rises even more sharply than from a uniform rent ceiling increase. Algebraically, $\frac{\partial q^*}{\partial c}$ can be decomposed as

$$\text{(A7)} \qquad \frac{\partial q^*}{\partial c} = \underbrace{\frac{\partial q^*}{\partial r_{base}} q^*}_{\text{Uniform ceiling increase}} + \underbrace{\frac{-f(.)V(.)}{SOC}}_{\text{Decreased penalty for good neighborhoods}} .$$

The impact of a tilt in the rent ceiling is equal to the sum of (1) a uniform increase in the rent ceiling and (2) a policy which lowers the probability of matching in low-quality neighborhoods and raises it in high-quality neighborhoods. We call this second policy a "compensated tilt". Each of these policy changes are depicted visually in Figure 1.

Two lessons emerge from the comparative statics. The first major lesson from our model is that a uniform increase in the rent ceiling may accrue to landlords through higher voucher rents (Proposition 1) or to tenants if they optimally decide to search in a higher-quality neighborhood (Proposition 2). The voucher rent response is larger when when the effectiveness of recruiting activities α is higher and when the cost of recruiting activities e_i is lower. The quality response is larger when tenants put a relatively high weight on neighborhood quality (embodied by $V(q)$) or when the probability of finding a unit is already high.

The second major lesson is that a compensated tilt – unlike a uniform increase – is a cost-effective way to raise neighborhood quality. Algebraically, by subtracting the impact of the change in r_{base} in equation A7, the expected change in neighborhood quality is

$$\frac{\partial q^*}{\partial c}\bigg|^{Compensated} = \frac{-f(\cdot)V(\cdot)}{SOC}.$$

To be specific, consider a policy that decreases r_{base} by Δr and increases c by $\Delta r/q^*$. This policy is cost-effective because it holds $\bar{r}(q^*)$ constant ($\bar{r}(q^*) = r_{base} - \Delta r + (c - \Delta r/q^*)q^* = r_{base} + cq^*$) and since $\bar{r}(q^*)$ is unchanged, there is no opportunity for increased price discrimination. Nevertheless, optimal neighborhood quality rises because the penalty for searching in a higher-quality neighborhood ($1-c$ from the left-hand side of the tenant's first-order condition in equation A5) is diminished. Government expenditure increases only if q^* rises. This ensures that every dollar of extra government expenditure goes to neighborhood quality.

4. Relation to Prior Models

As far as we know, our emphasis on price discrimination and search frictions is new to the literature studying vouchers and does a better job of explaining this paper's empirical findings than two existing benchmark models. In one benchmark model, people frictionlessly trade-off housing and non-housing consumption and housing vouchers introduce a kink into the budget constraint (Collinson, Gould Ellen and Ludwig 2015, Olsen (2003)). This model predicts that housing voucher holders should rent units with prices at least as high as the rent ceiling. This prediction is inconsistent with the data. In fact, 60 percent of housing voucher holders rent units below the ceiling (Figure 2, bottom panel).

A second class of benchmark model argues that voucher holders derive relatively more utility from living in low-quality neighborhoods (Geyer 2011, Galiani, Murphy and Pantano 2015). This model makes two predictions which are inconsistent with research on housing vouchers. The first prediction that differs from the data is that a preference model with voucher holders valuing structure over neighborhood quality predicts that voucher holders in low-quality neighborhoods will live in high-quality units. However, as shown in Figure B.5, voucher holders actually live in units with rents below the ceiling and as we document in Section III, when there is a uniform increase in the rent ceiling, there is at most a modest improvement in observable structure quality. Second, the dynamic path of voucher holders' neighborhood choices is consistent with it being hard to find a good unit upon initial admission to the voucher program rather than a preference for low-quality neighborhoods. Eriksen and Ross (2013) document that in the Welfare to Work Voucher experiment, voucher holders signed their first lease in neighborhoods of no better quality than their prior residence (as measured by poverty and employment rates); however, neighborhood quality improved subsequently over the next four years. This is qualitatively consistent with a model where at first voucher holders worry about finding a unit to lease and only then worry about neighborhood quality.[36]

Appendix B

1. *Sample Construction*

We use HUD's "PIH Information Center" database, also known as PIC. In principle, every voucher is supposed to appear in PIC when admitted, when leaving the voucher program, for a regularly scheduled annual recertification, and for any unscheduled interim recertification due to, for example, a change in tenant payment or a move. Coverage is quite good for an administrative dataset with decentralized data entry; HUD estimates that in 2012, some record appeared in PIC for 91% of vouchers (Public and Indian Housing Delinquency Report (2012)). We construct years according to the federal government's fiscal year (e.g. FY2012 starts in October 2011), since this is the calendar used for applying Fair Market Rent changes. We consider observations with non-missing rent, household id, address text, and lease date (also known as "effective date"). Addresses are standardized using HUD's Geocoding Service Center, which uses Pitney and Bowes' Core-1 Plus address-standardizing software. For each raw text address, this produces a cleaned text address, a 9-digit ZIP code and an 11-digit ZIP code. Within each household-year, we choose the observation with the most recent lease date and most recent server upload date. Our final step is to drop duplicate household-year observations, which amount to 2.3% of the sample and project-based vouchers, where the housing authority chooses the unit, rather than the tenant, which are less than 1% of the sample. This leaves us with a sample

[36]One interesting question is why, after voucher holders find their first unit, they do not then move later on to units priced more closely to the rent ceiling.

of about 1.6 million annual household records. Conditional on appearing in the sample in 2004, the probability of that household appearing in 2005 is 75%, and the probability of appearing in 2005, 2006, or 2007 is 84%, indicating that there often are substantial lags between appearances in PIC.

2. 2005 FMR Rebenchmarking

Constructing the FMR Cells: We use HUD's published Fair Market Rent rates, with slight modifications (http://www.huduser.org/portal/datasets/fmr.html). Fair Market Rents are published on an annual basis corresponding to the federal fiscal year, so FY2005 rents were effective from October 1, 2004 to September 30, 2005. FMR geographies are largely stable over time; HUD added 14 new city geographies in Virginia, and we code prior FMRs for these cities using the county-level FMRs. Our policy variation is at the county-bed cell level and measurement error $\varphi_{2000} - \varphi_{1990}$ is larger for thinner cells. To maximize the variation in our instrument which can be attributed to classical measurement error, we weight each county-bed equally. In New England, FMRs are set by NECTAs, which cross county lines and we merge on FMRs to the appropriate sub-state geographies there. However, we weight each county-bed pair equally everywhere, including New England; were we to give equal weight to each geographic unit, then 1/3 of the sample weight would be in New England. Gordon (2004) and Serrato and Wingender (2016) also use decennial Census rebenchmarkings as source of exogenous variation to examine the incidence of federal expenditures.

*Sample Restrictions:*The rebenchmarking resulted in large swings in local rents, and many housing authorities lobbied HUD for upward revisions to their local FMRs. In a revision to the 2005 FMRs, HUD accepted proposals from 14 counties. All documentation associated with the rebenchmarking is posted here. For these counties, we recode the FMR back to its pre-lobbying level. Coincident with the rebenchmarking, HUD administered Random Digit Dialing (RDD) surveys in 49 metropolitan areas. The results from these surveys, where available, superseded the results from the 2000 Census. Since these surveys were initiated and administered by HUD, we are less concerned about endogeneity of this data source, and we use the post-RDD FMRs for these areas. For these areas, the orthogonality restriction is that rental market changes from 1990 to 2004 need to be uncorrelated with subsequent short-run changes ($E(\Delta r_{2004-t}^{Nonvoucher} | \Delta r_{1990-2004}^{Nonvoucher}) = 0$). Finally we drop eight geographies, with specific reasons listed for each geographic unit:

- Miami, FL, Honolulu, HI, Navarro County, TX, and Assumption Parish, LA – rebenchmarked in 2004
- Okanogan County, WA – Lobbied for higher FMR in 2005, no counterfactual available
- Louisiana – Hurricane Katrina severely disturbed rental markets
- Kalawao County, HI – No FMR published before 2005

Measuring the First Stage: The administrative data report the rent ceiling $\bar{r}$ at the household level. We compute $\bar{r}_{jt}$ as the unconditional mean of all observations in a county-bed-year cell. *Trimming and Standard Errors:* We winsorize county-by-bed FMR changes at the 1st and 99th percentile, so that our results will not be unduly influenced by outliers. While FMRs are published at the county-bed level, sometimes counties are grouped together for the purpose of setting a common FMR. Throughout our rebenchmarking analysis, we cluster our standard errors at the FMR group level (n=1,484).

3. Nonvoucher Rents and 2005 FMR Rebenchmarking

In Section III.A, our key identification condition is

$$\eta \perp FMR_{2005}|FMR_{2004} = 0$$

Here we examine the correlation of the FMR change with contemporaneous changes in nonvoucher rents. Data availability make it difficult to measure nonvoucher rents at a high frequency and with a high degree of geographic specificity. Using the notation developed in Section III.A,

(B1)

$$Cov(\Delta\hat{r}_t, \Delta FMR) = Cov(r_t + \varphi_t - r_{2000} - \varphi_{2000}, \Delta FMR) = Var(\varphi_{2000}) < 0$$

Even if $E(\Delta r_t|\Delta r_{t-1}) = 0$, we estimate a negative covariance because of the negative auto-correlation of gains measured with error. Similarly, Glaeser and Gyourko (2006) calculate serial correlation in housing price changes and rent changes at five-year horizons and find negative serial correlation.

First, we compare changes in voucher rents to changes in tract-level median rents published by the Census. [37]

Data at the tract level are available from the 2000 Census (Minnesota Population Center (2011)) and the 2005-2009 American Community Survey with a consistent geographic identifier. In regression form, with i indexing tracts and j indexing counties, we estimate

$$r^{Nonvoucher}_{2005-2009,ij} - r^{Nonvoucher}_{2000,ij} = \alpha + \beta_1 \Delta FMR_j + \varepsilon_{ij}$$

where ΔFMR_j is the average FMR change across bedroom sizes. We find that rent changes from 2000 onward are negatively correlated with FMR changes ($\beta_1 < 0$), as reported in reported in Appendix Table 1, column 2. This is consistent with measurement error, as described in equation B1. This generates a sharp contrast – places with relative *increases* in voucher rents had relative *decreases* in nonvoucher rents. This mean reversion pattern is most pronounced in rural areas. When we limit the sample to counties with at least 100,000 residents, we find that β_1 is not statistically different from zero (column 4).[38]

[37]The Census estimates include voucher holders themselves, making this an imperfect measure of nonvoucher rent changes. Internal HUD data indicate that subsidized households typically report their rental payment (30% of income) in the Census, rather than the total rent received by the landlord. This measurement error means that rent reports by voucher holders are unlikely to change in response to changes in the FMR.

[38]This is consistent with plausible parameterizations of a tract-level data-generating process. Suppose that tract-level rents follow an auto-regressive process, with $Y_j = \rho Y_{j-1} + \eta_j$. A regression of *tract-level* rent changes from 2000 to 2005-2009 on *county-level* FMR changes, which are effectively rent

Finally, we pool the observations in columns 1 and 2 to estimate $\Delta r_{ij}^{\{Voucher,Nonvoucher\}} = \alpha + \beta_1 \Delta FMR_j + \beta_2 \Delta FMR_j \times Voucher_{ij} + \varepsilon_{ij}$ where $Voucher_{ij}$ is an indicator for whether the rental change is observed for voucher stayers or nonvouchers. Then, we compute the probability that we would observe data like this or more extreme, under the null hypothesis that the two coefficients are equal ($\beta_1 = \beta_2$), and find $p < 0.01$. Likewise, we find that the probability $\beta_1 = \beta_2$ for in the urban sample is very low.

Another source of data on nonvoucher rents comes from the ACS public use microdata. These data are preferable because they more closely correspond to the time horizon of interest (data observed in 2000 and annually from 2005 to 2009) and because they identify the number of bedrooms the unit has, rather than just the location, allowing us to exploit the county-by-bed variation in FMR changes. However, since this is a public use file, geographic identifiers are available only for units located in counties which have more than 100,000 residents. We find a strong negative coefficient from 2000 to 2005 (column 5), consistent with measurement error at the bedroom level within counties. Analyzing the correlation of rent changes from 2005 to 2009 with FMR changes, which is perhaps our strongest test of $E(\Delta r_{2004-t}^{Nonvoucher} | \Delta FMR) = 0$, we find a coefficient of 0.02, very close to zero, although the estimate is imprecise. These estimates offer a joint test of two distinct hypotheses: (1) selection – contemporaneous neighborhood trends were correlated with FMR changes and (2) general equilibrium spillovers – FMR changes causally affected nonvoucher rents. The data are not consistent with these hypotheses.

4. Hedonic Quality

We build our hedonic quality measure using regression coefficients from a model of rents in the ACS along with building age, structure type, number of bedrooms and median tract rent. For our hedonic measures in the analyses of the re-benchmarking change and the Dallas ZIP-level ceiling change, we use administrative data from our PIC database and coefficients from a model of rents in the 2005-2009 public use sample of the American Community Survey, inflated to 2009 \$ (Ruggles et al. (2010)). The following unit covariates appear in both the Census and in PIC: Public Use Microdata Area (PUMA), number of bedrooms, structure type, and structure age. The PIC file reports an exact building age, which we code into the 10 bins for structure age available in the ACS. The PIC file reports 6 different structure categories and the ACS has 10 categories. We crosswalk these categories as best as we can, as

changes from 1990 to 2000, of the form $\Delta Y_j^{tract} = \alpha + \beta \Delta Y_{j,t-1}^{county} + \varepsilon_j$ would yield a biased estimate $\hat{\beta} - \beta = -\frac{n_{tract}}{n_{county}}(1-\rho)\frac{Var(\eta)}{Var(\Delta Y_{j,t-1})}$. Analyzing tract-level rent changes indicates that $Var(\eta) \approx Var(\Delta Y_{j,t-1})$, $\rho = 0.88$. Tracts in counties with 40,000 units or more have small values of $\frac{n_{tract}}{n_{county}}$, such that $\hat{\beta} - \beta = -0.005$ and tracts in counties with less than 40,000 units have large $\frac{n_{tract}}{n_{county}}$, resulting in $\hat{\beta} - \beta = -0.070$.

PIC	ACS 2005-2009
Single family detached	Single family detached
Semi-detached	1-family house, attached, 2-family building
Rowhouse/townhouse	3-4 family building
Low-rise	5-9 family building, 10-19 family building
High-rise	20-49 family building, 50+ family building
Mobile home or trailer	Mobile home or trailer

We have 710,957 observations of households with positive cash rent in the ACS. Unfortunately, we have no way to drop subsidized renters (13% of sample). This is an added source of measurement error. We estimate using least squares

$$Rent_{ijklm} = \alpha + Bed_j + StrucType_k + Age_l + PUMA_m + \varepsilon_i \tag{B2}$$

where Bed_j is a set of indicators for 5 possible numbers of bedrooms, $StrucType_k$ is a set of indicators for 6 possible structure types, Age_l is a set of indicators for 10 possible structure age bins, and $PUMA_m$ is a set of indicators for 2,067 PUMAs. The results from this regression appear in Appendix Table 2. This regression computes a vector of hedonic coefficients $\hat{\beta}_{census}$. This hedonic regression has substantial predictive power, with an R-squared of 0.48. We then apply the coefficients from this hedonic regression to the voucher covariates for bedrooms, structure type and building age to construct a measure of hedonic unit quality $q^{hedonic} = \hat{\beta}_{census} x_{voucher} + r^{tract}_{voucher}$ where $r^{tract}_{voucher}$ is the median tract rent. The standard deviation of actual rent is \$497 and the standard deviation of predicted rent is \$331. For our Dallas analysis in Appendix Table 6, where we are interested in only structure quality and not neighborhood quality, we instead compute $q^{hedonic} = \hat{\beta}_{census} x_{voucher}$, omitting neighborhood quality. To evaluate whether these limited variables can approximate more detailed measures of unit quality, we compare the explanatory power of these same covariates in the American Housing Survey against a benchmark "kitchen-sink" regression of all hedonic characteristics in the AHS (60+ variables) in Appendix Table 4. The AHS hedonic regression using the subset of variables in the ACS approximates the full model fairly well with an R^2 of 0.30 compared to 0.42 with the full model.

To evaluate the effect of the 40th to 50th percentile FMR policy change on housing quality we construct a quality measure with building age, structure type, number of bedrooms and median tract rent plus 26 questions from HUD's Customer Satisfaction Survey (CSS) and hedonic coefficients from a model of rents in the 2011 American Housing Survey (AHS). We identify 26 quality measures which can be matched to variables in the AHS. These are:

We estimate the contribution of unit characteristics to rent using equation 13 where vector s includes the 26 measures listed above along with the number of bedrooms, age of housing, structure type and is a set of indicators for the

- Building has working elevator
- Working cooktop/burners
- Unit lacks hot water
- Access to a laundry room
- Working outlets
- Unit has safe porch or balcony
- Working refrigerator
- Use oven to heat the unit
- Large open cracks
- Windows have broken glass
- Roof sagging, holes, or missing roofing
- Home has cockroaches
- Home has rodents
- Home cold for 24 hours or more
- Fuses blown or circuit breakers tripped regularly
- Heating break down for 6 hours or more
- Wiring metal coverings
- Water leaking inside
- Mildew, mold ,or water damage
- Smell bad odor such as sewer, natural gas
- Large peeling paint
- Toilet not working for 6 hours or more
- Unsafe handrails, steps or stairs
- Electrical outlets/switches have cover plates
- Rate unit good
- Rate unit poor

American Housing Survey "Zone" a coarser analog to ACS Public Use MicroData Areas (the coefficient on median Zone rents is approximately \$1). This regression produces a vector of coefficients $\hat{\gamma}$. We then construct our hedonic measure: $q_{css}^{hedonic} = \hat{\gamma}_{AHS}x_{css} + r_{voucher}^{tract}$. The CSS adds many more time-varying quality factors, and together with the basic ACS variables this model achieves about 75 percent of the predictive performance of the full "kitchen-sink" AHS model (Appendix Table 4). We believe that our actual hedonic measure, which uses tract rent rather than PUMA or Zone rents, likely explains much more of the actual variation in cross-sectional rents than the AHS R^2 numbers suggest. Impressively, our hedonic measures explain nearly 70 percent of the cross sectional variation in voucher rents in the CSS.

$$Rent_{ijklm} = \pi + s_i'\gamma + \varepsilon_i \tag{B3}$$

5. *Dallas ZIP-Level FMRs*

Constructing the Analysis Sample: This Dallas "Small Area FMR Demonstration" applied to eight counties: Collin, Dallas, Delta, Denton, Ellis, Hunt, Kaufman, and Rockwall. Several housing authorities administer vouchers in these counties. Most adopted the new policy in December 2010, but the Dallas Housing Authority adopted the policy in March 2011. We use a balanced panel of all vouchers in these eight counties from 2010 to 2013 because beginning in 2009 the Dallas Housing Authority allocated many of its new vouchers to homeless individuals. These individuals also needed other non-housing services and are a very different population from standard voucher holders.

Constructing the Neighborhood Quality Measures: Tract-level data on poverty rate, unemployment rate, and share with a bachelor's degree are for 2006-2010 in the American Community Survey. Tract-level 2010 violent crime offense data was provided to HUD by the Dallas Police Department under a privacy certificate between HUD and Dallas (March 2012). For crime data outside the city of Dallas, crime is measured at the jurisdiction level using the FBI's Uniform Crime Reports from 2010. Data on the percent of 4th grade students' scoring proficient or higher on state exams in the 2008-2009 academic year was provided to HUD by the U.S. Department of Education. We map these scores to zoned schools at the block group level. "Single Mothers" is defined as share of own children under 18 living with a female householder and no husband present.

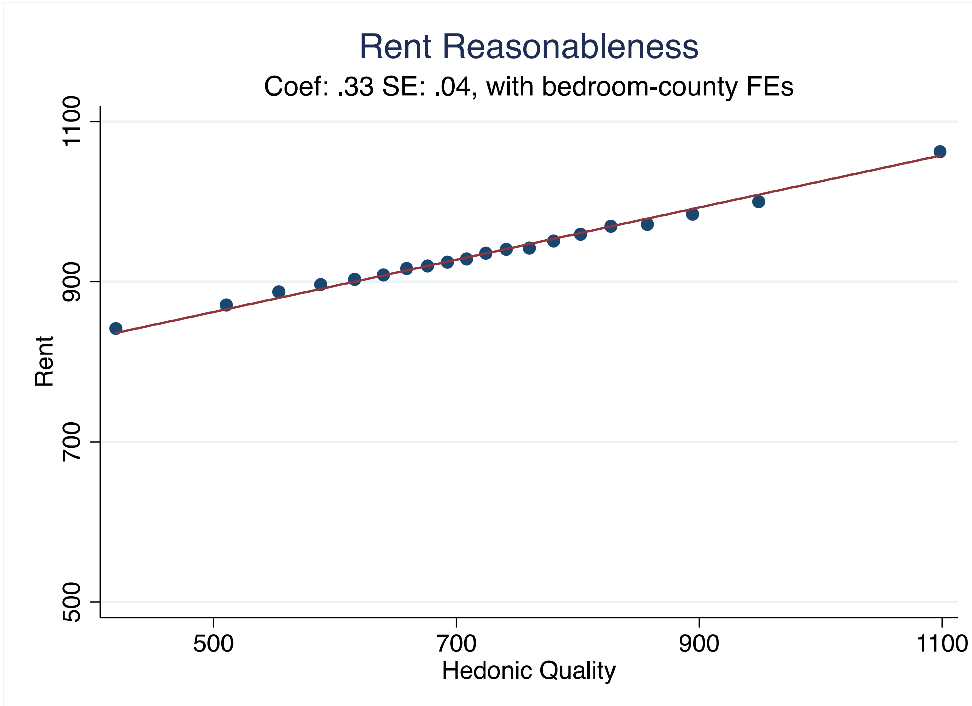

Figure B.1. Rent Reasonableness

Note: This figure plots conditional means of unit rent for twenty quantiles of hedonic quality. The method for constructing hedonic quality is described in Section III.A. We include fixed effects for the number of bedrooms interacted with the county, because each voucher holder's number of bedrooms is fixed by family size and it is usually quite difficult to switch counties. We find that a $1 increase in hedonic quality is associated with a 33 cent increase in rents. This indicates that even for a fixed rent ceiling, the government paid less for lower-quality units.

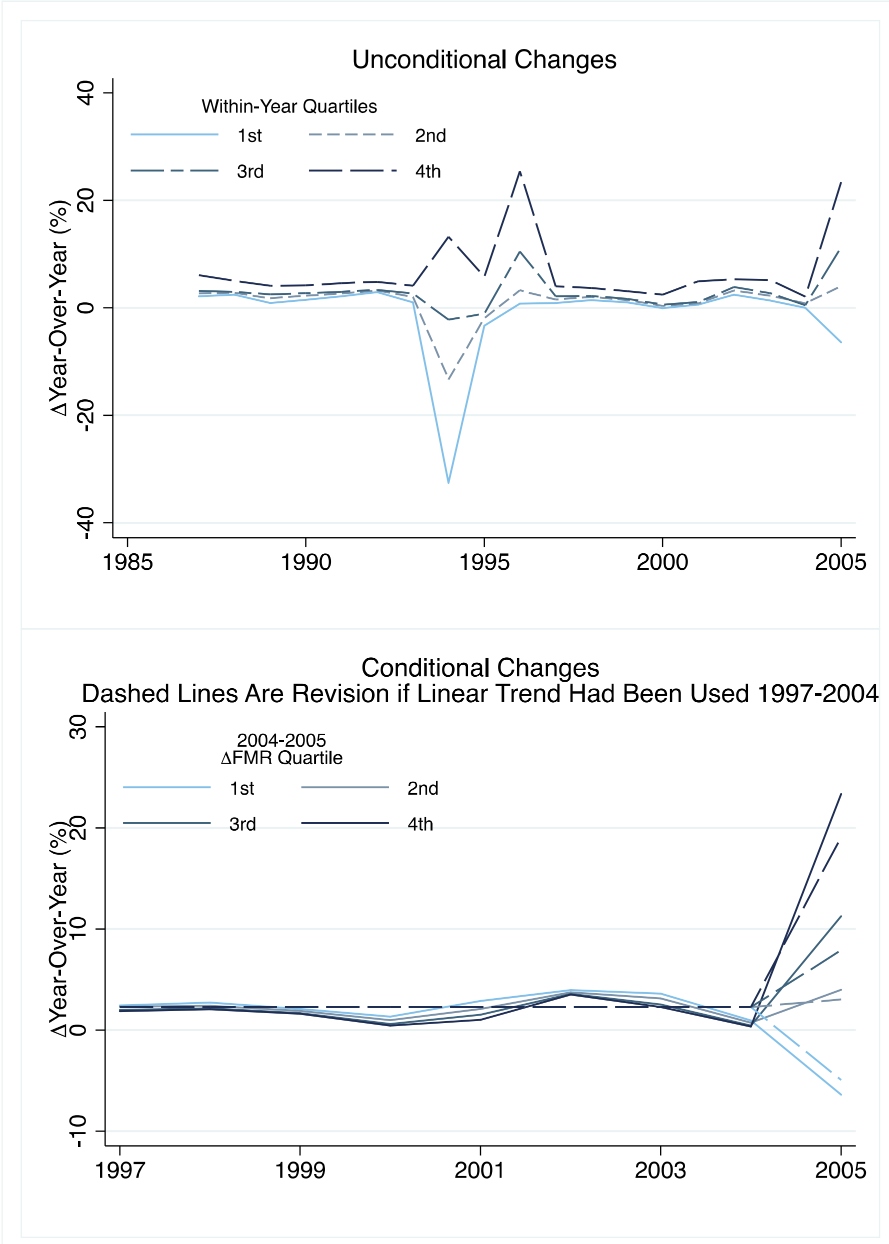

Figure B.2. County-Level FMR Changes

Note: The top panel plots average Fair Market Rent (FMR) changes at the county-level within year-specific quartiles. The large swings in 1994-1996 and 2005 reflect decennial rebenchmarkings, when new Census data from 1990 and 2000 respectively were incorporated into the FMRs.
The bottom panel plots FMR changes for the same sample within quartiles defined over the 2004-2005 FMR change, as in Figure 5. The four groups exhibit similar trends in terms of changes prior to the rebenchmarking. There is some evidence of mean reversion: places which had higher revisions from 1997 to 2004 were revised downward in 2005. The dashed lines represent a counterfactual of what the magnitude of annual changes would have been if a single national index had been applied from 1997 through 2004, followed by an update which brought FMRs to observed 2005 levels. Observed revisions are more dispersed than the counterfactual revisions, indicating substantial measurement error in intercensal FMR changes.

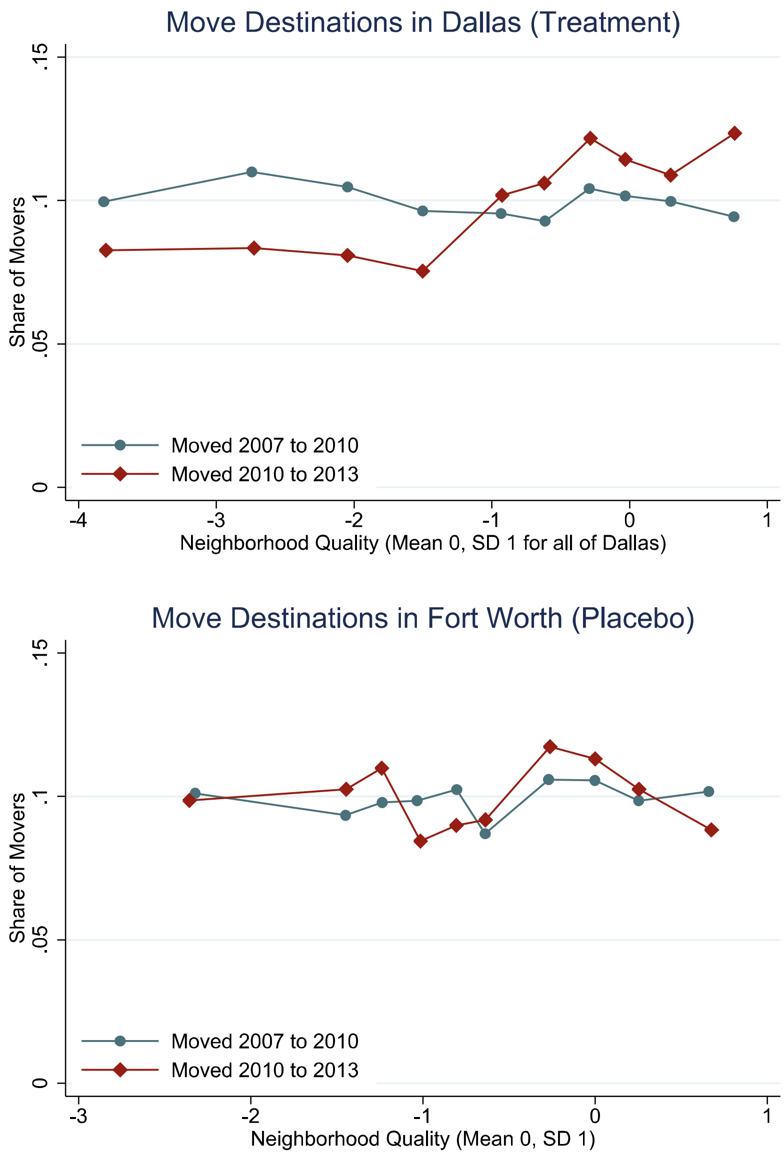

Figure B.3. Impact of Tilting on Neighborhood Quality (Distribution)

Note: The top panel shows the distribution of destination quality for people who moved from 2007 to 2010 (before the policy) and people who moved from 2010 to 2013 (after the policy). There is a broad-based improvement in destination quality in Dallas, with no change in nearby Fort Worth, which did not implement the policy.

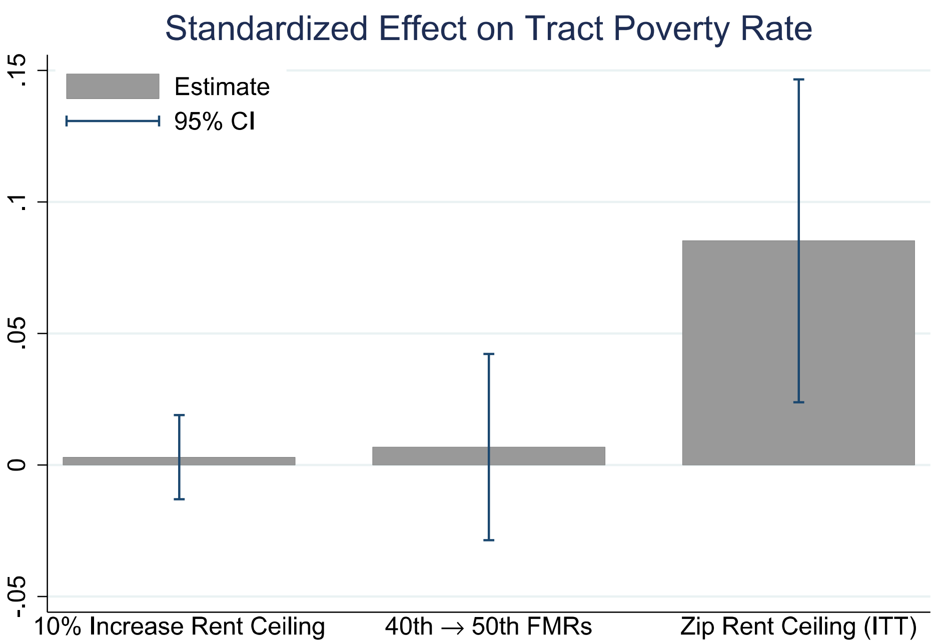

FIGURE B.4. POLICY COMPARISON – IMPACT ON NEIGHBORHOOD POVERTY

Note: This figure plots the standardized impact of three policies on census tract poverty rates of voucher holders: 1) a 10% increase in the rent ceiling using the 2005 re-benchmarking variation from Section III.A, 2) the 40th →50th percentile FMR change from Section III.B 3) Dallas ZIP Code-Level rent ceiling from Section IV. Positive standardized effects represent *reductions* in the tract poverty rate.

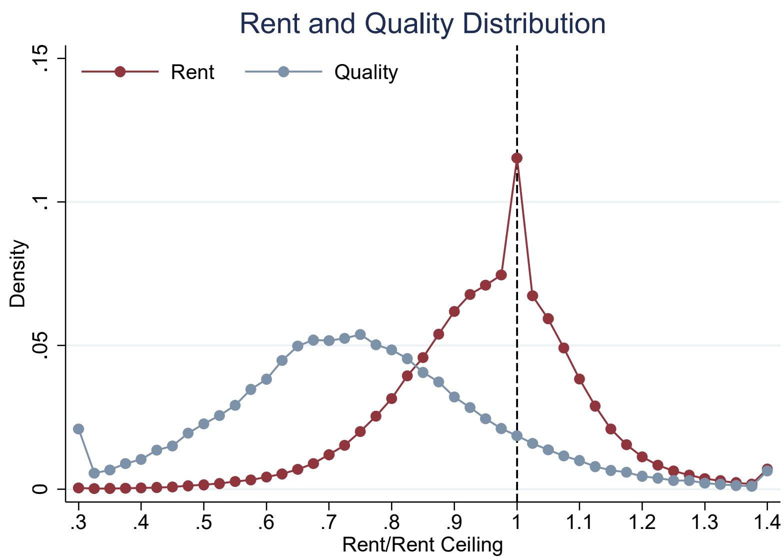

Figure B.5. Distribution of Rents

Note: The bottom panel plots rents and hedonic quality relative to the local rent ceiling. Of rent observations, 0.03% are left censored and 0.62% are right censored. Of quality observations, 1.8% are left censored and 0.58% are right censored. We report gross rent (contract rent + utilities) to facilitate comparison with the rent ceiling, which is set in terms of gross rent. In the rest of the paper, we use contract rent alone, to focus on landlord behavior. Notes: 2009 data, n=1.7 million. Our methods for constructing hedonic quality are described in Section III.A.

Appendix Table 1 - Placebo Tests with Nonvoucher Rents
Research Design: Rebenchmarking

	Dep Var: Change in Log Rent					
Sample	All Units		Units in Counties with 100K+ Residents			
	Voucher	Nonvoucher	Voucher	Nonvoucher		
Time Horizon	04-09	00-09	04-09	00-09	00-05	05-09
Data Source	HUD Admin[a]	Tract[b]	HUD Admin	Tract	IPUMS[c]	
	(1)	(2)	(3)	(4)	(5)	(6)
	0.0831	-0.046	0.175	0.066	-0.193	0.021
dLog FMR, 2004-2005	(0.0179)	(0.020)	(0.049)	(0.049)	(0.102)	(0.099)
Voucher Coef != Nonvoucher Coef						
F-statistic		28.9		5.7		2.3
p-value		<0.0001		0.0174		0.129
n	365,667	312,045	240,525	144,920	1,778	1,772

Notes: This table shows the correlation of the 2005 Fair Market Rent rebenchmarking with contemporaneous changes in nonvoucher rents. Regressions give equal weight to each county-bed pair. Standard errors shown in parentheses are clustered at FMR group level (n=1,484). See Appendix A.3 for discussion of these results.
a. Voucher estimates in columns (1) and (3) are from HUD Admin data for households that stayed at the same address from 2004 to 2009.
b. Tract-level estimates in columns (2) and (4) use the change in log median rent from the 2000 Census to the 2005-2009 ACS.
c. Change in log rent at the county-bed level constructed from public-use micro data. These data only identify counties with more than 100,000 people due to confidentiality restrictions.

Appendix Table 2: Hedonic Model (American Community Survey)

	Model Fit: R^2	0.487	
ACS		Coef	S.E.
	Single Family Attached [Excluded]		
	Semi-Detached SF	49.44	(1.93)
	3-4 Unit Building	-64.90	(2.02)
	5-9 Units	-85.34	(2.01)
	20+ Units	-33.51	(2.18)
	Mobile home	-223.8	(2.74)
	Built in 2005 or Later [Excluded]		
	Pre 1940s	-286.8	(2.73)
	40-50	-310.5	(3)
	50-60	-297.5	(2.76)
	60-70	-280.0	(2.7)
	70-80	-250.9	(2.59)
	80-90	-194.8	(2.64)
	1990's	-134.2	(2.69)
	2000's	-58.98	(2.8)
	0 or 1-Bed [Excluded]		
	2-Bed	146.3	(1.26)
	3-Bed	254.7	(1.47)
	4-bed	-111.2	(3.27)
	5+ Bed	512.4	(3.24)
	PUMA FE	Yes	
	Observations	710957	

Notes: This table presents results from the hedonic regression of rents in the American Community Survey (2005-2009). Sample is restricted to units with cash rent and excludes not-standard housing structure types (boats, RVs etc). Dependent variable is cash rent in $2009. We estimate the model with PUMA fixed Effects.

Appendix Table 3 - Robustness: Effect of Uniform Rent Ceiling Increase on Rents
Research Design: Rebenchmarking

	Baseline Specification	County Fixed Effects	Unlikely to be Residual Payer	Address Fixed Effects
	(1)	(2)	(3)	(4)
IV Rent Estimate		Y: ΔLog Voucher Rent, 2004-2010		
ΔLog Rent Ceiling 2010	0.458	0.499	0.519	0.151
	(.0304)	(0.035)	(0.052)	(0.036)
			Y: ΔLog Tenant Payment	
ΔLog Rent Ceiling 2010			-0.044	
			(0.118)	
			Y: ΔLog Govt Payment	
ΔLog Rent Ceiling 2010			1.078	
			(0.125)	
Unit of Observation	County-Bed	County-Bed	Household	Address
n	12,333	12,195	897,110	844,308

Notes: This table presents robustness checks for the the rent impacts of a countywide or metrowide increase in the rent ceiling using variation from the 2005 Fair Market Rent (FMR) rebenchmarking. Standard errors shown in parentheses are clustered at FMR group level. See Section 5.1 for details. Column (1) is our baseline specifcation.
Column (2) adds county fixed effects to equation (9) from 5.1.
Column (3) presents estimates from three separate regressions with three different dependent variables. Each regression uses estimates equation (9) from 5.1 but the dependent variables are changes in log voucher rent, changes in log tenant payment and changes in log government housing assistance payments from 2004-2010.
Column (4) estimates equation (9) for the subset of units continuously occupied by voucher holders.

Appendix Table 4: Hedonic Comparison

						Number of X's	
Sample	Variables	Outcome	sd(rent)/ mean(rent)	R^2 (In-Sample)	R^2 (Out of Sample)	Time-Varying	Time-Invariant
AHS	ACS	Unsub Rents		0.305	0.283	0	4
AHS	ACS+CSS	Unsub Rents	0.82	0.313	0.279	26	4
AHS	ACS+CSS+AHS	Unsub Rents		0.418	0.376	43	26
CSS	ACS	Voucher Rents	0.38	0.693	0.635	0	4
CSS	ACS+CSS	Voucher Rents		0.695	0.635	26	4
ACS	ACS	Unsub Rents	0.62	0.487	0.418	0	4

Notes: This table compares the fit of hedonic regressions using three sets of variables: our hedonic measures in the ACS (structure type, age of building, number of bedrooms and PUMA/AHS Zone Fixed Effects); the 26 time-varying measures from HUD's Customer Satisfaction Survey (CSS); and 69 total hedonic characteristics from the AHS. The AHS Sample uses the American Housing Survey 2011 micro data file. The CSS sample consists of responds in years 2000 to 2003. The ACS Sample uses the 2005-2009 ACS PUMS file. The table report the R^2, as well as the an out-of-sample R^2 calculated over a held out random 50 percent sample.

Appendix Table 5 - Effect of Uniform Rent Ceiling Increase on Rent and Quality

Research Design: 50th Percentile FMRs

	Hedonic Quality				
	Neighborhood	Unit	Unit and Neighborhood	Neighborhood Poverty	Voucher Rents
	(1)	(2)	(3)	(4)	(5)
	Y: Log Median Tract Rent	Y: Log Unit Hedonic Quality	Y: Log Composite Hedonic Quality	Y: Tract Poverty Rate	Y: Log Rent Ceiling[a]
1(fmr 50 × Post)	0.00672	0.000617	0.00503	-0.000738	0.112
	(0.007)	(0.007)	(0.011)	(0.002)	(0.022)
Unit of Observation	Household	Household	Household	Household	County-Year
Observations	315629	315629	315629	315629	11829

Notes: This table shows the quality and rent impacts of a metrowide increase in the rent ceiling using variation from the 40th -> 50th percentile FMR change from 2000 to 2003. he sample is voucher households in the Customer Satisfaction Survey in years 2000-2003 for columns (1)-(4). The sample for column (5) is all county-years with valid rent data in our pooled MTCS and PIC data sets. This table reports the average effect of the policy from a difference-in-difference specification described in Section 5.2. Standard errors are clustered at the FMR group level.

a. Uses county-level average rent ceilings from HUD's PIC and MTCS administrative data sets for 2000-2003.

Appendix Table 6 - Effect of Tilting Rent Ceilings to ZIP-level on Rents and Building Quality

Research Design: Dallas

Sample	Log Price Ceiling	Log Voucher Rent	Log Hedonic Quality
	(1)	(2)	(3)
First Stage			
Log ZIP FMR×Post	0.624		
	(0.050)		
IV Rent Estimate			
Log ZIP Rent Ceiling×Post		0.566	
		(0.038)	
IV Quality Estimate			
Log ZIP Rent Ceiling×Post			0.192
			(0.043)
Control for ZIP FMR	Yes	Yes	Yes
Indicators for Bedroom-Year	Yes	Yes	Yes
n	17290	17290	17290

Notes: This table shows the rent and building quality impact of moving from a single, metro-wide FMR in Dallas to ZIP-level FMRs using a balanced panel of units in 2010 and 2013.
Column (1) shows the coefficient b from the first stage equation: Rent_Ceiling = a + b*FMR*post + FMR + e.
Column (2) displays the the the coefficient b from the second stage equation y = a + b*Rent_Ceiling_hat*post + FMR + e where FMR*post is the instrument for Rent_Ceiling_hat*post. This coefficient is the treatment estimate for the effect of a $1 rent ceiling change on Voucher rents
Column (3) repeats the specifcation from (2) with hedonic building quality as the dependent variable.
Standard errors are clustered by ZIP (#=132). See Section 6.1 for details.

Appendix Table 7 - Mobility Counseling in Dallas

		Neighborhood Quality Index		
Sample	N	Before Move	After Move	Change
(1) Total Movers	8189	-1.10	-0.92	0.19
(2) Movers With Mobility Counseling	303	-0.94	0.23	1.17
(3) Movers Without Mobility Counseling	7886	-1.11	-0.96	0.15

Notes: This table decomposes the neighborhood quality improvement in Dallas for households which received vouchers in 2010 and moved by 2012 by receipt of voluntary mobility counseling. This counseling was offered to all voucher Data in row (1) are locations in 2010 and 2012 for all movers and come from HUD administrative records. Data in row (2) are locations immediately prior to and after moving and come from the Inclusive Communities Project, which provided the counseling. Data in row (3) are calculated as y_notCounseled = (y_all - shareCounseled*y_counseled)/(1-shareCounseled).