Investment Incentives in Tradable Emissions Markets with Price Floors*

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Abstract

Concerns about cost containment and price volatility have led regulators to include price controls in many cap-and-trade markets. We study how these controls affect firms' incentives to invest in the adoption of abatement technologies in a model with abatement cost uncertainty. Price floors increase investment incentives because they raise the expected benefits from lowering abatement costs. We also report a market experiment that features abatement cost uncertainty and the opportunity for cost-reducing investment, with and without a price floor. Consistent with the theoretical model, investment is significantly greater with the price floor in place. Emissions permit prices also respond as predicted to abatement investments and emissions shocks. In particular, prices are only responsive to investment and shocks when the price floor is not implemented.

Keywords: Emissions trading; Technology adoption; Technological innovation; Price controls; Market design; Laboratory experiments

JEL Classification: C91; D47; O33; Q55; Q58

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1 Introduction

A fundamental issue in market-based environmental policy is the extent to which tradable emissions markets can steer investment towards energy-saving and advanced abatement technology in the long run. In the context of climate change, for instance, investment in developing and adopting low-carbon technologies is crucial to reducing the cost of climate mitigation. Some carbon permit markets, however, have experienced considerable price volatility, particularly some extremely low prices. For example, allowance prices in the European Union Emissions Trading System (EU ETS) were below €10 per ton from November 2011 to February 2018. (Current prices are significantly higher.) Allowance auction clearing prices in the Regional Greenhouse Gas Initiative (RGGI) were at the very low reserve price (set at $1.86 per ton in 2008, increasing slowly to $2.26 in June 2019) for auctions conducted between June 2010 and December 2012, and have only recently exceeded $10.00 per ton (US Congressional Research Service, 2019). Similarly, in California's cap-and-trade market for greenhouse gases, auction prices and secondary market prices have been at or close to the auction reserve price throughout the program's history (California Air Resources Board, 2021).[1] Lower-than-expected prices can undermine investors' confidence in future market conditions, adversely affecting the expected rewards from investment strategies (Burtraw et al., 2010), and resulting in reduced investment in environmental innovation (Taylor, 2012). Introducing price floors can guard against the threat of (too) low allowance prices, and the potential for under-investment in abatement technology (Philibert, 2009; Wood and Jotzo, 2011).[2]

However, the theoretical and empirical literature concerning the effects of price floors on investment in abatement technologies is limited. In particular, to our knowledge the literature does not include a positive model of how price controls in emissions markets affect the incentives to adopt new cost-saving abatement technologies with empirical tests of the results of such a model. Our paper tries to fill this gap. First, we develop a formal, tractable model of an emissions trading market comprising heterogeneous firms that allows us to make theoretical predictions about the firms' investment decisions, with and without a price floor. Second, we test this model's predictions in a market experiment, providing empirical evidence on investment behavior in such market conditions.[3] Our main research question is: how does the introduction

[1] Burtraw and Keyes (2018, pp. 212-214) discuss a number of factors that have led to low prices in several programs. These include, but are not limited to, the over-supply of emissions allowances, source efforts to reduce abatement costs, competition among abatement options, and the existence of related and sometimes overlapping policies that reduce allowance demand.

[2] Incorporating price controls in emissions markets was first suggested by Roberts and Spence (1976). Although they considered implementing both price ceilings and price floors, the first recommendations for controlling abatement cost uncertainty in carbon markets focused on price ceilings (Pizer, 2002; Jacoby and Ellerman, 2004). However, a price ceiling cannot address the problem of low-side abatement cost risk, and it has become evident that emissions markets are more often plagued by (too) low prices rather than price spikes (Burtraw et al., 2010).

[3] We restrict our attention to the implementation of price floors in existing tradable emissions markets and their effects on investment in abatement technology. Our experimental evidence is unique for such settings, but complements empirical research on feed-in tariffs and investment in renewable energy technologies (e.g., Johnstone et al., 2010). Feed-in tariffs tend to be long-term contracts for renewable energy at minimum prices above market prices to encourage adoption of renewable energy (e.g., Tanaka et al., 2017). In this respect, feed-in tariffs act like the price floors in our model.

of a price floor in emissions trading markets affect firms' incentives to invest in the adoption of cost-saving abatement technologies?

Our theoretical model suggests that in a market with a mix of firms that invest and do not invest in a cost-reducing technology, only firms with high abatement costs will invest in the technology. The introduction of a price floor expands the set of investors to include medium-cost firms who would not invest in the absence of the price floor. The results of our experiment are consistent with these hypotheses. The main policy lesson is clear: a price floor in an emissions market can motivate increased investment in technologies that reduce firms' abatement costs. Although outside the scope of our analysis, a logical conjecture is that this additional demand for cost-reducing technologies can spur additional innovation in abatement technologies. Indeed, as a recent IMF report by Parry et al. (2021) proposes, an international carbon price floor may act as a means to focus coordination on a transparent and "essential price signal for redirecting new investment to clean technologies" (p. 5).

Our work contributes to the theoretical and experimental literature on price controls in emissions markets. In the last decade or so, the theoretical literature expanded to include analyses of alternative price stabilization schemes (Fell et al., 2012; Grüll and Taschini, 2011); the relationship between price controls and banking (Fell and Morgenstern, 2010); and the optimal design of emissions markets with price controls accounting for enforcement (Stranlund and Moffitt, 2014) and co-pollutants (Stranlund and Son, 2019). The study by Borenstein et al. (2019) highlights the continuing importance of analyzing the design and effects of implementing price controls, because their work reveals that relatively large uncertainty in business-as-usual emissions implies that permit prices are likely to be determined by price floors and ceilings rather than permit supplies. Recently, Salant et al. (2022a) theoretically show that the introduction of price floors in emissions trading markets (as well as other "storable" markets) raises the current and expected future price, where the new equilbrium price can exceed the floor level.

The experimental literature addressing price controls and other price stabilization policies is more limited than the theoretical literature. Building on the seminal work of Isaac and Plott (1981) and Smith and Williams (1981), who examined price controls in laboratory settings, the more recent experimental literature related to the design of emissions markets has mainly focused on comparing alternative schemes in terms of their ability to limit permit price risk. For example, Stranlund et al. (2014) studied the effects of price controls and banking, separately and together. Holt and Shobe (2016) examined alternative price and quantity controls motivated by the market stability reserve of the EU ETS. Perkis et al. (2016) examined hard and soft price ceilings, while Friesen et al. (2019) examined soft price ceilings with an alternative design for auctioned permits. Here we examine a *hard* price floor, which entails a lower absolute limit on the permit price. This can be implemented in markets where allowances are distributed for free and where the government commits to buy back any unused allowances at the floor price.[4] Friesen et al. (2022) investigated the use of dual allowance reserves and trigger prices. Finally,

[4]In contrast, in emissions markets where allowances are auctioned, a *soft* price floor can be implemented through a minimum reserve price for newly auctioned permits (see Murray et al., 2009).

Salant et al. (2022b) studied the impact of non-binding hard and soft floors on permit prices in a dynamic setting with permit banking. In contrast to these studies of alternative mechanisms to stabilize permit prices, we examine the effects of a hard price floor on investments in a cost-saving abatement technology under uncertainty.[5]

None of the aforementioned papers is concerned with the effects of price controls on investments in cost-reducing abatement technologies. To our knowledge, only Weber and Neuhoff (2010) and Brauneis et al. (2013) addressed technology investments and price controls in emissions markets. In particular, Weber and Neuhoff (2010) is a normative theoretical study of the optimal design of an emissions market with price controls; however, they do not address how price controls affect firms' investments in reducing their abatement costs. Brauneis et al. (2013) employ a simulation model in conjunction with a real options approach to determine the optimal carbon price floor and its effect on the timing of investment in low-carbon technology in the electricity sector. In contrast to these two papers, our contribution is a positive study that examines how a price floor affects the adoption of a cost-saving abatement technology, both theoretically and experimentally.

In this respect, our paper also adds to the literature on environmental policy induced technology adoption (for a survey, see Requate, 2005).[6] Under certainty about firm's abatement costs, Requate and Unold (2003) argued that a fixed emissions tax provides a greater incentive for firms to adopt a cost-saving technology than a competitive emissions market with a fixed number of emissions permits. The reason is that a significant number of adopters will lower the permit price in a market, which in turn reduces the adoption incentive and the number of adopters. We show, both theoretically and experimentally, that adding a price floor to an emissions market under uncertainty about firms' abatement costs can increase the adoption incentives in the market and increase the number of adopters of a new technology. This occurs because the price floor truncates the lower range of potential permit prices when abatement costs are uncertain.

The paper is structured as follows. In Section 2 we develop the theory and derive the main propositions. The experimental design, implementation and hypotheses are described in Section 3, followed by the analyses and discussion of results in Section 4. Conclusions are drawn in Section 5.

2 Theoretical Framework

Our experiment is based on a theoretical model of n heterogeneous risk-neutral competitive firms who participate in a market to control a uniformly mixed pollutant. Firm i in the market has a linear marginal abatement cost function

$$m^i(q^i, x^i, u) = b^i(1 - \beta x^i) + u - cq^i, \tag{1}$$

[5] Vidal-Meliá et al. (2022) experimentally examined technology adoption incentives under emissions taxes and tradable permits, but their focus is on (imperfect) compliance without consideration of price controls.

[6] Generally, our work fits into a broader literature that studies how market design can affect market performance by affecting investment decisions (Fabra et al., 2011).

where q^i is the firm's emissions and b^i, c, and β are positive constants. The random variable u affects the abatement costs of all firms, and is distributed on support $[\underline{u}, \overline{u}]$ with probability density function $g(u)$ and zero expectation.[7] The firm can invest in an existing technology that reduces its marginal and total abatement costs.[8] Specifically, $x^i = \{0, 1\}$ is the firm's irreversible dichotomous adoption choice. If the firm chooses to adopt the technology so that $x^i = 1$, the intercept of its marginal abatement cost function, b^i, is reduced by a constant percentage $\beta \in (0, 1)$. Firms are only distinguished from one another by the parameter b^i, which varies across firms on the interval $[b^{min}, b^{max}]$. We will sometimes refer to b^i as firm i's "type."[9]

Given a realization of u and an investment choice x^i, a firm's total abatement cost is minimized at $q_0^i(x^i, u)$, the solution to $m^i(q^i, x^i, u) = 0$; that is,

$$q_0^i(x^i, u) = \frac{b^i(1 - \beta x^i) + u}{c}. \tag{2}$$

We assume that $b^i(1 - \beta x^i) + u > 0$ for every firm and their investment choices, and every realization of u. An emissions market will motivate the firm to reduce its emissions to some $q^i < q_0^i(x^i, u)$. In doing so it will incur total abatement cost

$$\begin{aligned} a^i(q^i, x^i, u) &= \int_{q^i}^{q_0^i(x^i,u)} (b^i(1 - \beta x^i) + u - cq^i)dq^i, \\ &= \frac{(b^i(1 - \beta x^i) + u)^2}{2c} - (b^i(1 - \beta x^i) + u)q^i + \frac{c(q^i)^2}{2}. \end{aligned} \tag{3}$$

We analyze an emissions trading program with and without a price floor with the following features. A total of L permits are distributed to the firms (free of charge), and firm i receives l_0^i permits from this initial distribution.[10] Each permit confers the legal right to emit one unit of

[7]The firm's marginal abatement cost function is linear with uncertainty in the intercepts, which is frequently assumed in the theoretical and experimental literature on emissions control instrument choice, including policies involving price controls (e.g., Weitzman 1974; Weber and Neuhoff, 2010; Fell et al., 2012; Stranlund et al., 2014; Stranlund and Son, 2019). Due to the way in which this common shock u enters the abatement cost function, it could also be thought of as a common shock to emissions, given an emissions price. This could arise, for example, through regional weather variation or macroeconomic shocks (such as, most dramatically, a global pandemic).

[8]Our research question is focused on the incentives to invest in the adoption of an existing cost-saving abatement technology. This is different from innovation in terms of investment in R&D with the aim of developing more advanced abatement technologies. The literature that distinguishes between technology adoption (i.e., deployment) and innovation suggests there is no consistent welfare ranking of emissions taxes, auctioned emissions permits and grandfathered permits when innovation is endogenous (e.g., Fischer et al., 2003). An alternative design could relate to investment in R&D and feature stochastic investment success (see Cason and De Vries, 2019). This would, however, imply a random shock at the firm level in addition to the common shock that affects the abatement costs of all firms as in our current setup. We leave investigation of this more complex design allowing for endogenous innovation for future research.

[9]Our assumption that the slope of firms' marginal abatement cost functions, c, does not vary across firms is not essential. All of our theoretical results hold if we assume heterogeneous slope parameters instead (the proofs of these results are available from the authors upon request). Assuming that the slope parameter does not vary across firms simplifies the implementation of our experiment.

[10]While we model a free initial allocation of permits, which is a feature of many existing emissions markets, over time there has been a shift toward allocating more allowances via auctions. See MacKenzie (2022) for a review of the auctions used in the EU ETS, RGGI, and California markets for greenhouse gas emissions. The auctions in these programs are uniform-price auctions with features that allow flexible allowance supplies, including reserve (minimum) prices that work like the price floor in our analysis. Uniform-price multi-unit auctions are prone to demand reduction as firms are motivated to shade their bids for allowances. Price floors can mitigate some of this demand reduction, but we are not aware of theoretical or empirical work that examines technology adoption under auctioned permits with flexible allowance supplies. This seems to be a worthwhile topic for future study.

emissions and enforcement is assumed to be perfect, implying that firms' final permit holdings are equal to their emissions. Emissions permits trade at a competitive price p. When the market includes a price floor the government commits to buying back unused permits at a fixed price s. For the market to clear we must have $s \leq p$. Throughout we assume that the price floor has a strictly positive probability of binding.

The timing of events in our model is as follows. Given the elements of the market policy, in the first stage all firms choose whether to make their irreversible investments in reducing their abatement costs. In the second stage the value of u is revealed and, given u, firms choose their emissions, trade in the permit market (including potential sales to the government), the market clears, and the firms release their allowed levels of emissions.[11]

2.1 A Pure Market without Price Controls

In this subsection we specify the equilibrium for a market without a price floor, starting with the second stage. Given the realization of u, a permit price (to be determined) and investments from the first stage, a firm chooses its emissions to minimize its compliance cost, consisting of its abatement cost and the value of its permit transactions:

$$\begin{aligned} c^i(q^i, x^i, u) &= a^i(q^i, x^i, u) + p(q^i - l_0^i) \\ &= \frac{(b^i(1-\beta x^i)+u)^2}{2c} - (b^i(1-\beta x^i)+u)q^i + \frac{c(q^i)^2}{2} + p(q^i - l_0^i). \end{aligned} \tag{4}$$

The familiar rule of equalizing marginal abatement cost and the permit price gives us the firm's choice of emissions,

$$q^i(x^i, p, u) = \frac{b^i(1-\beta x^i)+u-p}{c}. \tag{5}$$

Using (5) to solve the market clearing condition, $\sum_{i=1}^n q^i(x^i, p, u) = L$, the equilibrium permit price is

$$p(\boldsymbol{x}, u) = \frac{\sum_{i=1}^n b^i(1-\beta x^i) - cL}{n} + u, \tag{6}$$

where $\boldsymbol{x} = (x^1, ..., x^n)$ is the vector of individual investments in abatement cost reductions. Clearly the permit price is lower when the random variable u is lower and when more firms invest in reducing their abatement costs. (Throughout we ignore the fact that the permit price also depends on the supply of permits.)

It is convenient to write (6) as

$$p(\boldsymbol{x}, u) = p(\boldsymbol{x}) + u, \tag{7}$$

where $p(\boldsymbol{x})$ is the expected permit price (i.e., when $u = 0$), given investments $\boldsymbol{x}$. Substitute (5) and (7) into (4) to obtain a firm's equilibrium compliance cost in the second stage as a function of the first-stage investment

$$c^i(\boldsymbol{x}, u) = (p(\boldsymbol{x}) + u)\left(\frac{b^i(1-\beta x^i)+u}{c} - \frac{p(\boldsymbol{x})+u}{2c} - l_0^i\right). \tag{8}$$

[11] The model is static, which precludes a real options approach to analyzing investments under uncertainty. Zhao (2003) takes a real options approach to show how abatement cost uncertainty affects irreversible investments in abatement capital or technologies under emissions markets and emissions taxes. To our knowledge there is no published work that extends this approach to consider investments under emissions markets with price controls.

Having characterized the second-stage equilibrium emissions, permit price and firms' compliance costs, we are now in a position to consider a firm's choice of investment in reducing its abatement cost in the first stage. We begin by calculating a firm's expected benefit of investment, given the investment choices of the other firms. Given a realization of u, the change in firm i's compliance cost if it invests in the first stage is

$$\Delta c^i(\boldsymbol{x}, u) = c^i(x^i = 1, x^{-i}, u) - c^i(x^i = 0, x^{-i}, u), \tag{9}$$

where $x^{-i} = \boldsymbol{x} \backslash (x^i)$. Define a firm's expected reduction in its compliance cost from its investment in the first stage as

$$r^i(\boldsymbol{x}) = -\mathbb{E}\left(\Delta c^i(\boldsymbol{x}, u)\right), \tag{10}$$

where $\mathbb{E}$ denotes the expectation operator. Under perfect competition a single firm's adoption of the abatement technology does not affect the equilibrium permit price.[12] Under this assumption, in Appendix A we show that

$$r^i(\boldsymbol{x}) = \frac{p(x^i = 1, x^{-i}) b^i \beta}{c}. \tag{11}$$

We are now able to characterize a firm's investment choice. Suppose that the cost of the investment is f, which does not vary across firms. We assume that if a firm is indifferent about making the investment in reducing its abatement cost then it chooses to make the investment. The firm then invests in reducing its abatement cost if and only if

$$f \leq r^i(\boldsymbol{x}); \tag{12}$$

that is, the firm invests if and only if the cost of the investment is not greater than the expected reduction in its compliance cost. Given an equilibrium vector of investments $\boldsymbol{x}^*$ that includes $x^i = 1$,

$$r^i(\boldsymbol{x}^*) = r(b^i, \boldsymbol{x}^*) = \frac{b^i \beta p(\boldsymbol{x}^*)}{c}, \tag{13}$$

where $p(\boldsymbol{x}^*)$ is the expected equilibrium permit price. We write $r^i(\boldsymbol{x}^*) = r(b^i, \boldsymbol{x}^*)$ to recognize that, given $\boldsymbol{x}^*$, $r^i(\boldsymbol{x}^*)$ differs over firms only as b^i varies. The following proposition tells us which firms will invest in reducing their abatement cost. All proposition proofs are in Appendix A.

Proposition 1. *Under a competitive emissions market without a price floor, there exists a unique firm type, b^*, defined by*

$$f = \frac{b^* \beta p(\boldsymbol{x}^*)}{c}, \tag{14}$$

such that if $b^* \in [b^{min}, b^{max}]$, then firm types $b^i \in [b^*, b^{max}]$ invest in reducing their abatement costs and firm types $b^i \in [b^{min}, b^*)$ do not. No firm invests if $b^* > b^{max}$, and every firm invests if $b^* < b^{min}$.

[12] With a small number of polluters it is possible that a single firm's investment in reducing its abatement cost in the first stage can influence the equilibrium permit price in the second stage. Firms could also have market power in the permit market, in contrast with our simplifying assumption that the permit market is perfectly competitive. For example, permit markets for effluent emissions to waterways sometimes have a small number of large emitters, as discussed in Cason et al. (2003). Our model is more appropriate for competitive markets with a large number of regulated sources, such as the greenhouse gas markets discussed in the introduction.

Proposition 1 indicates that a cut-off firm type, b^*, typically separates the investors who have higher abatement costs (i.e., $b^i \geq b^*$) from the non-investors who have lower abatement costs (i.e., $b^i < b^*$). The reason for this pattern of investment is that the expected value of investing in reducing abatement costs is higher for firms with higher abatement costs. To be complete, Proposition 1 also characterizes corner solutions at which all firms invest or no firm invests.

2.2 A Market with a Price Floor

To set up the investment objective for a firm when a price floor is placed on a market we first need to specify the value of the random variable u at which the price floor and the permit market bind together. This value of u is u^s, the solution to $p(\boldsymbol{x}) + u = s$; that is,

$$u^s = s - p(\boldsymbol{x}). \tag{15}$$

To make sure that the price floor has a strictly positive probability of binding, we restrict ourselves to values of s such that $u^s \in (\underline{u}, \overline{u})$. For realizations of $u > u^s$ the permit cap binds, each firm chooses emissions equal to $q^i(x^i, p, u)$ from (5) and the permit market clears at price $p(\boldsymbol{x}, u)$ from (6). For $u < u^s$ the price floor binds so that $p = s$. In this case, from (5) a firm chooses emissions

$$q^i(x^i, s, u) = \frac{b^i(1 - \beta x^i) + u - s}{c}.$$

Moreover, we can modify (8) to write the firm's compliance cost when the price floor binds as

$$c^i(\boldsymbol{x}, s, u) = s\left(\frac{b^i(1 - \beta x^i) + u}{c} - \frac{s}{2c} - l_0^i\right). \tag{16}$$

From the perspective of the first-stage investment, a firm's expected compliance cost when it faces a price floor is

$$\int_{\underline{u}}^{u^s} c^i(\boldsymbol{x}, s, u) g(u) du + \int_{u^s}^{\overline{u}} c^i(\boldsymbol{x}, u) g(u) du,$$

and the firm's expected reduction in its compliance cost from investing in reducing its abatement cost is

$$r^i(\boldsymbol{x}, s) = -\int_{\underline{u}}^{u^s} \Delta c^i(\boldsymbol{x}, s, u) g(u) du - \int_{u^s}^{\overline{u}} \Delta c^i(\boldsymbol{x}, u) g(u) du. \tag{17}$$

In Appendix A we show that

$$r^i(\boldsymbol{x}, s) = \frac{b^i\beta}{c}\left\{\int_{\underline{u}}^{u^s} s g(u) du + \int_{u^s}^{\overline{u}} \left(p(x^i = 1, x^{-i}) + u\right) g(u) du\right\}. \tag{18}$$

As usual, the firm invests in reducing its abatement cost if and only if

$$f \leq r^i(\boldsymbol{x}, s), \tag{19}$$

and does not invest otherwise. Given an equilibrium vector of investments $\boldsymbol{x}^{**}$ that includes $x^i = 1$,

$$r^i(\boldsymbol{x}^{**}, s) = r(b^i, \boldsymbol{x}^{**}, s) = \frac{b^i\beta}{c}\left\{\int_{\underline{u}}^{u^{s**}} s g(u) du + \int_{u^{s**}}^{\overline{u}} (p(\boldsymbol{x}^{**}) + u) g(u) du\right\}, \tag{20}$$

where $u^{s**} = s - p(\boldsymbol{x}^{**})$ from (15). As with (13), we write $r^i(\boldsymbol{x}^{**}, s) = r(b^i, \boldsymbol{x}^{**}, s)$, because, given $\boldsymbol{x}^{**}$, $r^i(\boldsymbol{x}^{**}, s)$ varies across firms only as b^i varies across firms. In addition, we note that the bracketed term on the right side of (20) is the equilibrium expected permit price under the price floor, given investments $\boldsymbol{x}^{**}$. To make this explicit, denote the expected equilibrium permit price under the price floor as $\mathbb{E}(p(\boldsymbol{x}^{**}, s))$ and rewrite (20) as

$$r(b^i, \boldsymbol{x}^{**}, s) = \frac{b^i \beta \mathbb{E}(p(\boldsymbol{x}^{**}, s))}{c}. \tag{21}$$

The following proposition, which is the analogue to Proposition 1, characterizes equilibrium investment decisions in the case of a market with a price floor and a large number of firms.

Proposition 2. *Under a competitive emissions market with a price floor that has a strictly positive probability of binding, there exists a firm type, b^{**}, defined by*

$$f = \frac{b^{**} \beta \mathbb{E}(p(\boldsymbol{x}^{**}, s)}{c}, \tag{22}$$

such that if $b^{**} \in [b^{min}, b^{max}]$, then firm types $b^i \in [b^{**}, b^{max}]$ invest in reducing their abatement costs and firm types $b^i \in [b^{min}, b^{**})$ do not. No firm invests if $b^{**} > b^{max}$, and every firm invests if $b^{**} < b^{min}$.

As in Proposition 1, when there is a mix of investing and non-investing firms only high abatement-cost firms make the first-stage investment in reducing their abatement costs. However, the cut-off firm type under Proposition 2 is likely different from the cut-off firm type in Proposition 1, so it remains to be seen whether the price floor expands or contracts the set of firms that invest in reducing their abatement costs.

2.3 Investment with and without a Price Floor

We are now ready to show how the set of firms that invest in reducing their abatement costs changes with the implementation of a price floor. Our results are contained in the following proposition.

Proposition 3. *Assume that the cut-off firm types b^* and b^{**} in Propositions 1 and 2, respectively, are contained in the interval $[b^{min}, b^{max}]$. Then:*

(1) $b^{**} < b^*$.

(2) The price floor causes the set of firms that invest in reducing their abatement costs to expand to include firm types in the interval $[b^{**}, b^*)$, provided that there are firm types in this interval.

Proposition 3 is the main result of our analysis, because it gives us a prediction about how a price floor affects the pattern of investment in a technology to reduce abatement costs in a competitive emissions market with a relatively large number of firms. In cases in which there is a mix of investors and non-investors, only high abatement-cost firms invest whether an emissions market includes a price floor or not. However, a price floor will expand the set of investors (except in a special case) so that there are "intermediate" abatement-cost firms that invest when a price floor is in place, but would not invest in the absence of the price floor.

Figure 1 illustrates the main results of Propositions 1 through 3. We have graphed $r(b^i, \boldsymbol{x}^*)$ from (13), noting that it is a linearly increasing function of the firm types, given the equilibrium investments in the absence of a price floor, $\boldsymbol{x}^*$. In an equilibrium outcome with a mix of investors and non-investors, there is a firm type, b^*, such that firm types at b^* and above are the investors, and firm types below b^* do not invest in the new technology. Thus, as revealed by Proposition 1, only the high-abatement-cost firms invest in the new technology. We have also graphed $r(b^i, \boldsymbol{x}^{**}, s)$ from (20). This function is also linearly increasing in the firm types, given the equilibrium investments $\boldsymbol{x}^{**}$ in the presence of a price floor. Again, as revealed by Proposition 2, in an equilibrium with a mix of investors and non-investors, there is a cut-off firm type b^{**} that separates the investors with higher abatement costs from the non-investors with the lower abatement costs.

Proposition 3 reveals that $b^{**} < b^*$ so that a price floor can expand the set of investors to include those firm types in the interval $[b^{**}, b^*)$. The proof of Proposition 3 rests on showing that the expected permit price with a price floor that has a non-zero chance of binding is strictly greater than the expected permit price without the price floor. In fact, using (13) and (21), $r(b^i, \boldsymbol{x}^{**}, s) > r(b^i, \boldsymbol{x}^*)$ as shown in Figure 1 is implied by $\mathbb{E}(p(\boldsymbol{x}^{**}, s)) > p(\boldsymbol{x}^*)$. There are two effects at work here. The first is that the price floor truncates the lower part of the distribution of potential prices. Holding investments in the new abatement technology constant, truncating the lower part of the price distribution increases the expected permit price. However, increased investments in reducing abatement costs pushes the expected permit price down. This countervailing effect is not large enough to offset the effect of truncating the price distribution, so the expected permit price is higher with the price floor and, in turn, the set of investors is larger.

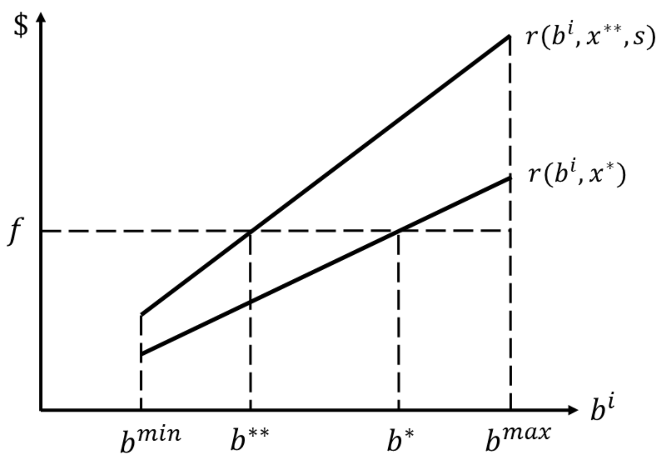

Figure 1: Impact of Price Floor on Firms' Investments in Reducing Abatement Costs

3 Experimental Design and Hypotheses

3.1 Experimental Parametrization and Trading Institution

The experimental implementation of the preceding model of abatement and investment with and without price controls required several simplifications. The quantity of emissions (q) was discretized, since emission permits are typically traded in discrete units of (e.g., tons of CO_2 equivalent). The random variable affecting abatement costs (u) was also simplified to take on a limited set of 5 equiprobable values. In this description the "firms" who make investment, abatement and trading choices were human subjects recruited to the laboratory. Their investments, abatement and permit trading decisions determined their monetary payments, which were distributed in cash at the conclusion of each experimental session.

Each market included 8 heterogeneous firms. Although it may seem relatively thin, this market size is common in laboratory studies and can result in relatively competitive pricing when trade is organized using continuous double auction rules (Smith, 1982). The double auction market used in the experiment provides a competitive environment where traders are free to submit public offers to purchase and sell permits at any prices. Firms could choose whether to take the buying or selling side of a transaction—a so-called trader setting (Kotani et al., 2019; Sherstyuk et al., 2021). Those wishing to buy permits can submit bid prices to buy or accept sellers' offer prices in continuous time. Symmetrically, those wishing to sell permits can submit offer prices to sell or accept buyers' bid prices at any time.[13] This creates a centralized, multilateral negotiation process that is relatively competitive even with a small number of traders.

Firm heterogeneity arises from differences in b^i, which take on values of $100, 200, \ldots, 800$ for the 8 different firms. The discrete shift in abatement costs due to cost-reducing investment is $\beta = 0.252$ and parameter is $c = 15$ for all firms. Abatement cost uncertainty, the motivation for the implementation of price controls, is modeled through the mean zero random variable u, which is drawn each period from the set $\{-40, -20, 0, 20, 40\}$ with all values equally likely. A total of 184 emission permits are distributed equally to the 8 firms, so that each began the trading period holding 23 permits. The heterogeneity in abatement costs creates gains from trading permits. It also leads the investment incentives to differ across firms, as characterized in Propositions 1 and 2. The firms with the highest b^i have the greatest incentive to invest to reduce costs. The investment cost f was fixed at 200 Experimental Dollars for all firms.

3.2 Period Timing and Equilibrium Prices

The experiment employs stationary repetition. This means that firms make similar investment and trading decisions in a stable environment across 16 consecutive periods with firm type being

[13]Throughout the trading period, firms can adjust their offers but new offers must be an improvement over previous offers. That is, any new buy offers must be higher than the current highest buy offer and any new sell offers must be lower than the current lowest sell offer.

fixed.[14] Such repetition is commonly employed in market experiments to allow participants to gain experience and to provide more opportunity for prices to converge to (or at least approach) equilibrium levels. New random draws occur each period for the variable affecting abatement costs (u), however, and these draws affect the equilibrium price.[15] Therefore, the equilibrium price is not stationary.

At the start of each period, traders receive fixed revenues and permits. Those firms with greater abatement costs receive greater revenues to roughly equate the equilibrium distribution of net profits across firm types. This allowed different subjects to earn similar amounts of cash earnings regardless of their random type assignment. Following this allocation of fixed revenues and permits, traders make (binary) investment decisions. They make this investment decision in each of the 16 cycles of stationary repetition, in order to maximize the number of observations collected for this focus of our study. Consistent with the theoretical model developed in Section 2, this investment lowers the marginal cost for each unit abated but does not affect the slope of the marginal abatement cost function. Firms make this decision simultaneously and they never learn the investment decisions of others. (Individual firms' marginal abatement costs are always their own private information.) Firms then learn the realization of the random variable affecting abatement costs (u).[16] Traders' investment decisions and this realization of u lead to a new abatement cost profile across traders of each type. Equilibrium permit prices therefore depend on investment choices and random factors affecting abatement costs, as summarized in Table 1. Equilibrium prices are a multiple of 15 due to the marginal cost parameter choice of $c = 15$.

Table 1: Equilibrium Permit Prices by Abatement Cost Shock and Number of Investors

	Abatement Cost Shock (u)				
(#) Investors	-40	-20	0	20	40
(0) None	75	90	105	135	150
(1) $b^i = 800$	45	60	75	105	120
(2) $b^i = 800, 700$	30	45	60	90	105
(3) $b^i = 800, 700, 600$	15	30	45	75	90
(4) $b^i = 800, 700, 600, 500$	0	15	30	60	75
(5) $b^i = 800, 700, 600, 500, 400$	0	0	15	45	60
(6) $b^i = 800, 700, 600, 500, 400, 300$	0	0	0	30	45
(7) $b^i = 800, 700, 600, 500, 400, 300, 200$	0	0	0	30	45
(8) $b^i = 800, 700, 600, 500, 400, 300, 200, 100$	0	0	0	30	45

Trading periods lasted for 3 minutes until period 6, when the length was reduced to 2 minutes.

[14]One session with two markets conducted for the no-control baseline had to be restarted due to a configuration error, so these two markets were terminated after 13 rather than the full 16 periods.

[15]Recall that the u draw each period affects all firms identically. Two sequences of u realizations were drawn before the first sessions, and these specific drawn sequences were re-used for all subsequent sessions, equally allocated across markets in both treatments. This reduces the between-session and between-treatment variability arising from the differing realizations of the random shocks.

[16]This random shock to abatement costs effectively shifted traders along their marginal abatement cost function, so it was easiest to describe to subjects as an allocation of additional permits that they all received before trading opened for the period.

Prior to these 16 periods of stationary repetition, subjects first participated in 8 (paid) training periods to familiarize them with the mechanics of continuous double auction trading through the computer interface. These training periods also included an investment stage, but they employed different abatement cost parameters and permit allocations so that transaction prices were very different from the prices in the main experiment.[17] The training periods never employed price controls. The training periods and the main periods each began with one practice period without financial stakes.

3.3 Price Floor

The treatment variable in the experiment is the price floor, imposed for this chosen parameterization at 70. This particular level of 70 is not set at an optimal (or second-best) level, which is not defined as we leave the marginal environmental damages unspecified. To implement the floor no offers or transactions were allowed at prices below 70; they were automatically disallowed by the market software. Obviously, this led to an excess supply of permits at the floor price when the floor was binding. Consistent with the implementation of hard price floors in emissions permit markets in practice, firms wishing to sell these excess permits were able to sell them to "the computer," analogous to the regulator standing ready to buy excess permits at the floor. In order to create a marginal incentive to sell to actual traders wishing to buy at the floor during the trading period, the computer made these purchases at the close of trading and at a price of 69. Firms decided how many permits to sell at this price floor.[18]

3.4 Laboratory Procedures and Power Analysis

In order to determine subjects' understanding of the investment decisions and different ways of implementing the price floor, we initially ran 3 pilot sessions.[19] These pilots generated realized effect sizes and variance estimates that were used in a power analysis to design the main experiment. These power calculations led to the conclusion that 11 markets would be sufficient to detect a difference in investment rates with power 0.80 and significance level 0.05. The power analysis also prescribed a greater allocation of markets to the price control condition due to a higher variance observed in this treatment for the pilot sessions.

We therefore collected data from a total of 11 markets, with the price floor treatment implemented in 6 markets and the no-control baseline in the other 5 markets. Each market included 8 traders as described above. The subjects were all undergraduate students at Purdue University, recruited from a database of approximately 3,000 volunteers drawn across a wide range of academic disciplines and randomly allocated to treatment conditions using ORSEE (Greiner, 2015).

[17] Equilibrium prices in the training periods ranged between 120 and 300, and had virtually no overlap with the prices shown in Table 1 for the main periods.

[18] Firms could sell as many permits at the floor as they wished. The software implemented a decision aid on-screen, which indicated the number of profitable permits they could sell; i.e., the number of currently held permits that correspond to avoided abatement costs lower than the price floor.

[19] These pilot sessions led us to add the 8 training periods described earlier, so that subjects did not have to learn the mechanics of trading at the same time they learned how permit prices depend on investment decisions and investment incentives depend on prices and the price floor.

The z-Tree program (Fischbacher, 2007) was used for the implementation of the experiment. For the purpose of maintaining as much experimental control as possible, we used neutral framing in the experiment and did not refer to the specific environmental economics setting explicitly, since environmental framing could affect subjects' preferences differently (Cason and Raymond, 2011). In particular, tradable emission permits were referred to as "coupons," and abatement and marginal abatement cost were referred to as "production" and "production costs," respectively that firms could avoid by holding more coupons. Details are provided in the written instructions given to subjects (see online Appendix B).

Each session lasted about 2 hours and after each session earnings were paid out privately in cash at a pre-announced conversion rate from the Experimental Dollars earned across all (non-practice) periods. On average, subjects earned $33.47 per person.

3.5 Testable Hypotheses

The implications of the theoretical model and corresponding experimental design allow us to test several hypotheses. We first consider the impact of price controls on investment levels. As described earlier, all eight firms make their investment choice simultaneously. The competitive equilibrium permit prices shown in Table 1 indicate that the price floor of 70 is often binding. This was a deliberate design choice so that the differences in investment incentives would be large enough to substantially change the number of equilibrium investors. As noted earlier, analysis of costs and prices in large emissions trading markets such as California's GHG market has concluded that market prices are very likely to be limited by administrative price floors or ceilings (Borenstein et al., 2019).

Table 2: Increase in Expected Profits from Investing in Abatement Cost Reductions, Gross of Investment Cost

Firm Investor Type	No Price Floor	Price Floor = 70
$b^i = 800$	**1788**	**1706**
$b^i = 700$	**1077**	**1105**
$b^i = 600$	**720**	**834**
$b^i = 500$	**408**	**600**
$b^i = 400$	192	**492**
$b^i = 300$	48	**350**
$b^i = 200$	45	**210**
$b^i = 100$	30	140

Notes: Amounts shown in experimental dollars, based on equiprobable likelihood of the 5 abatement cost shocks. Entries in **bold** indicate firms with incentive to invest for the investment cost used in experiment (200).

Those firms with the highest abatement costs have the greatest incentive to invest to reduce their abatement costs, as indicated by the cutoff firm types as derived in Propositions 1 and 2. For the experimental parameterization, the highest cost types (i.e., those with the greatest b^i) always have the incentive to invest and the lowest cost types never have the incentive to invest, regardless whether a price floor exists. The price floor affects the investment decision of the intermediate-cost firms. Table 2 shows that in equilibrium 4 firms have an incentive to invest without a price floor but 7 firms would invest with the price floor. This leads to our primary hypothesis in connection to Proposition 3.

Hypothesis 1 (Investment): In a competitive permit market,

(a) A price floor increases the total number of firms investing in reducing their abatement costs; and

(b) The change in investment frequency is greatest for firms with intermediate abatement costs.

The investment incentives arise through the price implications on the permit market, so a necessary condition for support of Hypothesis 1 is a correlation between prices and abatement shocks and investment. This is summarized by the second hypothesis:

Hypothesis 2 (Prices): Emission permit prices are

(a) lower on average without the price floor than with the price floor in place;

(b) lower in periods with favorable shocks that lower abatement costs for all firms; and,

(c) lower in periods in which a greater number of firms invest in reducing abatement costs.

Hypothesis 2(a) is based on the primary implication of a price floor that has a non-zero chance of binding, since it truncates the lower part of the distribution of potential prices. For the other two parts of this hypothesis, Table 1 illustrates the specific amounts in equilibrium that prices change due to investment and cost shocks without the price floor. Of course, these price differences are limited by the price floor when it is imposed. When investment is sufficiently high or the abatement cost shock is favorable, the price floor will bind and parts (b) and (c) of Hypothesis 2 will not apply.

4 Experimental Results

This section is divided into two subsections, corresponding to the two hypotheses regarding cost-reducing investment and emission permit prices.

4.1 Cost-Reducing Investment

The price floor theoretically increases the number of investing firms because it helps to preserve the benefits of lower abatement costs even when favorable cost shocks cause prices to fall to low levels. For the parameters used in the experiment, 7 of the 8 firms can profitably invest in the price floor treatment, while only 4 firms can invest profitably without the price floor. Figure 2 displays the average number of investing firms across periods, pooling over all 11

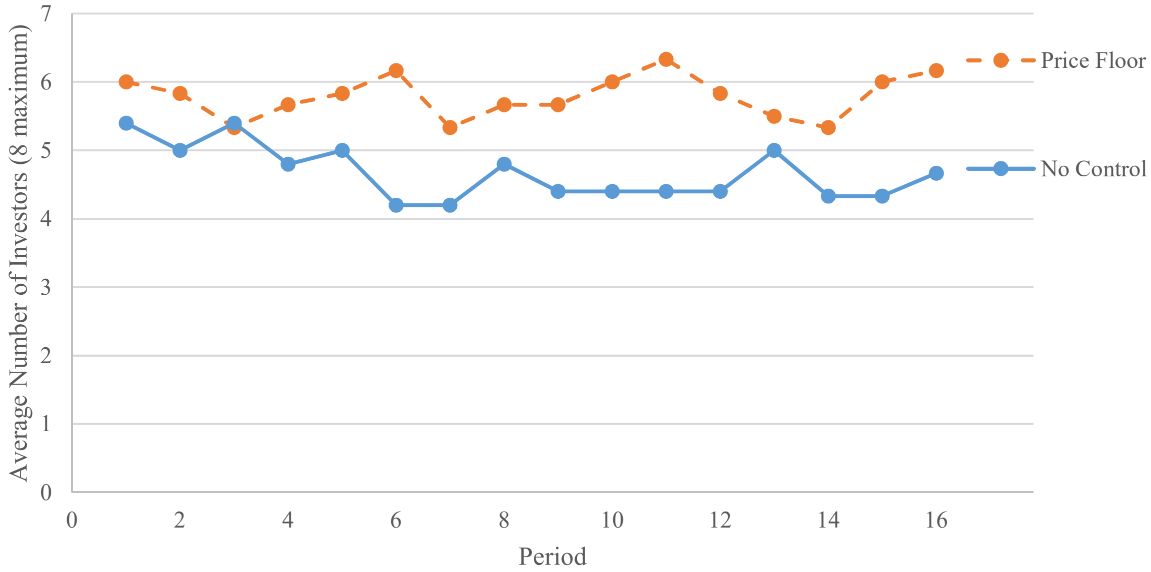

Figure 2: Mean Number of Investors, by Period

markets. Although the difference in the investment frequency is similar for the first few periods, a persistent gap across treatments emerges over time. The difference is in the direction predicted in Hypothesis 1(a).

The most conservative statistical test of this hypothesis is a nonparametric test that requires no assumptions on the underlying distribution or error structure. The only requirement is that observations in the test be statistically independent, which is the case for our 11 different markets. Figure 3 illustrates that only one market in the price floor treatment has a lower investment frequency than any market in the treatment without the price control. Since the distributions are nearly non-overlapping, a nonparametric Mann-Whitney test strongly rejects the null hypothesis of no treatment effect in favor of the directional prediction in Hypothesis 1(a) (one-tailed p-value $= 0.004, n = 11$).[20] The number of investors without the price control ranges mostly between 4 and 5, modestly exceeding the predicted number of 4 investors. The deviation below the prediction of 7 is larger for the price floor treatment, so the realized average treatment effect is smaller than the predicted level.

Hypothesis 1(b) concerns which specific firm types should change their investment choice due to the price floor. The lowest cost type ($b^i = 100$) should never invest, and the highest cost types ($b^i \geq 500$) should always invest. Only the intermediate-cost firms should change their investment decision due to the price floor.

Figure 4 shows that investment patterns are broadly consistent with this prediction. The lowest cost type invests less than 10 percent of the time, and the highest 4 types invest more than 90 percent of the time. The figure displays p-values from one-tailed nonparametric Mann-Whitney tests comparing average investments for the 3 firm types where the model predicts that the price floor increases investment incentives. Differences are statistically significant at

[20]Figure 3 and this test are based on periods 6-16, after dropping the initial periods 1-5. The significance level is similar when including all periods, with a one-tailed p-value $= 0.008$.

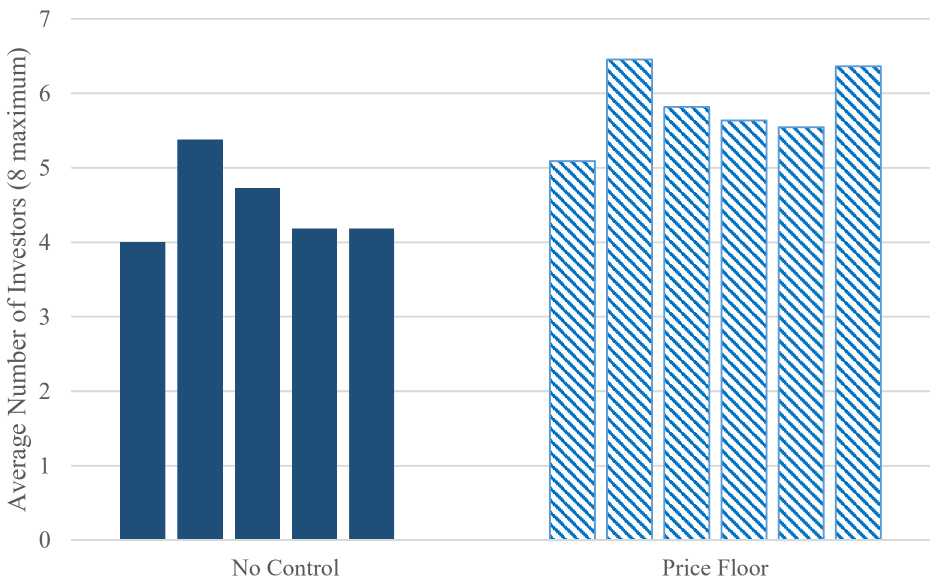

Figure 3: Mean Number of Investors, by Market (Periods 6-16 only)

conventional levels for 2 of these 3 types. None of the other 5 types have significantly different investment rates.[21] The variance within individual firm types across periods is not systematically different across treatments, except that type $b^i = 400$ has lower variation in investment frequency in the price floor treatment (Mann-Whitney p-value = 0.004).

4.2 Emissions Permit Prices

The first and prerequisite implication of the price floor is that it raises transaction prices on average (Hypothesis 2(a)). Pooling across all periods and markets, the mean transaction price is 49.7 (se=0.58) without the price floor and is 81.7 (se=0.46) with the price floor. A nonparametric Mann-Whitney test strongly rejects the null hypothesis of no treatment effect in favor of the directional prediction in Hypothesis 2(a) (one-tailed p-value $= 0.002, n = 11$). Similar conclusions obtain when considering only the later market periods or the later transaction prices within a period. The price floor limits downward price movements, as expected.

The stronger incentives that firms have for investment in the presence of a price floor stem from the limitations imposed on price variability arising from changes in marginal abatement costs. Prices are predicted to decrease following favorable shocks to abatement costs or when additional firms invest in lowering their costs. The previous subsection provides support for these hypothesized differences in investment, which suggests that prices also vary as expected.

Realized prices in these types of experimental markets vary considerably over time. Price variation is large even within trading periods when the abatement costs are fixed and competitive equilibrium prices are unchanging. Previous experiments using this continuous double auction trading institution show that prices converge eventually when the competitive equilibrium is

[21]These tests employ only one observation per market ($n = 11$ for each test). They are based on periods 6-16, after dropping the initial periods 1-5. Results are similar based on all 16 periods, except that investment rates are significantly different for type $b^i = 700$ because the investment rate is exactly 100 percent in the price floor treatment.

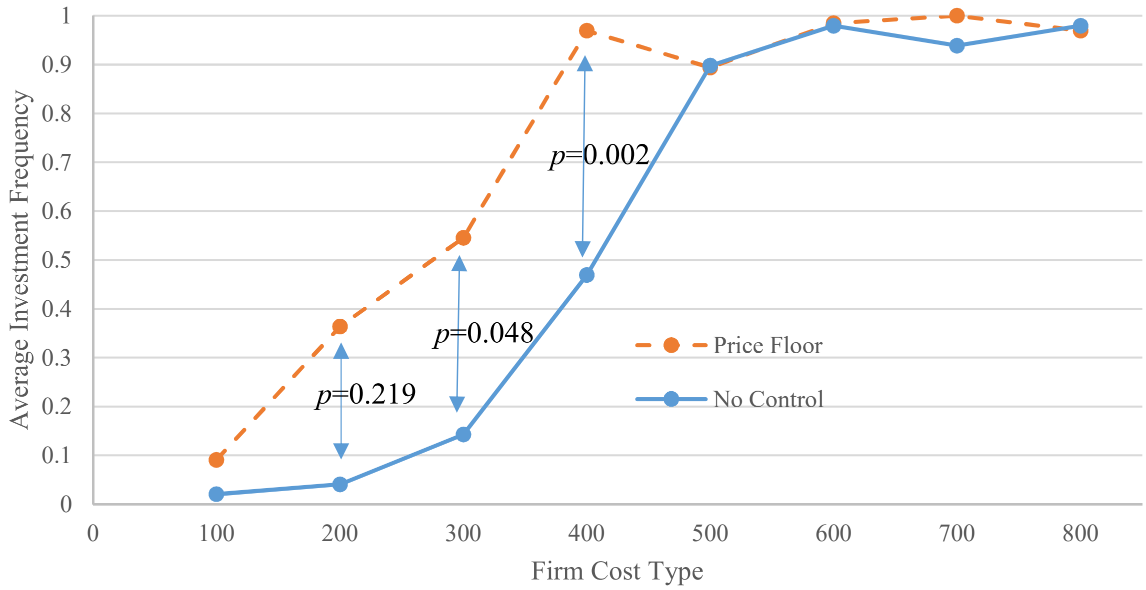

Figure 4: Mean Investment Rate, Across Firm Types (Periods 6-16 only). P-values shown for key firm types $b^i = 200, 300, 400$ where Hypothesis 1(b) predicts a significant difference.

stable across periods. Not surprisingly, however, prices do not converge to equilibrium in an environment like this one where prices change randomly due to cost shocks and through firm-specific, cost-reducing investments.

Table 1 above indicates that equilibrium prices typically decline by 15 experimental dollars for each additional shift down to a more favorable cost shock, or when an additional firm invests in cost reduction.[22] We summarized these directional predictions above in Hypothesis 2. These price reductions are limited by the zero lower bound on prices, or limited by the price floor (70). Due to their already low abatement costs, cost reductions by firm types $b^i \leq 200$ do not impact equilibrium prices.

The early trades in each period are especially volatile and often occur far from equilibrium levels. As trades occur within a period, however, the market conveys information about underlying abatement costs (which are, recall, firms' private information). The later trading prices therefore reveal more about market conditions and become closer to equilibrium levels. For this reason we focus our analysis of the transaction prices to the later trades that occur each period.

Figure 5 displays the mean transaction prices for the baseline treatment without a price control, considering only the final 5 trades each period. Each bar corresponds to a different combination of a number of investors and abatement cost shock. Only the most common number of investors (4, 5 and 6) are displayed. Although in equilibrium prices should be 0 or 15 in nearly half of these cases (cf. rows (4) through (6) of Table 1), the displayed average prices are always 20 or greater. Average prices nevertheless tend to rise, as predicted, for more unfavorable cost shocks. The decrease in prices due to an increase in investment, moving rightward across blocks of similarly-colored bars, is less systematic.

[22] The price difference is larger (30) between the 0 and 20 cost shock due to rounding.

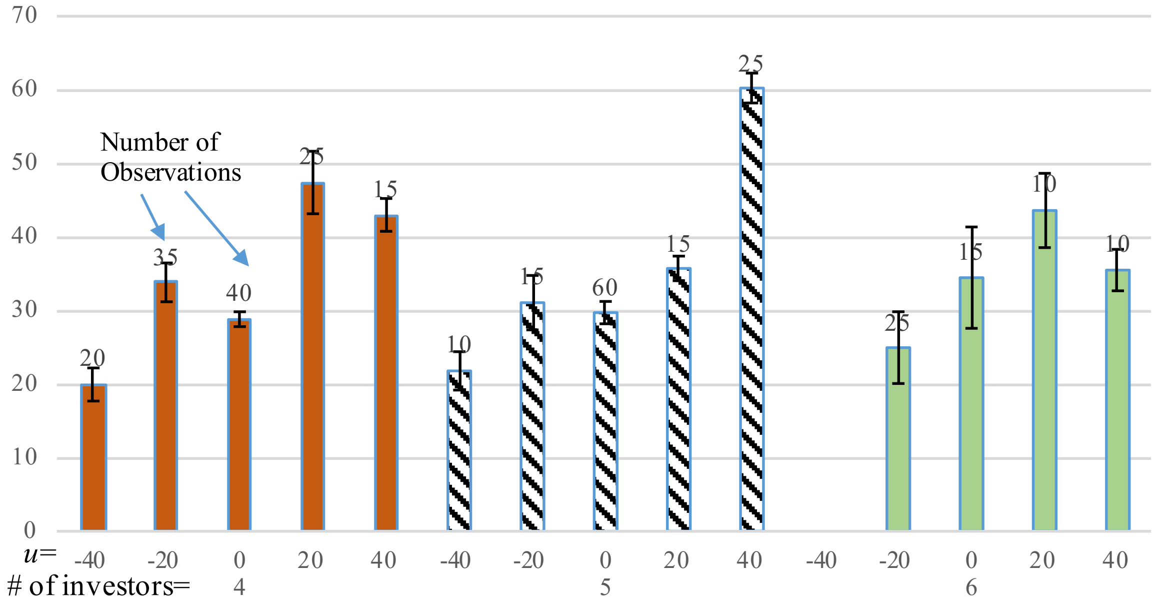

Figure 5: Mean Transaction Prices for Baseline (No Price Control) Treatment, Final 5 Trades each Period, by Cost Shock and Number of Investors. Error bars indicate standard errors.

The impact of the price floor on transaction prices is substantial, as expected. Figure 5 shows that average late period prices are always below 70 without the price floor; by contrast, Figure 6 indicates that prices are usually constrained by the floor. Average prices typically range between 70 and 80 in this treatment, and they are less sensitive to changes in cost shocks and investment choices than are prices in the treatment without the price floor.[23]

To formalize these observations, Table 3 reports a set of regressions to test Hypothesis 2. The dependent variable is the mean price across the final 5 transactions of each period (columns 1 and 3) or across the final 3 transactions of each period (columns 2 and 4). Columns 1 and 2 use data from the markets without a price control, and columns 3 and 4 are based on the price floor treatment. Panel A uses data from all periods, and panel B excludes the initial 5 periods that exhibit greater noise as traders initially trade at higher prices before later negotiating lower prices closer to equilibrium. This downward trend is reflected in the negative and significant Period Number time trend in panel A. This time trend is completely nonexistent when restricting analysis to the later periods in panel B.

The Cost Shock coefficient is predicted to be positive, and the estimates indicate that it is usually significantly greater than zero. This provides support for Hypothesis 2(b). The estimates are much larger in the baseline treatment without the price control, but even in this case they are still far below the predicted level of $15/20 = 0.75$ (cf. Table 1).[24] The coefficient on the Number of Investors should be negative, but it is only significantly less than zero for markets without

[23]The within-period standard deviation in individual transaction prices is about 50 percent higher without the price control (9.46) than with the price floor (6.14). Although the difference is large, it is not statistically significant (Mann-Whitney test p-value $= 0.329$).

[24]Technically this simple linear function is misspecified, as the precise equilibrium impact on prices depends on the specific investors and cost shock. A full series of interactions between cost shock and investor identities would "consume" many degrees of freedom, however, so we limit ourselves to this more parsimonious approximation.

Table 3: Emission Permit Prices and Abatement Cost Shocks

Panel A: All Periods 1-16				
	No Price Control		Price Floor Treatment	
Mean Price in:	Final 5	Final 3	Final 5	Final 3
	Transactions		Transactions	
	(1)	(2)	(3)	(4)
Cost Shock (-40 to 40)	0.34**	0.40**	0.07**	0.05
	(0.05)	(0.05)	(0.03)	(0.04)
Number of Investors (0 to 8)	-2.13	-2.73*	-0.74	-0.10
	(1.62)	(1.61)	(1.00)	(1.46)
Period Number (1 to 16)	-0.89**	-0.73*	-0.77**	-0.80**
	(0.32)	(0.32)	(0.15)	(0.23)
Constant	52.96**	52.96**	85.38**	82.04**
	(9.04)	(8.97)	(6.10)	(8.73)
R-squared	0.409	0.464	0.234	0.125
Observations	74	74	96	96

Panel B: Periods 6-16 Only				
	No Price Control		Price Floor Treatment	
Mean Price in:	Final 5	Final 3	Final 5	Final 3
	Transactions		Transactions	
	(1)	(2)	(3)	(4)
Cost Shock (-40 to 40)	0.37**	0.41**	0.04**	0.04**
	(0.07)	(0.07)	(0.01)	(0.02)
Number of Investors (0 to 8)	-3.37*	-3.86*	-0.70	-0.34
	(2.03)	(2.05)	(0.52)	(0.57)
Period Number (6 to 16)	-0.10	-0.11	-0.09	-0.10
	(0.53)	(0.53)	(0.10)	(0.11)
Constant	48.55**	50.52**	76.77**	74.76**
	(10.21)	(10.27)	(3.33)	(3.62)
R-squared	0.426	0.477	0.051	0.074
Observations	49	49	66	66

Notes: Panel regression models with market random effects. Standard errors shown in parentheses. ** and * denote significantly different from 0 at one- and five-percent levels (one-tailed tests for only Cost Shock and the Number of Investors).

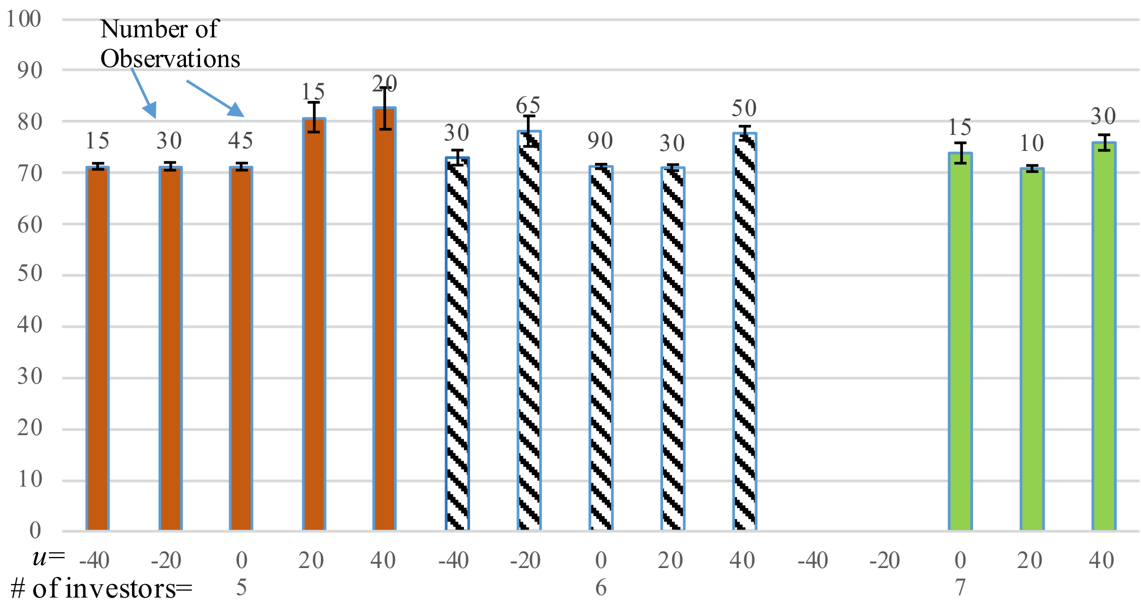

Figure 6: Mean Transaction Prices for Price Floor Treatment, Final 5 Trades each Period, by Cost Shock and Number of Investors. Error bars indicate standard errors.

the price control and particularly when excluding the initial 5 periods (panel B). The evidence for Hypothesis 2(c) is therefore weak and is only seen without the price floor. These transaction price regressions establish that prices are much more sensitive to changes in abatement costs (either through the cost shock or due to investment) in the treatment without the price control. In the treatment with the price floor (columns 3 and 4), Figure 6 illustrates that the floor is usually binding and so prices change little as costs shift.

4.3 Emissions and Social Costs

By design, emissions are limited by the total supply of permits, and the experimental environment imposed perfect compliance so the "cap" is always binding. Additional reductions below the permit supply cap do occur in the experiment, however, for a couple of reasons. First, the hard price control requires permits to be purchased by the regulator to support the price floor. This encourages abatement up to the marginal cost level of the floor, and the unused permits are not used to cover emissions. Thus, the price floor mechanically reduces emissions when it binds. A second reason that emissions can fall below the cap is (low cost) sellers do not sell excess permits when prices are very low. This can occur especially in the treatment without price controls, where prices sometimes fell below the lowest marginal cost of abatement. These unused permits also lead to lower emissions.

On balance, the reduction of emissions due to the price control incentivizing greater abatement is stronger empirically for our experimental parameterization. The maximum level of emissions is 184, as 23 permits were allocated to each of the 8 firms. The unused permits in the no control treatment result in an emissions average of 177.6 (se=0.60), compared to 153.9 (se=1.11) for the price floor treatment. This difference is highly significant (Mann-Whitney

p-value $= 0.004$). The price floor therefore leads to greater investment, lower price volatility, more abatement and less emissions.

However, we cannot say whether the additional investments in abatement costs and the reduction in emissions results in a welfare gain unless we are willing to specify an ad hoc marginal damage function. We can, however, derive a range of marginal damages that would imply that the price floor in our experiment lowers expected social costs. To do so, suppose that marginal damage is a constant, d, which is close to reality if we are considering carbon emissions (Pizer, 2002). Let *observed* aggregate emissions with the price floor and without the price floor be Q_s and Q_{ns}, respectively. Likewise, let A_s and A_{ns} denote the firms' aggregate abatement costs plus their aggregate investments in reducing their abatement costs, with and without the price floor. Finally, define expected social costs to be $SC_k = A_k + dQ_k$, $k = \{s, ns\}$. We do not include government's expenditure on buying unused permits under the price floor, because this is a simple transfer from one part of society to another. However, there is likely a cost to generate these funds in the first place, so we acknowledge that a fuller accounting of the social costs would include the deadweight cost of an additional dollar of government revenue times the government's expenditure on buying permits.

Calculate $SC_{ns} - SC_s = A_{ns} - A_s + d(Q_{ns} - Q_s)$. Given $Q_{ns} - Q_s > 0$ as we observe in our experiment, there exists a cut-off value of d,

$$\overline{d} = \frac{A_s - A_{ns}}{Q_{ns} - Q_s},$$

for which $d > (<)\, \overline{d}$ implies $SC_{ns} > (<)\, SC_s$. That is, if actual marginal damage is greater than (less than) $\overline{d}$ then the price floor reduces (increases) expected social costs.

We noted above that over all 16 periods of our experiment the mean *observed* levels of aggregate emissions are $Q_s = 153.9$ and $Q_{ns} = 177.6$. The mean *observed* levels of aggregate abatement costs plus investment costs are $A_s = 2864.4$ and $A_{ns} = 1905.7$. Thus, the firms' costs of reducing their emissions under the price floor increased despite the significant increase in investments to reduce their abatement costs. With these emissions and cost values, $\overline{d} = 40.45$. This implies that the price floor in our experiment would lead to an increase in social welfare if marginal damage exceeds this value. (This value is only a bit higher at 43.05 if we consider only periods 6-16.) Note that this value is below our price floor of 70. Actual price floors in existing markets tend to be well below estimates of the marginal damage from greenhouse gas emissions. If that was also true in our experimental markets then we would conclude that the hard price floor we consider leads to lower social costs.

One final note is warranted. The cut-off value $\overline{d}$ would be higher if we included the social costs of the government's purchases of unused permits under the price floor. Typical corrections for the marginal excess burden of taxation (i.e., the deadweight costs of raising an additional dollar of government revenue) are less than 50 percent (Bos et al., 2019). Even if we assumed a 100 percent correction, $\overline{d}$ would only increase from 40.45 to 41.72.

5 Conclusion

This paper develops a theoretical model that identifies firms' investment incentives in abatement technology for emissions trading markets characterized by cost uncertainty and regulated by price floors. The establishment of a price floor is pivotal in mitigating permit price uncertainty and limits market prices from becoming too low, which impedes investment and undermines the dynamic efficiency of markets. A price floor acts as an implicit subsidy for firms, as it increases the expected benefits from investment in lower abatement cost technology.

In a model featuring abatement cost uncertainty and a set of heterogeneous firms that interact in a competitive emissions trading market, our model reveals that, compared to an unregulated market, investment incentives are stronger when price floors are in place. In a market with a mix of investors and non-investors, the price floor expands the number of investors in equilibrium. This key result is also supported empirically in a laboratory market experiment, which also indicates how transaction prices are sensitive to cost shocks and the number of investors. The policy lesson to be drawn from this is that additional investments in cost-saving technologies can be achieved through the implementation of a price floor; ultimately, this has the potential to promote innovation and development of advanced abatement technology.

The experiment, of course, must impose a specific numerical parameterization for the laboratory market, and so we do not claim to provide broad empirical conclusions that can apply generally to the wide range of current and potential markets for emissions permits in the field. The experiment's structure is guided closely by the theoretical model, however, and we believe it captures the important economic forces that cause price floors to promote abatement cost-reducing investment. The identification of clear causal channels with direct theoretical support helps promote confidence in external validity. When the price floor has a positive probability of binding, which is commonly the case for many emissions markets in practice (discussed in the Introduction), investment is likely to increase when the market is composed of a mixture of heterogeneous firms who invest at different levels.

Finally, for the purpose of the experiment we studied the effect of a price floor in a single emissions trading market in isolation, without consideration of endogenous policy choices that could arise in the field. Markets in the field are subject to multiple interacting policies that influence investment decisions. For instance, price floors may differ across nations for political economy reasons. Individual countries in the EU ETS with more ambitious climate targets may prefer to enhance market signals by implementing a relatively high price floor domestically. As a result, asymmetric price controls across nations may undermine the harmonization of international emissions trading markets. However, Newbery et al. (2019) argue that domestic and EU-wide price floors could be mutually enhancing. Either way it is important to assess how price floors shape and affect the functioning of emissions markets. While our paper has shed light on the impacts of price floors on investments in abatement technology, future research could incorporate adjusting permit supply, for instance through the lens of the Market Stability Reserve in the EU ETS, complemented with a price floor (e.g., Flachsland et al., 2020).

Appendix A: Model Derivations and Proofs

Derivation of Equation (11)

Start with

$$\Delta c^i(\boldsymbol{x}, u) = c^i(x^i = 1, x^{-i}, u) - c^i(x^i = 0, x^{-i}, u).$$

To conserve notation, let $p(1) = p(x^i = 1, x^{-i})$ and $p(0) = p(x^i = 0, x^{-i})$. Moreover, define $\Delta^i p = (p(1) + u) - (p(0) + u)$. Then, using equation (8),

$$\begin{aligned}\Delta c^i(\boldsymbol{x}, u) =& (p(1) + u)\left(\frac{b^i(1-\beta) + u}{c} - \frac{p(1) + u}{2c} - l_0^i\right) - (p(0) + u)\left(\frac{b^i + u}{c} - \frac{p(0) + u}{2c} - l_0^i\right) \\ =& \Delta^i p\left(\frac{b^i}{c} - l_0^i - \frac{p(1) + p(0)}{2c}\right) - \frac{(p(1) + u)b^i\beta}{c}.\end{aligned}$$

Under perfect competition a single firm's adoption of the abatement technology does not affect the equilibrium permit price, so so we set $\Delta^i p = 0$. Then,

$$\Delta c^i(\boldsymbol{x}, u) = -\frac{(p(1) + u)b^i\beta}{c}. \tag{23}$$

Taking the expectation of $\Delta c^i(\boldsymbol{x}, u)$ and multiplying by -1 gives us equation (11).

Derivation of Equation (18)

From equation (16), $\Delta c^i(\boldsymbol{x}, s, u) = -sb^i\beta/c$, and from (23), $\Delta c^i(\boldsymbol{x}, u) = -\left(p(x^i = 1, x^{-i}) + u\right) b^i\beta/c$. Substitute $\Delta c^i(\boldsymbol{x}, s, u)$ and $\Delta c^i(\boldsymbol{x}, u)$ into (17) to obtain equation (18).

Proposition 1

Proof. Note that $r(b^i, \boldsymbol{x}^*)$, given by (13), is linearly increasing in b^i. Therefore, b^* defined by (14) is unique. Moreover, $f \le r(b^i, \boldsymbol{x}^*)$ and $x^i = 1$ for firm types $b^i \ge b^*$, and $f > r(b^i, \boldsymbol{x}^*)$ and $x^i = 0$ for firm types $b^i < b^*$. If $b^* \in [b^{min}, b^{max}]$, then $f \le r(b^i, \boldsymbol{x}^*)$ and $x^i = 1$ for firm types $b^i \in [b^*, b^{max}]$, and $f > r(b^i, \boldsymbol{x}^*)$ and $x^i = 0$ for firm types $b^i \in [b^{min}, b^*)$. If $b^* > b^{max}$, then $f < r(b^i, \boldsymbol{x}^*)$ and $x^i = 1$ for all firms; if $b^* < b^{min}$, then $f > r(b^i, \boldsymbol{x}^*)$ and $x^i = 0$ for all firms. □

Proposition 2

Proof. Proposition 2 is proved in the same way as Proposition 1. First note that $r(b^i, \boldsymbol{x}^{**}, s)$, given by (20), is linearly increasing in b^i. Therefore, b^{**} defined by (22) is unique. Moreover, $f \le r(b^i, \boldsymbol{x}^{**}, s)$ and $x^i = 1$ for firm types $b^i \ge b^{**}$, and $f > r(b^i, \boldsymbol{x}^{**}, s)$ and $x^i = 0$ for firm types $b^i < b^{**}$. If $b^{**} \in [b^{min}, b^{max}]$, then $f \le r(b^i, \boldsymbol{x}^{**}, s)$ and $x^i = 1$ for firm types $b^i \in [b^{**}, b^{max}]$, and $f > r(b^i, \boldsymbol{x}^{**}, s)$ and $x^i = 0$ for firm types $b^i \in [b^{min}, b^{**})$. If $b^{**} > b^{max}$, then $f < r(b^i, \boldsymbol{x}^{**}, s)$ and $x^i = 1$ for all firms; if $b^{**} < b^{min}$, then $f > r(b^i, \boldsymbol{x}^{**}, s)$ and $x^i = 0$ for all firms. □

Proposition 3

Proof. To prove part (1) of the proposition, first note that (14) and (22) imply

$$b^* p(\boldsymbol{x}^*) = b^{**}\mathbb{E}(p(\boldsymbol{x}^{**}, s)). \tag{24}$$

Subtracting $b^{**}p(\boldsymbol{x}^*)$ from both sides of (24) allows us to obtain

$$sgn(b^* - b^{**}) = sgn\left\{\mathbb{E}(p(\boldsymbol{x}^{**}, s)) - p(\boldsymbol{x}^*)\right\}. \tag{25}$$

Thus, what happens to the equilibrium set of investors when a price floor is imposed depends on what happens to the expected permit price.

We have

$$\mathbb{E}(p(\boldsymbol{x}^{**}, s)) = \int_{\underline{u}}^{u^{s**}} sg(u)du + \int_{u^{s**}}^{\overline{u}} (p(\boldsymbol{x}^{**}) + u)g(u)du. \tag{26}$$

From (15), $s = p(\boldsymbol{x}^{**}) + u^{s**}$. Substitute this into (26) to obtain

$$\mathbb{E}(p(\boldsymbol{x}^{**}, s)) = p(\boldsymbol{x}^{**}) + u^{s**}\int_{\underline{u}}^{u^{s**}} g(u)du + \int_{u^{s**}}^{\overline{u}} ug(u)du. \tag{27}$$

Note that $p(\boldsymbol{x}^*)$ can be written as

$$\begin{aligned} p(\boldsymbol{x}^*) &= \int_{\underline{u}}^{u^{s**}} (p(\boldsymbol{x}^*) + u)g(u)du + \int_{u^{s**}}^{\overline{u}} (p(\boldsymbol{x}^*) + u)g(u)du. \\ &= p(\boldsymbol{x}^*) + \int_{\underline{u}}^{u^{s**}} ug(u)du + \int_{u^{s**}}^{\overline{u}} ug(u)du. \end{aligned} \tag{28}$$

Subtract (28) from (27) to obtain

$$\mathbb{E}(p(\boldsymbol{x}^{**}, s) - p(\boldsymbol{x}^*) = p(\boldsymbol{x}^{**}) - p(\boldsymbol{x}^*) + \int_{\underline{u}}^{u^{s**}} (u^{s**} - u)g(u)du. \tag{29}$$

Toward signing (29), first note that our assumption that there is a strictly positive probability that the price floor will bind implies $u^{s**} > \underline{u}$, which in turn implies

$$\int_{\underline{u}}^{u^{s**}} (u^{s**} - u)g(u)du > 0. \tag{30}$$

To determine the relationship between $p(\boldsymbol{x}^{**})$ and $p(\boldsymbol{x}^*)$, use the price equation (6) to write

$$\begin{aligned} p(\boldsymbol{x}^{**}) - p(\boldsymbol{x}^*) &= \frac{\sum_{j=1}^n b^j(1 - \beta x^{j**}) - cL}{n} - \frac{\sum_{j=1}^n b^j(1 - \beta x^{j*}) - cL}{n} \\ &= \left(\frac{1}{n}\right)\left(\sum_{j=1}^n b^j\beta x^{j*} - \sum_{j=1}^n b^j\beta x^{j**}\right), \end{aligned} \tag{31}$$

where x^{j**} and x^{j*} are equilibrium investment choices by firm j, with and without a price floor, respectively. Given $b^j\beta > 0$ for all firm types, (31) implies

$$sgn\left(p(\boldsymbol{x}^{**}) - p(\boldsymbol{x}^*)\right) = sgn\left(\sum_{j=1}^n x^{j*} - \sum_{j=1}^n x^{j**}\right). \tag{32}$$

Let the equilibrium set of investors in the absence of a price floor be I^* and let the set of investors with the price floor be I^{**}. In addition, let $|I^*|$ and $|I^{**}|$ denote the cardinality (i.e., number of elements) of I^* and I^{**}, respectively. Note that

$$|I^*| = \sum_{j=1}^{n} x^{j*} \text{ and } |I^{**}| = \sum_{j=1}^{n} x^{j**}.$$

Then,

$$sgn\left(p(\boldsymbol{x}^{**}) - p(\boldsymbol{x}^{*})\right) = sgn\left(|I^*| - |I^{**}|\right). \tag{33}$$

Toward a contradiction of $b^* > b^{**}$ in the Proposition, suppose instead that $b^* \leq b^{**}$. From (25), this would imply $\mathbb{E}(p(\boldsymbol{x}^{**}, s)) - p(\boldsymbol{x}^{*}) \leq 0$. However, from (29) and (30), $\mathbb{E}(p(\boldsymbol{x}^{**}, s)) - p(\boldsymbol{x}^{*}) \leq 0$ requires $p(\boldsymbol{x}^{**}) - p(\boldsymbol{x}^{*}) < 0$, which from (33) implies $|I^*| < |I^{**}|$. However, $|I^*| < |I^{**}|$ requires $b^* > b^{**}$, which contradicts $b^* \leq b^{**}$. Since $b^* \nleq b^{**}$, we have $b^* > b^{**}$.

Part (2) of Proposition 3 follows directly from Propositions 1, 2 and part (1) of Proposition 3. □

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Web Appendixes

Open Space in U.S. Urban Areas: Where Might There Be Too Much or Too Little of a Good Thing?

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A. Data Sources

We compiled a database that covers 345 metropolitan statistical areas (MSAs). MSAs are geographic entities defined by the United States Office of Management and Budget (OMB) to collect, tabulate, and publish federal statistics. Each MSA consists of a city and its suburbs, plus any surrounding communities that are closely linked to the city economically or socially.

The main data sources for the study are summaried in Table A1. Land use and open space data for MSAs are generated using the National Land Cover Database (NLCD), which was compiled by the Multi-Resolution Land Characteristics (MRLC) Consortium (Jin et al., 2013). The NLCD provides the capability to assess wall-to-wall, spatially explicit, national land cover changes and trends across the United States from 2001 to 2011. The NLCD provides land cover data for 16 land cover classes at a spatial resolution of 30 meters, based on the Anderson Land Cover Classification System. Dwarf scrub, sedge/serbaceous, lichens, and moss exist only in Alaska, which is excluded from our study because of the short growing season and scarcity of cloud free imagery. The remaining 12 land cover classes and some summary statistics are listed in Table A2. One of the land cover classes that is particularly relevant to this study is “Developed, Open Space,” which is defined as the “areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes” (The Multi-Resolution Land Characteristics (MRLC) consortium, 2015). “Developed, Open Space” may include both public open space and private open space.

Data on median housing prices and housing units are taken from the 1970, 2000, and 2010 US Census. The property tax rates in each MSA are calculated using data from the US Census Public Use Microsamples (PUMA) dataset. Two PUMA’s responses are used in the calculation of the property tax rates: the self-reported value of the property, and the self-reported amount of property tax paid. We use per-capita expenditures on education, libraries, parking facilities, housing and community development, sewerage, solid waste management, general public buildings, fire protection, and police protection to proxy for the level of municipal services in a MSA. The data on these expenditures are obtained from US Census of Governments and are aggregated to the MSA level.

The Wharton Residential Land Use Regulation Index (WRLURI) created by Gyourko et al. (2008) is used to measure the stringency of land-use regulation in each MSA. This index was generated by surveying over 2000 jurisdictions across the US. The survey included questions about the regulatory process for housing, the rules for residential land use, and outcomes of the regulatory process (Gyourko et al., 2008). Responses to the surveys were used to generate 10 sub-indices, which Gyourko et al. used in a factor analysis to generate an overall index value for each MSA.

Other variables used in the empirical analysis include population in 1970, metropolitan industrial composition, average hours of sun in January, number of new immigrants, public expenditure share in protective inspection, the nontraditional Christian share, construction cost, wages in construction sector, travel time to work, median household income, and building permits. Saiz (2010) provides a detailed description of the sources for these variables.

Table A1
Data Documentation

VARIABLE	SOURCE	NOTES
$\boldsymbol{\Delta lnP}$ (1970-2010)	HUD State of the Cities Data Systems (From Census and 2010 U.S. Decennial Census	
$\boldsymbol{\Delta lnH}$ (1970-2010)	HUD State of the Cities Data Systems (From Census and 2010 U.S. Decennial Census	
SHARE OF NATURAL OPEN SPACE IN 2011	Calculated by author from elevation and land use GIS data from USGS (2001-2011)	Calculated following the description in Saiz (2010)
SHARE OF PRESERVED OPEN SPACEIN 2011 (WITHIN THE 50-KM RADIUS OF THE CENTRAL CITY'S CENTROID)	Calculated by author from land use GIS data from USGS (2001-2011)	
SHARE OF PRESERVED OPEN SPACEIN 2011 (WITHIN URBAN DELINEATION)	Calculated by author from land use GIS data from USGS (2001-2011)	
$\boldsymbol{ln}$(WHARTON LAND USE REGULATION INDEX)	Gyourko, Saiz, and Summers (2008)	
SHARE OF NEW IMMIGRANTS BETWEEN 1970 TO 2010	HUD State of the Cities Data Systems (From Census and 2010 U.S. Decennial Census	
SHARE OF PUBLIC EXPENDITURE ON PROTECTIVE INSPECTION (1982)	The Government Finance Database (Pierson, et al. 2016)	Aggregated from county level data
$\boldsymbol{\Delta ln}$ (PUBLIC EXPENDITURE ON MUNICIPAL SERVICES PER CAPITA) (1982-2012)	The Government Finance Database (Pierson, et al. 2016)	Aggregated from county level data

SHIFT-SHARE OF INDUSTRIAL COMPOSITION (1970-2010)	County Business Patterns Series (1970-2010)	Bartik instrument, aggregated from county level data
Δln(POPULATION) (1970-2010)	HUD State of the Cities Data Systems (From Census and 2010 U.S. Decennial Census	
Δln(MEDIAN FAMILY INCOME) (1970-2010)	HUD State of the Cities Data Systems (From Census and 2010 U.S. Decennial Census	
ln(AVERAGE SUN HOURS IN JANUARY)	Natural Amenities Scale—USDA Economic Research Service	Aggregated from county level data
Δln(TRAVEL TIME TO WORK) (1980-2010)	American Community Survey (ACS 1980-2010)	
SHARE OF CHRISTIAN "NONTRADITIONAL" DENOMINATIONS	Churches and church membership in the United States, 1971—the Association of Religion data archives	Calculated as one minus the share of Catholic Church adherents and main line Protestants (Saiz, 2010). Aggregated from county level data
COAST MSA (DUMMY VARIABLE)	Percentage of coastal MSAs, calculated by author from MSA delineation map	A dummy that takes value 1 if the minimum distance in an MSA's county is below 100km

Land use data citations:

Homer, C.G., Dewitz, J.A., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N.D., Wickham, J.D., and Megown, K., 2015, Completion of the 2011 National Land Cover Database for the conterminous United States-Representing a decade of land cover change information. *Photogrammetric Engineering and Remote Sensing* 81(5): 345-354

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Table A2
Summary Statistics for Land Cover in the 345 US Metropolitan Statistical Areas, in Square Kilometers

Types of Land Cover	min			max			mean			sd		
	2001	2006	2011	2001	2006	2011	2001	2006	2011	2001	2006	2011
Open Water	0.23	0.21	0.21	6200	6199	6203	404	403	405	836	835	838
Developed, Open Space	26.97	26.30	26.18	2388	2648	2676	322	328	330	354	365	367
Developed	27.58	28.58	29.48	4756	5014	5176	334	357	373	531	567	591
Barren Land (Rock/Sand/Clay)	0.00	0.00	0.00	7399	7664	7610	115	117	118	610	619	617
Forest	0.00	0.26	0.23	12690	12547	12473	1678	1652	1622	1976	1943	1904
Shrub/Scrub	0.00	0.00	0.00	55381	55318	55294	1258	1267	1281	4457	4451	4442
Grassland/Herbaceous	0.00	0.03	1.51	10920	10953	10943	623	627	633	1488	1480	1478
Cultivated Crops	2.36	2.85	2.59	13397	13287	13237	1493	1476	1468	1704	1686	1677
Wetlands	0.02	0.02	0.03	7679	7671	7667	400	399	398	818	812	809

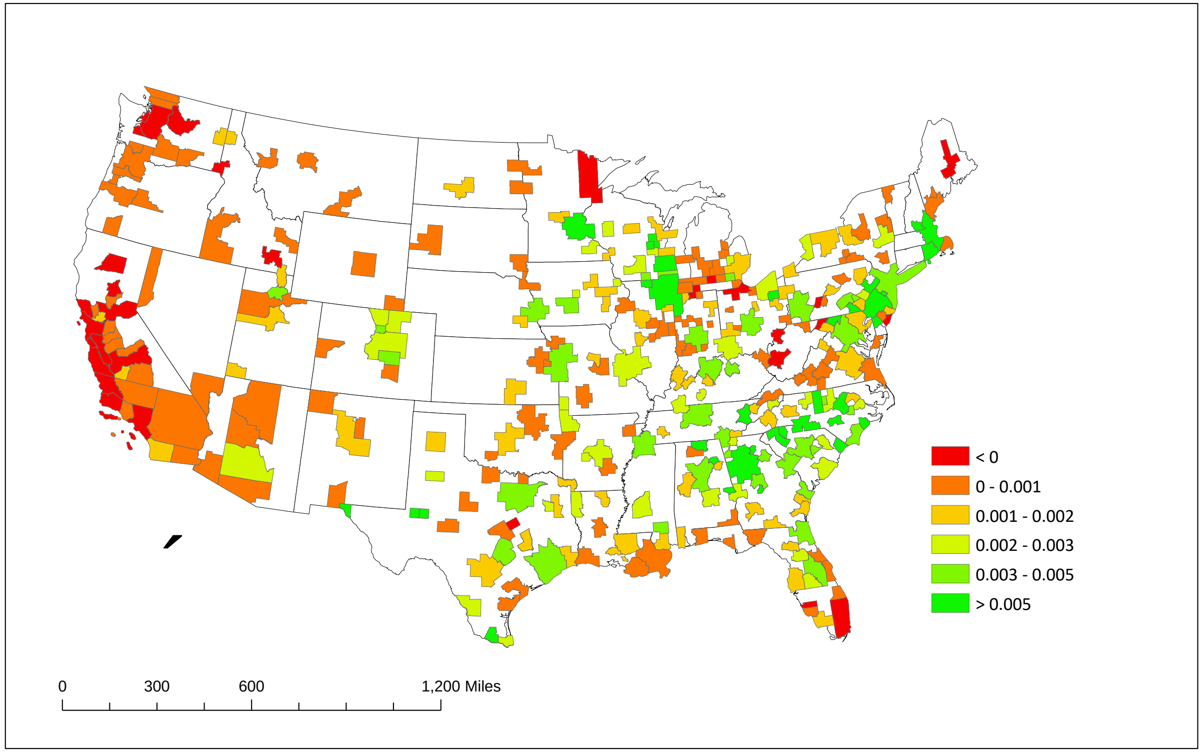
Table A3

Open Space Shares by Location and Size of U.S. Metropolitan Statistical Areas in 2011

Variables	By coastal status		By region				By land area		By population in 2010	
	Coastal	Noncoastal	Northeast	West	Midwest	South	The smallest 20%	The largest 20%	The Smallest 20%	The largest 20%
Natural open space	0.373	0.178	0.323	0.379	0.139	0.253	0.267	0.241	0.249	0.261
Slope > 15%	0.090	0.135	0.121	0.329	0.010	0.067	0.087	0.136	0.145	0.102
Water surface	0.154	0.017	0.129	0.043	0.087	0.068	0.099	0.056	0.057	0.092
Wetlands	0.135	0.030	0.073	0.015	0.043	0.127	0.081	0.051	0.053	0.067
Preserved open space	0.060	0.051	0.067	0.026	0.060	0.063	0.069	0.049	0.044	0.069
Developable open space	0.498	0.728	0.540	0.563	0.735	0.630	0.598	0.645	0.673	0.578
Barren	0.009	0.006	0.005	0.020	0.002	0.004	0.005	0.018	0.004	0.012
Forest	0.168	0.233	0.326	0.079	0.147	0.280	0.214	0.161	0.198	0.195
Shrubland	0.057	0.082	0.019	0.185	0.004	0.067	0.024	0.160	0.072	0.087
Herbaceous	0.030	0.090	0.005	0.135	0.047	0.054	0.027	0.111	0.073	0.065
Cultivated land	0.227	0.312	0.185	0.137	0.534	0.215	0.328	0.192	0.321	0.220
Developed land	0.075	0.044	0.074	0.040	0.068	0.054	0.069	0.065	0.034	0.094
N of observations	143	202	37	75	88	145	70	71	70	71

Notes: Coastal metropolitan areas are defined as those that are within 100 km of the oceans or Great Lakes, following Saiz (2010). The definition of regions follows Census Bureau Regions.

Figure A1. Change in the Share of Preserved Open Space between 2001 and 2011 in U.S. Matropolitan Statistical Areas



B. Derivation of Key Results

Derivation of (10) and (11)

At the optimum, the budget constraint (7) must be binding; otherwise, a smaller τ exists that satisfies the budget constraint and increases the objective function. Substituting (3), (4) and (5) into (7) and then adding $cA(1-s_n-s_p)V(s_n,s_p,\tau,g)$ to both sides, the budget constraint can be rewritten as

$$cA(1-s_n)\,V(s_n,s_p,\tau,g)+g\left[A(1-s_n-s_p)\right]^{\lambda}=(c+\tau)A(1-s_n-s_p)V(s_n,s_p,\tau,g) \quad \text{(B1)}$$

$$A(1-s_n)V(S_n,S_p,\tau,g)=\frac{1}{c}\left[A(1-s_n-s_p)p(s_n,s_p)g^{\mu}-g\left[A(1-s_n-s_p)\right]^{\lambda}\right] \quad \text{(B2)}$$

Substituting (B2) into the objective function, the maximization problem (7) becomes

$$\max_{g,s_p}\ \frac{1}{c}\left[A(1-s_n-s_p)p(s_n,s_p)g^{\mu}-g\left[A(1-s_n-s_p)\right]^{\lambda}\right]-V_0+B(s_n,s_p) \quad \text{(B3)}$$

Differentiating (B3) with respect to *g* and then solving for *g*, we obtain

$$g^*=\left[\frac{\mu p(s_n,s_p)}{\left[A(1-s_n-s_p)\right]^{\lambda-1}}\right]^{\frac{1}{1-\mu}} \quad \text{(B4)}$$

Substituting (B4) into (B2) and solving for τ, we obtain

$$\tau^*=\frac{c}{1-\mu}\left(\mu+\frac{s_p}{1-s_n-s_p}\right) \quad \text{(B5)}$$

Substituting (B4) into (B2), the total value of developable land in the urban area $TLV=(1-s_n)A\,V(s_n,s_p,\tau,g)$ can be written as

$$TLV=\frac{1-\mu}{c}\left[\mu^{\mu}p(s_n,s_p)\left[A(1-s_n-s_p)\right]^{1-\lambda\mu}\right]^{\frac{1}{1-\mu}} \quad \text{(B6)}$$

From (B6) $\frac{dTLV}{ds_p}\geq 0$ if and only if $f(s_p)\equiv p(s_n,s_p)\left[A(1-s_n-s_p)\right]^{1-\lambda\mu}$ increases with S_p. Differentiating $f(s_p)$ with respect to s_p gives

$$f'(s_p)=\frac{\partial p}{\partial s_p}\left[A(1-s_n-s_p)\right]^{1-\lambda\mu}-p(s_n,s_p)(1-\lambda\mu)\left[A(1-s_n-s_p)\right]^{-\lambda\mu}A\geq 0$$

$$=\frac{\partial p}{\partial s_p}\frac{f(s_p)}{p(s_n,s_p)}-(1-\lambda\mu)\frac{f(s_p)}{(1-s_n-s_p)} \quad \text{(B7)}$$

which is non-negative if and only if

$$\frac{1}{p(s_n,s_p)}\frac{\partial p}{\partial s_p}-\frac{(1-\lambda\mu)}{(1-s_n-s_p)}\geq 0 \quad \text{(B8)}$$

Substituting (1) into (B8) gives

$$\frac{1}{s_p(\varepsilon_p^{H^s}-\varepsilon_p^{H^d})}\left[\frac{s_p}{(1-s-s_p)}+\varepsilon_{s_p}^{H^d}\right]-\frac{(1-\lambda\mu)}{(1-s_n-s_p)}\geq 0 \quad \text{(B9)}$$

or

$$\phi_p + \varepsilon_{S_p}^{H^d} - \phi_p(1-\lambda\mu)(\varepsilon_P^{H^s} - \varepsilon_P^{H^d}) \geq 0 \quad \text{(B10)}$$

where $\phi_p = \frac{s_p}{A - s_n - s_p}$.

To derive (9), note that $SW = TLV - V_0 + B(s_n, s_p)$,where $TLV = \frac{1-\mu}{c}[\mu^\mu f(s_p)]^{\frac{1}{1-\mu}}$.

Differentiating it with respect to s_p gives

$$\frac{\partial SW}{\partial s_p} = \frac{TLV f'(s_p)}{(1-\mu)f(s_p)} + \frac{\partial B}{\partial s_p} \quad \text{(B11)}$$

Substituting (B7) into (B11) gives

$$\frac{\partial SW}{\partial s_p} = \frac{TLV}{(1-\mu)}\left[\frac{1}{p}\frac{\partial p}{\partial s_p} - \frac{(1-\lambda\mu)}{(1-s_n - s_p)}\right] + \frac{\partial B}{\partial s_p} \quad \text{(B12)}$$

Substituting (2) into (B12) gives

$$\frac{\partial SW}{\partial S_p} = \frac{TLV}{(1-\mu)}\left\{\frac{1}{s_p(\varepsilon_p^{H^s} - \varepsilon_p^{H^d})}\left[\frac{s_p}{(1-s_n - s_p)} + \varepsilon_{S_p}^{H^d}\right] - \frac{(1-\lambda\mu)}{(1-s_n - s_p)}\right\} + \frac{\partial B}{\partial s_p} \quad \text{(B13)}$$

which is non-negative if and only if

$$\frac{1}{(\varepsilon_p^{H^s} - \varepsilon_p^{H^d})}\left[\frac{s_p}{(1-s_n - s_p)} + \varepsilon_{S_p}^{H^d}\right] - \frac{s_p(1-\lambda\mu)}{(1-s_n - s_p)} + \frac{(1-\mu)s_p}{TLV}\frac{\partial B}{\partial s_p} \geq 0 \quad \text{(B14)}$$

$$\frac{1}{(\varepsilon_p^{H^s} - \varepsilon_p^{H^d})}\left[\phi_p + \varepsilon_{S_p}^{H^d}\right] - \phi_p(1-\lambda\mu) + \frac{(1-\mu)s_p}{TLV}\frac{\partial B}{\partial s_p} \geq 0 \quad \text{(B15)}$$

$$\phi_p + \varepsilon_{S_m}^{H^d} - [\phi_p(1-\lambda\mu) - (1-\mu)v](\varepsilon_p^{H^s} - \varepsilon_p^{H^d}) \geq 0 \quad \text{(B16)}$$

where $v = \frac{\partial B}{\partial s_p}\frac{s_p}{TLV}$.

Derivation of Comparative Statics Results in (13)

Let A and B denote the denominator and numerator of (12), respectively. Differentiating the log of (12) with respect to $s_n, \lambda, v, \varepsilon_{S_p}^{H^d}$, and $(\varepsilon_p^{H^s} - \varepsilon_p^{H^d})$, respectively gives:

$$\frac{\partial log s_p^*}{\partial s_n} = -\frac{1}{1-s_n} < 0$$

$$\frac{\partial log s_p^*}{\partial \lambda} = \frac{\mu}{A}(\varepsilon_p^{H^s} - \varepsilon_p^{H^d}) > 0$$

$$\frac{\partial log s_p^*}{\partial v} = \frac{(A-B)}{AB}(1-\mu)(\varepsilon_p^{H^s} - \varepsilon_p^{H^d}) > 0$$

$$\frac{\partial log s_p^*}{\partial \varepsilon_{S_p}^{H^d}} = \frac{(A-B)}{AB} > 0$$

$$\frac{\partial log s_p^*}{\partial(\varepsilon_p^{H^s} - \varepsilon_p^{H^d})} = -\frac{1}{A(\varepsilon_p^{H^s} - \varepsilon_p^{H^d})}\left[\frac{(A-B)}{B}\varepsilon_{S_p}^{H^d} + 1\right] < 0.$$

Results (13) follow by noting that $\frac{\partial s_p^*}{\partial x} = s_p^* \frac{\partial log s_p^*}{\partial x}$.

C. Replication of Saiz's Data and Results

In this appendix, we present results from our replication of Saiz (2010)'s data and estimates of the housing supply equation. To do this, we first reconstruct all the variables using the 1999 definition of MSAs, which Saiz (2010) uses in his analysis. We then use the data to replicate Saiz's estimation results. Finally, we reconstruct all the variables using the 2003 definition of MSAs and re-estimate the model.

Data replication

Table C1 presents summary statistics of the dataset we constructed and those reported in Appendix I of Saiz (2010).

Table C1

Comparison of Summary Statistics

	Saiz's dataset		**Our dataset**	
	mean	std. dev.	mean	std. dev.
Ocean dummy	0.33	0.47	0.46	0.50
Undevelopable area, 50-km radius	0.26	0.21	0.23	0.20
Log(WRI)	1.03	0.28	1.02	0.26
Δlog housing units	0.60	0.32	0.60	0.32
Log housing price (1970)	9.66	0.23	9.64	0.24
Log (inspection expenditures/local tax revenues)	-5.83	0.97	-6.15	0.83
Share of Christian "nontraditional" denominations	0.35	0.21	0.32	0.23
Midwest	0.26	0.44	0.25	0.43
South	0.38	0.49	0.40	0.49
West	0.20	0.40	0.20	0.40

One of the key variables in Saiz (2010) is the share of undevelopable area within the 50-km radius of the central city's centroid. To provide a more detailed comparison of this variable we construct and the one listed in Table I of Saiz (2010), we regress the later on the former: $\Lambda_{Saiz} = \alpha + \beta\Lambda_{our} + \varepsilon$. The regression results, reported in Table C2, show that although our estimats are not exactly the same as Saiz's, there are highly correlated.

Table C2

Regression of Our Estimates of Unavailable Land with Saiz's Estimates

	Λ_{Saiz}
Λ_{our}	1.049
	(0.024)
Constant	0.958
	(0.758)
Observations	94
R-squared	0.95

Figure C1

The correlation of two estimates of unavailable land

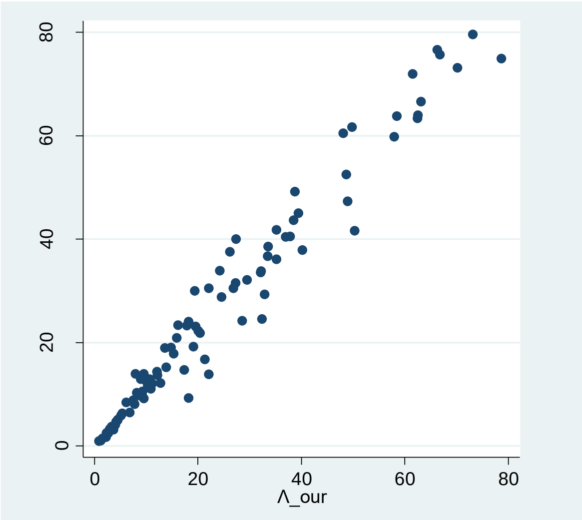
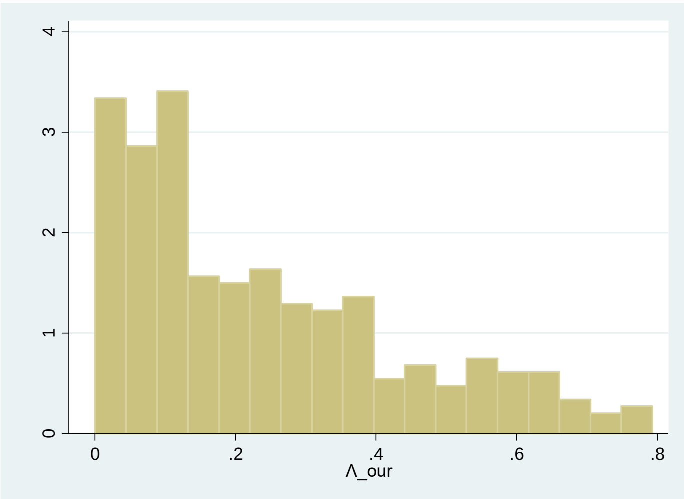


Figure C2
Histograms of Unavailable Land Shares (our estimates)



Replicating Saiz (2010)'s estimates of the housing supply equation

Saiz (2010) uses the following specification to estimate the (inverse) housing supply equation:

$$\Delta lnp_k = \beta^{LAND}(1-\Lambda_k)\Delta lnH_k + \beta^{LAND,POP} lnPOP_{k,T-1}(1-\Lambda_k)\Delta lnH_k$$

$$+\beta^{REG} lnWRI_k \Delta lnH_k + \sum \beta^{R_k^j} R_k^j + \varepsilon_k^S$$

where Δ denotes the difference between 1970 and 2000, p_k is the median housing price in urban area k, H_k is the number of housing units in urban area k, $(1-\Lambda_k)$ is the share of total surface area unsuitable for real estate development within the 50-km radius of the central city's centroid (*i.e.*, $1-\Lambda_k = s_{n,k}$), $POP_{k,T-1}$ is the total population in 1970, WRI_k is the Wharton land-use regulation index, R_k^j is a regional dummy variable, and ε_k^S is an error term. Two endogenous variables in the supply equation are the housing quantity shocks ΔlnH_k and the log of land use regulation index $lnWRI_k$. Saiz (2010) uses the number of new immigrants (1970 to 2000) divided by the total population in 1970 ($NewImm_k^{74-00}$), a shift-share of the 1974 metropolitan industrial composition ($InduCom_k^{74}$), and the log of average hours of sunshine in January ($SunnyHrs_k$) to instruments for ΔlnH_k; and uses the share of local public expenditures on "protective inspection" and the share of nontraditional Christian denominations are used to instrument for $lnWRI_k$; and uses the instruments for $lnWRI_k$ and ΔlnH_k and their interaction terms to instrument for $lnWRI_k \times \Delta lnH_k$. Table C3 presents the results from our replication of Saiz's housing supply eqaution estimates.

Table C3
A Comparison of Estimates of The Housing Supply Equation

Variables	(a) MSA 1999 Saiz's results (1970-2000)	(b) MSA 1999 Replicating Saiz results (1970-2000)	(c) MSA 2003 1970-2010 2SLS	(d) MSA 2003 1970-2010 GMM
$(1-\Lambda_k)\Delta lnH_k$	-5.26***	-6.898*	-2.653***	-2.615***
	(1.396)	(3.95)	(0.824)	(0.812)
$lnPOP_{T-1}(1-\Lambda_k)\ \Delta lnH_k$	0.475***	0.559*	0.294***	0.289***
	(0.119)	(0.31)	(0.0642)	(0.0630)
$lnWRI_k\Delta lnH_k$	0.280***	0.255**	0.222***	0.220***
	(0.077)	(0.12)	(0.0740)	(0.0725)
Midwest	0.002	-0.067*	-0.234***	-0.211***
	(0.048)	(0.04)	(0.0539)	(0.0551)
South	-0.109***	-0.027	-0.144***	-0.123**
	(0.049)	(0.04)	(0.0536)	(0.0547)
West	0.059	0.135**	0.0738	0.101
	(0.065)	(0.06)	(0.0617)	(0.0622)
Constant	0.577***	1.782***	2.246***	2.225***
	(0.048)	(0.05)	(0.0591)	(0.0587)
Number of observations		314	345	345
F-stat		14.22	52.46	
R2		0.03	0.46	
Weak identification test (Cragg-Donald Wald F statistic)		1.188	5.335	
Hansen J tatistics		23.303	5.933	
(p-value)		0.003	0.655	
LM test statistic for under-identification		10.402	34.293	
(p-value)		032	0.0001	

Notes:

1. The table shows estimation of a metropolitan housing supply equation. The instruments include shift-share of the 1974 metropolitan industrial composition, the magnitude of immigration shocks, the log of January average hours of sun, the share of local public expenditures on "protective inspection" and the share of nontraditional Christian denominations.
2. Four columns use the same specification. Column (a) is the results in Saiz (2010, Table V), and column (b) is our estimates replicating Saiz. Column (c) and (d) use the dataset with 2003 MSA delineation and covering year between 1970 to 2010. Column (c) estimates with two stage-least square. Column (d) estimates supply equation and demand equation simultaneously with GMM (we use the estimates in Column (d) in our further analysis).
3. Hansen J statistics is for Sargan-Hansen overidentification test, Hansen J statistics is reported with robust option (reporting robust standard errors).
4. Standard errors in parentheses. *significant at 5%; **significant at 1%; ***significant at 0.1%.

Comparison of housing supply elasticity estimates

Table C4 presents summary statistics of the housing supply elasticity estimtes from our replication efforts and the ones from Saiz (2010).

TABLE C4

SUMMARY STATISTICS OF HOUSING SUPPLY ELASTICITY ESTIMATES

	(a)	(b)	(c)	(d)	(e)	(f)
	Elasticities estimated with Saiz's coefficient estimates, but our reconstructed data (1970-2000, 1999 MSA delineation)	Our estimation replicating Saiz (1970-2000, 1999 MSA delineation)	Elasticities with Saiz's coefficients, but updated data (1970-2010, 2003 MSA delineation)	Our estimation but updated data and the 2003 MSA definition (1970-2010, 2003 MSA delineation) 2SLS	Our estimation with updated data the 2003 MSA definition (1970-2010, 2003 MSA delineation) GMM	Saiz (2010)
# of obs	78	78	78	78	78	78
Mean	2.16	2.73	2.03	2.65	2.65	1.98
Std. Dev.	0.99	1.15	0.96	0.83	0.82	1.01
Min	0.70	0.71	0.68	1.27	1.27	0.63
Max	5.48	6.45	5.36	5.56	5.55	5.45

Notes:

(1) This table reports summary statistics of the estimates for the 74 MSAs contained in our dataset that are comparable with estimates reported in Table VI of Saiz (2010).

(2) Elasticities in column (a) and (c) are calculated using coefficient estimates from Saiz (2010) and our data, defined by the 1999 MSA delineation and the 2003 MSA delineation respectively.

(3) Elasticities in column (b), (d) and (e) are estimated using models (b), (c) and (d) in Table C3.

(4) Column (g) are estimates reported in in Table VI of Saiz (2010).

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Table C5

Correlations Between Various Housing Supply Elasticity Estimates

	(a)	(b)	(c)	(d)	(e)	(f)	(g)
	Elasticity estimates in Saiz (2010)			Elasticities estimated using Saiz's coefficient estimates (1970-2000, 1999 MSA)	Elasticities estimated using Saiz's coefficients, but updated data and the 2003 MSA definition (1970-2010, 2003 MSA)		
Elasticities Column (a)	1.008*** (0.0216)						
Elasticities Column (b)		0.810*** (0.0398)		0.824*** (0.0278)			
Elasticities Column (c)			0.987*** (0.0440)				
Elasticities Column (d)					1.070*** (0.0497)		
Elasticities Column (e)						1.077 *** (0.0490)	
Elasticities Column (f)							0.880*** (0.039)
Constant	-0.197*** (0.0513)	-0.231* (0.118)	-0.030 (0.099)	-0.0911 (0.0822)	-0.805*** (0138)	-0.817*** (0.136)	0.294*** (0.087)
Number of observation	78	78	78	78	78	78	78
Adj. R-squared	0.966	0.843	0.867	0.919	0.857	0.862	0.867

D. Additional Estimation Results

Table D1. Overidentification and Weak-instruments Tests

	Model A	Model D	Model E
GMM Hansen's J chi2 statistics (Overidentification test)		10.50	11.20
p-value		0.57	0.43
Supply equation			
First stage regressions			
F test ($(\mathbf{1}-\mathbf{\Lambda_k})\mathbf{\Delta lnH_k}$)	5.57	5.57	5.67
p-value	0.000	0.000	0.000
F test ($\mathbf{lnPOP_{70k}(1-\Lambda_k)\Delta lnH_k}$)	5.32	5.32	5.89
p-value	0.000	0.000	0.000
F test ($\mathbf{lnWRI_k\Delta lnH_k}$)	21.85	21.85	16.32
p-value	0.000	0.000	0.000
F test ($\mathbf{\Delta ln}\ (\boldsymbol{s}_{\boldsymbol{p}.\mathbf{citv}})$)			7.27
p-value			0.000
F test ($\mathbf{\Delta ln}\ (\boldsymbol{s}_{\mathbf{u}.\mathbf{citv}})$)			16.08
p-value			0.000
Instrument tests			
Underidentification test (Kleibergen-Paap rk LM statistic)	34.293	34.293	27.67
p-value	0.000	0.000	0.010
Weak identification test			
(Cragg-Donald Wald F statistic)	5.218	5.218	NA
(Kleibergen-Paap Wald rk F statistic)	5.335	5.335	2.955
30% maximal IV relative bias	5.87	5.87	NA
Overidentification test (Hansen's J chi2 statistic)	4.44	4.44	18.172
p-value	0.655	0.655	0.111
Demand equation			
First stage regressions			
F test ($\mathbf{\Delta lnH_k}$)	16.32	2.43	2.43
p-value	0.000	0.008	0.008
F test ($\mathbf{lnPOP_{70k}\Delta lnH_k}$)	28.06	3.71	3.71
p-value	0.000	0.000	0.000
F test ($\mathbf{lnPOP_{70k}(1-\Lambda_k)\Delta lnH_k}$)		2.36	2.36
p-value		0.010	0.010
F test($\mathbf{\Delta ln}\ (\boldsymbol{s}_{\boldsymbol{u}.\mathbf{citv}})$)		6.73	6.73
p-value		0.000	0.000
F test ($\mathbf{\Delta ln}\ (\boldsymbol{s}_{\mathbf{p}.\mathbf{citv}})$)		18.21	18.21
p-value		0.000	0.000
Instrument tests			
Underidentification test (Kleibergen-Paap rk LM statistic)	39.314	7.383	7.383
p-value	0.000	0.287	0.287
Weak identification test			
(Cragg-Donald Wald F statistic)	22.796	NA	NA
(Kleibergen-Paap Wald rk F statistic)	14.745	1.23	1.23
5% maximal IV relative bias	11.04	NA	NA
Overidentification test (Hansen's J chi2 statistic)	1.579	8.452	8.452
p-value	0.454	0.133	0.133

Notes: The STATA estimation provide critical values for the 5% maximal IV relative bias test only when there are no more than three endogenous regressors (Stock and Yogo, 2005).

Table D2. Estimates of Housing Demand and Supply Elasticities for Individual Matropolitan Statistical Areas
(Based on Model (d) in Table 3)

MSA	Price Elasticity of Housing supply	Price Elasticity Housing Demand	Income Elasticity of Housing Demand	Housing Demand Elasticity w.r.t. Preserved Open Space Share	Housing Demand Easticity w.r.t. the Municipal Service Level	ν^*	$\frac{dTLV}{ds_p}$
Abilene, TX	3.234**	-0.487**	0.691**	0.432	0.018	-0.357	+
Akron, OH	3.803**	-1.331**	1.084**	2.668**	0.042**	-1.547**	+
Albany, GA	3.759**	-0.483**	0.438	1.225**	0.003	-0.888**	+
Albany-Schenectady-Troy, NY	3.714**	-0.39	0.842**	0.694	0.036**	-0.508	+
Albuquerque, NM	4.079**	-0.294	0.533	0.836	0.035**	-0.592	+
Alexandria, LA	14.055	-0.569**	1.097**	0.808	0.033**	-0.128	+
Allentown-Bethlehem-Easton, PA-NJ	3.913**	-0.633**	1.011**	0.568	0.043**	-0.35	+
Altoona, PA	7.046**	-0.402	0.382	0.49	0.015	-0.16	+
Amarillo, TX	6.353**	-0.579**	0.595**	1.439**	0.01	-0.635**	+
Ames, IA	4.830**	-0.412**	0.37	0.553	0.003	-0.308	+
Ann Arbor, MI	3.015**	-0.533**	0.650**	1.304**	0.007	-1.134**	+
Anniston-Oxford, AL	4.031**	-0.389	0.233	0.729	0.004	-0.481	+
Appleton, WI	4.173**	-0.631**	0.52	1.298**	-0.018**	-0.827	+
Asheville, NC	2.665	-3.799**	4.439**	1.543	0.037	-0.606	+
Athens-Clarke County, GA	3.296**	-0.505**	0.349	0.366	-0.033**	-0.288	+
Atlanta-Sandy Springs-Marietta, GA	2.566**	-0.359	0.48	1.177**	0.012	-1.266**	+

Atlantic City, NJ	3.919**	-0.608	0.953**	1.683**	0.049**	-1.114	+
Auburn-Opelika, AL	7.665**	-0.349	0.637**	0.853**	0.018	-0.288	+
Augusta-Richmond County, GA-SC	5.116**	-0.701**	0.914**	1.933**	-0.009	-1.008**	+
Austin-Round Rock, TX	2.400**	-0.476**	0.783**	1.311**	0.014	-1.431**	+
Bakersfield, CA	2.065**	-0.566	0.451	0.414	0.005	-0.5	+
Baltimore-Towson, MD	3.306**	-0.374	0.516	0.526	0.026	-0.42	+
Bangor, ME	3.901**	-1.021**	0.455	3.363**	0	-2.124**	+
Barnstable Town, MA	2.203**	-0.688	0.793	0.768	0.031	-0.842	+
Baton Rouge, LA	2.969**	-0.532	0.796	0.918	0.032	-0.81	+
Battle Creek, MI	2.724**	-0.313	0.424	1.101	0.005	-1.136**	+
Bay City, MI	2.195**	-0.626	0.53	0.566	0.012	-0.633	+
Beaumont-Port Arthur, TX	3.470**	-0.499	0.883	0.861	0.034	-0.66	+
Bellingham, WA	8.540**	-0.641	1.002	1.008	0.048	-0.298	+
Bend, OR	4.083**	-0.530**	0.877**	1.102**	0.002	-0.740**	+
Billings, MT	3.436**	-0.476**	0.566**	0.733	0.023**	-0.583	+
Binghamton, NY	4.065**	-0.648**	0.881**	0.850**	0.012	-0.54	+
Birmingham-Hoover, AL	3.554**	-0.606**	0.421	1.285**	-0.006	-0.945**	+
Bismarck, ND	5.244**	-0.425	0.660**	0.948**	-0.001	-0.509	+
Blacksburg-Christiansburg-Radford, VA	2.838**	-0.73	0.524	0.439	0.03	-0.375	+
Bloomington, IN	4.173**	-0.715**	0.612**	1.804**	0.032**	-1.133**	+
Bloomington-Normal, IL	4.482**	-0.343**	0.624**	0.132	0.034**	-0.074	+
Boise City-Nampa, ID	2.780**	-0.490**	1.003**	0.815	0.019	-0.778	+
Boston-Cambridge-Quincy, MA-NH	1.857**	-0.794	1.029**	1.584	0.046**	-1.890**	+

Boulder, CO	3.471**	-0.938**	1.907**	3.418**	0.032**	-2.403**	+
Bowling Green, KY	3.705**	-0.371	0.443	0.708	0.013	-0.528**	+
Bremerton-Silverdale, WA	2.454**	-0.630**	0.527	0.663	0.007	-0.674	+
Brownsville-Harlingen, TX	4.661**	-0.432	0.701	0.583	0.019	-0.332	+
Brunswick, GA	5.782**	-1.181**	0.438	0.304	0.004	-0.081	+
Buffalo-Cheektowaga-Tonawanda, NY	2.141**	-0.687	0.956	0.923	0.058**	-1.031	+
Burlington, NC	5.581**	-0.469**	0.821**	0.638	0.023**	-0.279	+
Burlington-South Burlington, VT	2.805**	-1.151**	1.828**	1.532**	-0.003	-1.198	+
Canton-Massillon, OH	5.634**	-0.388	0.445	0.544	0.004	-0.224	+
Cape Coral-Fort Myers, FL	4.171**	-5.664**	4.450**	7.166**	0.035	-1.911**	+
Casper, WY	7.432**	-0.395	0.282	1.198**	0.016	-0.475**	+
Cedar Rapids, IA	3.713**	-0.306	0.236	0.046	0.018	-0.025	+
Champaign-Urbana, IL	3.711**	-0.649**	0.297	0.916**	0.01	-0.646**	+
Charleston, WV	2.946	-2.145**	1.955**	7.916**	0.058**	-4.832**	+
Charleston-North Charleston, SC	4.018**	-0.518	0.867	0.663	0.037	-0.417	+
Charlotte-Gastonia-Concord, NC-SC	3.581**	-0.3	0.36	0.435	0.008	-0.321	+
Charlottesville, VA	5.017**	-0.567**	0.960**	1.232**	0.034**	-0.661**	+
Chattanooga, TN-GA	3.778**	-0.472	0.997**	0.852	0.016	-0.597	+
Cheyenne, WY	4.003**	-0.265	0.284	0.51	0.016	-0.369	+
Chicago-Naperville-Joliet, IL-IN-WI	1.944**	-0.864**	0.973**	1.362	0.060**	-1.525**	+
Chico, CA	3.150**	-13.670**	17.539**	24.516**	-0.122**	-4.523**	+
Cincinnati-Middletown, OH-KY-IN	2.879**	-0.328	0.308	0.935**	0.02	-0.909**	+
Clarksville, TN-KY	5.677**	-0.362	0.531**	-0.022	0.013	0.039	-

Cleveland, TN	6.222**	-0.364	0.429	1.011	0.012	-0.436	+
Cleveland-Elyria-Mentor, OH	1.456**	-0.778	0.973	1.786	0.046	-2.569**	+
Coeur d'Alene, ID	12.853**	-11.142**	7.446**	15.359**	-0.044**	-1.958**	+
College Station-Bryan, TX	2.571**	-0.257	0.319	0.29	-0.002	-0.325	+
Colorado Springs, CO	2.823**	-0.514	0.747**	0.8	0.006	-0.746	+
Columbia, MO	9.047**	-0.326	0.39	0.749	0.009	-0.223	+
Columbia, SC	4.016**	-0.259	0.431	0.496	0.008	-0.341	+
Columbus, GA-AL	3.848**	-0.477**	0.638**	1.147**	-0.004	-0.814**	+
Columbus, IN	3.857**	-0.744**	0.812**	1.130**	0.012	-0.747**	+
Columbus, OH	4.391**	-0.521**	0.646**	0.771	0.070**	-0.463	+
Corpus Christi, TX	2.714**	-0.525	0.6	1.055	-0.003	-1.016**	+
Corvallis, OR	6.135**	-6.357**	7.446**	14.355**	0.257**	-3.548**	+
Cumberland, MD-WV	2.953**	-0.778**	0.731	0.198	-0.020**	-0.155	+
Dallas-Fort Worth-Arlington, TX	3.067**	-0.399	0.539**	1.204**	0.003	-1.078**	+
Dalton, GA	4.132**	-0.329	0.481	0.321	-0.001	-0.191	+
Danville, IL	3.763**	-0.782**	0.898**	1.296**	0.045**	-0.878**	+
Danville, VA	5.644**	-1.745**	0.793**	2.570**	0.181**	-1.060**	+
Davenport-Moline-Rock Island, IA-IL	7.173**	-0.561**	0.392	0.937**	-0.005	-0.353	+
Dayton, OH	4.838**	-0.523**	0.602**	1.244**	0.030**	-0.681**	+
Decatur, AL	5.500**	-0.337	0.301	0.501	0.035**	-0.239	+
Decatur, IL	6.130**	-1.548**	0.949**	3.218**	-0.015**	-1.279**	+
Deltona-Daytona Beach-Ormond Beach, FL	2.948**	-0.563	0.56	1.15	0.016	-1	+
Denver-Aurora, CO	1.662**	-0.620**	0.640**	2.480**	-0.003**	-3.414**	+

Des Moines, IA	3.200**	-0.315	0.558**	0.635	0.023**	-0.559**	+
Detroit-Warren-Livonia, MI	2.816**	-0.455**	0.468**	0.796**	0.006	-0.754**	+
Dothan, AL	6.782**	-1.063**	1.049**	2.160**	-0.037**	-0.826**	+
Dover, DE	4.110**	-0.48	0.472	0.879	0.023	-0.563	+
Dubuque, IA	3.516**	-0.891**	0.843**	1.436**	-0.054**	-1.004**	+
Duluth, MN-WI	3.262**	-3.316**	4.010**	6.349**	0.02	-2.994**	+
Durham, NC	2.324**	-0.460**	0.833**	0.585	0.022**	-0.669	+
Eau Claire, WI	2.929**	-2.175**	2.238**	5.618**	-0.079**	-3.420**	+
El Centro, CA	3.005**	-0.348	0.298	0.806**	0.006	-0.750**	+
Elizabethtown, KY	3.604**	-0.384**	0.558**	0.614	0.002	-0.469	+
Elkhart-Goshen, IN	5.096**	-0.409	0.47	1.097**	0.023	-0.570**	+
Elmira, NY	5.708**	-0.576**	0.811**	0.309	0.019	-0.108	+
El Paso, TX	3.484**	-0.36	0.512**	0.248	0.040**	-0.194	+
Erie, PA	4.859**	-2.124**	3.159**	3.186**	0.087**	-1.384**	+
Eugene-Springfield, OR	2.998**	-0.705	0.946	0.665	0.060**	-0.556	+
Evansville, IN-KY	12.167**	-0.313	0.504	0.607	0.025	-0.107	+
Fargo, ND-MN	7.514**	-0.423**	0.588**	1.742**	0.025**	-0.660**	+
Farmington, NM	3.129**	-0.860**	1.163**	-0.164**	0.089**	0.130**	-
Fayetteville, NC	3.166**	-0.46	0.472	0.929	0.013	-0.785	+
Fayetteville-Springdale-Rogers, AR-MO	3.562**	-0.817**	0.43	1.051**	0.01	-0.732**	+
Flagstaff, AZ	3.122**	-1.314**	1.412**	1.995**	0.037**	-1.404**	+
Flint, MI	2.885**	-0.543**	0.676**	1.562**	0.035**	-1.409**	+
Florence-Muscle Shoals, AL	4.923**	-0.241	0.281	0.435	0.004	-0.239	+

Florence, SC	3.759**	-0.846**	1.053**	1.529**	0.063**	-1.004**	+
Fond du Lac, WI	3.059**	-0.721**	0.693**	1.055**	-0.018**	-0.865**	+
Fort Collins-Loveland, CO	2.761**	-1.621**	1.600**	3.087**	-0.036**	-2.191**	+
Fort Smith, AR-OK	4.636**	-0.695**	0.742**	1.751**	0.022	-1.010**	+
Fort Walton Beach-Crestview-Destin, FL	2.923**	-0.387	0.408	0.621	0.003	-0.582	+
Fort Wayne, IN	3.437**	-0.470**	0.734**	0.444	0.027**	-0.34	+
Fresno, CA	1.884**	-1.120**	0.810**	2.702**	0.008	-2.812**	+
Gadsden, AL	3.777**	-0.598**	0.542	1.533**	0.031**	-1.066**	+
Gainesville, FL	2.984**	-1.660**	1.030**	2.367**	0.026**	-1.569**	+
Gainesville, GA	3.521**	-0.613**	0.237	0.511	-0.003	-0.353	+
Glens Falls, NY	9.534**	-4.164**	3.975**	1.291**	0.036**	-0.256**	+
Goldsboro, NC	3.837**	-0.357	0.569	0.571	0	-0.401	+
Grand Forks, ND-MN	5.003**	-0.818**	0.751**	0.928**	-0.005	-0.48	+
Grand Junction, CO	5.085**	-1.051**	0.807**	2.481**	0.025**	-1.257**	+
Grand Rapids-Wyoming, MI	3.195**	-0.624**	0.691**	0.305	0.01	-0.236	+
Great Falls, MT	4.277**	-0.374	0.405	0.473	0.006	-0.313	+
Greeley, CO	2.267**	-0.302	0.460**	0.579	0.005	-0.709**	+
Green Bay, WI	4.157**	-0.815	0.773	0.935	0.007	-0.565**	+
Greensboro-High Point, NC	3.098**	-0.242**	0.266**	0.598**	0.012**	-0.552**	+
Greenville, NC	2.876**	-0.42	0.814**	0.409	0.025	-0.383	+
Greenville, SC	4.193**	-0.463	0.342	0.376	0.025	-0.21	+
Gulfport-Biloxi, MS	9.067**	-0.705	0.643	0.796	0.006	-0.183	+
Hagerstown-Martinsburg, MD-WV	2.750**	-0.648**	0.766**	1.315**	-0.020**	-1.203**	+

Hanford-Corcoran, CA	2.969**	-0.453**	0.343	1.052**	0.018	-0.959**	+
Harrisburg-Carlisle, PA	3.468**	-0.501**	0.818**	1.361**	-0.005	-1.053	+
Harrisonburg, VA	3.708**	-1.181**	1.994**	2.997**	0.047**	-1.892**	+
Hattiesburg, MS	4.906**	-0.811**	1.147**	1.058**	0.026**	-0.551	+
Hickory-Morganton-Lenoir, NC	3.626**	-0.401	0.377	1.046**	0.002	-0.784	+
Hinesville-Fort Stewart, GA	15.374**	-0.618**	0.235**	0.871**	-0.011**	-0.106**	+
Hot Springs, AR	8.884**	-0.479**	0.578**	1.783**	-0.004	-0.537**	+
Houma-Bayou Cane-Thibodaux, LA	2.582**	-5.401**	8.879**	12.920**	0.493**	-5.016**	+
Houston-Baytown-Sugar Land, TX	2.698**	-0.860**	1.086**	0.988**	0.049**	-0.855	+
Huntington-Ashland, WV-KY-OH	4.436**	-1.211**	1.988**	2.465**	0.086**	-1.334**	+
Huntsville, AL	6.109**	-0.352	0.24	0.697	0.008	-0.282	+
Idaho Falls, ID	4.539**	-0.376	0.497	0.373	0.009	-0.229	+
Indianapolis, IN	4.037**	-1.230**	2.134**	2.017**	0.081**	-1.158**	+
Iowa City, IA	5.303**	-0.485**	0.710**	1.087**	0.045**	-0.569**	+
Ithaca, NY	3.262**	-0.385	0.369	0.957	-0.023**	-0.810**	+
Jackson, MI	2.643**	-0.648**	0.608	1.447**	0.024	-1.369**	+
Jackson, MS	2.834**	-0.505**	0.726**	0.113	0.02	-0.101	+
Jackson, TN	5.139**	-0.859**	1.391**	0.938**	0.031**	-0.459**	+
Jacksonville, FL	2.452**	-0.931**	1.416**	1.035	0.021	-0.945	+
Jacksonville, NC	3.737**	-0.696	0.794	2.057**	0.012**	-1.424**	+
Janesville, WI	3.476**	-0.302	0.403	0.248	0.01	-0.197	+
Jefferson City, MO	4.997**	-0.626**	0.900**	-0.127**	0.028**	0.088**	-
Johnson City, TN	6.956**	-0.728	1.047**	2.437**	0.055**	-0.907**	+

Johnstown, PA	3.905**	-0.641**	0.506	0.8	0.023**	-0.525	+
Jonesboro, AR	5.076**	-0.682**	0.640**	1.791**	-0.008	-0.948**	+
Joplin, MO	9.390**	-0.314	0.368	0.408	0.005	-0.094	+
Kalamazoo-Portage, MI	2.292**	-0.571	0.687	0.573	0.013	-0.633	+
Kankakee-Bradley, IL	2.731**	-0.266	0.291	0.776	-0.005	-0.810**	+
Kansas City, MO-KS	3.241**	-0.439**	0.513**	0.77	0.017	-0.645**	+
Kennewick-Richland-Pasco, WA	2.475**	-0.550**	1.129**	0.941**	0.050**	-0.973**	+
Killeen-Temple-Fort Hood, TX	5.308**	-0.309	0.282	0.261	-0.010**	-0.126	+
Kingsport-Bristol, TN-VA	3.349**	-0.577	0.625	1.825**	0.053**	-1.431**	+
Kingston, NY	2.983**	-0.634	0.694	0.743	0.043**	-0.63	+
Knoxville, TN	4.870**	-0.674**	1.067**	0.824	-0.005	-0.399	+
Kokomo, IN	5.343**	-0.255	0.411**	0.262	0.004	-0.12	+
La Crosse, WI-MN	3.513**	-0.466	0.715**	1.211**	0.024	-0.942**	+
Lafayette, IN	4.062**	-0.292	0.388	0.59	0.014	-0.411	+
Lafayette, LA	4.367	-0.729	0.757	1.558	-0.024	-0.916	+
Lake Charles, LA	3.638	-0.708	1.089	2.409**	0.052**	-1.716**	+
Lakeland-Winter Haven, FL	4.969**	-0.42	0.554	0.938	0.034	-0.473	+
Lancaster, PA	4.395**	-0.684**	1.315**	1.479**	0.026**	-0.867**	+
Lansing-East Lansing, MI	3.268**	-0.31	0.341	0.893	0.016	-0.771**	+
Laredo, TX	3.484**	-0.302	0.432**	0.597	0.022	-0.491	+
Las Cruces, NM	3.022**	-0.333	0.495	0.893	0.014	-0.831**	+
Las Vegas-Paradise, NV	4.786**	-0.344	0.569	0.938	0.033	-0.566	+
Lawrence, KS	6.480**	-0.443**	0.690**	0.122	-0.004	-0.028	+

Lawton, OK	3.119**	-0.710**	0.986**	0.764	0.006	-0.616**	+
Lebanon, PA	3.309**	-0.459	0.688**	0.045	0.022	-0.023	+
Lewiston, ID-WA	5.119**	-0.949**	1.007**	1.09	0.062**	-0.541	+
Lewiston-Auburn, ME	3.846**	-0.374	0.754**	0.796	0.026	-0.574	+
Lexington-Fayette, KY	4.319**	-0.794**	0.932**	1.284**	0.022	-0.762	+
Lima, OH	3.172**	-0.466**	0.946**	0.842**	0.040**	-0.710**	+
Lincoln, NE	3.627**	-0.443**	0.514	1.189**	0.02	-0.904**	+
Little Rock-North Little Rock, AR	4.909**	-0.464**	0.648**	1.487**	0.022	-0.839**	+
Logan, UT-ID	4.475**	-0.438	0.545	1.169	0.02	-0.728	+
Longview, TX	10.439**	-0.419	0.572	0.691	0.023	-0.171	+
Longview-Kelso, WA	4.363**	-0.934	1.801**	2.557**	0.038	-1.481**	+
Los Angeles-Long Beach-Santa Ana, CA	0.972**	-3.249**	4.748**	-0.066	0.073**	0.075	-
Louisville, KY-IN	4.112**	-0.34	0.407	0.980**	0.016	-0.665	+
Lubbock, TX	3.783**	-0.254	0.138**	0.763	0.009	-0.580**	+
Lynchburg, VA	3.879**	-1.123**	0.951**	2.773**	0.015	-1.711**	+
Macon, GA	5.962**	-0.446	0.547	0.777	0.012	-0.347	+
Madera, CA	4.007**	-0.65	0.925**	0.85	0.036**	-0.560**	+
Madison, WI	2.379**	-0.498**	0.550**	0.155	0.021	-0.173	+
Manchester-Nashua, NH	2.920**	-1.214**	1.658**	1.369**	0.086**	-1.017**	+
Mansfield, OH	5.990**	-0.343	0.560**	0.52	0.02	-0.216	+
McAllen-Edinburg-Pharr, TX	3.474**	-0.312	0.282	0.608	0.006	-0.491	+
Medford, OR	2.754**	-0.464	0.627**	0.564**	0.016**	-0.547**	+
Memphis, TN-MS-AR	2.690**	-0.628**	0.925**	1.536**	0.063**	-1.442**	+

Merced, CA	3.362**	-0.442	0.502	0.561	0.011	-0.455	+
Miami-Fort Lauderdale-Miami Beach, FL	0.984	-1.158	0.88	3.758**	-0.004	-5.573**	+
Michigan City-La Porte, IN	7.425**	-0.424**	0.567**	0.854**	0.027**	-0.313	+
Midland, TX	3.986**	-0.658**	0.572**	1.024**	0.013	-0.676**	+
Milwaukee-Waukesha-West Allis, WI	2.833**	-2.942**	3.271**	2.248**	0.116**	-1.153**	+
Minneapolis-St. Paul-Bloomington, MN-WI	2.171**	-0.592**	0.620**	0.627	0.008	-0.723	+
Missoula, MT	10.732**	-2.250**	4.206**	5.197**	0.023	-1.235**	+
Mobile, AL	6.561**	-2.522**	2.669**	4.349**	-0.045**	-1.409**	+
Modesto, CA	2.263**	-0.373	0.501	0.671	0.007	-0.802	+
Monroe, LA	7.617**	-0.46	0.763**	0.237	0.035**	-0.053	+
Monroe, MI	3.514**	-0.512	0.786**	1.591**	0.032**	-1.215**	+
Montgomery, AL	3.941**	-0.297	0.481	0.374	0.014	-0.261	+
Morgantown, WV	9.435**	-1.952**	2.453**	2.714**	0.057**	-0.687**	+
Morristown, TN	4.499**	-0.229	0.339	0.337	0.022	-0.189	+
Mount Vernon-Anacortes, WA	6.875**	-0.967**	1.536**	2.866**	0.083**	-1.108**	+
Muncie, IN	4.108**	-0.364	0.547**	0.658	0.028**	-0.435**	+
Muskegon-Norton Shores, MI	6.086**	-0.971	1.018	2.744**	0.029	-1.162	+
Myrtle Beach-Conway-North Myrtle Beach, SC	7.400**	-0.437	0.618	0.822	0.031	-0.225	+
Napa, CA	3.072**	-0.665	0.676	0.904	-0.016	-0.748	+
Naples-Marco Island, FL	6.620**	-0.558**	0.452**	0.139**	-0.009**	0.056**	-
Nashville-Davidson--Murfreesboro, TN	3.727**	-0.346	0.326	-0.001	0.005	0.022	-

New Orleans-Metairie-Kenner, LA	2.042**	-3.417**	4.616**	2.657	0.029	-1.467**	+
New York-Newark-Edison, NY-NJ-PA	2.079**	-0.407**	0.424**	1.214**	0.034**	-1.587**	+
Niles-Benton Harbor, MI	6.646**	-1.294	1.392	0.134	0.048	0.012	-
Ocala, FL	2.995**	-0.487**	0.553**	0.739	0.015	-0.65	+
Ocean City, NJ	4.375**	-0.613	0.332	1.38	0.048**	-0.79	+
Odessa, TX	4.020**	-0.547**	1.040**	1.242**	0.026**	-0.835**	+
Ogden-Clearfield, UT	2.118**	-1.501**	1.188	0.41	0.036	-0.343	+
Oklahoma City, OK	5.657**	-0.621**	0.664**	0.867**	0.018	-0.403	+
Olympia, WA	2.997**	-0.578**	0.605	1.215	0.024	-1.048**	+
Omaha-Council Bluffs, NE-IA	6.045**	-0.321	0.571**	0.897**	0.027**	-0.42	+
Orlando, FL	1.917**	-2.864**	2.492**	7.274**	0.160**	-4.690**	+
Oshkosh-Neenah, WI	3.254**	-0.513	0.474	0.804	-0.008	-0.656	+
Owensboro, KY	3.285**	-0.431	0.31	1.040**	0.028**	-0.866**	+
Oxnard-Thousand Oaks-Ventura, CA	1.759**	-0.917	1.355	0.372	-0.01	-0.449	+
Palm Bay-Melbourne-Titusville, FL	1.765**	-1.014**	0.851**	1.653**	-0.027**	-1.897**	+
Panama City-Lynn Haven, FL	4.665**	-0.531	1.026**	0.506	0.041**	-0.245	+
Parkersburg-Marietta, WV-OH	3.667**	-0.624**	0.48	2.048**	0.026	-1.471**	+
Pensacola-Ferry Pass-Brent, FL	3.732**	-0.957**	1.497**	0.958	0.028**	-0.599	+
Peoria, IL	3.490**	-0.34	0.299	0.627	-0.006	-0.504	+
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1.907**	-1.031**	0.814**	2.138**	0.064**	-2.288**	+
Phoenix-Mesa-Scottsdale, AZ	2.275**	-0.481**	0.448	0.725	0.009	-0.827	+
Pine Bluff, AR	17.844**	-0.722**	1.042**	0.334	0.012	-0.027	+
Pittsburgh, PA	3.151**	-0.473	0.632**	1.941**	0.018	-1.659**	+

Pocatello, ID	6.377**	-1.296**	1.683**	0.794	-0.003	-0.307	+
Portland-South Portland, ME	2.032**	-0.555	0.546	1.114	0.003	-1.364**	+
Portland-Vancouver-Beaverton, OR-WA	4.906**	-4.756**	2.412**	4.808**	0.150**	-1.512	+
Port St. Lucie-Fort Pierce, FL	4.150**	-0.649	0.808	1.04	0.031	-0.62	+
Prescott, AZ	2.940**	-0.864**	1.465**	1.735**	0.011	-1.423**	+
Providence-New Bedford-Fall River, RI-MA	1.302**	-1.059**	1.084	1.704	0.041	-2.286**	+
Provo-Orem, UT	4.291**	-1.173**	1.174**	3.653**	-0.003	-2.081**	+
Pueblo, CO	2.121**	-0.325	0.274	1.191**	0.025**	-1.527**	+
Punta Gorda, FL	9.863**	-0.59	0.725	0.832	0.035	-0.051	+
Racine, WI	4.840**	-1.022**	1.665**	2.692**	0.003	-1.405	+
Raleigh-Cary, NC	3.246**	-0.434**	0.474	1.624**	0.017	-1.356**	+
Rapid City, SD	4.808**	-0.328	0.429	0.238	0.003	-0.141	+
Reading, PA	3.794**	-0.337	0.670**	0.887	0.019	-0.643	+
Redding, CA	3.586**	-0.596	1.259**	-0.488	0.04	0.375	-
Reno-Sparks, NV	3.636**	-0.607	0.289	2.121**	0.014	-1.560**	+
Richmond, VA	3.225**	-0.546**	0.722**	0.552	0.022**	-0.445	+
Riverside-San Bernardino-Ontario, CA	2.296**	-0.303	0.596	0.618	0.001	-0.748	+
Roanoke, VA	4.528**	-0.632**	0.437	1.261**	0.032**	-0.735	+
Rochester, MN	3.869**	-0.271	0.145	0.418	0.015	-0.305	+
Rochester, NY	2.506**	-0.493	0.406	1.131	0.001	-1.182	+
Rockford, IL	4.960**	-0.660**	0.735**	0.896**	0.030**	-0.466	+

Rocky Mount, NC	4.300**	-0.519	0.293	0.91	0.026	-0.566	+
Rome, GA	3.006**	-0.520**	0.694**	0.916	0.012	-0.803**	+
Sacramento-Arden-Arcade-Roseville, CA	2.439**	-1.338**	2.054**	4.687**	0.015	-3.867**	+
Saginaw-Saginaw Township North, MI	2.664**	-0.352	0.421	0.121	0.029**	-0.128	+
St. Cloud, MN	3.935**	-0.686**	1.381**	2.245**	0.043**	-1.506**	+
St. George, UT	7.698	-0.401	0.519	0.441	0.028	-0.158	+
St. Joseph, MO-KS	12.555**	-0.272	0.313	0.352	0.025	-0.055	+
St. Louis, MO-IL	3.257**	-0.318	0.374	0.711	0.002	-0.614	+
Salem, OR	2.937**	-0.689	0.583	1.382	0.049**	-1.185**	+
Salinas, CA	2.611**	-0.449	0.723	1.459	0.01	-1.491	+
Salisbury, MD	3.941**	-0.508	0.543	0.138	0.021	-0.064	+
Salt Lake City, UT	3.434**	-0.453	0.756**	0.681	0.030**	-0.546	+
San Angelo, TX	5.715**	-0.530**	0.662**	1.222**	0.028**	-0.601	+
San Antonio, TX	3.400**	-0.407**	0.487**	0.776**	0.018	-0.627	+
San Diego-Carlsbad-San Marcos, CA	3.845**	-1.392**	2.211**	2.122**	0.065**	-1.226	+
Sandusky, OH	5.670**	-0.77	0.625	0.913	0.009	-0.407	+
San Francisco-Oakland-Fremont, CA	1.364**	-1.118	1.363	3.034**	0.044	-3.852**	+
San Jose-Sunnyvale-Santa Clara, CA	1.950**	-1.151	1.418	2.049	0.086**	-2.066	+
San Luis Obispo-Paso Robles, CA	2.303**	-0.612	0.544	0.846	0.046**	-0.911	+
Santa Barbara-Santa Maria-Goleta, CA	2.134**	-0.604	0.624	1.71	0.042	-1.961	+
Santa Cruz-Watsonville, CA	2.173**	-2.603**	2.197**	6.035**	0.045	-3.890**	+

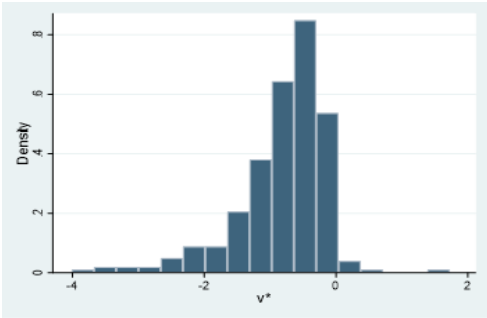
Santa Fe, NM	4.822**	-0.495**	0.557	0.97	0.033**	-0.560**	+
Santa Rosa-Petaluma, CA	2.730**	-2.466**	2.922**	4.486**	-0.042	-2.662**	+
North Port-Bradenton-Sarasota, FL	4.138**	-0.464	0.612	1.358	0.035	-0.859	+
Savannah, GA	4.088**	-0.519	0.49	1.374	0.019	-0.89	+
Scranton--Wilkes-Barre, PA	3.105**	-0.603	0.862**	1.895**	0.033	-1.585**	+
Seattle-Tacoma-Bellevue, WA	1.936**	-0.436	0.603	0.529	0.033	-0.736	+
Sheboygan, WI	9.741**	-0.518	0.244	0.538	-0.003	-0.128	+
Sherman-Denison, TX	5.531**	-1.757**	1.967**	5.377**	-0.008	-2.275**	+
Shreveport-Bossier City, LA	3.909**	-1.133**	1.410**	1.987**	0.077**	-1.214**	+
Sioux City, IA-NE-SD	5.737**	-0.748**	1.129**	0.355	0.057**	-0.15	+
Sioux Falls, SD	5.926**	-0.643**	1.137**	0.159	0.027**	-0.05	+
South Bend-Mishawaka, IN-MI	5.962**	-0.626**	0.814**	2.349**	-0.005	-1.064**	+
Spartanburg, SC	6.162**	-0.232	0.466	1.047**	0.009	-0.436**	+
Spokane, WA	2.529**	-0.271	0.453	0.980**	0.012	-1.099**	+
Springfield, IL	2.813**	-1.840**	1.301**	0.479	0.124**	-0.309	+
Springfield, MO	4.443**	-0.771**	0.809**	1.201**	0.022**	-0.704**	+
Springfield, OH	5.047**	-0.34	0.404	0.757	0.002	-0.402	+
State College, PA	3.559**	-0.890**	0.862**	1.954**	0.036**	-1.355**	+
Stockton, CA	2.409**	-0.716**	1.017**	1.761**	0.011	-1.762**	+
Sumter, SC	5.803**	-1.077**	0.667	2.987**	-0.059**	-1.289**	+
Syracuse, NY	2.512**	-0.636**	0.65	0.701	0.008	-0.696	+
Tallahassee, FL	3.813**	-0.483	0.614	1.246**	-0.001	-0.882	+
Tampa-St. Petersburg-Clearwater, FL	1.664**	-0.983**	1.284**	1.692	0.041**	-2.041**	+

Terre Haute, IN	10.451**	-0.331	0.517**	0.62	0.013	-0.139	+
Texarkana, TX-Texarkana, AR	4.869**	-0.413	0.445	1.259**	0.001	-0.728**	+
Toledo, OH	3.584**	-1.428**	2.297**	3.076**	0.140**	-1.890**	+
Topeka, KS	5.610**	-0.346	0.273	0.422	0.017	-0.204	+
Trenton-Ewing, NJ	2.494**	-1.654**	1.339**	4.873**	0.007	-3.599**	+
Tucson, AZ	2.452**	-0.504**	0.557	0.471	0.006	-0.499	+
Tulsa, OK	4.847**	-0.396**	0.564**	1.407**	0.012	-0.818**	+
Tuscaloosa, AL	3.743**	-0.4	0.497	0.648	0.011	-0.475	+
Tyler, TX	5.408**	-0.277	0.423	0.967	0.016	-0.507	+
Utica-Rome, NY	4.502**	-1.057**	1.289**	1.963**	0.030**	-1.083**	+
Valdosta, GA	3.668**	-0.47	0.494	0.335	-0.022**	-0.237	+
Vallejo-Fairfield, CA	2.987**	-0.353	0.341	0.312	0.017	-0.288	+
Sebastian-Vero Beach, FL	5.025**	-1.046**	0.869	2.009**	0.006	-0.954**	+
Victoria, TX	3.833**	-0.369	0.543	0.053	0.006	-0.031	+
Vineland-Millville-Bridgeton, NJ	2.353**	-0.591	0.781	1.676**	0.022	-1.786	+
Virginia Beach-Norfolk-Newport News, VA-NC	1.417**	-1.856**	0.739	3.317**	0.033	-3.159**	+
Visalia-Porterville, CA	2.391**	-0.425	0.196	0.893	-0.017	-0.994	+
Waco, TX	3.243**	-0.698**	0.662**	0.914**	0.009	-0.708**	+
Warner Robins, GA	4.648**	-0.884**	0.653**	1.146**	0.035**	-0.596**	+
Washington-Arlington-Alexandria, DC-VA-MD-WV	2.235**	-0.756**	0.788**	1.179**	0.031**	-1.238**	+
Waterloo-Cedar Falls, IA	6.995**	-0.598**	0.623**	1.136**	0.028**	-0.442**	+
Wausau, WI	3.374**	-0.293	0.542**	0.495	0.016	-0.415	+

Weirton-Steubenville, WV-OH	4.768**	-0.655**	0.473	2.196**	-0.003	-1.228**	+
Wenatchee, WA	7.296**	-0.438	0.627	0.439	-0.006	-0.159	+
Wheeling, WV-OH	7.211**	-0.353	0.461	0.775	0.019	-0.274	+
Wichita, KS	4.676**	-0.503**	0.708**	-0.129**	-0.008	0.093**	-
Wichita Falls, TX	3.947**	-0.453**	0.441	0.256	0.01	-0.175	+
Williamsport, PA	3.337**	-1.319**	2.491**	2.131**	0.091**	-1.409**	+
Wilmington, NC	3.296**	-0.884**	1.571**	1.538**	0.018**	-1.123**	+
Winchester, VA-WV	4.358**	-0.621**	0.976**	1.241**	0.034**	-0.756**	+
Winston-Salem, NC	4.114**	-0.411**	0.615**	0.514	0	-0.315	+
Yakima, WA	2.518**	-2.171**	2.034**	3.576**	0.01	-2.372**	+
York-Hanover, PA	3.201**	-0.322	0.172	0.58	-0.005	-0.501	+
Youngstown-Warren-Boardman, OH-PA	2.659**	-0.412**	0.346	0.353	0.029**	-0.361	+
Yuba City-Marysville, CA	3.020**	-0.261	0.362	0.116	0.019	-0.109	+
Yuma, AZ	3.778**	-0.563**	0.459	1.214**	0.038**	-0.871**	+

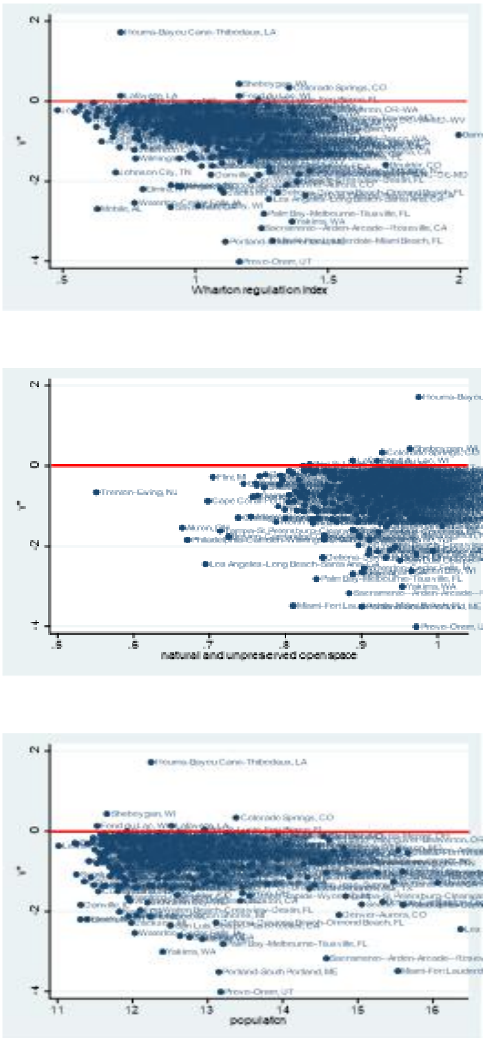
Notes: ** is significant at 5%. The significant level is calculated from bootstrap bias-corrected and accelerated confidence intervals.

Figure D1. The Histogram of ν^*



Note: The histogram of ν^* is left skewed, and the vast majority of MSAs have an estimated ν^* below zero, implying that they have too little open space. MSAs with a negative ν^* farther away from 0 are more deviated from the optimum.

Figure D2. Scatterplots of ν^* and Slelected MSA Chacteristics



E. Robustness Checks

Saiz (2010) estimates the supply equation in discrete changes between 1970 and 2000. As a robustness check, we also estimate the housing demand and supply equations in changes between 1970 and 2010 and between 1980 and 2010. The results are reported in Table E1.

In the models reported in table 3, we use the share of natural, preserved and unpreserved open space within the urban area as explanatory variables. As Saiz (2010) pointed out, when estimating land scarcity imposed by geography, it might be better to use a measure of original constraints, as opposed to one based on ex post ease of development. As a robustness check, we also estimate the models using the share of natural, preserved and unpreserved open space within the 50-km radius of the central city's centroid as explanatory variables. The results are reported in Table E2. We also estimate the two equations separately using 2SLS with IV using STATA command *ivreg2*, that is, model (a). The rest of the models are estimated jointly using GMM, which allows us to specify different sets of instruments for supply and demand equations respectively.

Table E1

Robustness Checks: Estimates of The Housing Supply and Demand Equations with With Different Time Spans

	(1) (1970-2010)	(1') (1970-2010)	(2) (1980-2010)	(2') (1980-2010)
Housing supply equation: Dependent variable $\Delta\ln(P)$				
$(1-\Lambda_k)\Delta\ln H_k$	-2.511***	-2.481***	-1.832	-1.481
	(0.856)	(0.842)	(2.650)	(2.666)
$\ln POP_{70}(1-\Lambda_k)\Delta\ln H_k$	0.211***	0.207***	0.228	0.199
	(0.0771)	(0.0757)	(0.221)	(0.223)
$\ln WRI_k \Delta\ln H_k$	0.293***	0.282***	0.197**	0.192**
	(0.0629)	(0.0626)	(0.0855)	(0.0860)
Midwest	-0.121**	-0.117**	-0.259***	-0.259***
	(0.0549)	(0.0553)	(0.0177)	(0.0177)
South	0.104*	0.114*	-0.270***	-0.268***
	(0.0629)	(0.0633)	(0.0271)	(0.0272)
West	-0.207***	-0.211***	-0.260***	-0.257***
	(0.0547)	(0.0553)	(0.0428)	(0.0422)
Constant	2.220***	2.231***	1.327***	1.328***
	(0.0590)	(0.0598)	(0.0296)	(0.0294)
Housing demand equation: Dependent variable $\Delta\ln(P)$				
$\Delta\ln H_k$	-2.303***	-2.382**	-1.595***	-1.690*
	(0.728)	(0.974)	(0.576)	(0.900)
$\ln(POP_{70k})\,\Delta\ln H_k$	0.0533	0.112	0.0820	0.0542
	(0.0669)	(0.0805)	(0.0735)	(0.0767)
$(1-\Lambda_k)\ln(POP_{70k})\,\Delta\ln H_k$	0.240	0.187**	0.0656	0.122
	(0.154)	(0.0884)	(0.104)	(0.0873)
$\Delta\ln(s_p)$	2.498*	1.770*	0.829	1.169
	(1.475)	(0.954)	(0.869)	(0.758)
$\Delta\ln(s_d)$		2.224		-0.661
		(4.232)		(1.763)
Δln(g)	0.0377	0.0331	-0.0204	-0.0144
	(0.0411)	(0.0332)	(0.0227)	(0.0242)
Δln(Income)	1.735***	1.212***	1.110***	1.362***
	(0.659)	(0.363)	(0.407)	(0.260)
Δln(commute)	1.172***	1.003***	0.387**	0.455**
	(0.418)	(0.304)	(0.191)	(0.203)
ln(jansunhrs)	-0.0708*	-0.0986**	0.000295	0.000149
	(0.0403)	(0.0425)	(0.00156)	(0.00165)
Coast	-0.109	-0.140	-0.266**	-0.230*
	(0.231)	(0.180)	(0.108)	(0.123)
Immshock	0.371	0.179	0.612	0.758*
	(0.408)	(0.313)	(0.519)	(0.413)

Shift-share of industrial	-2.145	-1.600*	-0.300	-0.584
composition	(1.527)	(0.863)	(0.623)	(0.529)
Unavailable land	0.0733	0.0540	0.0465*	0.0419
	(0.0488)	(0.0379)	(0.0253)	(0.0272)
Midwest	-0.172	-0.205**	-0.229***	-0.200***
	(0.114)	(0.0945)	(0.0593)	(0.0619)
South	0.138	0.0387	-0.0646	-0.00136
	(0.151)	(0.0944)	(0.105)	(0.0773)
West	0.674***	0.496***	-0.0266	0.0411
	(0.226)	(0.119)	(0.106)	(0.0732)
Constant	0.219	1.117	1.540**	1.153
	(2.006)	(1.512)	(0.663)	(0.729)
Number of observations	345	345	345	345

Notes:

Instruments for the supply equation are

ΔlnH_k: a shift-share of the 1974 metropolitan industrial composition ($InduCom_k^{74}$), the log of average hours of sun in January ($SunnyHrs_k$), and the number of new immigrants (1970 to 2000) divided by the total population in 1970 ($NewImm_k^{74-00}$).

$lnWRI_k$: public expenditure share in protective inspection in 1970 ($PubExp_k^{70}$) and nontraditional Christian share in 1970 ($Christian_k^{70}$).

$\mathrm{lnWRI_k \Delta lnH_k}$: the instruments for $\mathrm{lnWRI_k}$ and $\mathrm{\Delta lnH_k}$ and the interaction terms of these instruments.

Instruments for the demand equation are:

ΔlnH_k, $\ln(POP_{70k})\,\Delta lnH_k$ and $(1-\Lambda_k)\ln(\mathrm{POP}_{70})\,\Delta\mathrm{lnH_k}$: public expenditure share in protective inspection in 1970 ($PubExp_k^{70}$), nontraditional Christian share in 1970 ($Christian_k^{70}$), log of the change of construction workers' wage ($\Delta\ln(wage_k)$), the change of the log of the RSMeans construction costs ($\Delta\ln(RSMcost_k)$).

Table E2

Robustness Checks: Estimates of The Housing Supply and Demand Equations with Different Open Space Measures

	(1) (1970-2010)	(1') (1970-2010)	(2) (1980-2010)	(2') (1980-2010)
	Housing supply equation: Dependent variable $\Delta\ln(P)$			
$(1-\Lambda_k)\Delta\ln H_k$	-2.510***	-2.447***	-3.832	-0.673
	(0.885)	(0.888)	(3.182)	(3.433)
$\ln POP_{70}(1-\Lambda_k)\Delta\ln H_k$	0.222***	0.215***	0.388	0.141
	(0.0769)	(0.0769)	(0.260)	(0.282)
$\ln WRI_k\Delta\ln H_k$	0.244***	0.234***	0.0314	0.00980
	(0.0899)	(0.0898)	(0.132)	(0.137)
Midwest	-0.193***	-0.199***	-0.274***	-0.260***
	(0.0573)	(0.0580)	(0.0213)	(0.0231)
South	-0.114**	-0.110*	-0.241***	-0.248***
	(0.0565)	(0.0570)	(0.0260)	(0.0253)
West	0.120*	0.124*	-0.158***	-0.170***
	(0.0650)	(0.0652)	(0.0335)	(0.0370)
Constant	2.220***	2.232***	1.388***	1.377***
	(0.0600)	(0.0607)	(0.0417)	(0.0452)
	Housing demand equation: Dependent variable $\Delta\ln(P)$			
$\Delta\ln H_k$	-1.786***	-4.192**	-1.674***	-1.762
	(0.426)	(1.893)	(0.565)	(1.280)
$\ln(POP_{70k})\,\Delta\ln H_k$	0.111***	0.274*	0.103**	0.0940
	(0.0316)	(0.150)	(0.0436)	(0.109)
$(1-\Lambda_k)\ln(POP_{70k})\,\Delta\ln H_k$	0.129**	0.234	0.0710	0.0445
	(0.0589)	(0.151)	(0.0613)	(0.116)
$\Delta\ln(s_{p,50})$	1.021	1.412	0.605	0.579
	(0.994)	(1.408)	(0.648)	(0.655)
$\Delta\ln(s_{d,50})$		4.710		0.0902
		(3.845)		(1.560)
Δln(g)	-0.00105	0.00730	-0.0401**	-0.0226
	(0.0251)	(0.0427)	(0.0194)	(0.0237)
Δln(Income)	1.076***	1.211**	1.232***	1.307***
	(0.313)	(0.490)	(0.176)	(0.310)
Δln(commute)	0.603***	1.084**	0.332**	0.483**
	(0.187)	(0.448)	(0.131)	(0.205)
ln(jansunhrs)	-0.101	-0.150	-0.169**	-0.195
	(0.114)	(0.247)	(0.0824)	(0.143)
Coast	0.0419	0.0227	0.0458*	0.0224
	(0.0312)	(0.0456)	(0.0239)	(0.0262)
Immshock	-0.0558	0.0203	0.125	0.554
	(0.217)	(0.447)	(0.238)	(0.413)

Shift-share of industrial	-0.0891***	-0.124**	0.00262***	0.00169
composition	(0.0328)	(0.0570)	(0.000926)	(0.00129)
Unavailable land	-1.055*	-1.995	-0.265	-0.0861
	(0.630)	(1.584)	(0.410)	(0.777)
Midwest	-0.200***	-0.208	-0.162***	-0.177***
	(0.0757)	(0.134)	(0.0434)	(0.0657)
South	-0.0904	-0.0194	-0.0575	-0.0258
	(0.0667)	(0.138)	(0.0455)	(0.0866)
West	0.343***	0.433**	0.0501	0.00675
	(0.0857)	(0.178)	(0.0505)	(0.0898)
Constant	0.968	1.188	0.864	0.920
	(1.108)	(2.054)	(0.545)	(0.841)
Number of observations	345	345	345	345

Notes:

Instruments for the supply equation are

ΔlnH_k: a shift-share of the 1974 metropolitan industrial composition ($InduCom_k^{74}$), the log of average hours of sun in January ($SunnyHrs_k$), and the number of new immigrants (1970 to 2000) divided by the total population in 1970 ($NewImm_k^{74-00}$).

$lnWRI_k$: public expenditure share in protective inspection in 1970 ($PubExp_k^{70}$) and nontraditional Christian share in 1970 ($Christian_k^{70}$).

$\mathrm{lnWRI_k \Delta lnH_k}$: the instruments for $\mathrm{lnWRI_k}$ and $\Delta \mathrm{lnH_k}$ and the interaction terms of these instruments.

Instruments for the demand equation are:

ΔlnH_k, $\ln(POP_{70\mathrm{k}})\,\Delta lnH_k$ and $(1-\Lambda_\mathrm{k})\ln(\mathrm{POP}_{70})\,\Delta\mathrm{lnH_k}$: public expenditure share in protective inspection in 1970 ($PubExp_k^{70}$), nontraditional Christian share in 1970 ($Christian_k^{70}$), log of the change of construction workers' wage ($\Delta\ln(wage_k)$), the change of the log of the RSMeans construction costs ($\Delta\ln(RSMcost_k)$).

Table E3

Robustness Checks: Estimates of The Housing Supply and Demand Equations with Different Open Space Measures

	(a) 2SLS	(b) GMM	(c) GMM	(d) GMM	(e) GMM
Housing supply equation: Dependent variable $\Delta\ln(P)$					
$(1-\Lambda_k)\Delta\ln H_k$	-2.691***	-2.404***	-2.343***	-2.116**	-3.054***
	(0.806)	(0.844)	(0.876)	(0.878)	(0.908)
$\ln POP_{70}(1-\Lambda_k)\Delta\ln H_k$	0.237***	0.211***	0.206***	0.184**	0.263***
	(0.0678)	(0.0717)	(0.0757)	(0.0753)	(0.0756)
$\ln WRI_k\Delta\ln H_k$	0.241***	0.241***	0.237***	0.256***	0.277**
	(0.0907)	(0.0900)	(0.0897)	(0.0895)	(0.119)
Midwest	-0.228***	-0.199***	-0.200***	-0.208***	-0.221***
	(0.0536)	(0.0577)	(0.0577)	(0.0566)	(0.0544)
South	-0.144***	-0.113**	-0.113**	-0.121**	-0.143***
	(0.0531)	(0.0564)	(0.0568)	(0.0560)	(0.0536)
West	0.0812	0.118*	0.121*	0.105	0.0757
	(0.0621)	(0.0648)	(0.0652)	(0.0647)	(0.0673)
$\Delta\ln(s_{p,50})$					-0.0732
					(0.670)
Constant	2.252***	2.229***	2.233***	2.234***	2.240***
	(0.0590)	(0.0602)	(0.0604)	(0.0599)	(0.0586)
Housing demand equation: Dependent variable $\Delta\ln(P)$					
$\Delta\ln H_k$	-0.558***	-0.204	-2.534***	-2.182**	-2.453***
	(0.173)	(0.279)	(0.911)	(0.861)	(0.952)
$\ln(POP_{70})\,\Delta\ln H_k$	0.0456***	0.0293*	0.0512*		
	(0.0144)	(0.0170)	(0.0287)		
$(1-\Lambda_k)\ln(POP_{70})\,\Delta\ln H_k$				0.0442**	0.0483*
				(0.0223)	(0.0250)
$\Delta\ln(s_{p,50})$			-0.138	0.124	0.496
			(1.025)	(1.001)	(1.094)
$\Delta\ln(s_{p,50}+s_{d,50})$					
Δln(g)			0.169	0.0359	0.0259
			(0.110)	(0.0328)	(0.0329)
Δln(population)			1.648*	1.892**	2.167**
			(0.865)	(0.786)	(0.872)
Δln(Income)	1.180***	0.916***	1.526***	1.540***	1.569***
	(0.129)	(0.212)	(0.281)	(0.383)	(0.419)
Δln(commute)	0.373***	0.211	0.597**	0.345	0.312
	(0.116)	(0.154)	(0.238)	(0.210)	(0.227)
ln(jansunhrs)	-0.0159	0.00410	-0.0343*	-0.0406**	-0.0349*

	(0.0131)	(0.0131)	(0.0191)	(0.0191)	(0.0189)
Coast	0.0499	0.00199	0.105	0.0588	0.0646
	(0.0306)	(0.0345)	(0.0674)	(0.0636)	(0.0674)
Immshock	0.0260	-0.0116	0.0441	-0.0495	-0.184
	(0.103)	(0.126)	(0.211)	(0.236)	(0.267)
Shift-share of industrial	0.0697***	0.0656***	0.0376	0.0886*	0.0902
composition	(0.0244)	(0.0240)	(0.0340)	(0.0524)	(0.0566)
Unavailable land	0.250***	0.204***	0.588***		
	(0.0631)	(0.0687)	(0.182)		
Midwest	-0.121***	-0.137***	0.00204	-0.105	-0.110
	(0.0435)	(0.0503)	(0.0724)	(0.0674)	(0.0694)
South	-0.101**	-0.131**	-0.0129	-0.112	-0.124
	(0.0468)	(0.0553)	(0.0815)	(0.0806)	(0.0834)
West	0.257***	0.201***	0.244*	0.0824	0.0637
	(0.0506)	(0.0664)	(0.135)	(0.121)	(0.126)
Constant	2.229***	0.415	-0.996	-0.340	-0.327
	(0.0602)	(0.492)	(0.742)	(0.819)	(0.888)
Number of observations	345	345	345	345	345

Notes:

Instruments for the supply equation are

ΔlnH_k: a shift-share of the 1974 metropolitan industrial composition ($InduCom_k^{74}$), the log of average hours of sun in January ($SunnyHrs_k$), and the number of new immigrants (1970 to 2000) divided by the total population in 1970 ($NewImm_k^{74-00}$).

$lnWRI_k$: public expenditure share in protective inspection in 1970 ($PubExp_k^{70}$) and nontraditional Christian share in 1970 ($Christian_k^{70}$).

$\mathrm{lnWRI_k \Delta lnH_k}$: the instruments for $\mathrm{lnWRI_k}$ and $\mathrm{\Delta lnH_k}$ and the interaction terms of these instruments.

Instruments for the demand equation are:

ΔlnH_k, $\ln(POP_{70k})\,\Delta lnH_k$ and $(1-\Lambda_k)\ln(\mathrm{POP_{70}})\,\Delta \mathrm{lnH_k}$: public expenditure share in protective inspection in 1970 ($PubExp_k^{70}$), nontraditional Christian share in 1970 ($Christian_k^{70}$), log of the change of construction workers' wage ($\Delta\ln(wage_k)$), the change of the log of the RSMeans construction costs ($\Delta\ln(RSMcost_k)$).

Table E4

Robustness Checks: Estimates of The Housing Supply and Demand Equations with Different Open Space Measures

	(a)
	GMM
	Housing Supply Equation: Dependent Variable $\Delta ln(P)$
$(1-\Lambda_k)\Delta \ln H_k$	-2.152**
	(0.859)
$\ln POP_{70k}(1-\Lambda_k)\Delta \ln H_k$	0.171**
	(0.0769)
$\ln WRI_k \Delta \ln H_k$	0.336***
	(0.0650)
Midwest	-0.206***
	(0.0546)
South	-0.115**
	(0.0548)
West	0.101
	(0.0631)
Constant	2.214***
	(0.0598)
	Housing Demand Equation: Dependent Variable $\Delta ln(P)$
$\Delta \ln H_k$	-0.0554
	(0.771)
$\ln(POP_{70k})\, \Delta \ln H_k$	-0.0527
	(0.0778)
$(1-\Lambda_k)\ln(POP_{70k})\, \Delta \ln H_k$	0.148***
	(0.0558)
$\Delta \ln(s_{p,public})$	5.928*
	(3.475)
$\Delta \ln(s_{p,private})$	-0.926
	(1.741)
$\Delta \ln(s_{d,public})$	49.01
	(43.69)
$\Delta \ln(s_{d,private})$	-0.0571
	(1.926)
Δln(g)	-0.0199
	(0.0381)
Δln(income)	1.642***
	(0.451)
Δln(commute)	0.717***
	(0.238)
ln(jansunhrs)	0.0995
	(0.201)

Coast	0.165***
	(0.0621)
Immshock	-0.281
	(0.388)
Shift-share of industrial composition	0.00205
	(0.0195)
Unavailable land	-1.258**
	(0.553)
Midwest	-0.194**
	(0.0860)
South	-0.0336
	(0.107)
West	0.370***
	(0.124)
Constant	-0.974
	(1.670)
Number of observations	328

Notes:

Instruments for the supply equation are

ΔlnH_k: a shift-share of the 1974 metropolitan industrial composition ($InduCom_k^{74}$), the log of average hours of sun in January ($SunnyHrs_k$), and the number of new immigrants (1970 to 2000) divided by the total population in 1970 ($NewImm_k^{74-00}$).

$lnWRI_k$: public expenditure share in protective inspection in 1970 ($PubExp_k^{70}$) and nontraditional Christian share in 1970 ($Christian_k^{70}$).

$\mathrm{lnWRI_k \Delta lnH_k}$: the instruments for $\mathrm{lnWRI_k}$ and $\mathrm{\Delta lnH_k}$ and the interaction terms of these instruments.

Instruments for the demand equation are:

ΔlnH_k, $\ln(POP_{70k})\,\Delta lnH_k$ and $(1-\Lambda_k)\ln(\mathrm{POP_{70}})\,\mathrm{\Delta lnH_k}$: public expenditure share in protective inspection in 1970 ($PubExp_k^{70}$), nontraditional Christian share in 1970 ($Christian_k^{70}$), log of the change of construction workers' wage ($\Delta\ln(wage_k)$), the change of the log of the RSMeans construction costs ($\Delta\ln(RSMcost_k)$).

The number of observations is 328. The 17 MSAs absent in the protected area dataset are Bend, OR; Bloomington-Normal, IL; Decatur, IL; El Paso, TX; Florence-Muscle Shoals, AL; Fort Walton Beach-Crestview-Destin, FL; Huntington-Ashland, WV-KY-OH; Laredo, TX; Las Cruces, NM; Las Cruces, NM; Lubbock, TX; Midland, TX; Odessa, TX; North Port-Bradenton-Sarasota, FL; Sherman-Denison, TX; Sebastian-Vero Beach, FL; Weirton-Steubenville, WV-OH; and Wichita Falls, TX.