Do Financial Constraints Cool a Housing Boom?

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Abstract

In this paper we seek to understand the role of financial constraints in the housing market and their effectiveness as a macroprudential policy tool aimed at cooling a housing boom. We exploit a natural experiment arising from the 2012 Canadian law change that restricts access to mortgage insurance (MI) to homes under one million dollars ($1M). Our empirical analysis is motivated by a directed search model that features auction mechanisms and financially constrained bidders. We model the MI regulation as a tightening of the financial constraint faced by a subset of prospective buyers. This prompts some sellers in the near $1M segments to strategically adjust their asking price to $1M, which attracts both constrained and unconstrained buyers. Competition between bidders dampens the impact of the policy on sales prices. Using transaction data from the Toronto housing market, we find that the limitation of MI causes a sharp bunching of homes listed at the $1M, with two-thirds of bunching coming from houses that have otherwise been listed below $995,000, and the remaining from houses that have otherwise been listed above $1M. In addition, we find a smaller degree of bunching of the sales price at $1M, most of which comes from houses that would have otherwise been sold above $1M. Thus the MI cools down the targeted segment in the desired direction, although its impact is attenuated by heightened competition among bidders. Overall, our analysis points to the importance of strategic and equilibrium considerations in assessing the effectiveness of macroprudential policies.

Keywords: macroprudential regulation, directed search, financial constraints, bunching estimation

JEL classification:

1 Introduction

Financial constraints are a fundamental feature of the housing market (Stein, 1995; Genesove and Mayer, 1997; Ortalo-Magne and Rady, 2006; Favilukis et al., 2017). On the buyer side, the required downpayment (e.g. loan-to-value ratio) and mortgage payment (e.g. debt-to-income ratio) reflect the two underwriting constraints, on wealth and income respectively, that limit how much a buyer can bid on a property. On the seller side, the decision to list a house for sale and the choice of asking price depend on the perceived ability to pay among potential buyers. The central role of financial constraints makes them by far the most widespread policy vehicles that have been used to influence housing markets. For example, Kuttner and Shim (2016) document 94 actions on the loan-to-value ratio and 45 actions on the debt-service-to-income ratio in 60 countries between 1990–2012.[1] In particular, since the global financial crisis of 2008, tightening financial constraints has become one of the primary macroprudential tools that aim to create a buffer in a boom to ensure that "shocks from the housing sector do not spill over and threaten economic and financial stability" (IMF Speech, 2014).[2] In light of this, a large and important literature has emerged to examine how such policies affect house price growth through their impact on borrower credit worthiness(e.g., Mian and Sufi (2009)). However, despite the importance of understanding the link between financial constraints and behaviour in housing markets where buyers and sellers face optimization frictions such as search costs, there is virtually no existing micro analysis from such settings. This paper aims to fill this gap by providing a search theoretical analysis to explore strategic and equilibrium implications of financial constraints in housing markets, and by empirically exploiting a natural experiment arising from a mortgage insurance policy implemented in Canada in 2012.

We exploit variations in the required downpayment created by a recent policy that restricts access to mortgage insurance (the transfer of mortgage default risk from lenders to

[1] Also see Elliott et al. (2013) for a comprehensive survey of the history of cyclical macroprudential policies in the U.S.

[2] Source: "Managing House Price Boom: The Role of Macroprudential Policies." December 2014, https://www.imf.org/external/np/speeches/2014/121114.htm.

insurers; henceforth MI) when the purchase price of a home exceeds 1 million Canadian dollars.[3] Given that Canadian lenders, like those in the US and other developed countries, are required to insure mortgages with over 80% loan-to-value ratio, the policy effectively imposes a 20% minimum downpayment constraint for buyers of homes of $1M or more. Despite the government's clear intention to restrain price appreciation in the higher-end segments of housing markets,[4] it is not straightforward whether and how market participants would respond to such policy. Like many other financial constraints, the million dollar policy not only reduces the set of buyers able to afford million dollar homes; but also creates incentives for sellers to adjust asking price to attract both constrained and unconstrained buyers, resulting in "a 'red hot' market for homes under $999,999" (Financial Post, 2013). Thus, understanding the impact of the million dollar policy on transaction outcomes requires an equilibrium analysis of a two-sided housing market. In this sense, although the focus in this paper is on the down payment discontinuity at a specific threshold of house price, our analysis has a broad applicability to examining the behavorial responses to financial constraints in a market with frictions.

We begin by advancing a search theoretical model of the million dollar housing market segment that guides the subsequent empirical analysis. The model is one of directed search and auctions, and features financial constraints on the buyer side and free entry on the seller side. Sellers pay a cost to list their house and post an asking price, and buyers allocate themselves across sellers subject to search/coordination frictions governed by a many-to-one meeting technology. Prices are determined by an auction mechanism: a house is sold at the asking price when a single buyer arrives; when multiple buyers meet the same seller, the house is sold to the highest bidder. In that sense, our model draws from the competing auctions literature (e.g., McAfee 1993, Peters and Severinov 1997, Julien et al. 2000, Albrecht et al. 2014, Lester et al. 2015). The distinguishing feature of the model is the financial constraints

[3] In July 2012, when the policy was implemented one Canadian dollar was approximately equal to one US dollar.

[4] Jim Flaherty made the following statement in 2012 regarding house price appreciation and the corresponding policy reform: "I remain concerned about parts of the Canadian residential real estate market, particularly in Toronto... [and] we need to calm the... market in a few Canadian cities." Source: "Canada Tightens Mortgage-Financing Rules." *Wall Street Journal*, June 21, 2012.

faced by buyers which limit how much they can bid on a house.[5] We assume that buyers initially face a common income constraint that is not too restrictive, but that the introduction of the million dollar policy imposes a minimum wealth requirement that further constrains a subset of buyers.

We characterize the pre- and post-policy equilibria and derive a set of empirical predictions. Under appropriate parameter restrictions, the post-policy equilibrium features some sellers with asking prices exactly at the bidding limit imposed by the policy (i.e., \$1M). In some circumstances, this represents an *increase* in the set of equilibrium asking prices relative to the pre-policy equilibrium. The intuition is that sellers can make up for the reduction in expected sales revenue in multiple offer situations by increasing the asking price to extract a higher payment from the buyer in a bilateral situation. In other circumstances, this represents a *reduction* in the set of equilibrium asking prices. Sellers can attract offers from constrained buyers by lowering their asking price to the threshold. At the same time, they continue to attract unconstrained buyers. Heightened bidding war intensity sometimes pushes the sales price above the asking price, leading to a less severe reduction in sales prices. As a final empirical prediction, we show that the consequences of the policy should be more dramatic when a larger share of prospective buyers are constrained.

We test the model's predictions using the 2010-2013 housing market transaction data for single-family homes in the Greater Toronto Area, Canada's largest housing market. The Toronto market provides a particularly suitable setting for this study for two reasons. First, home sellers in Toronto typically initiate the search process by listing the property and specifying a particular date on which offers will be considered (often 5-7 days after listing). This institutional practice fits well with our model of competing auctions and hence enables us to explore the model's implications about the strategic interactions between buyers and sellers. Second, the million dollar policy was implemented in the midst of a housing boom in Toronto. It induced a jump of the minimum downpayment from 5% to 20% as the

[5] Others have studied auction mechanisms with financially constrained bidders (e.g., Che and Gale, 1996a,b, 1998; Kotowski, 2016), but to our knowledge this is the first paper to consider bidding limits in a model of competing auctions.

sales price crossed the \$1M threshold, creating an increase in required downpayment of \$150,000. The policy thus caused two discrete changes in the market: one at the time the policy was implemented, and another at the \$1M threshold. Figure 1 plots smoothed percentage changes in sales volume before and after the change in MI policy by sale price.[6] The substantial jump of sales volume at \$1M in the wake of the policy is consistent with strong incentives for bunching at the threshold, allowing for a nonparametric identification of market responses not only in agents' strategic decisions (listing and searching) but also in transaction outcomes (price and time on the market).

Despite the appealing setting, estimating the policy's impact is complicated by two factors. First, the implementation of the policy coincided with a number of accompanying government interventions[7] as well as a booming market. These confounding factors make it difficult to isolate the effects of the policy. Second, housing composition may shift around the time when the policy was implemented. If the quality of houses in the million dollar segment depreciates over time, then a finding of lower asking price in the post-policy period cannot be attributed to sellers' response to the policy but rather the change of house characteristics.

Our solution relies on a two-stage estimation procedure. First, borrowing the distribution regression approach from Chernozhukov et al. (2013) and leveraging the richness of our data on house characteristics, we decompose the observed before-after-policy change in the distribution of house prices (both asking and sales) into: (1) a component that is due to changes in house characteristics; and (2) a component that is due to changes in sellers' listing strategy. The latter yields a quality-adjusted distribution of house prices that would have

[6] To create this figure, we count the number of sales in price bins of \$10,000 and perform a local linear regression on data points below and above \$1M, separately. The pre-treatment period is the first six months of 2012 and the post-treatment period is the first six months of 2013. The same calendar months are used in both 2012 and 2013 to remove seasonal effects.

[7] As noted in Wachter et al. (2014), the macroprudential policies are "typically used in combination with macroeconomic policy and direct interventions, complicating the challenge to attribute outcomes to specific tools." The law that implemented the million dollar policy also reduced the maximum amortization period from 30 years to 25 years for insured mortgages; limited the amount that households can borrow when refinancing to 80 percent (previously 85 percent); and limited the maximum gross debt service ratio to 39 percent (down from 44 percent), where the gross debt service ratio is the sum of annual mortgage payments and property taxes over gross family income. Source: "Harper Government Takes Further Action to Strengthen Canada's Housing Market." *Department of Finance Canada*, June 21, 2012.

prevailed in the post-policy period if the characteristics of houses stayed the same as in the pre-period. Next, using this quality-adjusted distribution, we measure the effects of the MI on listings and sales by comparing the observed post-policy distributions of asking price and sales price to their counterfactual distributions assuming there were no change policy. To this end, we adopt the recently developed bunching estimation approach (e.g., Chetty et al. 2011, Kleven and Waseem 2013, DeFusco et al. 2017).

Our main findings are the following. First, the distribution of asking price features a large and sharp bunching right at the million dollar combined with holes both above and below the million dollar. For example, in central Toronto, the additional homes that MI adds to the million dollar price bin represents about 46% increase in homes that would have been listed in this bin in the absence of the policy. Among these additional listings, about two-thirds would have otherwise been listed below $\$995,000$; the remaining one-third would have otherwise been listed above \$1M. Both are consistent with sellers' strategic responses predicted by the theory.

Second, even though the sellers' bunching responses in asking price are large, these responses are attenuated by price escalation in the event of multiple offers, resulting in a lower degree of bunching at the sales price. In central Toronto, the number of sales that the MI adds to the million dollar price bin represents about 96% increase in homes that would have been sold in this region in the absence of the policy. The majority of bunching in sales price come from homes that would have otherwise been sold above \$1M. This suggests that the policy cools down the targeted segment in the desired direction, although its magnitude is dampened by the heightened competition between constrained and unconstrained bidders.

Third, consistent with the notion of heightened competition and increased buyer-seller ratio below \$1M, we find sharp, non-parametric evidence that housing markets right below \$1M experience a shorter time on the market and a larger fraction of above asking sales.

Fourth, the estimated bunching effects on asking and sales price are about twice in central Toronto than in suburban Toronto. This evidence, along with the observation that buyers of million dollar homes in Toronto's periphery are less financially constrained than their counterparts in the urban core, aligns well with the theoretical prediction.

Overall, we find that the estimated market responses to the policy are remarkably consistent with the model. Everything considered, the analysis points to the importance of designing macroprudential policies that recognize strategic responses in sellers' listing choice and buyers' search decision.

We emphasize that mortgage insurance is a key component of housing finance systems in many countries, including the United States, the United Kingdom, the Netherlands, Hong Kong, France, and Australia. These countries share two important institutional features with Canada: (i) the requirement that most lenders insure high loan-to-value (LTV) mortgages, and (ii) the central role of the government in providing such insurance.[8] These features give policymakers "exceptional power to affect housing finance through the key role of government-backed mortgage insurance" (Krznar and Morsink, 2014). Thus the lessons learned in this paper are important not only for Canada, but also for many nations around the world.

The paper proceeds as follows. The next section discusses related literature. In Section 3 we provide an overview of the Canadian housing market and the institutional details of the mortgage insurance market. In section 4 we develop a theoretical model, characterize the directed search equilibrium, and derive a set of empirical implications. In sections 5 and 6 we discuss the data, outline our empirical strategy, and present our results on the impact of the MI policy. Section 7 concludes.

[8] The MI market in the U.S., for example, is dominated by a large government-backed entity, the Federal Housing Administration (FHA), and MI is required for all loans with a LTV ratio greater than 80 percent. Indeed, in the US, over 1.1 trillion US dollars of mortgages are insured by the government-backed Federal Housing Administration (FHA) and the US Congress is reviewing proposals that would make the US MI system similar to that used in Canada. See Option 3 in "Reforming America's Housing Finance Market, A Report to Congress." February 2011. *The US Treasury and the US Department of Housing and Urban Development.*

2 Literature Review

Financial constraints (sometimes called "credit" or "borrowing" or "collateral" or "financing" or "liquidity" constraints) are a recurring theme of the literature on the housing markets. While much of the literature has focused on the impact of financial constraints on individual households' consumption-savings decision (Hayashi, 1985; Hurst and Lusardi, 2004; Lehnert, 2004) and rent versus buy choice (Linneman and Wachter, 1989; Gyourko et al., 1999), less work examines the macro consequences of financial constraints on house price, trading volume, and price volatility. Our paper is closely linked to the latter. On the theory front, a typical form of financial constraints that has been modelled is down-payment requirements. Focusing on repeated homebuyers, Stein (1995) demonstrates that tight down-payment constraints can result in lower house prices and fewer transactions. Extending Stein's idea into a dynamic setting, Ortalo-Magne and Rady (2006) show that down-payment constraints delay some households' first home purchase and force other to buy a house smaller than they would like, resulting in a lower house price. Both Stein (1995) and Ortalo-Magne and Rady (2006) take a partial equilibrium approach as they assume fixed housing supply. Favilukis et al. (2017) are among the first that explicitly incorporates housing production response in modelling the impact of financial constraints. In dong so, they show that in a general equilibrium setting the only way that a relaxation of financial constraints could lead to a housing boom is through a reduction in the housing risk premium. Our paper adds to this literature by taking an alternative approach to the general equilibrium analysis. In particular, we provide a search theoretical analysis to model buyers and sellers' search and listing decisions in a two-sided housing market. In this regard, our work is also close to a line of literature on search and matching in housing (e.g., Wheaton 1990, Krainer 2001, Williams 1995, Genesove and Han 2012). Unlike our paper, none of these search papers incorporates credit market imperfections. In this sense, the theoretical analysis in our paper is the first search theoretical analysis that models the role of financial constraints in housing markets.[9]

[9]For other studies that consider downpayments or credit frictions in housing markets, see Corbae and Quintin (2015), Landvoigt et al. (2015), Fuster and Zafar (2016), Duca et al. (2016), and Acolin et al. (2016).

Turning to the empirical literature, financial constraints are defined much more broadly.[10] In understanding the recent financial crisis, much focus has been placed on examining the role of financial constraints in explaining housing booms and busts. For example, Vigdor (2006), Duca et al. (2011), Berkovec et al. (2012) show that a relaxation of financial constraints results in a boom in house prices; Agarwal et al. (2017) show that increased intensity of mortgage renegotiations leads to reduced foreclosure rates and higher house price growth; Agarwal et al. (2017) show that credit supply restrictions can lead to adverse selection in the market for mortgage loans; Mian and Sufi (2009) link the expansion of mortgage credit to higher initial house prices and subsequent elevated default rates, which further lead to price declines; and Demyanyk and Van Hemert (2011) demonstrate that extreme credit constraints can result in a lower housing prices and fewer transactions because negative equity prevents some households from moving. Our empirical work differs from this body of work in the form of financial constraints, the level of the data, and the nature of the outcomes. As we emphasize above, the micro-level of the transaction data, combined with the natural experimental opportunity arising from the mortgage insurance restriction, greatly helps us in isolating the casual effect of the MI policy on the asking price, sales price and time on the market. We also exploit the geographical variation in the effects of the MI policy and linked that to the share of constrained households.

Finally, our paper contributes to work on macroprudential policies. Due to the carnage created by the Great Recession, macroproudential tools transformed from esoteric and rarely considered ideas, to prominent policy vehicles Blanchard et al. (2010). Naturally, with emergence of these policies, a growing literature developed to investigate their effects. For example, Allen et al. (2016) use loan-level data to examine the macroprudential policies on mortgage contract characteristics and mortgage demand. In contrast, our paper examines the policy impact on housing market outcomes.

[10] They take the form of downpayment constraints (Lamont and Stein, 1999; Genesove and Mayer, 2001), debt-to-income ratio (Demyanyk and Van Hemert, 2011), borrowing against existing housing equity (Mian and Sufi, 2011), mortgage contract terms (Berkovec et al., 2012), and innovations in easing the access to mortgages (Vigdor, 2006).

3 Background

Since 2000 Canada has experienced one of the world's largest modern house price booms, with prices surging 150 percent between 2000 and 2014. Moreover, in contrast to other large housing markets like those in the U.S., homes in Canada suffered only minor price depreciation during the Great Recession. Figure 2 plots the national house price indices for Canada and the U.S.[11] As home prices in Canada continued to escalate post-financial crisis, the Canadian government and outside experts became increasingly concerned that rapid price appreciation would eventually lead to a severe housing market correction.[12] To counter the potential risks associated with the house price boom, the Canadian government implemented four major rounds of housing market macroprudential regulation between July 2008 and July 2012.[13] Interventions included increasing minimum down payment requirements (2008); reducing the maximum amortization period for new mortgage loans (2008, 2011, 2012); reducing the borrowing limit for mortgage refinancing (2010, 2011, 2012); increasing homeowner credit standards (2008, 2010, 2012); and limiting government-backed high-ratio[14] MI to homes with a purchase price of less than \$1M (the focus of this paper).

3.1 Mortgage Insurance in Canada

Mortgage insurance is a financial instrument used to transfer mortgage default risk from the lender to the insurer. For federally regulated financial institutions in Canada, insurance is legally required for any mortgage loan with an LTV ratio higher than 80 percent.[15] Mort-

[11] These are monthly repeat-sales house price indices. Sources: Teranet (Canada) and S&P Case-Shiller (U.S.) downloaded from Datastream (series ID numbers: USCSHP20F and CNTNHPCMF).

[12] In 2013, Jim Flaherty, Canada's Minister of Finance from February 2006 to March 2014, stated: "We [the Canadian government] have to watch out for bubbles - always - . . . including [in] our own Canadian residential real estate market, which I keep a sharp eye on." Further, Robert Shiller observed in 2012 that "what is happening in Canada is kind of a slow-motion version of what happened in the U.S." Sources: "Jim Flaherty vows to intervene in housing market again if needed." *The Globe and Mail*, November 12, 2013; and "Why a U.S.-style housing nightmare could hit Canada." *CBC News*, September 21, 2012.

[13] For a summary of the changes made to the MI rules in Canada, see Box 2 on page 24 of the Bank of Canada's December 2012 Financial System Review.

[14] A *high-ratio* mortgage loan is defined as one with a LTV ratio above 80 percent.

[15] Most provincially regulated institutions are subject to this same requirement. Unregulated institutions, in contrast, are not required to purchase MI. The unregulated housing finance sector in Canada, however, accounts for only five percent of all Canadian mortgage loans (Crawford et al., 2013).

gage originators can purchase MI from private insurers, but the largest mortgage insurer in Canada is the government-owned Canada Mortgage and Housing Corporation (CMHC). The Canadian government provides guarantees for both publicly and privately insured mortgages, and therefore all mortgage insurers are subject to financial market regulation through the Canadian Office of the Superintendent of Financial Institutions (OFSI). The MI requirement for high LTV mortgage loans and the influence of the government in the market for MI make it a potentially effective macroprudential tool.

3.2 The Canadian Mortgage Insurance Regulation of 2012

In June of 2012, the Canadian federal government passed a law that limited the availability of government-back MI for high LTV mortgage loans to homes with a purchase price of less than one million Canadian dollars. To purchase a home for $1M or more, the 2012 regulation effectively imposes a minimum down payment requirement of 20 percent.[16] The aim of the regulation was twofold: to increase borrower creditworthiness and curb price appreciation in high price segments of the housing market. The law was announced on June 21, 2012, and effected July 9, 2012. Moreover, anecdotal evidence suggests that the announcement of the MI policy was largely unexpected by market participants.[17]

4 Theory

To understand how the MI policy affects strategies and outcomes in the million dollar segment of the housing market, we present a two-sided search model that incorporates auction mechanisms and financially constrained buyers. We characterize a directed search equilibrium and describe the implications of the MI policy on transaction outcomes and the social welfare derived from housing market transactions.

[16]Under the new rules, even OFSI-regulated private insurers are prohibited from insuring mortgage loans when the sales price is greater than or equal to $1M and the LTV ratio is over 80 percent (see Crawford et al. 2013 and Krznar and Morsink 2014).

[17]See "High-end mortgage changes seen as return to CMHC's roots." *The Globe and Mail*, June 23, 2012

4.1 Environment

Agents. There is a fixed measure $\mathcal{B}$ of buyers, and a measure of sellers determined by free entry. Buyers and sellers are risk neutral. Each seller owns one indivisible house that she values at zero (a normalization). Buyer preferences are identical; a buyer assigns value $v > 0$ to owning the home. No buyer can pay more than some fixed $u \leq v$, which can be viewed as a common income constraint (e.g., debt-service constraint).

MI policy. The introduction of the MI policy causes some buyers to become more severely *financially constrained*. Post-policy, a fraction Λ of buyers are unable to pay more than c, where $c < u$. Parameter c corresponds to the \$1M threshold, and Λ reflects the share of potential buyers with insufficient wealth from which to draw a 20 percent down payment. Parameter restrictions $c < u \leq v$ can be interpreted as follows: all buyers may be limited by their budget sets, but some are further financially constrained by a binding wealth constraint (i.e., minimum down payment constraint) following the implementation of the MI policy. Buyers with financial constraint c are hereinafter referred to as *constrained* buyers, whereas buyers willing and able to pay up to u are termed *unconstrained*.

Search and matching. The matching process is subject to frictions which we model with an urn-ball meeting technology. Each buyer meets exactly one seller. From the point of view of a seller, the number of buyers she meets is a random variable that follows a Poisson distribution. The probability that a seller meets exactly $k = 0, 1, \ldots$ buyers is

$$\pi(k) = \frac{e^{-\theta}\theta^k}{k!}, \tag{1}$$

where θ is the ratio of buyers to sellers and is often termed *market tightness*. The probability that exactly j out of the k buyers are unconstrained is

$$\phi_k(j) = \binom{k}{j}(1-\lambda)^j \lambda^{k-j}, \tag{2}$$

which is the probability mass function for the binomial distribution with parameters k and

$1 - \lambda$, where λ is the share of constrained buyers. Search is *directed* by asking prices in the following sense: sellers post a listing containing an asking price, $p \in \mathbb{R}_+$, and buyers direct their search by focusing exclusively on listings with a particular price. As such, θ and λ are endogenous variables specific to the group of buyers and sellers searching for and asking price p.

Price determination. The price is determined in a second-price sealed-bid auction. The seller's asking price, $p \in \mathbb{R}_+$, is interpreted as the binding reserve price. If a single bidder submits an offer at or above p, he pays only p. In multiple offer situations, the bidder submitting the highest bid at or above p wins the house but pays either the second highest bid or the asking price, whichever is higher. When selecting among bidders with identical offers, suppose the seller picks one of the winning bidders at random with equal probability.

Free entry. The measure of sellers is determined by free entry so that overall market tightness is endogenous.[18] Supply side participation in the market requires payment of a fixed cost x, where $0 < x < c$. It is worthwhile to enter the market as a seller if and only if the expected revenue exceeds the listing cost.

4.2 Equilibrium

4.2.1 The Auction

When a seller meets k buyers, the auction mechanism described above determines a game of incomplete information because bids are sealed and bidding limits are private. In a symmetric Bayesian-Nash equilibrium, it is a dominant strategy for buyers to bid their maximum amount, c or u. When $p > c$ ($p > u$), bidding limits preclude constrained (and unconstrained) buyers from submitting sensible offers.

[18] Entry on the supply side of the market is a common approach to endogenizing housing market tightness in directed search models with auctions (e.g., Albrecht et al., 2016 and **?**, **?**). The alternative (i.e., buyer entry) would be less straightforward in our context given that the demand side of the market is homogeneous pre-policy but heterogeneous thereafter.

4.2.2 Expected payoffs

Expected payoffs are computed taking into account the matching probabilities in (1) and (2). These payoffs, however, are markedly different depending on whether the asking price, p, is above or below a buyer's ability to pay. Each case is considered separately in Appendix A.1. In the *submarket* associated with asking price p and characterized by market tightness θ and buyer composition λ, let $V^s(p, \lambda, \theta)$ denote the sellers' expected net payoff. Similarly, let $V^c(p, \lambda, \theta)$ and $V^u(p, \lambda, \theta)$ denote the expected payoffs for constrained and unconstrained buyers.

For example, if the asking price is low enough to elicit bids from both unconstrained and constrained buyers, the seller's expected net payoff is

$$V^s(p \leq c, \lambda, \theta) = -x + \pi(1)p + \sum_{k=2}^{\infty} \pi(k) \left\{ [\phi_k(0) + \phi_k(1)]\, c + \sum_{j=2}^{k} \phi_k(j) u \right\}.$$

Substituting expressions for $\pi(k)$ and $\phi_k(j)$ and recognizing the power series expansion of the exponential function, the closed-form expression is

$$\begin{aligned} V^s(p \leq c, \lambda, \theta) = -x + \theta e^{-\theta} p + \left[1 - e^{-\theta} - \theta e^{-\theta}\right] c \\ + \left[1 - e^{-(1-\lambda)\theta} - (1-\lambda)\theta e^{-(1-\lambda)\theta}\right] (u - c). \end{aligned}$$

The second term reflects the surplus from a transaction if she meets only one buyer. The third and fourth terms reflect the surplus when matched with two or more buyers, where the last term is specifically the additional surplus when two or more bidders are unconstrained.

The expected payoff for a buyer, upon meeting a particular seller, takes into account the possibility that the seller meets other constrained and/or unconstrained buyers as per the probabilities in (1) and (2). The expected payoff for a constrained buyer in this case is

$$V^c(p \leq c, \lambda, \theta) = \pi(0)(v - p) + \sum_{k=1}^{\infty} \pi(k)\phi_k(0) \frac{v - c}{k + 1}$$

and the closed-form expression is

$$V^c(p \leq c, \lambda, \theta) = \frac{e^{-(1-\lambda)\theta} - e^{-\theta}}{\lambda\theta}(v - c) + e^{-\theta}(c - p).$$

The first term is the expected surplus when competing for the house with other constrained bidders; the last term reflects the possibility of being the only buyer. Note that whenever an unconstrained buyer visits the same seller, the constrained buyer is outbid with certainty and loses the opportunity to purchase the house. Finally, the expected payoff for an unconstrained buyer can be similarly derived to obtain

$$\begin{aligned} V^u(p \leq c, \lambda, \theta) &= \pi(0)(v - p) + \sum_{k=1}^{\infty} \pi(k) \left[\phi_k(0)(v - c) + \sum_{j=1}^{k} \phi_k(j) \frac{v - u}{j + 1} \right] \\ &= \frac{1 - e^{-(1-\lambda)\theta}}{(1 - \lambda)\theta}(v - u) + e^{-(1-\lambda)\theta}(u - c) + e^{-\theta}(c - p). \end{aligned}$$

The first term is the expected surplus when competing for the house with other unconstrained bidders, and the second term is the additional surplus when competing with constrained bidders only. In that scenario, the unconstrained bidder wins the auction by outbidding the other constrained buyers, but pays only c in the second-price auction. The third term represents the additional payoff for a monopsonist. Closed-form solutions for the other cases are derived in Appendix A.1.

4.2.3 Directed Search

Agents perceive that both market tightness and the composition of buyers depend on the asking price. To capture this, suppose agents expect each asking price p to be associated with a particular ratio of buyers to sellers $\theta(p)$ and fraction of constrained buyers $\lambda(p)$. We will refer to the triple $(p, \lambda(p), \theta(p))$ as *submarket p*. When contemplating a change to her asking price, a seller anticipates a corresponding change in the matching probabilities and bidding war intensity via changes in tightness and buyer composition. This is the sense in which search is *directed*. It is convenient to define $V^i(p) = V^i(p, \lambda(p), \theta(p))$ for $i \in \{s, u, c\}$.

Definition 1. A *directed search equilibrium* (DSE) is a set of asking prices $\mathbb{P} \subset \mathbb{R}_+$; a distribution of sellers σ on $\mathbb{R}_+$ with support $\mathbb{P}$, a function for market tightness $\theta : \mathbb{R}_+ \to \mathbb{R}_+ \cup +\infty$, a function for the composition of buyers $\lambda : \mathbb{R}_+ \to [0, 1]$, and a pair of values $\{\bar{V}^u, \bar{V}^c\}$ such that:

1. optimization:

   (i) sellers: $\forall p \in \mathbb{R}_+$, $V^s(p) \leq 0$ (with equality if $p \in \mathbb{P}$);

   (ii) unconstrained buyers: $\forall p \in \mathbb{R}_+$, $V^u(p) \leq \bar{V}^u$ (with equality if $\theta(p) > 0$ and $\lambda(p) < 1$);

   (iii) constrained buyers: $\forall p \in \mathbb{R}_+$, $V^c(p) \leq \bar{V}^c$ (with equality if $\theta(p) > 0$ and $\lambda(p) > 0$);

   where $\bar{V}^i = \max_{p \in \mathbb{P}} V^i(p)$ for $i \in \{u, c\}$; and

2. market clearing:

$$\int_{\mathbb{P}} \theta(p)\, d\sigma(p) = \mathcal{B} \quad \text{and} \quad \int_{\mathbb{P}} \lambda(p)\theta(p)\, d\sigma(p) = \Lambda\mathcal{B}.$$

The definition of a DSE is such that for every $p \in \mathbb{R}_+$, there is a $\theta(p)$ and a $\lambda(p)$. Part 1(i) states that θ is derived from the free entry of sellers for active submarkets (*i.e.*, for all $p \in \mathbb{P}$). Similarly, parts 1(ii) and 1(iii) require that, for active submarkets, λ is derived from the composition of buyers that find it optimal to search in that submarket. For inactive submarkets, parts 1(ii) and 1(iii) further establish that θ and λ are determined by the optimal sorting of buyers so that off-equilibrium beliefs are pinned down by the following requirement: if a small measure of sellers deviate by posting asking price $p \notin \mathbb{P}$, and buyers optimally sort among submarkets $p \cup \mathbb{P}$, then those buyers willing to accept the highest buyer-seller ratio at price p determine both the composition of buyers $\lambda(p)$ and the buyer-seller ratio $\theta(p)$. If neither type of buyer finds asking price p acceptable for any positive buyer-seller ratio, then $\theta(p) = 0$, which is interpreted as no positive measure of buyers willing to search in submarket p. The requirement in part 1(i) that $V^s(p) \leq 0$ for $p \notin \mathbb{P}$ guarantees that no deviation to an off-equilibrium asking price is worthwhile from a seller's perspective. Finally, part 2 of the definition makes certain that all buyers search.

4.2.4 Pre-Policy Directed Search Equilibrium

We first consider the initial setting with identically unconstrained buyers by setting $\Lambda = 0$.[19] Buyers in this environment direct their search by targeting the asking price that maximizes their expected payoff given bidding limit u. Because the buyer correctly anticipates the free entry of sellers, the search problem can be written

$$\bar{V}^u = \max_{p,\theta} V^u(p, 0, \theta) \quad \text{s.t.} \quad p \leq u \quad \text{and} \quad V^s(p, 0, \theta) = 0. \tag{P$_0$}$$

We construct a DSE with a single active submarket with asking price and market tightness determined by the solution to problem P_0, denoted $\{p_0, \theta_0\}$.[20] If the first constraint is slack, the solution is a pair $\{p^*_u, \theta^*_u\}$ satisfying the following first-order condition and the second constraint:

$$x = [1 - e^{-\theta^*_u} - \theta^*_u e^{-\theta^*_u}]v \tag{3}$$

$$\theta^*_u e^{-\theta^*_u} p^*_u = [1 - e^{-\theta^*_u} - \theta^*_u e^{-\theta^*_u}](v - u). \tag{4}$$

If the first constraint in problem P_0 binds, the solution is instead $\{u, \theta_u\}$, where θ_u satisfies the free entry condition $V^s(u, 0, \theta_u) = 0$.

The following proposition provides a partial characterization of the pre-policy DSE constructed using the solution to problem P_0.

[19] A DSE when $\Lambda = 0$ is defined according to Definition 1 except that we impose $\lambda(p) = 0$ for all $p \in \mathbb{R}_+$ and ignore condition 1(iii).

[20] The same active submarket can instead be determined by solving the seller's price posting problem and imposing free entry. Specifically, sellers set an asking price to maximize their expected payoff subject to buyers achieving their market value $\bar{V}^u$. The seller must also take into account buyers' bidding limit, u. The seller's asking price setting problem is therefore

$$\max_{p,\theta} V^s(p, 0, \theta) \quad \text{s.t.} \quad p \leq u \quad \text{and} \quad V^u(p, 0, \theta) = \bar{V}^u. \tag{P$'_0$}$$

Proposition 1. *There is a DSE with $\mathbb{P} = \{p_0\}$, $\theta(p_0) = \theta_0$ and $\bar{V}^u = V^u(p_0, 0, \theta_0)$.*

As buyers' ability to pay approaches their willingness to pay (i.e., as $u \to v$), the equilibrium asking price tends to zero (i.e., $p_0 = p_u^* \to 0$), which is the seller's reservation value. This aligns with standard results in the competing auctions literature in the absence of bidding limits (McAfee, 1993; Peters and Severinov, 1997; Albrecht et al., 2014; Lester et al., 2015). When buyers' bidding strategies are somewhat limited (i.e., $p_0 = p_u^* \leq u < v$), sellers set a higher asking price to capture more of the surplus in a bilateral match. The equilibrium asking price is such that the additional bilateral sales revenue (the left-hand side of equation (4) exactly compensates for the unseized portion of the match surplus when two or more buyers submit offers but are unable to bid up to their full valuation (the right-hand size of equation (4). Equilibrium expected payoffs in this case are independent of u. When buyers' bidding strategies are too severely restricted (i.e., $p_0 = u < p_u^*$), the seller's choice of asking price is constrained by the limited financial means of prospective buyers. Asking prices in equilibrium are then set to the maximum amount, namely u. In this case, a seller's expected share of the match surplus is diminished, and consequently fewer sellers choose to participate in the market (i.e., $\theta_u > \theta_u^*$).[21]

4.2.5 Post-Policy Directed Search Equilibrium

As in section 4.2.4, an active submarket with $p \leq c$ is determined by an optimal search strategy. The search problem of a constrained buyer takes into account the participation of both sellers and unconstrained buyers:

$$\bar{V}^c = \max_{p,\lambda,\theta} V^c(p, \lambda, \theta) \quad \text{s.t.} \quad p \leq c, \quad V^s(p, \lambda, \theta) = 0 \quad \text{and} \quad V^u(p, \lambda, \theta) \geq \bar{V}^u. \tag{P$_1$}$$

Let $\{p_1, \lambda_1, \theta_1\}$ denote the solution to problem P$_1$ when $\bar{V}^u$ is set equal to the maximized objective of problem P$_0$. If the first constraint is slack, the solution is $\{p_c^*, \lambda_c^*, \theta_c^*\}$ satisfying

[21] Using (3) and (4) to define p_u^*, inequality $u < p_u^*$ can be written $\left[1 - e^{-\theta_u^*}\right] u < x$. Moreover, the free entry condition $V^s(u, 0, \theta_u) = 0$ is equivalent to $\left[1 - e^{-\theta_u}\right] u = x$. Combining this equality with the previous inequality yields $\theta_u > \theta_u^*$.

the last two constraints with equality and a first-order condition derived in Appendix **??**. If the first constraint binds, the solution is instead $\{c, \lambda_c, \theta_c\}$, where λ_c and θ_c satisfy the free entry condition $V^s(c, \lambda_c, \theta_c) = 0$ and an indifference condition for unconstrained buyers $V^u(c, \lambda_c, \theta_c) = \bar{V}^u$. As long as the aggregate share of constrained buyers, Λ, does not exceed λ_1, we can construct an equilibrium with two active submarkets associated with asking prices p_0 and p_1.

Proposition 2. *Suppose $\Lambda \leq \lambda_1$. There is a DSE with $\mathbb{P} = \{p_0, p_1\}$, $\lambda(p_0) = 0$, $\theta(p_0) = \theta_0$, $\lambda(p_1) = \lambda_1$, $\theta(p_1) = \theta_1$, $\bar{V}^c = V^c(p_1, \lambda_1, \theta_1)$ and $\bar{V}^u = V^u(p_0, 0, \theta_0) = V^u(p_1, \lambda_1, \theta_1)$.*

Intuitively, some unconstrained buyers prefer to search alongside constrained buyers because they can out-bid them. If the fraction of constrained buyers is not too high (i.e., $\Lambda < \lambda_c^*$), the DSE features partial pooling (i.e., only some unconstrained buyers search for homes priced at p_1 while the rest search in submarket p_0). As $\Lambda \to \lambda_1$, it can be shown that $\sigma(p_0) \to 0$ and the DSE converges to one of full pooling (i.e., all buyers and sellers participate in submarket p_1). Finally, if $\Lambda > \lambda_1$, market clearing (part 2 of Definition 1) is incompatible with unconstrained buyer indifference between these two submarkets, which begets the possibility of full pooling with unconstrained buyers strictly preferring to pool with constrained buyers. We sacrifice completeness for conciseness and convenience by restricting attention to settings with $\Lambda \leq \lambda_1$.[22]

For many sets of parameter values satisfying $0 < x < c < u \leq v$, the financial constraint $p \leq c$ in problem P_1 binds and a consequence of the MI policy is therefore a mass of asking prices and sales prices at threshold c. These and other empirical implications are the focus of the next section.

[22]We construct fully pooling DSE numerically when $\Lambda > \lambda_1$ by increasing $\bar{V}^u$ above the maximized objective of problem P_0 until the share of constrained buyers in the submarket that solves problem P_1 is exactly Λ. A thorough analysis of such DSE, however, would require abandoning the analytical convenience of block recursivity (i.e., the feature that equilibrium values and optimal strategies do not depend on the overall composition of buyers).

4.3 Empirical Predictions

This section summarizes the consequences of the MI policy by comparing the pre- and post-policy directed search equilibria. There are four possible cases to consider depending on whether the financial constraints $p \leq u$ and $p \leq c$ bind in problems P_0 and P_1. In this section we focus on the case where the relevant financial constraint is slack in problem P_0 but binds in problem P_1. In other words, we consider the possibility that pre-existing financial constraints are not restrictive enough to affect expected payoffs and seller entry in the pre-policy equilibrium, but that the additional financial constraint imposed by the MI policy is sufficiently severe to bind some households. Under this assumption, the equilibrium asking prices are $p_0 = p_u^*$ and $p_1 = c$. There are still two possible subcases: (i) $p_u^* \leq c$ and (ii) $p_u^* > c$.

Under the restrictions discussed above, the model has several testable predictions that we bring to the data in Section 6. Some of these predictions rely on additional analytical results, which are summarized in the following lemma:

Lemma 1. *(i) $\sigma(p_0) = \mathcal{B}/\theta_0$ in the pre-policy DSE. In the post-policy DSE,*

$$\sigma(p_0) = \frac{(\lambda_1 - \Lambda)\mathcal{B}}{\lambda_1 \theta_0} \quad \textit{and} \quad \sigma(p_1) = \frac{\Lambda \mathcal{B}}{\lambda_1 \theta_1}. \tag{5}$$

(ii) $p_0 \leq p_1$ implies $(1 - \lambda_1)\theta_1 \leq \theta_0$.

(iii) $p_0 > p_1$ implies $\theta_0 < (1 - \lambda_1)\theta_1 < \theta_1$.

Prediction 1. *The MI policy motivates some sellers to change their asking price from p_0 to p_1. This represents an increase (decrease) in the set of asking asking prices if $p_u^* \leq c$ ($p_u^* > c$).*

As per Propositions 1 and 2, the set of asking prices changes from just $\mathbb{P} = \{p_0\}$ pre-policy to $\mathbb{P} = \{p_0, p_1\}$ post-policy. Following the introduction of the policy, some or all sellers find it optimal to target buyers of both types by asking price $p_1 = c$. The measure of sellers participating in submarket p_0 is lower post-policy (see part (i) of Lemma 1). Both the introduction of homes listed at p_1 and the smaller measure of homes listed at p_0 contribute to the increase (decrease) in the set of equilibrium asking prices when $p_0 = p_u^* \leq c$ ($p_0 = p_u^* > c$).

Prediction 1 suggests that the MI can generate large behavioural response among sellers in the segments nearby \$1M. It induces some sellers who would have otherwise listed below \$1M ($p_0 \leq c$) to raise the asking price. It also induces some sellers who would have otherwise listed above \$1M ($p_0 > c$) to reduce the asking price. Together, these create an excess mass of sellers listing their homes at the \$1M. Figures 11 and 12 provide a graphical illustration for each of these two cases.

Prediction 2. *The MI policy decreases (increases) these sellers' matching probabilities with unconstrained buyers, resulting in a lower (higher) incidence of price escalation up to u if $p_0 \leq p_1$ ($p_0 > p_1$).*

If $p_1 = c < p_0$, an implication of the indifference condition for unconstrained buyers between submarkets p_0 and p_1 when $\Lambda \leq \lambda_1$ is $\theta_0 < (1 - \lambda_1)\theta_1$ (see part (iii) of Lemma 1). It follows that the MI policy shifts the Poisson distribution that governs the random number of unconstrained buyers meeting each particular seller in the sense of first-order stochastic dominance. The MI policy therefore increases the overall share of listed homes selling for u. If instead $p_0 \leq c = p_1$, the indifference condition for unconstrained buyers implies the opposite, namely $\theta_0 \geq (1 - \lambda_1)\theta_1$ (see part (ii) of Lemma 1). In that case, the MI policy lowers the probability of multiple offers from unconstrained buyers. Figures 13 and 14 present graphical illustrations.

Prediction 3. *Predictions 1 and 2 have opposing effects on equilibrium sales prices, resulting in a less dramatic impact of the MI policy on sales prices relative to asking prices.*

The MI policy's effect on sales prices is mitigated by the auction mechanism and the pooling of buyers. When sellers' equilibrium price-posting strategies are such that asking prices increase (decrease), the equilibrium search strategies of unconstrained buyers imply a lower (higher) incidence of price escalation up to u, resulting in a relatively smaller excess mass of sales price at the \$1M, compared to the asking price. Figures 15 and 16 present graphical illustrations.

Prediction 4. *The share of total post-policy market activity in submarket p_1 is increasing in Λ.*

Given that λ_1 and θ_1 are independent of Λ, $\sigma(p_1)$ increases linearly with Λ (see part (i) of Lemma 1). In contrast, the post-policy measure of sellers in submarket p_0 decreases linearly with Λ. It follows that higher values of Λ are associated with a higher relative share of activity in submarket p_1. Prediction 4 therefore implies a more dramatic impact of the the MI policy on asking and sales prices at bidding limit c if it constrains a larger fraction of potential buyers. To show this, Figures 17 and 18 plot the expected asking price and sales price as a function of the fraction of constrained buyers.

4.4 Welfare Discussion

To explore the normative implications of the MI policy, we compare the pre- and post-policy social surplus generated by housing market activity. As described in section 3, the MI policy was introduced to counter the potential risks associated with a house price boom. Characterizing the potential benefits to the financial system is beyond the scope of the model. The normative analysis that follows should instead be viewed as a description of the direct welfare implications of the MI policy on housing market participants.

The welfare of market participants (i.e., total social surplus net of listing costs, normalized by dividing by the fixed measure of buyers, $\mathcal{B}$) can be written

$$W(\theta) = \frac{\left[1 - e^{-\theta}\right] v - x}{\theta}. \tag{6}$$

The welfare maximizing level of market activity is implemented when the ratio of buyers to sellers is θ_u^*, which is achieved in the benchmark pre-policy DSE whenever $p_0 = p_u^* \leq u$. The post-policy DSE, however, features a change in the total number of sales as θ_1 is not generally equal to θ_0. For example, when $p_1 = c < p_0 \leq u$, part (iii) of Lemma 1 states that $\theta_0 < \theta_1$. The decline in overall market activity implies a reduction in the welfare of market participants (*i.e.* a decline in total social surplus net of listing costs). With free-entry on the supply side, these welfare costs are borne by the share of buyers that are financially constrained by the MI policy.[23]

5 Data

Our data set includes all transactions of single-family houses in the Greater Toronto Area from January 1 2010 to December 31 2013. For each transaction, we observe asking price, sales price, days on the market, transaction date, location, as well as detailed housing characteristics. Since the MI policy took effect in July of 2012, the *pre-policy period* is defined as July 2011 to June 2012 and the *post-policy period* is defined as July 2012 to June 2013. For the purposes of assigning a home to a pre- or post-policy date, we use the date the house was listed.

Table 1 contains summary statistics for detached, single-family homes in the city of Toronto. Our data include $15,882$ observations in the pre-policy period and $13,577$ observations in the post-policy period. The mean sales price in Toronto was $\$723,060.60$ in the pre-policy period and $\$761,472.48$ in the post-policy period, reflecting continued rapid price growth for single family houses. Our focus is on homes near the \$1M threshold, which corresponds to approximately the 86th percentile of the pre-policy price distribution. There were 955 homes sold within \$100,000 of \$1M in the pre-policy period, and 941 in the post-policy period.

Table 2 reports the same statistics for central Toronto. Homes in the central district are substantially more expensive: a million dollar home represents the median home in central Toronto; while a million dollar home lies at the top 5th percentile of the house price distribution in suburban Toronto (not shown). Nearly 60 percent of all homes sold pre-policy in Toronto for a price within \$100,000 of \$1M are located in central Toronto.

[23] When $\Lambda > \lambda_1$, the unconstrained buyers in fact benefit at the expense of the constrained buyers.

6 Empirical Evidence

We now present empirical tests of the four predictions derived in Section 4. Given that the policy was targeted at cooling the million dollar segment, our main analysis is restricted to central Toronto, where a home of $1M represent a median home. We begin in Subsection 6.1 with tests of Predictions 1 and 3. In Subsection 6.2 presents a test of Prediction 2. Later, in Section 6.3, we repeat the same analysis for suburban Toronto, where home buyers for million dollar homes are considered less financially constrained. This, combined with the evidence in central Toronto, is interpreted as the evidence for Prediction 4.

6.1 Predictions 1 and 3 : The Effects of MI on Asking Price and Sales Price

The main implication of the model is that the MI leads to a sharp bunching of the asking price and sales price at the million dollar, with the asking price effect larger than the sales price. To measure these market responses, we compare the observed distribution of post-policy price changes (relative to the pre-policy period) to a counterfactual distribution of price changes. The key assumption underlying our strategy is that we have an accurate estimate of the counterfactual distribution that mimics the empirical distribution assuming there were no shifts in housing characteristics and no policy changes. We do so in two steps. First, we construct a counterfactual price distribution that would have prevailed if there were no composition changes of housing stock in each price segment. Based on this, we further construct a counterfactual distribution in the absence of the MI policy.

6.1.1 First stage: controlling for housing composition

When taking the predictions to the data, one challenge we face is that the model is featured with homogenous housing while in reality houses differ along many dimensions. If houses listed or sold in the $1M segment in the post-policy year are generally in better condition than in the previous year, then the difference between the actual price distribution and the counterfactual price distribution could simply reflect the changes in the composition of housing rather than the policy effect. We rule out this concern by leveraging the richness of our data to flexibly control for the complete set of observed house characteristics to back out a counterfactual distribution of of house prices that would have prevailed period if the characteristics of houses in the post-period were the same as in the pre-period.

Let Y_t denote the (asking or sale) price of a house and let X_t denote the characteristics of a house that affect prices, for $t = 0$, the pre-policy period, and $t = 1$, the post-policy period. The conditional distribution functions $F_{Y_0|X_0}(y|x)$ and $F_{Y_1|X_1}(y|x)$ describe the stochastic assignment of prices to houses with characteristics x in each of the periods. Let $F_{Y\langle 0|0\rangle}$ and $F_{Y\langle 1|1\rangle}$ represent the observed distribution of house prices in each period. We are interested in $F_{Y\langle 1|0\rangle}$, the counterfactual distribution of house prices that would have prevailed in the post-period if the characteristics of the houses in the post-period were as in the pre-period. We can decompose the observed change in the distribution of house prices:

$$\underbrace{F_{Y\langle 1|1\rangle} - F_{Y\langle 0|0\rangle}}_{\Delta_O=\text{Observed}} = \underbrace{\left[F_{Y\langle 1|1\rangle} - F_{Y\langle 1|0\rangle}\right]}_{\Delta_X=\text{Composition}} + \underbrace{\left[F_{Y\langle 1|0\rangle} - F_{Y\langle 0|0\rangle}\right]}_{\Delta_S=\text{Price Structure}}. \tag{7}$$

Since the counterfactual is not observed, it must be estimated. Following Chernozhukov et al. (2013), we use the plug-in rule:

$$\hat{F}_{Y\langle 1|0\rangle} = \int \hat{F}_{Y_1|X_1}(y|x) d\hat{F}_{X_0}(x)$$

To estimate the covariate distribution, we use the empirical distribution function. The estimator for $\hat{F}_{Y\langle 1|0\rangle}$ is obtained with a distribution regression. Namely,

$$\hat{F}_{Y_1|X_1}(y|x) = \Lambda\left(x_1'\hat{\beta}_1(y)\right), \text{ for each } y \in Y.$$

To implement this estimator, we create a set of cut-off prices, $\{y_1, \ldots, y_J\}$. For each cut-off, we create a dummy variable $1[Y_i \leq y_j]$ indicating whether a house i had a price below the threshold y_j. The function $\Lambda(\cdot)$ is a link function. If $\Lambda(\cdot)$ is the identity function, then the procedure requires estimating a series of regressions (ie, linear probability models), one for each threshold $j \in J$. The coefficients $\beta_1(y)$ vary by threshold, providing a flexible way to estimate the conditional distribution function $\hat{F}_{Y_1|X_1}(y|x)$. Once the $\hat{\beta}(y)$ are obtained, the counterfactual distribution is estimated by averaging over the predicted values in using the $F_{X_0}(x)$ distribution:

$$\hat{F}_{Y\langle 1|0\rangle} = \int \Lambda \left(x_0' \hat{\beta}_1(y) \right) d\hat{F}_{X_0}(x).$$

In practice, we define cut-off prices using a grid with intervals of \$5,000.[24] The covariate vector contains indicators for district, month, the number of rooms, whether the basement is finished, and the housing type (detached, semi-detached). Since all of our covariants can be represented by indicators, we choose to use the identity function for $\Lambda(\cdot)$, which results in a linear probability model.[25]

Figure 3 examines the distribution of asking price for $p_j = 500,000, \ldots, 1,400,000$. In panel A, we plot the estimated CDF function for the pre- and post-policy period. The post-period CDF, representedd by the green line, lays everywhere below the pre-period survivor, indicating that all the housing market segments experienced a boom. In panel B, we plot the difference between the two CDF functions. If the CDFs were the same pre- and post-policy for a given bin, the difference would show up as a zero in the figure. We find that the actual difference in CDFs is always below zero and upward sloping, indicating that houses in general are becoming more expensive over time and this effect is larger for lowered priced segments than for higher ones.

Following equation (7), we then decompose the difference in CDFs into two components: (i) price difference due to shifting of housing characteristics in each segment (Panel C); and (ii) price difference due to changes in sellers' listing strategy caused by the MI (Panel D). The latter is the market response that we aim to measure. As shown in Panel C, the price change caused by shifting of housing characteristics is small in magnitude and relatively flat. In contrary, Panel D shows that the price change caused by sellers' listing strategy generally

[24] Smaller price bins allow more flexibility in estimating the underlying house price distribution, while larger bins allow for more precise estimates. All of our results are robust to reasonable deviations from the \$5,000 interval.

[25] We have also assessed robustness to using a logit link-function and the results are essentially the same.

increases smoothly with price, with a relatively large jump at the \$1M threshold. Given the minimal composition effects, nearly all of the shifts in the observed distribution of asking price are driven by sellers' listing strategy.

Figure 4 examines the distribution of sales price for $p_j = 500,000, \ldots, 1,400,000$. One key difference between the sales price in Figure 4 and the asking price in Figure 3 is that the former is much smoother than the latter. The lack of smoothness in the asking price can be attributed to a behavioural response in seller's listing strategy, which caused a fair degree of heaping at certain thresholds in the asking price. As before, Figure 4 shows that (1) the growth exhibits a discrete upward jump at the \$1M threshold, although the magnitude of the jump is smaller than the jump in asking price; and (2) little of the shifts in the distribution of the sales price is driven by the composition change.

Together, the discrete jumps at the \$1M in asking and sales price presented in Figures 3 and 4 are consistent with the model. However, this evidence alone does not distinguish the policy effects from the impact of other common macro forces around the time when the MI policy was implemented and hence is not sufficient for supporting the implications from the theory. To isolate the MI policy's effects on the price distribution, we now turn to the bunching estimation.

6.1.2 Second stage: bunching estimation

With the estimated $\hat{\Delta}_S(y_j) = \hat{F}_{Y\langle 1|0\rangle}(y_j) - \hat{F}_{Y\langle 0|0\rangle}(y_j)$ in hand, we are now ready to estimate the MI effects on asking and sales price. Our estimation is built on the bunching approach recently developed in public finance (Chetty et al. 2011 and Kleven and Waseem 2013), with two slight modifications. First, while previous work on bunching estimation has almost exclusively focused on the densities (e.g., Best and Kleven 2017, DeFusco et al. 2017), we choose to estimate the CDFs. The underlying idea is the same, but the latter allows us to present a more transparent decomposition of the market response to the policy. Nevertheless, we also present a graphical analysis in densities to facilitate our discussion. Second, we take a further step to consider the difference in CDFs to control for heaping at certain thresholds both before and after the MI was implemented. As shown in Figure 3, heaping in asking price could be due to factors such as marketing convention and psychology bias, which may not be well-captured even after including round number effects.

Specifically, we estimate the counterfactual distribution by fitting a flexible polynomial to the empirical distribution, excluding data in a range around \$1M.

$$\begin{aligned}\hat{\Delta}_S(y_j) = \sum_{i=0}^{p} \beta_i \cdot y_j^i + \beta_A \cdot 1[y_j = \$1M] + \beta_B \cdot 1[y_j = \$1M - h] \\ + \sum_{l=1}^{L} \gamma_l \cdot 1[y_j = \$1M - h \cdot (1+l)] + \sum_{r=1}^{R} \alpha_r \cdot 1[y_j = \$1M + h \cdot r] + \epsilon_j \quad (8)\end{aligned}$$

where p is order of polynomial, L is the excluded region to the left of bin just below the cut off, R is the excluded region to the right of the cut off, and h is the bin size.

The total observed jump at the cut-off \$1M is[26]

$$\underbrace{\hat{\Delta}_S(\$1M) - \hat{\Delta}_S(\$1M - h)}_{\text{Jump at threshold}} = \underbrace{\sum_{i=0}^{p} \hat{\beta}_i \cdot y_{\$1M}^i - \sum_{i=0}^{p} \hat{\beta}_i \cdot y_{\$1M-h}^i}_{\text{Counterfactual}} + \underbrace{\hat{\beta}_A - \hat{\beta}_B}_{\text{Total Policy Response}} \quad (9)$$

It is important to note that the interpretation of the total jump is not all causal. Since housing boom is larger in the lower-priced segments, we would expect that the difference in the CDFs to have a jump as we move from the bins from the left to the \$1M bin, even in the absence of the MI. This jump is considered as "counterfactual" and therefore should not be attributed to the policy.

After teasing out the "counterfactual jump," we are left with $\hat{\beta}_A - \hat{\beta}_B$, which is the policy response we aim to measure. A finding of $\hat{\beta}_A > 0$ is consistent with "bunching from above" since it indicates that sellers that would otherwise locate in bins above \$1M now move down to locate in the \$1M bin. A finding of $\hat{\beta}_B < 0$, on the other hand, is consistent

[26]Note that there is no residual component in equation (8) since, through the excluded region, every bin has its own dummy and the fit is exact. We observe the population of house sales during this time, thus, the error term in (8) reflects specification error in our polynomial fit rather than sampling variation. We discuss the computation of our standard errors of our estimates in more detail below.

with "bunching from below" since it indicates that sellers that would otherwise locate below the $\$1M$ bin now move up to locate in the $\$1M$ bin. Both responses are induced by the MI policy. Because of this, the counterfactual omits an excluded region to the left, L, and to the right, R, that are part of the policy response.

The two sources of response described above imply two adding up constraints. In particular, sellers locating from adjacent bins below the threshold come from bins in the region L. Thus, "bunching from below" should equal the the responses from lower adjacent bins, implying

$$R^B \equiv \beta_B - \sum_{l=1}^{L} \gamma_l \cdot 1[y_j = \$1M - h \cdot (1 + l)] = 0 \tag{10}$$

And similarly for those sellers coming from above the threshold:

$$R^A \equiv \beta_A - \sum_{r=1}^{R} \alpha_r \cdot 1[y_j = \$1M + h \cdot r] = 0 \tag{11}$$

Since the number of excluded bins to the below and above are unknown, our estimation procedure is iterative: we estimate a series of equation (8) with different values of L and R in the set $L, R \in \{2, 3, 4\}$ and test the restrictions. If our procedure does not identify a unique set of L and R, we choose the specification that minimizes the sum of the squared restriction errors: $R, L = \min(R^{B^2} + R^{A^2})$. This occurs becomes sometimes we are unable to statistically distinguish between 3 and 4 bins, for example.[27]

The counterfactual is defined by $\sum_{i=0}^{p} \beta_i \cdot y_j^i$, which approximates the difference in $\hat{F}_{Y\langle 1|0\rangle}(y_j) - \hat{F}_{Y\langle 0|0\rangle}(y_j)$ away from the excluded region. To construct this counterfactual, there are still two choices to make: the window of the global polynomial (how many bins on either side of the threshold to include) and the order. We take a pragmatic approach. First, we take a window of 15 bins on either side of the cut-off, which amounts to considering houses in the interval from \$915,000 to \$1075000, and use a third order polynomial. We

[27]It is important to note that our estimation does not depend on the two adding up constraints. As shown in the unreported tables, our results are extremely robust to the different choices of L and R.

choose to take a relatively narrow region around the threshold and a low order polynomial due to the issues raise by Gelman and Imbens (2014) with high-order global polynomials in similar context. We then consider a series of robustness checks to assess the sensitivity of our estimates to these choices.

6.1.3 Results

Figure 5 shows a graphical test of Prediction 1 based on the estimates of equation (8). In particular, we plot both the observed changes in CDFs of the asking price, $\hat{\Delta}_S(y_j) = \hat{F}_{Y\langle 1|0\rangle}(y_j) - \hat{F}_{Y\langle 0|0\rangle}(y_j)$, and the estimated counterfactual changes. The solid connected line plots the observed changes, with each dot representing the difference in the CDFs before and after the policy for each \$5,000 price bin indicated on the x-axis. The dashed connected line plots the counterfactual changes estimated as described in Section 6.1.2. The vertical dashed lines mark the lower limit of the bunching region ($\$975,000$) and the upper limit of the bunching region ($\$1,020,000$). Note that the CDF in each price bin is relative to the CDF in the year before the MI was implemented.

The pattern shown in the figure is striking. Consistent with Prediction 1, the empirical distribution exhibits a sharp discontinuity at the \$1M threshold: moving from the $\$995,000$ bin to the \$1M bin leads to a 0.96% increase in the mass of homes listed. In contrast, the increase in the counterfactual distribution between these two bins is minor — only about 0.06%. Thus much of the bunching we observed at the \$1M is driven by the MI policy.

Figure 6 further presents a graphical test of Prediction 1 based on the difference in densities. The spike in homes listed at the \$1M is accompanied by dips in homes listed to the right of and to the left of \$1M. The spike reflects excess of homes listed in $[\$995,000, \$1,000,000]$ after the implementation of the MI. The dips reflect missing homes that would have been listed away from the \$1M in the absence of the MI.

Column (1) of Table 2 reports the bunching estimates. Standard errors are calculated using the bootstrapping procedure.[28] We find that in total roughly 0.9% homes that would

[28]We calculate standard errors for all estimated parameters by bootstrapping from the observed sample, drawing 40 random samples with replacement and re-estimating the parameters at each iteration.

have otherwise been listed away from \$1M were shifted to the \$1M bin. In other words, the number of listings that the MI adds to the million dollar price bin represents about 46% increase in homes that would have been listed in this bin in the absence of the policy. Among these additional listings, about two-thirds are shifted from below $\$995,000$. The remaining one-third come from above \$1M. Both estimates are significant at the five-percent level. Interpreting these estimates in the context of our model, this means that the MI induces some sellers who would have otherwise listed homes below \$1M to increases the asking price to \$1M. By doing so, these sellers extract more surplus in the bilateral situation, which compensates for the losses that would have incurred in the multiple offer situation when the MI is imposed. On the other hand, the MI also induces some other sellers who would have otherwise listed homes above \$1M to lower their asking price to \$1M. Doing so allows these sellers to attract both constrained and unconstrained buyers.

Columns (2)-(7) provide a variety of robustness checks. Column (2) expands the sample window to 20 bins on each side of \$1M. Column (3) narrows the sample window to 10 bins on each side of \$1M. Column (4) includes a fourth-order, rather than third-order polynomial used in the baseline specification. Column (5) expands the exclusive region on each side of \$1M. Column (6) imposes the constraints in equations (10) and (11). Column (8) includes a set of indicators for asking price at the round-numbers that are multiples of $5,000$. Reassuringly, the bunching estimates are extremely robust, suggesting that our results are not driven by the assumptions on the sample window, functional form, and the choice of exclusive region.

Turning to Prediction 3, we report the bunching estimates for the sales price in Table 3, with a visualization of the estimates shown in Figures 7 and 8. Two clear patterns emerge. First, while there is a sharp bunching of sales price at the \$1M, the magnitude of bunching is much smaller than the asking price. This is consistent with Prediction 3. Specifically, we find that about 0.3% homes that would have been sold elsewhere are shifted to the \$1M bin. In other words, the MI adds about about 96% increase in homes that would have otherwise been sold in this region.

Second, while the theory shows that the bunching of sales at the million dollar could come from bins both above and below, Table 3 indicates that the majority of these additional sales are shifted from above, namely [$1,000,000, $1,020,000]. The dominance of "bunching from above" suggests that the million dollar home segment is cooled down by the policy in the desired direction, although the affected portion of the market is small. The small affected portion is not surprising given that the policy was targeted at a very specific segment. Moreover, the additional sales shifted to the $1M bin represent 14.7% of homes that would have been otherwise sold within [$1,000,000, $1,020,000]. Thus, despite a seemingly small number of sales being affected, the quantity effect relative to the size of the potentially affected segment of the market is quite large.

6.1.4 Robustness Checks

One legitimate concern is that our bunching estimates might be just picking up threshold effects in pricing that are caused, for example, by psychological biases around the $\$1M$, or other macro forces that affected the housing market at the time when the MI was implemented. We have already addressed this concern in two ways. First, we examine the the post-policy CDF relative to the CDF in the pre-policy year. To the extent that the threshold effect in pricing caused by the non-MI-related factors that is time invariant, it would be differenced our in our estimation. Second, we allow for round number fixed effects to capture potential rounding in the price data. As shown in Column (7) of Tables 2 and 3, this has almost no effect on the estimates in the baseline specification.

In this section, we present two "placebo" tests as an additional check. First, we designate two years prior to the implementation of the MI as "placebo" years. Specifically, we estimate the counterfactual CDF of house price for July 2011 - June 2012 relative to the CDF in the prior year and then compare this counterfactual CDF difference to the observed CDF difference. The middle row of Table 4 presents the results. The total observed jump of at $1M is 0.0018 for the asking price and -0.0012 for the sales price, both are statistically insignificant. Thus, we do not find any significant discontinuity in the difference of CDF prior to the implementation of the MI, as expected.

Second, we designate each alternative cut-off point that is well below or above \$1M as a "placebo" thresholds. The idea is that since the MI policy was targeted at the $\$1M$ segment, it should not affect houses priced well below or above the million dollar threshold and therefore home buyers in those segments face no changes in their financial constraints. To investigate this, for each alternative cut-off point at \$25,000 intervals from \$700,000 to \$1,400,000, we repeat our bunching estimation using this alternative cut-off as a threshold. Table 4 displays the estimates of the total observed jump at the cut-off. Reassuringly, most of the estimates are statistically insignificant, suggesting that the million dollar bunching estimate is unlikely to be driven by unobserved market forces. The only estimate that is economically large is at at the \$850,000 threshold for the asking price. However, its effect is much reduced once we control for round number effects.

Overall, Table 4 reports 41 placebo regressions where we repeat our main analysis for either a placebo year and/or a placebo threshold. Out of the 41 bunching estimates, only 3 are statistically significant and only 1 is economically large. Most of estimates are statistically insignificant and economically small. Taken individually, each estimate alone may not be sufficient to rule out the concern about psychology bias or other non-MI related factors. But taken together, the weight of the evidence provides compelling evidence that the bunching estimates in Section 6.1.3 provide an accurate measure of the effect of the MI policy on the asking and sales price.

6.2 Prediction 2: The Effects of MI on Sale Premium and Time on the Market

The evidence uncovered so far is consistent with the model's main predictions that the MI led to a sharp bunching in the million dollar segment, with a smaller bunching for the sales price than for the asking price. The smaller degree of bunching for the sales price, according to the model, is due to the mitigation by increased bidding intensity. In particular, Prediction 2 indicates that the MI drives up market tightness just below the million dollar, leading to a discrete decline in bidding intensity at the million dollar. In other words, we would expect that MI creates a hot market for houses listed right below the \$1M, reflected by higher probability of being sold above asking and shorter time on the market.

We test this prediction by employing a regression discontinuity design. The variables of interest are (1) the probability a house being sold above asking price conditional on being listed at $p = y_j^A$; and (2) the probability a house was on the market for more than two weeks condition on being listed at $p = y_j^A$, where two weeks is the median time on the market in the sample. We construct these two variables in three steps.

First, using the distribution approach described in Section 6.1.1, we estimate $\hat{S}_{Y\langle 1|1\rangle}(y_j^A) = 1 - \hat{F}_{Y\langle 1|1\rangle}(y_j^A)$, the probability of a house being listed for at least y_j^A. Holding the distribution of housing characteristics the same as the pre-policy period, we then estimate the counterfactual probability $\hat{S}_{Y\langle 1|0\rangle}(y_j^A) = 1 - \hat{F}_{Y\langle 1|0\rangle}(y_j^A)$.

Second, we estimate $RS_{Y\langle 1|1\rangle}(y_j^A, y^S \geq y^A)$, the joint probability that a house being listed for at least y_j^A and being sold above asking price. Similarly, we estimate $\hat{RS}_{Y\langle 1|0\rangle}(y_j^A, y^S \geq y^A)$, the counterfactual joint probability, holding the distribution of housing characteristics the same as the pre-policy period.

Finally, using the estimated probabilities above, we derive the conditional probability that a house is sold above asking conditional on being listed at least y_j^A in the pre-policy period:

$$\hat{S}_{Y\langle 0|0\rangle}(y^S \geq y^A | y_j^A) = \frac{\hat{RS}_{Y\langle 0|0\rangle}(y_j^A, y^S \geq y^A)}{\hat{S}_{Y\langle 0|0\rangle}(y_j)}$$

and a counterfactual post-policy conditional probability:

$$\hat{S}_{Y\langle 1|0\rangle}(y^S \geq y^A | y_j^A) = \frac{\hat{RS}_{Y\langle 1|0\rangle}(y_j^A, y^S \geq y^A)}{\hat{S}_{Y\langle 1|0\rangle}(y_j)}$$

Using this three-step procedure, we impute the two variables of interest: (1) $\hat{S}_{Y\langle 1|0\rangle}(y^S \geq y^A | y_j^A) - \hat{S}_{Y\langle 0|0\rangle}(y^S \geq y^A | y_j^A)$, the change in the probability of being sold above asking; and (2) $\hat{S}_{Y\langle 1|0\rangle}(D \geq 14 | y_j^A) - \hat{S}_{Y\langle 0|0\rangle}(D \geq 14 | y_j^A)$, the change of in the probability of being on the market for more than two weeks. Both are constructed relative to the pre-policy period, conditional on being listed for at least y_j^A and holding the distribution of the housing characteristics constant.

To test Prediction 2, we plot each of the two constructed variables above as a function of the asking price, along with a third order polynomial fits separately to each side of the \$1M. Figures 9 and 10 show clear visual evidence that is consistent with Prediction 2. The probability of being sold above asking exhibits a discrete downward jump at the \$1M, with an upward sloping curve to the left of the \$1M. The probability of being on the market for more than two weeks exhibits a discrete upward jump at the \$1M, with a downward sloping curve to the left of the \$1M. Together, they reflect higher bidding intensity right below \$1M induced by the MI, consistent with sellers' listing strategy and buyers' pooling response predicted by the theory.

6.3 Prediction 4: Cross-Market Analysis

Prediction 4 involves the cross-market comparison. It indicates that the MI policy effects on the asking and sales price should be stronger for markets where prospective buyers are more constrained by the policy. We test this prediction by comparing the MI effects in two submarkets of the Greater Toronto Area: central Toronto and suburban Toronto. While we do not have direct information on home buyers' financial constraints, we collect the information on the district level income and age for these two submarkets. As noted in the section 5, million dollar homes are at the median of house price distribution in central Toronto and about the top 5th percentile of house price distribution in suburban Toronto. It seems plausible to assume that average income of million dollar homes are at the median of income distribution in central Toronto and are at the top 5th percentile of the income distribution in suburban Toronto. Table ? confirms that the former is about half of the size of the latter. Thus we would should expect that the MI policy has less substantial impact on sellers' asking price and the final sales price in suburban Toronto.

Focusing on suburban Toronto, Tables 5 and 6 present the estimates of the MI policy effect on the asking price and sales price, respectively. For the asking price, the policy response in suburban Toronto is about half of that in central Toronto. For the sales price, the policy response is less than one third of that in central Toronto. This evidence, combined with the fact that buyers in suburban markets are less constrained by MI limitation, is strongly in line with Prediction 4.

7 Conclusion

In this paper we explore the price implications of financial constraints in a booming housing market. This is of particular interest and relevance because mortgage financing is a channel through which policymakers in many countries are implementing macroprudential regulation. In Canada, one such macroprudential policy was implemented in 2012 that obstructed access to high LTV mortgage insurance for homes purchased at a price of $1M or more. We exploit the policy's $1M threshold by combining bunching estimation and distribution regression to estimate the effects of the policy on prices and other housing market outcomes.

To facilitate interpretation of the empirical results, we first characterize a directed search equilibrium in a setting with competing auctions and exogenous bidding limits. We model the million dollar policy as an additional financial constraint affecting a subset of prospective buyers. We show that sellers respond strategically to the policy by adjusting their asking prices to $1M, which attracts both constrained and unconstrained buyers. Consequently, the policy's impact on final sales prices is dampened by the heightened bidding intensity.

Using housing transaction data from the city of Toronto, we find that the million dollar policy results in a large degree of bunching at the $1M for asking price and a smaller degree of bunching at the $1M for sales price. We also find evidence that the incidence of bidding wars and below average time-on-the-market are relatively higher for homes listed just below the $1M threshold, which agrees with the theoretical results. Overall, the MI policy appears to have cooled the housing market just above the $1M threshold and at the same time heated up the market just below.

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Table 1: Summary Statistics: City of Toronto

		Pre-Policy		Post-Policy	
		Asking	Sales	Asking	Sales
All Homes	Mean	718659.44	723060.60	767393.53	761472.48
	25th Pct	429900.00	431000.00	459900.00	461000.00
	50th Pct	559925.00	573000.00	599000.00	601000.00
	75th Pct	798900.00	812000.00	849000.00	850000.00
	N	15882.00	15882.00	13577.00	13577.00
	Median Duration	9.00	9.00	11.00	11.00
	1M Percentile	0.86	0.84	0.84	0.83
Homes 0.9-1M	N	521.00	588.00	556.00	592.00
	Median Duration	8.00	8.00	9.00	9.00
	Mean Price	967261.99	943465.15	967719.59	945917.91
Homes 1-1.1M	N	255.00	367.00	269.00	349.00
	Median Duration	8.00	8.00	10.00	9.00
	Mean Price	1073743.82	1044251.96	1075028.44	1044355.36

Table 2: Regression Buncing Estimates for Post policy period (Central Toronto)

	Asking Price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Jump at cut-off	0.0095**	0.0095**	0.0095**	0.0095**	0.0095**	0.0095**	0.0095**
	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
Total Response	0.0089**	0.0088**	0.0086**	0.0089**	0.0089**	0.0096**	0.0076**
	(0.0028)	(0.0029)	(0.0027)	(0.0028)	(0.0029)	(0.0034)	(0.0030)
From Below	-0.0056**	-0.0049**	-0.0048**	-0.0051**	-0.0057**	-0.0061**	-0.0056**
	(0.0020)	(0.0020)	(0.0017)	(0.0019)	(0.0022)	(0.0024)	(0.0020)
From Above	0.0033*	0.0039*	0.0038**	0.0038**	0.0032	0.0035	0.0020
	(0.0019)	(0.0020)	(0.0018)	(0.0019)	(0.0020)	(0.0022)	(0.0023)
Observations	9111	9111	9111	9111	9111	9111	9111
Excluded Bins:							
J	3	3	3	3	4	3	3
K	3	3	3	3	4	3	3
Tests of Fit:							
$B - \sum_j^J \beta_B^j$	-.0018	-.00091	-.0004	-.0014	-.0035	-5.6e-17*	-.0017
	(.0018)	(.002)	(.0013)	(.0015)	(.0039)	(.)	(.0018)
$A - \sum_k^K \beta_A^k$	.00056	.00098	.00033	.00097	.0019	-4.2e-17*	.0017
	(.0011)	(.0015)	(.00067)	(.0012)	(.0024)	(.)	(.0012)
Joint p-val.	0.58	0.77	0.87	0.59	0.49	.	0.35
Impact:							
%Δ at cutoff	46.1	45.6	44.2	46.1	46.3	49.9	37.2
Specifications:							
Poly. Order	3	3	3	4	3	3	3
Window	15	20	10	15	15	15	15
Other						Constrained	Round Number

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$

Table 3: Regression Buncing Estimates for Post policy period (Central Toronto)

	Sales Price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Jump at cut-off	0.0032**	0.0032**	0.0032**	0.0032**	0.0032**	0.0032**	0.0032**
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Total Response	0.0028**	0.0027**	0.0028**	0.0028**	0.0028**	0.0027	0.0037**
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0017)	(0.0017)
From Below	-0.00051	-0.0012	-0.0010	-0.0012	-0.00066	-0.00039	-0.00040
	(0.0018)	(0.0019)	(0.0016)	(0.0016)	(0.0020)	(0.0016)	(0.0018)
From Above	0.0023	0.0015	0.0017	0.0016	0.0021	0.0023	0.0033
	(0.0018)	(0.0020)	(0.0016)	(0.0017)	(0.0020)	(0.0020)	(0.0022)
Observations	9111	9111	9111	9111	9111	9111	9111
Excluded Bins:							
J	2	2	2	2	3	2	2
K	4	4	4	4	5	4	4
Tests of Fit:							
$B - \sum_j^J \beta_B^j$	.00023	.00033	.00027	.00028	-.00051	0*	.00021
	(.00087)	(.00088)	(.00087)	(.00087)	(.002)	(0)	(.00087)
$A - \sum_k^K \beta_A^k$	-.000021	-.0019	-.001	-.001	-.00092	-2.1e-17	-.00061
	(.0036)	(.0041)	(.0029)	(.0036)	(.0052)	(2.2e-11)	(.0035)
Joint p-val.	0.96	0.86	0.91	0.93	0.96	.	0.96
Impact:							
%Δ at cutoff	96.9	91.3	95.2	96.3	96.6	92.8	196.1
% from Above	14.7	9.43	11.5	10.8	11.5	14.7	19.0
% from Below	5.24	12.3	10.3	11.7	4.41	4.03	4.22
Specifications:							
Poly. Order	3	3	3	4	3	3	3
Window	15	20	10	15	15	15	15
Other						Constrained	Round Number

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$

Table 4: Regression Buncing Estimates for Post policy period (Central Toronto)

	Post-Policy Difference		Pre-Policy Difference	
	(1) Asking	(2) Sales	(3) Asking	(4) Sales
800000	0.0013	-0.00091	0.0037	0.00021
	(0.0037)	(0.0014)	(0.0030)	(0.0014)
825000	0.00035	0.00014	-0.00047	0.0020
	(0.00053)	(0.0013)	(0.00072)	(0.0016)
850000	0.0053*	0.00046	0.00091	0.00038
	(0.0031)	(0.0014)	(0.0027)	(0.0014)
875000	0.00022	0.0042**	0.00039	0.00053
	(0.00052)	(0.0017)	(0.00050)	(0.0013)
900000	0.0013	0.0023	0.0068**	0.0011
	(0.0031)	(0.0016)	(0.0032)	(0.0012)
925000	0.00020	0.0018	-0.000030	-0.00096
	(0.00031)	(0.0016)	(0.00032)	(0.0015)
950000	0.0032	0.00013	-0.00087	-0.00065
	(0.0022)	(0.0011)	(0.0022)	(0.0010)
1000000	0.0095**	0.0032**	0.0018	-0.0012
	(0.0028)	(0.0014)	(0.0031)	(0.0011)
1050000	0.00076	0.0015	0.0036**	0.00019
	(0.0019)	(0.0011)	(0.0016)	(0.00082)
1075000	0.00023	-0.00010	-0.00022	0.00095
	(0.00024)	(0.0010)	(0.00019)	(0.00091)
1100000	0.0042	-0.00070	0.0039**	0.00037
	(0.0032)	(0.00066)	(0.0017)	(0.00068)
1125000	0.00084	-0.00026	0.00035	0.00072
	(0.00066)	(0.00095)	(0.00022)	(0.00095)
1150000	0.00016	0.00076	-0.00029	-0.0013*
	(0.0015)	(0.00094)	(0.0014)	(0.00077)

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$

Table 5: Regression Buncing Estimates for Post policy period (Suburban Toronto)

	Asking Price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Jump at cut-off	0.0045**	0.0045**	0.0045**	0.0045**	0.0045**	0.0045**	0.0045**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Total Response	0.0042**	0.0042**	0.0041**	0.0042**	0.0042**	0.0046**	0.0039**
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0013)	(0.0012)
From Below	-0.0027**	-0.0023**	-0.0023**	-0.0024**	-0.0028**	-0.0030**	-0.0027**
	(0.00075)	(0.00077)	(0.00069)	(0.00070)	(0.00080)	(0.00086)	(0.00076)
From Above	0.0015**	0.0018**	0.0018**	0.0018**	0.0015**	0.0016**	0.0012
	(0.00067)	(0.00072)	(0.00064)	(0.00067)	(0.00071)	(0.00075)	(0.00076)
Observations	29459	29459	29459	29459	29459	29459	29459
Excluded Bins:							
J	3	3	3	3	4	3	3
K	3	3	3	3	4	3	3
Tests of Fit:							
$B - \sum_j^J \beta_B^j$	-.001	-.00056	-.00035	-.0008	-.0022	-6.9e-18*	-.001
	(.00064)	(.0007)	(.00051)	(.00057)	(.0014)	(.)	(.00064)
$A - \sum_k^K \beta_A^k$	.00014	.00026	.000072	.00034	.00066	0*	.00036
	(.00038)	(.00052)	(.00026)	(.0004)	(.00081)	(.)	(.00049)
Joint p-val.	0.31	0.68	0.79	0.37	0.23	.	0.28
Specifications:							
Poly. Order	3	3	3	4	3	3	3
Window	15	20	10	15	15	15	15
Other						Constrained	Round Number

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$

Table 6: Regression Buncing Estimates for Post policy period (Suburban Toronto)

	Sales Price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Jump at cut-off	0.0011**	0.0011**	0.0011**	0.0011**	0.0011**	0.0011**	0.0011**
	(0.00053)	(0.00053)	(0.00053)	(0.00053)	(0.00053)	(0.00053)	(0.00053)
Total Response	0.00082*	0.00081	0.00085*	0.00082*	0.00082	0.00018	0.0011*
	(0.00050)	(0.00051)	(0.00049)	(0.00050)	(0.00050)	(0.00053)	(0.00062)
From Below	0.000036	-0.000064	0.000074	-0.000028	0.000022	0.00017	0.000055
	(0.00067)	(0.00074)	(0.00057)	(0.00058)	(0.00074)	(0.00063)	(0.00067)
From Above	0.00086	0.00075	0.00093	0.00080	0.00084	0.00035	0.0011
	(0.00069)	(0.00074)	(0.00057)	(0.00060)	(0.00076)	(0.00058)	(0.00087)
Observations	29459	29459	29459	29459	29459	29459	29459
Excluded Bins:							
J	2	2	2	2	3	2	2
K	2	2	2	2	3	2	2
Tests of Fit:							
$B - \sum_j^J \beta_B^j$	.00027	.00029	.00024	.00028	.00026	0*	.00027
	(.00039)	(.00039)	(.00037)	(.00039)	(.00089)	(0)	(.00039)
$A - \sum_k^K \beta_A^k$	-.001	-.001	-.001	-.001	-.0012	0*	-.0013
	(.00054)	(.00054)	(.00053)	(.00053)	(.0009)	(0)	(.00068)
Joint p-val.	0.15	0.15	0.17	0.15	0.45	.	0.15
Specifications:							
Poly. Order	3	3	3	4	3	3	3
Window	15	20	10	15	15	15	15
Other						Constrained	Round Number

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$

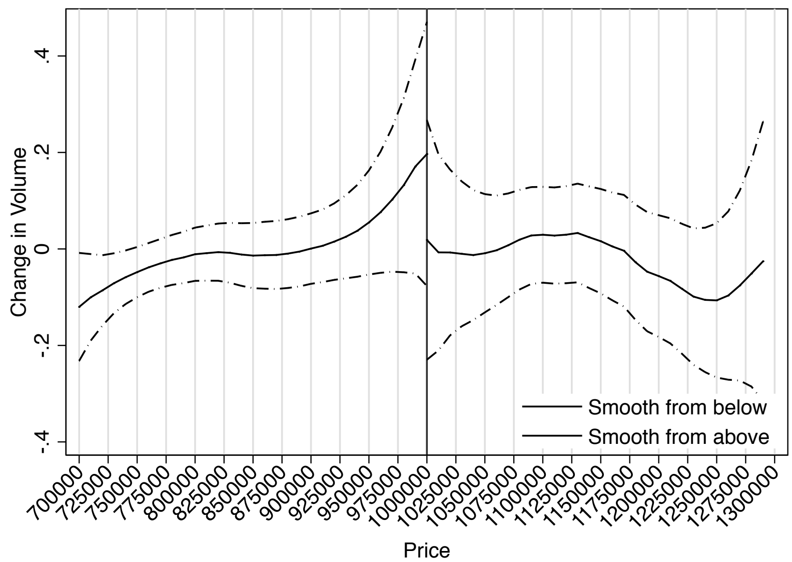


Figure 1: Smoothed Change in Sales Volume between 2012-2013 by Price

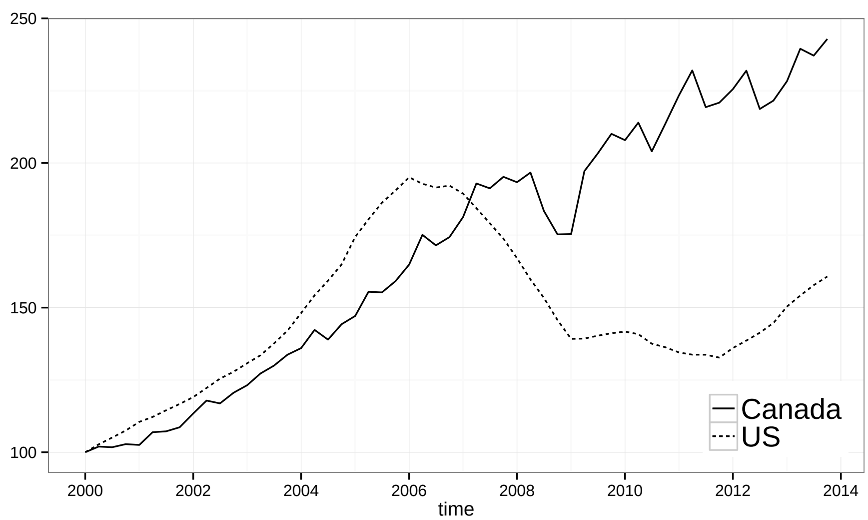


Figure 2: House Price Indices for Canada and the U.S.

Figure 3: Observed Distribution and Decomposition of Asking Prices

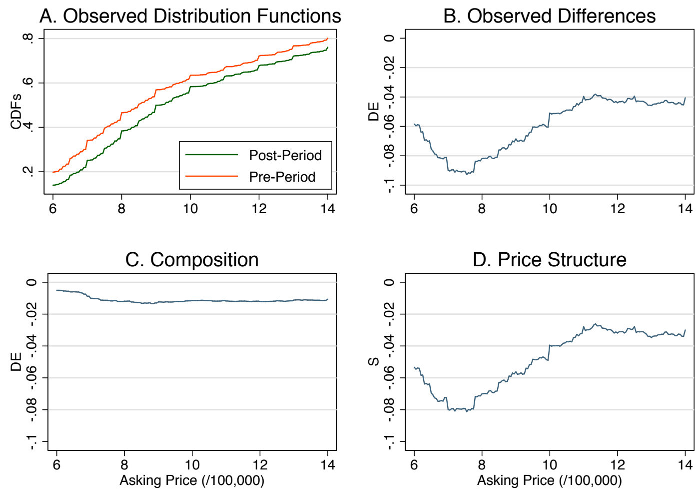


Figure 4: Observed Distribution and Decomposition of Sales Prices

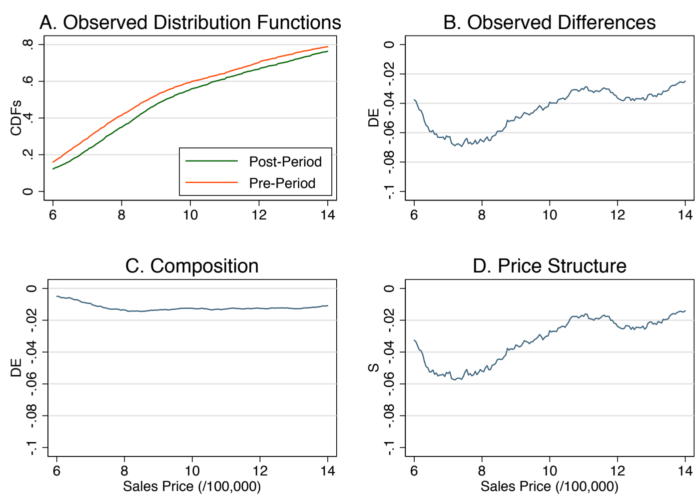
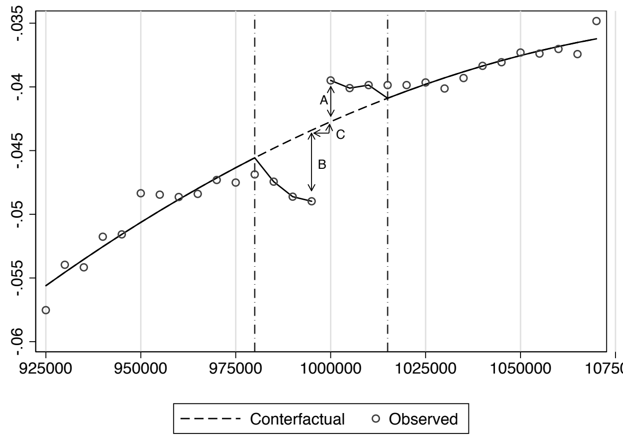


Figure 5: Observed Cumulative Distribution and Decomposition of Asking Prices



Note: A is the policy response from above, B is the policy response from Below, and C is the counterfactual change. Vertical Dashed lines indicate excluded region.

Figure 6: Observed Density Distribution of Asking Prices

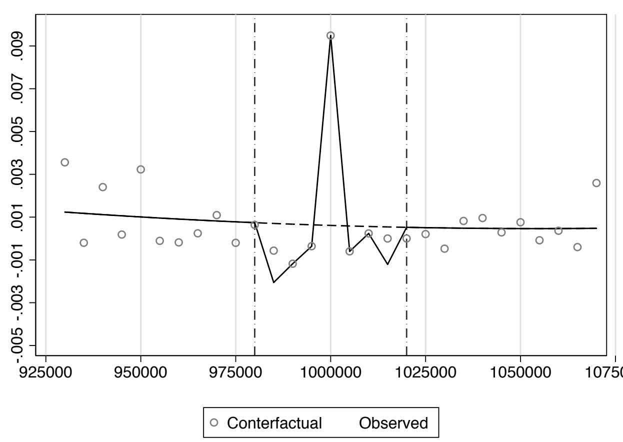
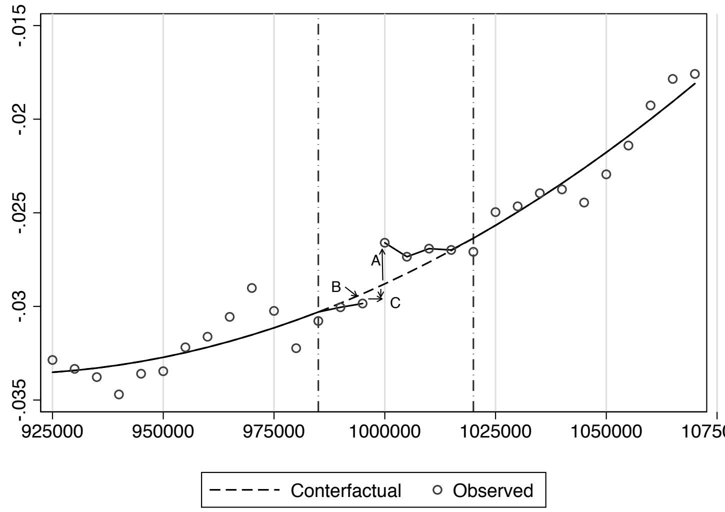


Figure 7: Observed Cumulative Distribution and Decomposition of Sales Prices



Note: A is the policy response from above, B is the policy response from Below, and C is the counterfactual change. Vertical Dashed lines indicate excluded region.

Figure 8: Observed Density Distribution of Sales Prices

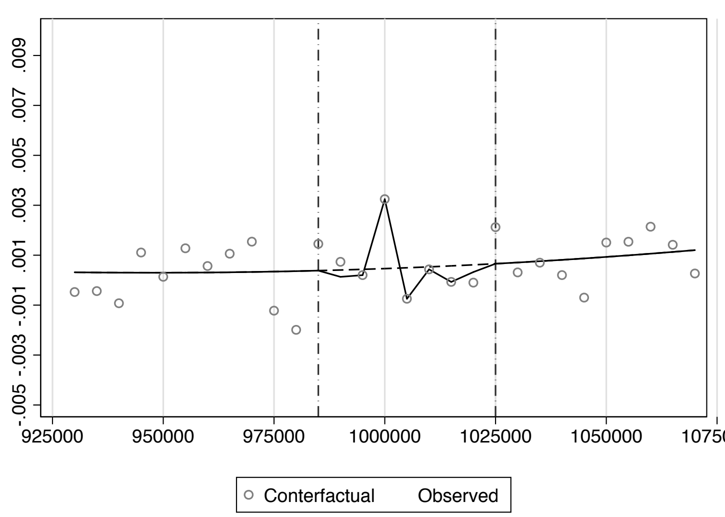


Figure 9: Probability of Sales above Asking Conditional on Asking Price

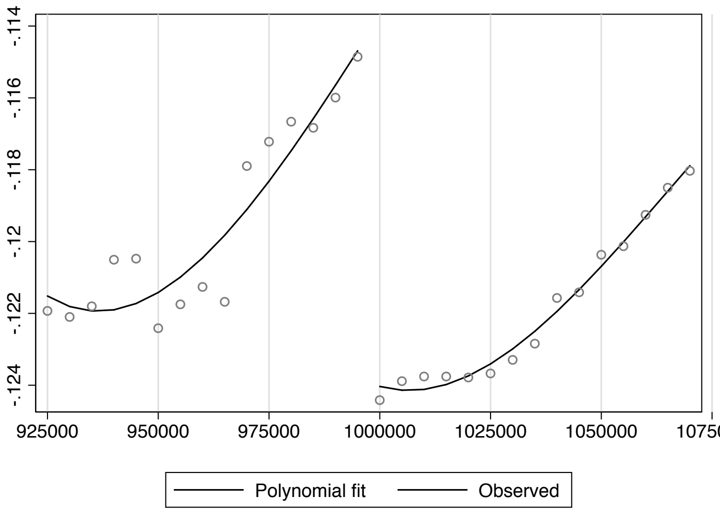
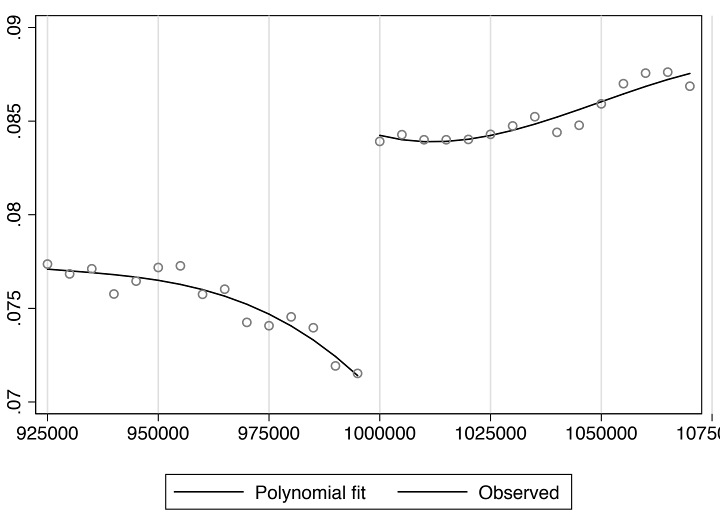


Figure 10: Probability of Being on Market for ≥ 2 weeks Conditional on Asking Price



A Theory: Details and Derivations

A.1 Expected Payoffs

Expected payoffs are markedly different depending on whether the asking price, p, is above or below buyers' ability to pay. Consider each scenario separately.

Case I: $p \leq c$. The seller's expected net payoff as a function of the asking price in this case is

$$V_I^s(p, \lambda, \theta) = -x + \pi(1)p + \sum_{k=2}^{\infty} \pi(k) \left\{ [\phi_k(0) + \phi_k(1)]\, c + \sum_{j=2}^{k} \phi_k(j) u \right\}.$$

Substituting expressions for $\pi(k)$ and $\phi_k(j)$ and recognizing the power series expansion of the exponential function, the closed-form expression is

$$\begin{aligned} V_I^s(p, \lambda, \theta) = -x + \theta e^{-\theta} p + \left[1 - e^{-\theta} - \theta e^{-\theta}\right] c \\ + \left[1 - e^{-(1-\lambda)\theta} - (1-\lambda)\theta e^{-(1-\lambda)\theta}\right] (u - c). \end{aligned} \tag{A.1}$$

The second term reflects the surplus from a transaction if she meets only one buyer. The third and fourth terms reflect the surplus when matched with two or more buyers, where the last term is specifically the additional surplus when two or more bidders are unconstrained.

The unconstrained buyer's expected payoff is

$$V_I^u(p, \lambda, \theta) = \pi(0)(v - p) + \sum_{k=1}^{\infty} \pi(k) \left[\phi_k(0)(v - c) + \sum_{j=1}^{k} \phi_k(j) \frac{v - u}{j + 1} \right].$$

The closed-form expression is

$$V_I^u(p, \lambda, \theta) = \frac{1 - e^{-(1-\lambda)\theta}}{(1-\lambda)\theta}(v - u) + e^{-(1-\lambda)\theta}(u - c) + e^{-\theta}(c - p). \tag{A.2}$$

The first term is the expected surplus when competing for the house with other unconstrained bidders; the second term is the additional surplus when competing with constrained bidders only; the last term reflects the possibility of being the only buyer.

The constrained buyer's expected payoff is

$$V_I^c(p, \lambda, \theta) = \pi(0)(v - p) + \sum_{k=1}^{\infty} \pi(k)\phi_k(0) \frac{v - c}{k + 1}.$$

The closed-form expression is

$$V_I^c(p, \lambda, \theta) = \frac{e^{-(1-\lambda)\theta} - e^{-\theta}}{\lambda\theta}(v - c) + e^{-\theta}(c - p). \tag{A.3}$$

The first term is the expected surplus when competing for the house with other constrained bidders; the last term reflects the possibility of being the only buyer.

Case II: $c < p \leq u$. The seller's expected net payoff is

$$V_{II}^{s}(p, \lambda, \theta) = -x + \sum_{k=1}^{\infty} \pi(k)\phi_k(1)p + \sum_{k=2}^{\infty} \pi(k) \sum_{j=2}^{k} \phi_k(j)u.$$

The closed-form expression is

$$V_{II}^{s}(p, \lambda, \theta) = -x + (1-\lambda)\theta e^{-(1-\lambda)\theta} p + \left[1 - e^{-(1-\lambda)\theta} - (1-\lambda)\theta e^{-(1-\lambda)\theta}\right] u. \tag{A.4}$$

The second term reflects the surplus from a transaction if she meets exactly one unconstrained buyer; the third term is the surplus when matched with two or more unconstrained buyers.

The unconstrained buyer's expected payoff is

$$V_{II}^{u}(p, \lambda, \theta) = \pi(0)(v-p) + \sum_{k=1}^{\infty} \pi(k) \left[\phi_k(0)(v-p) + \sum_{j=1}^{k} \phi_k(j) \frac{v-u}{j+1}\right].$$

The closed-form expression is

$$V_{II}^{u}(p, \lambda, \theta) = \frac{1 - e^{-(1-\lambda)\theta}}{(1-\lambda)\theta}(v-u) + e^{-(1-\lambda)\theta}(u-p). \tag{A.5}$$

The first term is the expected surplus when competing for the house with other unconstrained bidders; the second term reflects additional surplus arising from the possibility of being the exclusive unconstrained buyer.

Since constrained buyers are excluded from the auction, their payoff is zero:

$$V_{II}^{c}(p, \lambda, \theta) = 0. \tag{A.6}$$

Case III: $p > u$. In this case, all buyers are excluded from the auction. Buyers' payoffs are zero, and the seller's net payoff is simply the value of maintaining ownership of the home (normalized to zero) less the listing cost, x:

$$V_{III}^{s}(p, \lambda, \theta) = -x, \quad V_{III}^{u}(p, \lambda, \theta) = 0 \quad \text{and} \quad V_{III}^{c}(p, \lambda, \theta) = 0. \tag{A.7}$$

Using the expected payoffs in each of the different cases, define the following value functions: for $i \in \{s, u, c\}$,

$$V^{i}(p, \lambda, \theta) = \begin{cases} V_{III}^{i}(p, \lambda, \theta) & \text{if } p > u, \\ V_{II}^{i}(p, \lambda, \theta) & \text{if } c < p \leq u, \\ V_{I}^{i}(p, \lambda, \theta) & \text{if } p < c. \end{cases} \tag{A.8}$$

A.2 Graphical Illustration of the Model's Predictions

Implication 1. *The MI policy motivates some sellers to change their asking price from p_0 to $p_1 = c$.*

- *If $p_u^* \leq c$, an increase from p_u^* to c (bunching from below)*
- *If $p_u^* > c$, a decrease from p_u^* to c (bunching from above)*

(1). Equilibrium Asking Price: $p_u^* < c$:

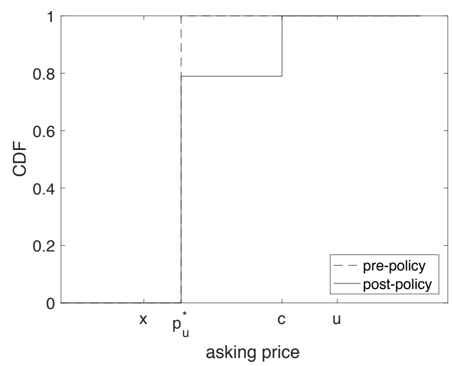


Figure 11: Asking Price CDF

(2). Equilibrium Asking Price: $p_u^* > c$:

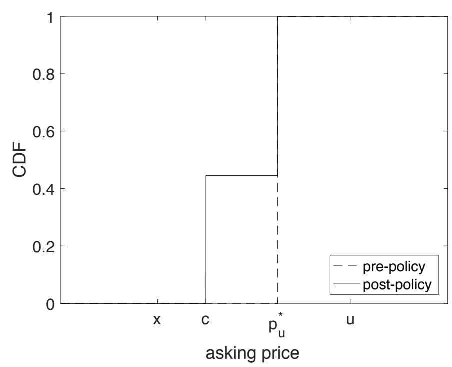


Figure 12: Ask Price CDF

Implication 2. *The MI drives up market tightness (θ) just below c, with a discontinuous decline in bidding intensity at c. This results in a lower (higher) incidence of price escalation up to u if $p_u^* \leq c$ ($p_u^* > c$).*

(1). Equilibrium Buyer-Seller Ratio: $p_u^* < c$

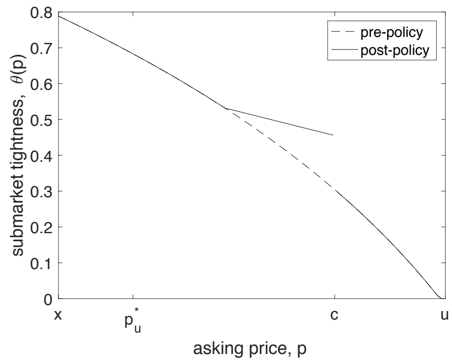


Figure 13: Market Tightness as a Function of the Asking Price

(2). Equilibrium Buyer-Seller Ratio: $p_u^* > c$

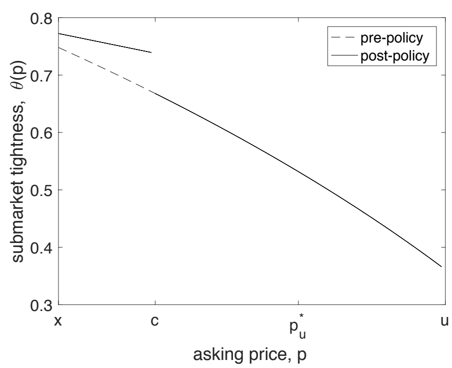


Figure 14: Market Tightness as a Function of the Asking Price

Implication 3. *The MI has a less dramatic impact on sales price relative to asking price.*

- *If $p_u^* \leq c$, an increase from p_u^* to c (bunching from below) and a decrease from u to c (bunching from above)*
- *If $p_u^* > c$, a decrease from p_u^* to c (bunching from above)*

(1). Equilibrium Sales Price: $p_u^* < c$

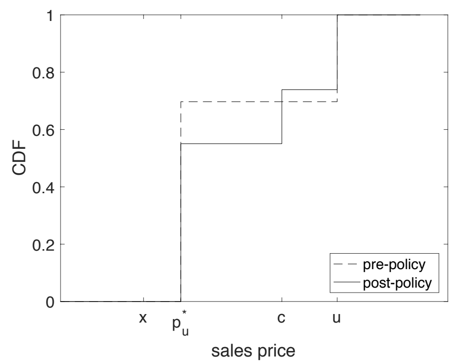


Figure 15: Sales Price CDF

(2). Equilibrium Sales Price: $p_u^* > c$

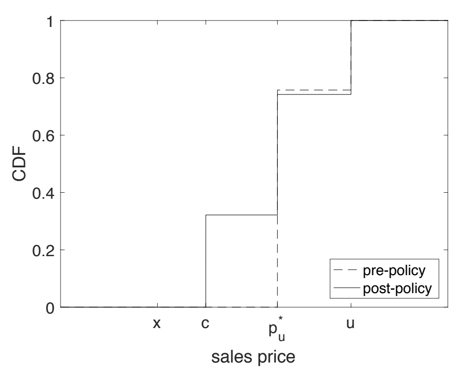


Figure 16: Sales Price CDF

Implication 4. *The share of activity in submarket c (relative to submarket p_u^*) is increasing in Λ.*

(1). Equilibrium Average Asking and Sales Price: $p_u^* < c$

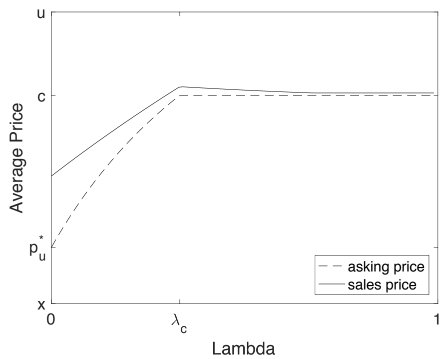


Figure 17: Average Price vs. Λ

(2). Equilibrium Average Asking and Sales Price: $p_u^* > c$

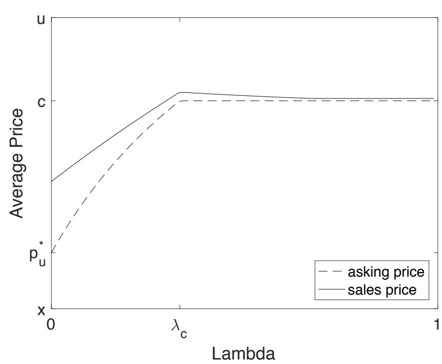


Figure 18: Average Price vs. Λ