Do Financial Constraints Cool a Housing Boom?*

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Abstract

In this paper we exploit a natural experiment arising from the 2012 Canadian law change that restricts access to mortgage insurance to homes under one million dollars ($1M), which effectively increases the minimum downpayment from 5% to 20% for homes of million dollars or more. Our empirical analysis is motivated by a directed search model that features auction mechanisms and financially constrained bidders. We model the regulation as a tightening of the financial constraint faced by a subset of prospective buyers. This prompts some sellers near the $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 policy causes a sharp bunching of homes listed at the $1M and a corresponding increase in the bidding intensity, which together result in muted response in the sales price. Despite failing to cool the boom in the million dollar segment, the policy improves borrowers creditworthiness by reallocating million dollar homes to those who are less constrained by the 20% downpayment. Everything considered, our analysis points to the importance of designing macroprudential policies that recognize the strategic responses of buyers and sellers in terms of listing, searching and bidding.

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

JEL classification: D40, D44, R31, R38, E65

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1 Introduction

This paper examines how the financial constraints faced by prospective home buyers affect buyers' and sellers' behavior and thereby housing market outcomes. Financial constraints are a fundamental feature of the housing market (Stein, 1995; Genesove and Mayer, 1997; Ortalo-Magne and Rady, 2006). For example, loan-to-value ratio and debt-to-income ratio reflect two typical underwriting constraints that limit how much a buyer can bid on a property, which in turn affects a seller's decision to list a house and choice of asking price if listing. The central role of financial constraints makes them by far the most widespread policy vehicle in 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] Recently in the aftermath of the global financial crisis, tightening borrowers' financial constraints has become a primary macroprudential tool that central banks used to create a buffer 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 financial constraints affect house price growth through homeowner default and mobility (Mian and Sufi, 2009; Demyanyk and Van Hemert, 2011). However, despite the importance of understanding the link between financial constraints and behaviour of home buyers and sellers facing optimization frictions such as search costs, there is virtually no existing micro analysis from such settings. This paper aims to fill this gap by exploiting a natural experiment that arose from a change in mortgage insurance policy implemented in Canada in 2012 and by developing a search theoretical model to facilitate the interpretation of empirical results.

Canada experienced one of the world's largest modern house price booms, with the real price doubling between 2000 and 2016. In an effort to cool this unprecedentedly long boom, the government tightened mortgage insurance rules eight times since 2008 – many of which

[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.

through stricter requirements on borrowers' down payment or income. Our focus is on the so-called "million dollar" policy that restricts access to mortgage insurance (the transfer of mortgage default risk from lenders to insurers) when the purchase price of a home exceeds 1 million Canadian dollars.[3] Note that lenders are required to insure mortgages with over 80% loan-to-value ratio. As such, the minimum downpayment jumps from 5% to 20% of the entire transaction price at a threshold of $1M, creating an increase in the minimum downpayment of $150,000 for million dollar homes. Such a notch in home buyers' budget constraint creates strong incentives for bunching at the threshold, allowing for nonparametric identification of house price responses using bunching techniques. The existence or lack of bunching around the threshold should provide compelling and transparent evidence about how households respond to constraints with considerable kinks. 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 policies in a market with frictions.

Bunching responses to financial constraints are not just behavioral but also rational. Understanding the mechanisms that generates bunching requires an equilibrium analysis of a two-sided market. To this end, we preface the empirical work with a search-theoretic model that 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 faced by buyers which limit how much they can bid on a house.[4] We assume that buyers initially

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

[4] 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

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., the $1M threshold). In some circumstances, this represents a *reduction* in the set of equilibrium asking prices. Sellers lower their asking price to the threshold in order to attract offers from buyers genuinely constrained by the policy. At the same time, they continue to attract unconstrained buyers which sometimes pushes the sales price above the asking price. In other circumstances, this represents an *increase* in the set of equilibrium asking prices relative to the pre-policy equilibrium. This may seem surprising at first glance, but is consistent with the intuition that sellers 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 both cases, the policy generates an excess mass (i.e., bunching) of homes listed at the $1M. However, the bunching response in the asking price is dampened by intensified bidding among constrained and unconstrained buyers pooled at the $1M, making the net impact of the policy on the sales price an ultimately empirical question.

We then 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. This 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 matches well with our model of competing auctions. Second, the million dollar policy was implemented in the midst of a housing boom in Toronto and caused two discrete changes in the market: one at the time the policy was implemented, and another at the $1M threshold. This provides a natural experimental opportunity for examining the

in a model of competing auctions.

price response to financial constraints.

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 as well as a booming market.[5] 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, using the well-known reweighting approach introduced by DiNardo et al. (1996) 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 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 policy 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. 2011a, 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 accompanied with holes both above and below the million dollar. In particular, the policy adds 93 homes to **listings** at the million dollar

[5] 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.

bin, which represent about a 42% increase relative to homes that would have been listed in this bin in the absence of the policy. Among these, about 60% would have otherwise been listed below \$1M; the remaining would have otherwise been listed above $\$995,000$. Both are consistent with sellers' strategic responses predicted by the theory.

On the contrary, the policy adds only about 12 homes to **sales** at the the million dollar bin, which is economically small and statistically insignificant. The lack of bunching in the sales price suggests that buyers' heightened competition pushes the sales price above asking price and mitigates the intended cooling impact from the policy. Consistent with this interpretation, we also find sharp, non-parametric evidence that housing segments right below the \$1M experience a shorter time on the market and a larger fraction of above asking sales.

Together, these results imply two useful policy implications. First, the mortgage insurance restriction did not achieve the specific goal of cooling the housing boom in the million dollar segment. This is not because market participants did not respond to the policy. Indeed, it is precisely the strategic responses by home sellers (in listing) and home buyers (in bidding) that interact to undermine the intended impact of the policy on the sales price. Everything considered, our analysis points to the importance of designing macroprudential policies that recognize the endogenous responses of buyers and sellers in terms of listing strategies, search decisions and bidding behaviour.

Second, despite failing to cool the boom in the targeted segment, the policy achieves the goal of improving borrowers creditworthiness. In particular, our results show that buyers who are not constrained by the 20% downpayment outbid those who are constrained in the post-policy equilibrium. Such reallocation of million dollar homes helps support a healthy housing market in a broad sense.

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.

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 others 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) incorporate a housing production response in the 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.[6]

Turning to the empirical literature, financial constraints are defined much more broadly. 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). In understanding the recent financial crisis, much focus has been placed on examining the role of financial constraints in explaining housing booms and busts through borrower creditworthiness.[7] Our paper differs from this body of work in that we examine how the mortgage insurance restriction affects sellers' listing strategy and buyers' search strategy, and thereby market outcomes such as 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.

On the methodology side, our work follows a recent and emerging literature that exploits the bunching behaviour of agents when faced with non-linear budget sets, often the product of the tax system. Bunching estimators were first developed in the context of tax kinks by Saez (2010) and Chetty et al. (2011a) before being extended to the analysis of tax notches by Kleven and Waseem (2013). Notches occur when there are discrete changes in agents' budget sets induced by policy. The policy analysed in this paper corresponds to a notch – that is, a discrete change in the required down-payment at the $1M threshold. In the context of real estate, there are several related papers that employ a related bunching empirical strategy. Kopczuk and Munroe (2015) analyse bunching behaviour in sales volume induced by discontinuities in the real-estate transfer taxation that occurs at the $1M

[6]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).

[7]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.

threshold in New York and New Jersey, Best et al. (2015) and Best et al. (2017) exploit variation in interest rates that produce notches in the loan-to-value ratio at various thresholds using a bunching estimator, and DeFusco et al. (2017) estimate leverage responses to a notch created by the conforming loan limit in the US. There are two main differences between our empirical design, relative to these papers. First, we use a two-step approach that exploits a standard reweighting estimator to account for changes in the distribution of housing characteristics between the pre-and post-policy period and, second, we consider a two-sided bunching estimator to accommodate the two-sided nature of bunching implied by our theoretical framework.

Finally, our paper contributes to work on macroprudential policies. In the aftermath of 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.

3 Background

3.1 Mortgage Insurance

A common way for central banks to impose financial constraints on the housing market is through mortgage insurance. Mortgage insurance is an instrument used to transfer mortgage default risk from the lender to the insurer, which has been 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 regulated lenders insure high loan-to-value (LTV) mortgages, and (ii) the central role of the government in providing such insurance.[8]

[8]The mortgage insurance 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

The combination of these two requirements gives the central government unparallelled power to influence housing finance (Krznar and Morsink, 2014).

We focus on Canada. Federally regulated financial institutions are required to purchase mortgage insurance on any loan with an LTV higher than 80 percent. The mortgage insurance premiums vary based on the LTV and are made as a single upfront payment at the time of loan origination that covers the entire amortization period. Typically, lenders pass the mortgage insurance premiums completely on to the mortgage borrower, so that the mortgage insurance premiums are included in the home loan. The mortgage insurance market is dominated by three main players: the government owned Canada Mortgage and Housing Corporation (CMHC) and two private insurers, Genworth Financial Mortgage Insurance and Canada Guaranty. The Canadian government provides 100 percent guarantee for home mortgages insured through CMHC, and 90 percent guarantee for home mortgages insured through Genworth Financial and Canada Guaranty. As a result, all mortgage insurers are subject to financial market regulation through the Canadian Office of the Superintendent of Financial Institutions (OFSI).

For the purpose of our paper, it is important to note that the 12 largest financial institutions – all regulated by the OSFI – originate over 90 percent of all home mortgages in Canada. The fraction of unregulated housing sector in the Canadian mortgage market is quite small, accounting for less than 1 percent of mortgage volume according to Coletti et al. (2016); Mordel and Stephens (2015).[9] While possible, it is in general difficult for a borrower to obtain a second mortgage at the time of origination to reduce the downpayment of the primary loan below 20%.[10] Thus, as stated by the IMF, "the pervasiveness of the mortgage

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.*

[9]These unregulated loans are largely issued by Mortgage Finance Companies and cannot be securitized into either Canada Mortgage Bonds or National Housing Act mortgage-backed bonds. Anecdotal evidence suggests that the interest rates on unregulated mortgages are 3 - 6 times higher than conventional mortgage rates. see "Ordinary Canadians turn bankers as shadow mortgage lending rises," *Reuters.* July 9, 2015.

[10]See the Government of Canada guidelines on borrowing against home equity.

insurance within housing finance system gives the Canadian authorities exceptional power to affect housing finance through the key role of government-backed mortgage insurance."

3.2 The Canadian Mortgage Insurance Regulation

Figure 4 plots the national house price indices for Canada and the U.S, supporting the observation that "what is happening in Canada is kind of a slow-motion version of what happened in the U.S" (Robert Shiller, 2012). As home prices in Canada continued to escalate post-financial crisis, the Canadian government became increasingly concerned that rapid price appreciation would eventually lead to a severe housing market correction.[11]

To counter the potential risks associated with this house price boom, the Canadian government implemented four major rounds of housing market macroprudential regulation – all through changes to the mortgage insurance rules – between July 2008 and July 2012. These 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 mortgage insurance to homes with a purchase price of less than one million Canadian dollars (2012).

This paper examines the impact of the million dollar policy. Since regulated lenders are required to insure mortgages with over 80% loan-to-value ratio, the policy effectively imposes a minimum down payment requirement of 20 percent for homes with a purchase price of $1M or more. The aim of the regulation was twofold: to increase borrower creditworthiness; and to curb price appreciation in high price segments. 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.[12]

[11]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." Sources: "Jim Flaherty vows to intervene in housing market again if needed." *The Globe and Mail*, November 12, 2013.

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

4 Theory

To understand how the million dollar policy affects strategies and outcomes in the housing market, we present a two-sided search model that incorporates auction mechanisms and financially constrained buyers. We characterize pre- and post-policy directed search equilibria and derive a set of empirical implications. The purpose of the model is to guide the empirical analyses that follow. As such, we present a simple model of directed search with auctions and bidding limits that features heterogeneity only along the financial constraints dimension. The clean and stylized nature of the model allows for a quick understanding of the intuition underlying plausible strategic reactions among buyers and sellers to the implementation of the policy.

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).

Million dollar policy. The introduction of the million dollar 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 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 sealed-bid second-price 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. 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.

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 $\Lambda = 0$.[13] Buyers in this environment direct their search by targeting the asking price that maximizes their expected payoff. Because the buyer correctly anticipates the free entry of sellers, the search problem can be written

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

We construct a DSE with a single active submarket with asking price and market tightness determined by the solution to problem P_0, denoted $\{p_0, 0, \theta_0\}$.[14] Given the auction mechanism and the role of the asking price, a strictly positive expected surplus from searching requires $p \leq u$. If the solution is interior it satisfies the following first-order condition and

[13] 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).

[14] 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's asking price setting problem is therefore

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

the 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 this solution is infeasible because of financial limit u, the solution is instead $\{u, \theta_u\}$, where θ_u satisfies the free entry condition $V^s(u, 0, \theta_u) = 0$, or

$$x = [1 - e^{-\theta_u}]u. \tag{5}$$

The solution to problem P_0 can therefore be summarized as $p_0 = \min\{p_u^*, u\}$ and θ_0 satisfying $V^s(p_0, 0, \theta_0) = 0$.

The following proposition provides a partial characterization of the pre-policy DSE constructed using this solution as per the algorithm in Appendix A.2.

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 side of equation (4)). 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., $\theta_u > \theta_u^*$).[15]

As long as $p_0 = p_u^* \leq u$, the equilibrium expected payoff $\bar{V}^u$ is independent of u (in particular, $\bar{V}^u = \theta_u^* e^{-\theta_u^*} v$). As long as the constraint remains relatively mild, a change to buyers' ability to pay, u, will cause the equilibrium asking price to adjust in such a way that market tightness and the expected sales price remain unchanged. This reflects the fact that the financial constraint does not affect the *incentive* to search. When $p_0 = u < p_u^*$, the constraint is sufficiently severe that it affects the *ability* to search in that it shuts down the submarket that would otherwise achieve the mutually desirable trade-off between market tightness and expected price. This feature highlights the distinction between the roles of financial constraints and reservation values, since a change to buyers' willingness to pay, v, would affect the incentive to search, the equilibrium expected payoff, and the equilibrium trade-off between market tightness and expected sales price.

4.2.5 Post-Policy Directed Search Equilibrium

As in the previous section, 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:

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

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. The bidding limit once again limits the set of worthwhile submarkets. In particular, the optimal submarket for constrained buyers must feature an asking price less than or equal to c. If the solution is interior, it satisfies the two constraints with equality and a first-order condition derived in Appendix A.3. This interior solution is denoted $\{p_c^*, \lambda_c^*, \theta_c^*\}$. The corner solution is denoted $\{c, \lambda_c, \theta_c\}$, 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

[15] Using (3) and (4) to define p_u^*, inequality $u < p_u^*$ can be written $\left[1 - e^{-\theta_u^*}\right] u < x$. Combining this inequality with the free entry condition in (5) yields $\theta_u > \theta_u^*$.

$V^u(c, \lambda_c, \theta_c) = \bar{V}^u$. In summary, the solution to problem P$_1$ is $p_1 = \min\{p_c^*, c\}$ with λ_1 and θ_1 satisfying $V^s(p_1, \lambda_1, \theta_1) = 0$ and $V^u(p_1, \lambda_1, \theta_1) = \bar{V}^u$.

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 the asking prices obtained by solving problems P$_0$ and P$_1$ in the manner described above.

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., $\Lambda < \lambda_1$), 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 restrict attention to settings with $\Lambda \leq \lambda_1$ for the analytical characterization of equilibrium and rely on numerical results for settings with $\Lambda > \lambda_1$.[16]

For many sets of parameter values satisfying $0 < x < c < u \leq v$, the financial constraint c determines the solution to problem P$_1$ 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.

[16] 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 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). We sacrifice completeness for conciseness and convenience by restricting the set of analytical results to settings with $\Lambda \leq \lambda_1$.

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 financial constraints u and c lead to corner solutions to 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 mild (i.e., 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 (i.e., restrictive enough that some households search among the highest priced homes within their financial means). Under this assumption, the equilibrium asking prices are $p_0 = p_u^*$ and $p_1 = c$. There are still two possible subcases, namely (i) $p_u^* \leq c$ and (ii) $p_u^* > c$, which we use to motivate bunching from both above and below the bidding limit for the empirical analysis that follows.

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,*

$$\sigma(p_0) = \frac{(\lambda_1 - \Lambda)\mathcal{B}}{\lambda_1 \theta_0} \quad \textit{and} \quad \sigma(p_1) = \frac{\Lambda \mathcal{B}}{\lambda_1 \theta_1}. \tag{6}$$

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

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

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

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 $p_0 \leq c$ ($p_0 > c$).

Prediction 1 suggests that the million dollar policy can induce strategic responses among sellers in market segments near the newly imposed financial constraint. Some sellers who would have otherwise listed below c might respond to the policy by increasing their asking price to the threshold. The intuition for *bunching from below* is the following: as buyers become more constrained, the distribution of possible sales prices features fewer extreme prices at the high end. Sellers respond by raising their asking price to effectively truncate the distribution of prices from below. The higher price in a bilateral situation can offset the unseized sales revenue in multiple offer situations arising from the additional financial constraint. The MI policy may also induce some sellers who would have otherwise listed above c to drop their asking price to exactly equal the threshold. In the case of *bunching from above*, the reduction in asking prices is designed to attract constrained buyers. Because there is pooling of both buyer types in submarket p_1, these sellers may still match with unconstrained buyers and sell for a price above c.

To illustrate the predictions of the theory, we simulate two parameterized versions of the model. Example 1 features *bunching from below* using parameter values $\mathcal{B} = 1$, $v = 1$, $x = 0.15$, $c = 0.40$, $u = 0.50$ and $\Lambda = 0.05$. The second example features *bunching from above* using the same set of parameter values except $x = 0.10$, $c = 0.15$, and $u = 0.30$. Figure 1 provides a graphical illustration of Prediction 1 by plotting the pre- and post-policy distributions of asking prices. The plot on the left corresponds to Example 1 (bunching from below) and the plot on the right corresponds to Example 2 (bunching from above).

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

Prediction 2 is related to the ratio of unconstrained buyers to sellers (see parts (ii) and

(iii) of Lemma 1) and relies on the indifference condition for unconstrained buyers between submarkets, p_0 and p_1. If $p_1 < p_0$, this ratio is higher in submarket p_1 (i.e., $\theta_0 < (1 - \lambda_1)\theta_1$), which 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 probability of multiple offers from unconstrained buyers and the overall share of listed homes selling for u. If instead $p_0 < p_1$, the indifference condition for unconstrained buyers implies the opposite, namely $\theta_0 \geq (1 - \lambda_1)\theta_1$. In that case, the MI policy lowers the probability of multiple offers from unconstrained buyers.

Figure 3 presents graphical illustrations of Prediction 2 by plotting market tightness, θ, for asking prices in $[x, u]$. In both cases, market tightness is only affected by the presence of constrained buyers for a subset of asking prices. Submarkets that attract both constrained and unconstrained buyers post-policy feature higher market tightness because unconstrained buyers have an advantage when competing bidders face tighter financial constraints. Following the implementation of the policy, unconstrained buyers are therefore willing to tolerate a higher ratio of buyers to sellers. The ratio of unconstrained buyers to sellers, $(1 - \lambda)\theta$, remains unchanged. Since this ratio is decreasing in the asking price to satisfy the indifference condition for unconstrained buyers, it follows that an increase (decrease) in asking price from p_0 to c is associated with a lower (higher) probability of selling at price u.

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

The frictional matching process and the auction mechanism imply a smaller mass of sales relative to listings at price c. Figure 2 plots the distributions of sales prices for the two numerical examples. In both cases, the post-policy share of sales at price c is less than the corresponding share of listings at price c in Figure 1. The MI policy's effect on sales prices is further mitigated by the post-policy equilibrium search strategies of buyers. In particular, upward (downward) pressure on sales prices resulting from sellers' adjustments to price-posting strategies is partly offset by the lower (higher) incidence of price escalation up to u. For example, the CDF plotted on the left of Figure 2 (Example 1: bunching from below) reveals relatively fewer transactions at p_0, but also fewer transactions at price u. The net impact of the policy on the sales price is ultimately an empirical question.

4.4 Caveats

A brief discussion of some of the features of the model is in order. First, since financial constraint c is intended to represent the maximum ability to pay among buyers affected by the MI policy, parameter c corresponds to the \$1M threshold (relative to the seller's reservation value) and Λ reflects the share of potential buyers with insufficient wealth from which to draw a 20 percent down payment.[17] If the parameter values for v, u and c are small, the scope of the model shrinks to a narrow segment of the market around \$1M.

Second, the determination of prices in practice differs in some ways from the simple auction mechanism modelled here. In a bilateral meeting, it is quite common for the buyer and seller to negotiate a final transaction price slightly below the asking price. In contrast, we assume that the asking price effectively represents a firm commitment to a minimum price. We rely on this assumption for deriving meaningful implications about the effect of the MI policy on asking prices. Embellishing the price determination mechanism[18] may allow for transaction prices below asking prices without compromising the asking price-related implications of the theory. Such extensions, however, would add considerably to the analytical complexity of the model.

Finally, 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 Arefeva, 2016). 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. With post-policy entry decisions on the demand side, buyers would self-select into the market in such a way that the effects of the policy would be mitigated or

[17]Since the MI policy effectively imposes a 20 percent down payment requirement when the purchase price is \$1M or more, c more precisely represents a bidding limit of $\$999,999$ (less the seller's minimum acceptable sales price).

[18]See Albrecht et al., 2016 and Han and Strange, 2016 for more sophisticated pricing protocols that can account for sale prices both above and below the asking price.

even non-existent. More specifically, suppose for a moment that both types of buyers face entry decisions subject to an entry fee or search cost. Provided there are sufficiently many unconstrained potential market participants, unconstrained buyers would enter the market until they reach indifference about market participation: their expected payoff would equal the participation cost. Because constrained buyers are outbid by unconstrained buyers, the expected payoff for a constrained buyer would be strictly less than the cost of market participation. It follows that constrained buyers would optimally choose not to participate in this segment of the housing market and consequently the post-policy equilibrium would be indistinguishable from the pre-policy equilibrium with identically unconstrained buyers. In contrast, we show in the analysis that follows that the MI policy does affect equilibrium strategies and outcomes when entry decisions are imposed on the supply side of the market.

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 Greater Toronto Area. Our data include 33,546 observations in the pre-policy period and 29,323 observations in the post-policy period. The mean sales price in Toronto was $\$64,900.19$ in the pre-policy period and $680,482.77 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 90th percentile of the pre-policy price distribution. There were 1,365 homes sold within $100,000 of $1M in the pre-policy period, and 1,655 in the post-policy period.

6 Empirical Evidence

We now present empirical tests of the predictions derived in Section 4. The main prediction of the model is that the million dollar policy leads to sellers adjusting the asking price, which results in changes in sales price, both at the million dollar segment (Predictions 1 and 3). To measure these market responses, we use a bunching approach recently developed in recent public finance literature (Saez (2010), Chetty et al. (2011b) and Kleven and Waseem (2013)). The key idea is to use the distribution of price segments that are not subject to the policy effect to form a valid counterfactual distribution of the price segment near the \$1M threashold in the absence of the policy. The two underlying assumptions are that, (1) the policy effect occurs locally in a segment near \$1M, leaving part of the distribution unaffected by the policy, and (2) that the counterfactual distribution is smooth and can be estimated using the unaffected part of the distribution. In forming the counterfactual, we use a two-step approach: first construct a counterfactual price distribution that would have prevailed if there were no composition changes of housing stock using a common reweighting method; then build a counterfactual composition-constant distribution of house prices in the absence of the MI policy using the bunching approach.

The core estimation is presented in Subsection 6.1 with an aim to test Predictions 1 and 3, followed by a test of prediction 2 on bidding intensity in Subsection 6.2. Finally, we present a cross-markets analysis in Subsection 6.3,

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

6.1.1 First step: 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.[19] 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. We use a simple reweighting method proposed by DiNardo et al. (1996) that is based on the following relation:

$$F_{Y\langle 1|0\rangle} = \int F_{Y_1|X_1}(y|x) \cdot \Psi(x) \cdot dF_{X_1}(x)$$

where $\Psi(x) = \frac{dF_{X_0}}{dF_{X_1}}$ is a reweighting factor that can be easily estimated by using a logit, for example (Fortin et al., 2011). In our implementation of this method, we obtain the weighting function by pooling pre- and post-period data and estimating a logit model where the dependent variable is a pre-period dummy. The covariate vector contains indicators for district, month, the number of rooms, whether the basement is finished, and the housing type (detached, semi-detached).[20] The estimated counterfactual distribution is given by

[19]Note that our bunching estimator, which we describe below, relies on agents sorting around the policy threshold. Thus, in comparison to a regression discontinuity design, where there is assumed to be no manipulation around the policy threshold, such concerns about composition are valid here.

[20]The weighting function is $\Psi(x) = \frac{p(x)}{1-p(x)} \cdot \frac{1-P(t=1)}{P(t=0)}$, where $p(x)$ is the propensity score, ie, the probability

$\hat{F}_{Y\langle 1|0\rangle} = \int \hat{F}_{Y_1|X_1}(y|x) \cdot \hat{\Psi}(x) \cdot d\hat{F}_{X_1}(x)$, where $\hat{F}_{Y\langle 1|0\rangle}$ is an empirical distribution function that is estimated using grid intervals of \$5,000 and is a reweighted version of the observed price distribution in the post-policy period; that is, $\hat{F}_{Y\langle 1|0\rangle}$ is the price distribution that would prevail if the characteristics of homes where the same in the same as in the pre-period.

Figure 5 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, represented 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 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 6 examines the distribution of sales price for $p_j = 500{,}000, \ldots, 1{,}400{,}000$. One key difference between the sales prices in Figure 6 and the asking prices in Figure 5 is that the former are 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. In addition, Figure 6 shows no

that $t = 0$ given x.

noticeable jump of the sales price at the million dollar threshold, suggesting that most of the jump of the asking price may be mitigated by buyers' bidding activities.

Together, the descriptive findings presented in Figures 5 and 6 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 step: bunching estimation

Set-up 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 using a bunching estimation procedure. This procedure requires separation of the observed $\hat{\Delta}_S(y_j)$ into two parts: the price segments near \$1M that are subject to the policy effect, and the segments that are not. The affected segment is known as the 'excluded' region in the bunching literature. Since knowledge of this region is not known *a priori*, we must also estimate this and we develop a procedure below to do so. Once this region is obtained, we use standard methods to estimate the counterfactual distribution by fitting a flexible polynomial to the empirical distribution, excluding data in a range around \$1M. We use the estimated polynomial to predict or 'fill in' the excluded region which forms our counterfactual. Our estimates of the policy effect are given by the difference between the observed $\hat{\Delta}_S(y_j)$ and the estimated counterfactual.

In particular, consider the equation:

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

where p is the order of the 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[21]

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

It is important to note that the interpretation of the total jump at the threshold 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 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.

Under the assumption that there is no extensive margin response, the two sources of response described above imply two adding up constraints. First, 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

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

[21]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.

And similarly for those sellers coming from above the threshold:

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

Estimation In order to implement our estimator, several decisions must be made about unknown parameters, as is the case for bunching approaches. In particular, the number of excluded bins to the left, L, and right, R, are unknown, as is the order of the polynomial, p. In addition to this we choose to limit our estimation to range of price bins around the $1M threshold. We do this because the success of our estimation procedure requires estimation of the counterfactual in the region local to the policy threshold. Using data points that are far away from the excluded region to predict values within the excluded region can be sensitive to polynomial choice and implicitly place very high weights on observations far from the threshold (**?**). Thus, we focus on a more narrow range, or estimation window, W, of house prices around the policy threshold. Since we are fitting polynomial functions, this can be thought of as a bandwidth choice for local polynomial regression with rectangular weights **?**. Thus, the parameters we require for estimation of the regression coefficients are (L, R, W, p).

We use a data-driven approach to select these parameters. The procedure we implement is a 5-fold cross-validation procedure, described more fully in Appendix **??**. Briefly, we randomly split our individual-level data into 5 equally sized groups and carry out both step 1 and 2 of our estimation procedure using 4 of the groups (i.e., holding out the last group), and then obtain predicted squared residuals from equation (8) for the hold-out group. We repeat this procedure 5 times, holding out a different group each time, and average the predicted squared residuals across each repetition. This is the cross-validated Mean Squared Error (MSE) for a particular choice of (L, R, W, p). We perform a grid search over several values of each parameter, and choose the specification which minimizes the MSE. This procedure is very similar to **?**, except in one important respect: in their implementation, they impose the adding up constraints similar to (10) and (11). We choose not to impose the constraints at the model selection stage, and instead test that the constraints hold in the data for a given selected model. This allows us to assess whether our data-driven model selection procedure produces a model that is consistent with the theoretical framework.[22]

6.1.3 Results

Figure 7 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, while 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) as described in Section 6.1.2. Note that the width of the estimation widow (\$75,000 dollars around the threshold), the order of the polynomial (quartic), and the width of the excluded region were chosen based on the cross-validation procedure outlined above.

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 0.45% increase in the mass of homes listed. In contrast, the increase in the counterfactual distribution between these two bins is minor — only about 0.03%. Thus much of the bunching we observed at the \$1M is driven by the MI policy.

Figure 8 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]

[22] We do not claim that this method for model selection is necessarily optimal. In the literature on bunching estimation, the excluded region is sometimes selected by visual inspection (**?**) in combination with an iterative procedure (**?**) that selects the smallest width consistent with adding-up constraints. Often, high-order global polynomials are used in estimation and robustness to alternative polynomial orders are shown. In the closely related regression discontinuity literature, free parameters are sometimes chosen by cross-validation (Lee and Lemieux, 2010). In a recent paper by **?**, the authors are faced with many different regions and time periods where bunching occurs, and so visual inspection is impractical. They develop a k-fold cross-validation procedure to choose the width of the manipulation region and polynomial order. Our approach closely follows theirs. However, we do consider a series of robustness checks to assess the sensitivity of our estimates to the choice of parameters (L, R, W, p). In practice, we find that our estimates are quite robust to reasonable deviations in the parameters selected by our cross-validation procedure.

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 7 reports the bunching estimates. Standard errors are calculated via bootstrap.[23] Overall, we find that approximately 94 homes that would have otherwise been listed away from \$1M were shifted to the \$1M bin. In other words, the MI policy increased the number of homes listed in the million dollar price bin by 44% compared to the counterfactual. Among these additional listings, about 60% are shifted from below $\$995,000$. The remaining 40% 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 increase their asking prices towards the \$1M mark. By doing so, these sellers extract more surplus in the bilateral situation, which compensates for the losses that they 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)-(8) 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) during estimation. Column (7) includes a set of indicators for asking price at the round-numbers that are multiples of $25,000$ and $50,000$. Reassuringly, the bunching estimates are extremely robust, suggesting that our results are not driven by the selection of the size of the estimation window, order of the polynomial, or the width of the excluded region. We discuss column 8 in section 6.1.5 below.

[23]We calculate standard errors for all estimated parameters by bootstrapping both step 1 and 2 of the estimation procedure. We draw 399 random samples with replacement from the house-hold level data, and calculate the standard deviation of our estimates for each of these samples.

Turning to Prediction 3, we report the bunching estimates for the sales price in Table 7, with a visualization of the estimates shown in Figures 9 and 10. Despite sharp bunching of the asking price, we do not find any bunching of the sales price at the million dollar segment; the evidence is robust across different specifications. In light of Prediction 3, the finding here suggests that the policy impact on the asking price is completely offset by the intensified biddings among unconstrained buyers. To facilitate this interpretation, we will directly estimate the policy effect on bidding intensities in Subsection 6.2.

6.1.4 Robustness Checks

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" threshold. 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 7 reports the estimates of the total observed jump at the cut-off from 48 placebo regressions where we repeat our main analysis for either a placebo year and/or a placebo threshold. Out of the 48 bunching estimates, only 5 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.

6.1.5 Extensive Margin Responses

As mentioned above, the counterfactual distribution is estimated by fitting a flexible polynomial through the empirical distribution, excluding an area around the $1M threshold. The behavioural responses that we estimate stem from comparing the fitted polynomial counterfactual estimate to the observed distribution. Because our approach uses data above the threshold in the counterfactual estimation it may be affected by extensive margin responses. That is, if the introduction of the MI policy caused potential sales above the threshold not to occur, our estimated counterfactual distribution would not reflect the distribution that would occur if the MI policy were removed. This is an issue that is common in the bunching literature (Best et al., 2015; Best and Kleven, 2017; Kopczuk and Munroe, 2015).

We confront this issue in two ways. First, as suggested in Kleven (2016), we construct the counterfactual using only data below $1M under the assumption that the distribution below the threshold is not affected by potential extensive margin responses. These results are presented in column 8 of Table 3, where we use the same excluded region and polynomial order as in column (1), but extend the estimation window leftward in order to have enough bins to identify the coefficients in (8). These results are similar to the other columns of the table, and suggest that any extensive margin responses are minimal.

Our second approach expands on this approach. We assume that the pre-policy house sales distribution is not affected by the policy and we continue to assume that the post-period distribution below $1M is not affected by potential extensive margin responses. In principle, we would like to compare the pre- and post-policy distribution above $1M in order to estimate extensive margin responses. However, due to other macro-forces affecting the housing market, this simple comparison will not identify an extensive margin response of the MI policy. Recall from Figure 3 that the entire post-period distribution is shifted leftward, indicating fewer sales at any given price. We assume that any shift in the pre- and post-distributions below \$1M is due to factors unrelated to the MI policy. We use this simple location shift below \$1M to create a counterfactual post-policy distribution that is shifted such that it coincides with the pre-policy distribution. Any extensive margin response could be visually detected by a bending in the post-policy counterfactual CDF above the policy threshold. We present the results of this exercise in Figure XX. As can be seen from the figure, there is very little evidence of an extensive margin response.

6.2 Prediction 2: The Policy Effects 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 lack of bunching for the sales price. The lack 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 approach described in Section 6.1.1, we estimate the survivor function, $\hat{S}_{Y\langle 1|1\rangle}(y_j^A) = 1 - \hat{F}_{Y\langle 1|1\rangle}(y_j^A)$, which represents 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 using the reweighting method, 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 the rescaled survivor function, $RS_{Y\langle 1|1\rangle}(y_j^A, y^S \geq y^A)$, which gives 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 and Bayes, 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 11 and 12 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 Cross-Market Analysis

Although not explicitly shown, the model also implies that the financial constraint effects on the asking and sales price should be stronger for markets where prospective buyers are more constrained by the policy. Given that we do not have the micro-level data on financial constraints, we do not aim to test this prediction formally. Instead, we provide some suggestive evidence in this subsection.

In particular, we compare two submarkets of the Greater Toronto Area: central Toronto and suburban Toronto. 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.

Tables 5 and 6 present the estimates of the policy effects on the asking price and sales price in central and suburban Toronto, 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 consistent with what the model predicts.

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 but lack of bunching for sales price. These results, together with the 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, agree well with the theoretical predictions. Finally, although the policy fails to cool the boom at the million dollar segment, it does help improve borrower creditworthiness by reallocating homes to less constrained buyers.

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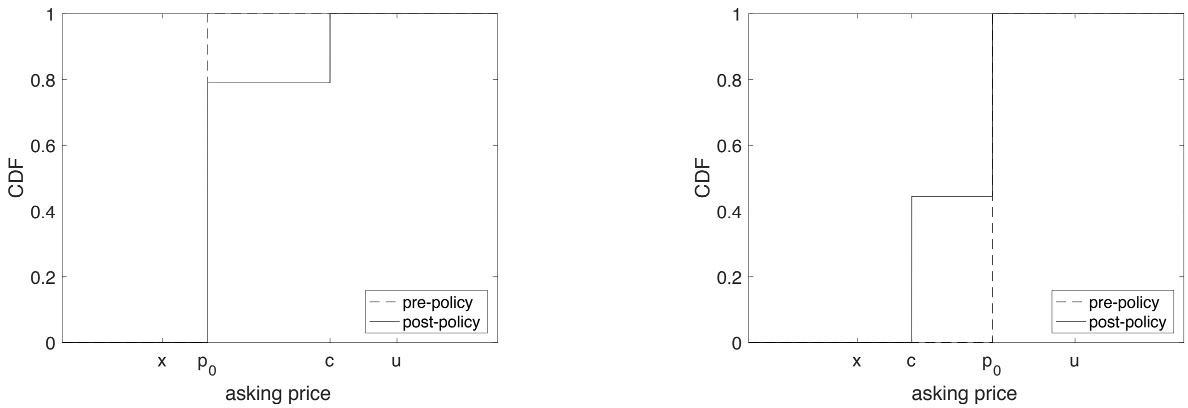


Figure 1: Distributions of Asking Prices, Examples 1 (left) and 2 (right)

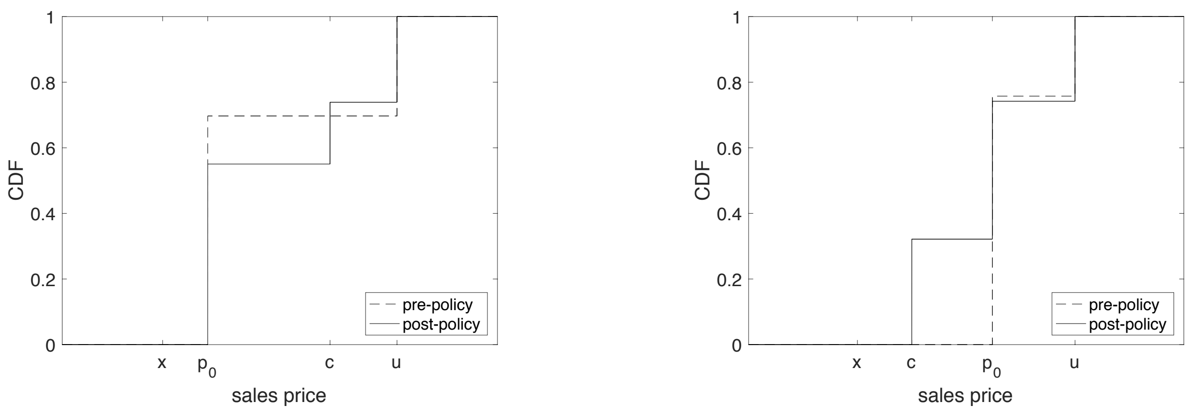


Figure 2: Distributions of Sales Prices, Examples 1 (left) and 2 (right)

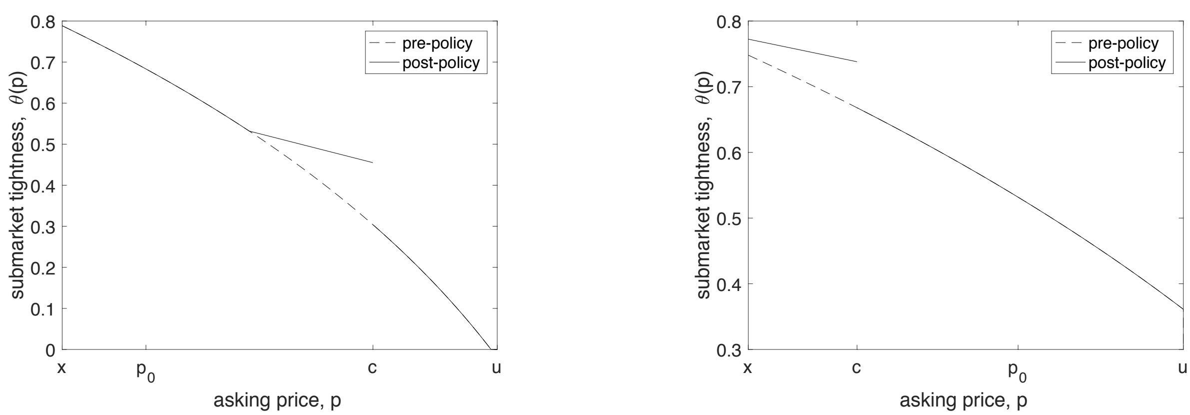


Figure 3: Tightness as a Function of the Asking Price, Examples 1 (left) and 2 (right)

Table 1:

		Pre-Policy		Post-Policy	
		Asking	Sales	Asking	Sales
All Homes	Mean	725910.18	726631.69	773706.53	763510.49
	25th Pct	459900.00	465000.00	499000.00	495000.00
	50th Pct	599000.00	610000.00	639900.00	638000.00
	75th Pct	799000.00	810000.00	849000.00	848000.00
	N	22333.00	22333.00	19337.00	19337.00
	Median Duration	10.00	10.00	13.00	13.00
	1M Percentile	0.87	0.86	0.85	0.84
Homes 0.9-1M	N	842.00	941.00	910.00	930.00
	Median Duration	9.00	8.00	13.00	12.00
	Mean Price	964459.06	942429.12	965717.95	946051.48
Homes 1-1.1M	N	375.00	532.00	426.00	536.00
	Median Duration	10.00	9.00	13.00	11.50
	Mean Price	1072005.01	1043719.95	1074124.55	1043931.75

Table 2: Regression Buncing Estimates for Post policy period

	Asking Price							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Jump at cut-off	0.0045*	0.0045*	0.0045*	0.0045*	0.0045*	0.0045*	0.0045*	0.0045*
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Total Response	0.0042*	0.0037*	0.0038*	0.0042*	0.0042*	0.0048*	0.0041*	0.0044*
	(0.0011)	(0.00100)	(0.00083)	(0.0010)	(0.0011)	(0.0014)	(0.0010)	(0.0016)
From Below	-0.0025*	-0.0021*	-0.0027*	-0.0024*	-0.0024*	-0.0028*	-0.0024*	-0.0024*
	(0.00076)	(0.00076)	(0.00077)	(0.00075)	(0.00077)	(0.00092)	(0.00075)	(0.0010)
From Above	0.0018*	0.0017*	0.0011*	0.0018*	0.0018*	0.0020*	0.0017*	0.0019
	(0.00077)	(0.00067)	(0.00045)	(0.00073)	(0.00077)	(0.00090)	(0.00064)	(0.0019)
Observations	41670	41670	41670	41670	41670	41670	41670	41670
Excluded Bins:								
L	4	4	4	4	5	4	4	4
R	3	3	3	3	4	3	3	3
Tests of Fit:								
$B - \sum_l^L \beta_B^L$	-.0024	-.0018	-.0029*	-.0023	-.003	2.1e-17*	-.0023	-8.3e-17
	(.0014)	(.0014)	(.0013)	(.0013)	(.002)	(.)	(.0014)	(1.6e-11)
$A - \sum_r^R \beta_A^r$	.000041	.00092	.00015	1.2e-06	.00059	4.2e-17	.00017	3.3e-16*
	(.00054)	(.00069)	(.00079)	(.00047)	(.001)	(1.5e-11)	(.0005)	(.)
Joint p-val.	0.20	0.30	0.13	0.20	0.33	.	0.26	.
Impact:								
Δ Houses at cutoff	94.3	83.7	85.7	93.9	93.7	107.1	92.4	97.2
%Δ at cutoff	43.7	36.9	38.2	43.4	43.3	49.5	42.4	41.9
% from Above	92.9	115.4	75.9	90.5	83.6	102.5	95.3	159.4
% from Below	25.6	22.0	28.1	25.4	19.3	29.5	24.9	25.8
Specifications:								
Poly. Order	2	2	2	3	2	2	2	2
Window	15	20	10	15	15	15	15	15
Other						Constrained	No Round Number	Extensive

Standard errors in parentheses

* $p < 0.05$

Table 3: Regression Buncing Estimates for Post policy period

	Sales Price							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Jump at cut-off	0.00089	0.00089	0.00089	0.00089	0.00089	0.00089	0.00089	0.00089
	(0.00046)	(0.00046)	(0.00046)	(0.00046)	(0.00046)	(0.00046)	(0.00046)	(0.00046)
Total Response	0.00086	0.00017	0.00086	0.00075	0.00085	0.00086	0.00056	0.00027
	(0.00056)	(0.00056)	(0.00087)	(0.00055)	(0.00055)	(0.00056)	(0.00045)	(0.00065)
From Below	0.00011	0.00010	0.000039	0.00012	0.00016	0.00011	0.000056	0.00086
	(0.00052)	(0.00058)	(0.00045)	(0.00052)	(0.00058)	(0.00052)	(0.00052)	(0.00087)
From Above	0.00097	0.00028	0.00090	0.00087	0.0010	0.00097	0.00061	0.0011
	(0.00069)	(0.00072)	(0.00090)	(0.00068)	(0.00073)	(0.00069)	(0.00054)	(0.0012)
Observations	41670	41670	41670	41670	41670	41670	41670	41670
Excluded Bins:								
L	1	1	1	1	2	1	1	1
R	1	1	1	1	2	1	1	1
Tests of Fit:								
$B - \sum_l^L \beta_B^L$	.	.	.	.	.00014	.	.	.
	(.)	(.)	(.)	(.)	(.00037)	(.)	(.)	(.)
$A - \sum_r^R \beta_A^r$	.	.	.	.	-.00073	.	.	.
	(.)	(.)	(.)	(.)	(.0006)	(.)	(.)	(.)
Joint p-val.	.	.	.	.	0.46	.	.	.
Impact:								
Δ Houses at cutoff	19.3	3.89	19.3	16.8	18.9	19.3	12.5	5.97
$\%\Delta$ at cutoff	56.0	7.80	55.8	45.2	54.3	56.0	30.1	12.5
% from Above	22.0	7.72	19.9	19.2	17.1	22.0	15.0	32.1
% from Below	2.96	2.96	1.07	3.29	2.75	2.96	1.58	25.5
Specifications:								
Poly. Order	2	2	2	3	2	2	2	2
Window	15	20	10	15	15	15	15	15
Other						Constrained	No Round Number	Extensive

Standard errors in parentheses

* $p < 0.05$

Table 4: Regression Buncing Estimates for Post policy period

	Post-Policy Difference		Pre-Policy Difference	
	(1) Asking	(2) Sales	(3) Asking	(4) Sales
800000	0.0016	-0.0013	0.0020	0.000056
	(0.0016)	(0.00080)	(0.0014)	(0.00077)
825000	0.00029	-0.00045	-0.00090*	0.00046
	(0.00049)	(0.00080)	(0.00044)	(0.00075)
850000	0.0012	0.00093	-0.000045	-0.00057
	(0.0013)	(0.00082)	(0.0011)	(0.00065)
875000	0.0000078	-0.00023	0.00029	0.00043
	(0.00044)	(0.00070)	(0.00035)	(0.00064)
900000	0.00075	0.00024	0.0031*	0.00026
	(0.0014)	(0.00067)	(0.0010)	(0.00058)
925000	-0.00038	0.00076	-0.00013	0.00025
	(0.00038)	(0.00070)	(0.00033)	(0.00056)
950000	-0.0011	-0.00073	-0.0016*	-0.00032
	(0.00093)	(0.00057)	(0.00083)	(0.00046)
1000000	0.0042*	0.00086	0.0011	-0.00022
	(0.0011)	(0.00056)	(0.00089)	(0.00045)
1050000	-0.0022*	0.0000059	-0.00048	0.00025
	(0.00064)	(0.00046)	(0.00056)	(0.00035)
1075000	-0.000076	-0.00060	-0.00022	0.00045
	(0.00019)	(0.00042)	(0.00016)	(0.00041)
1100000	0.0015	0.00022	0.0011	-0.00057
	(0.00082)	(0.00035)	(0.00067)	(0.00036)
1125000	-0.000023	-0.00067	0.00051*	0.00021
	(0.00028)	(0.00036)	(0.00022)	(0.00035)
1150000	-0.00072	0.00026	-0.0013*	-0.00043
	(0.00063)	(0.00036)	(0.00058)	(0.00032)

Standard errors in parentheses

Table 5: Regression Buncing Estimates for Post policy period

	Asking Price							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Jump at cut-off	0.0095*	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)	(0.0031)
Total Response	0.0072*	0.0068*	0.0076*	0.0075*	0.0072*	0.0081*	0.0089*	0.010*
	(0.0034)	(0.0030)	(0.0029)	(0.0028)	(0.0034)	(0.0034)	(0.0029)	(0.0050)
From Below	-0.0062*	-0.0055*	-0.0062*	-0.0062*	-0.0063*	-0.0067*	-0.0062*	-0.0038
	(0.0021)	(0.0020)	(0.0020)	(0.0020)	(0.0023)	(0.0025)	(0.0021)	(0.0038)
From Above	0.0010	0.0012	0.0014	0.0012	0.00093	0.0014	0.0027	0.0065
	(0.0024)	(0.0021)	(0.0017)	(0.0020)	(0.0025)	(0.0019)	(0.0018)	(0.0081)
Observations	9111	9111	9111	9111	9111	9111	9111	9111
Excluded Bins:								
J	3	3	3	3	4	3	3	3
K	2	2	2	2	3	2	2	2
Tests of Fit:								
$B - \sum_j^J \beta_B^j$	-.0021	-.0015	-.0023	-.0023	-.0041	0	-.0021	-2.5e-14*
	(.002)	(.0021)	(.0016)	(.0017)	(.0043)	(6.0e-11)	(.0019)	(.)
$A - \sum_k^K \beta_A^k$	.00047	.00076	.00015	.00031	.0016	2.8e-17	-.0012*	3.0e-14
	(.0012)	(.00091)	(.00098)	(.00097)	(.0011)	(2.9e-11)	(.00039)	(1.2e-10)
Joint p-val.	0.49	0.56	0.39	0.39	0.27	.	0.010	.
Impact:								
Δ Houses at cutoff	35.8	33.8	37.7	37.3	35.9	40.4	44.2	51.2
%Δ at cutoff	34.2	31.7	36.7	36.1	34.3	38.7	45.8	52.4
% from Above	166.2	240.6	150.5	183.3	75.3	196.0	114.4	-107.6
% from Below	35.9	31.7	35.8	36.7	35.0	39.3	37.6	24.4
Specifications:								
Poly. Order	4	4	4	5	4	4	4	4
Window	20	25	15	20	20	20	20	20
Other						Constrained	No Round Number	Extensive

Standard errors in parentheses

* $p < 0.05$

Table 6: Regression Buncing Estimates for Post policy period

	Sales Price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Jump at cut-off	0.00089	0.00089	0.00089	0.00089	0.00089	0.00089	0.00089
	(0.00045)	(0.00045)	(0.00045)	(0.00045)	(0.00045)	(0.00045)	(0.00045
Total Response	0.00050	0.00054	0.00046	0.00046	0.00050	0.00016	0.00050
	(0.00045)	(0.00045)	(0.00045)	(0.00044)	(0.00045)	(0.00064)	(0.00045
From Below	-0.000034	0.00014	-0.000075	-0.0000030	-0.00015	0.000063	-0.00003
	(0.00056)	(0.00057)	(0.00055)	(0.00058)	(0.00062)	(0.00066)	(0.00056
From Above	0.00047	0.00068	0.00038	0.00046	0.00035	0.00022	0.00047
	(0.00058)	(0.00058)	(0.00057)	(0.00058)	(0.00064)	(0.00058)	(0.00058
Observations	41670	41670	41670	41670	41670	41670	41670
Excluded Bins:							
J	3	3	3	3	4	3	3
K	2	2	2	2	3	2	2
Tests of Fit:							
$B - \sum_j^J \beta_B^j$	.00016	.00018	.00027	.0003	-.00074	-2.1e-17*	.00016
	(.00087)	(.0009)	(.00082)	(.00083)	(.0013)	(.)	(.00087
$A - \sum_k^K \beta_A^k$	-.00048	-.00045	-.00052	-.00052	-.00058	2.8e-17*	-.00048
	(.00048)	(.00048)	(.00048)	(.00048)	(.00089)	(.)	(.00048
Joint p-val.	0.61	0.65	0.56	0.54	0.65	.	0.61
Impact:							
Δ Houses at cutoff	11.2	12.1	10.2	10.3	11.2	3.57	11.2
$\%\Delta$ at cutoff	26.2	29.0	23.5	23.8	26.4	8.10	26.2
% from Above	8.17	12.0	6.64	7.93	5.11	3.96	8.17
% from Below	0.39	1.63	0.86	0.035	1.49	0.75	0.39
Specifications:							
Poly. Order	4	4	4	5	4	4	4
Window	20	25	15	20	20	20	20
Other						Constrained	No Round N

Standard errors in parentheses

* $p < 0.05$

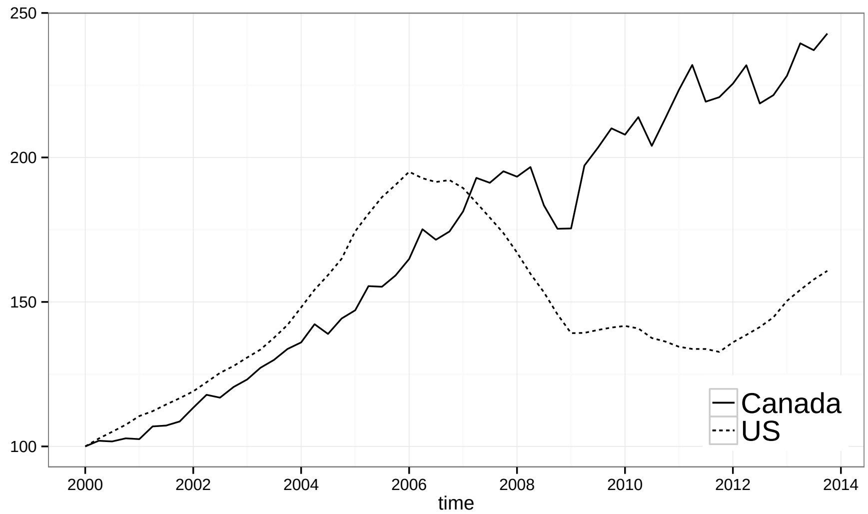


Figure 4: House Price Indices for Canada and the U.S.

Figure 5: Observed Distribution and Decomposition of Asking Prices

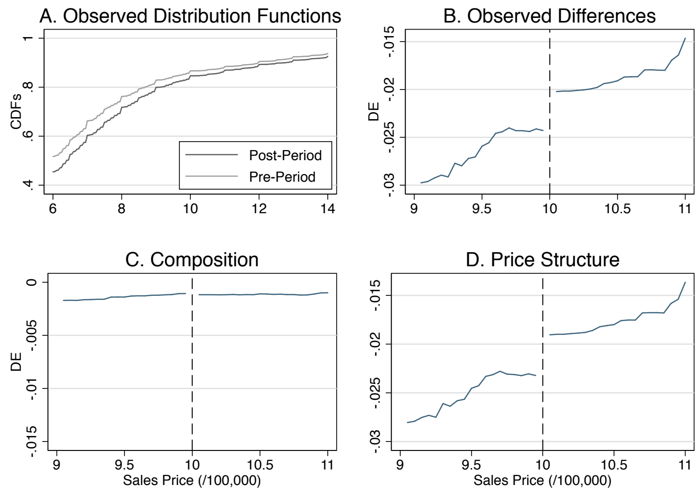


Figure 6: Observed Distribution and Decomposition of Sales Prices

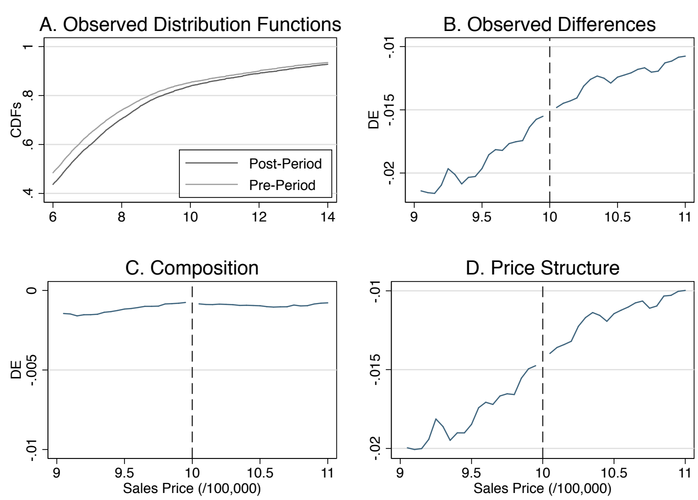
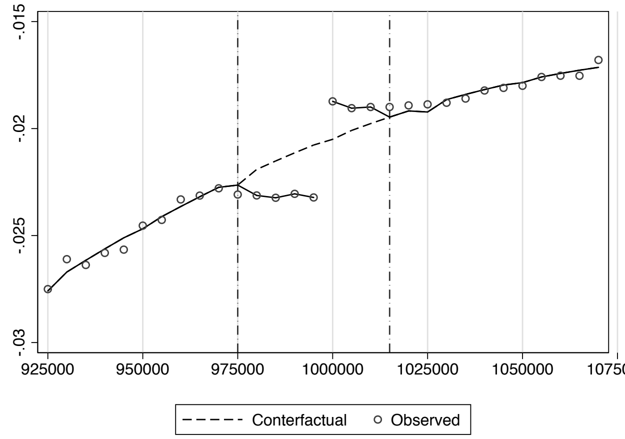


Figure 7: Observed Cumulative Distribution and Decomposition of Asking Prices



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 8: Observed Density Distribution of Asking Prices

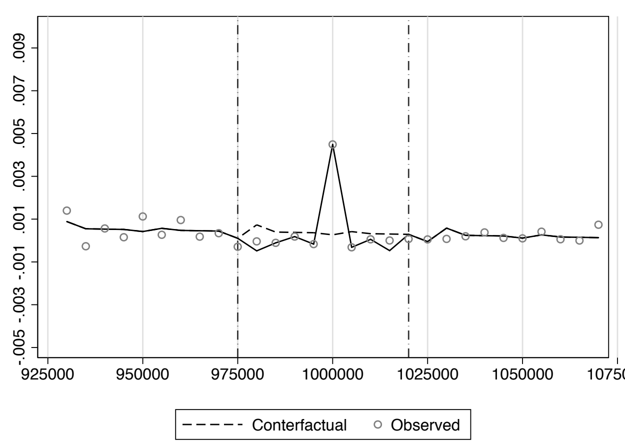
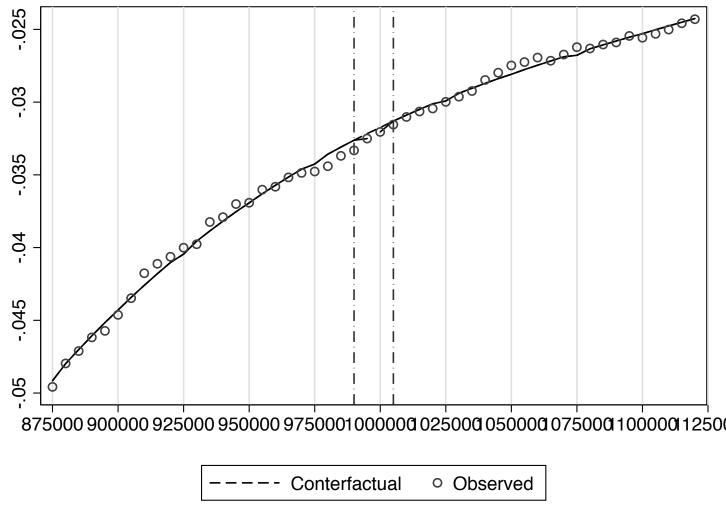


Figure 9: Observed Cumulative Distribution and Decomposition of Sales Prices



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 10: Observed Density Distribution of Sales Prices

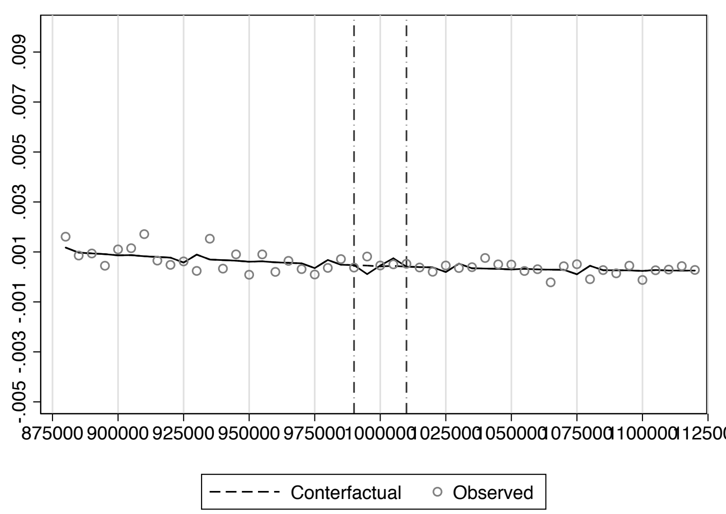


Figure 11: Probability of Sales above Asking Conditional on Asking Price

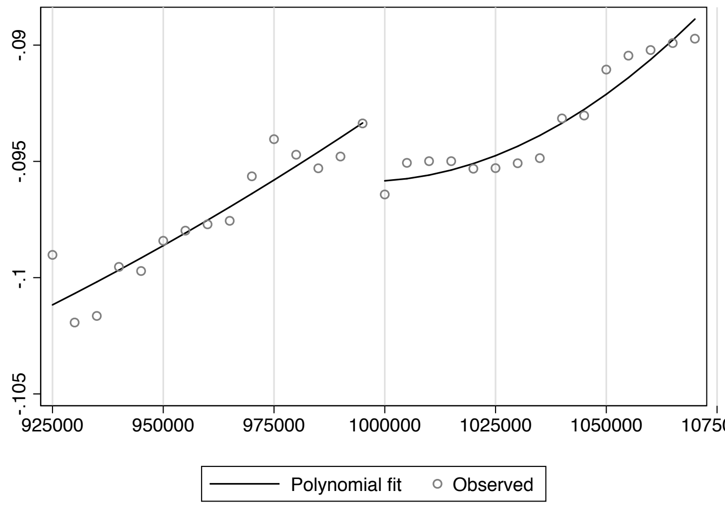
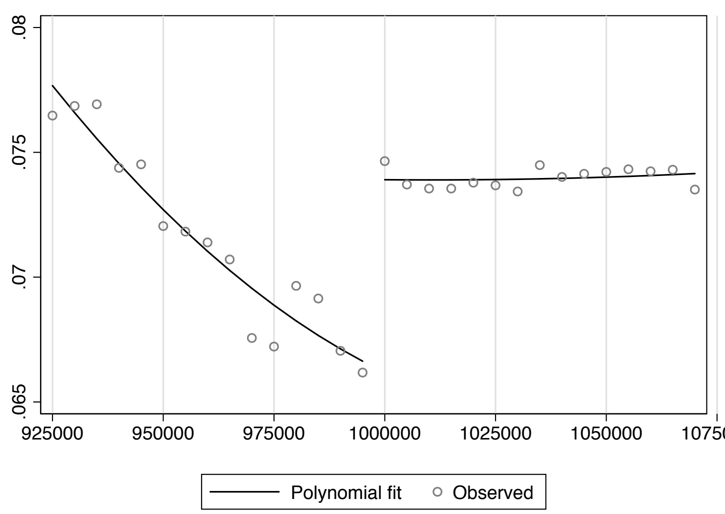


Figure 12: Probability of Being on Market for ≥ 2 weeks Conditional on Asking Price



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: $p \leq c$. Expected payoffs in this case, denoted $V_I^i(p, \lambda, \theta)$ for $i \in \{s, u, c\}$, are the ones derived in Section 4.2.2.

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

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

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

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

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:

$$V_{II}^c(p, \lambda, \theta) = 0. \tag{A.3}$$

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:

$$V_{III}^s(p, \lambda, \theta) = -x, \quad V_{III}^u(p, \lambda, \theta) = 0 \quad \text{and} \quad V_{III}^c(p, \lambda, \theta) = 0. \tag{A.4}$$

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

$$V^i(p,\lambda,\theta) = \begin{cases} V^i_{III}(p,\lambda,\theta) & \text{if } p > u, \\ V^i_{II}(p,\lambda,\theta) & \text{if } c < p \leq u, \\ V^i_{I}(p,\lambda,\theta) & \text{if } p \leq c. \end{cases} \tag{A.5}$$

A.2 Algorithm for Constructing Pre-Policy DSE

Solution to Problem P_0: Assuming (for the moment) an interior solution, the solution to problem P_0 satisfies the following first-order condition with respect to θ and the free-entry condition:

$$x = [1 - e^{-\theta_u^*} - \theta_u^* e^{-\theta_u^*}]v$$
$$x = \theta_u^* e^{-\theta_u^*} p^* + [1 - e^{-\theta_u^*} - \theta_u^* e^{-\theta_u^*}]u,$$

which combine to yield

$$p_u^* = \frac{[1 - e^{-\theta_u^*} - \theta_u^* e^{-\theta_u^*}](v-u)}{\theta_u^* e^{-\theta_u^*}}. \tag{A.6}$$

Now taking into account the constraint imposed by bidding limit u, the solution is $p_0 = \min\{u, p_u^*\}$ and θ_0 satisfying $V^s(p_0, 0, \theta_0) = 0$.

Algorithm: If $\Lambda = 0$, set $\mathbb{P} = \{p_0\}$, $\theta(p_0) = \theta_0$, $\sigma(p_0) = \mathcal{B}/\theta_0$ and $\bar{V}^u = V^u(p_0, 0, \theta_0)$. For $p \leq u$, set θ to satisfy $\bar{V}^u = V^u(p, 0, \theta(p))$ or, if there is no solution to this equation, set $\theta(p) = 0$. For $p > u$ set $\theta(p) = 0$.

A.3 Algorithm for Constructing Post-Policy DSE

Solution to Problem P_1: Assuming (for the moment) an interior solution, the solution to problem P_1 satisfies the two constraints with equality, $V^s(p_c^*, \lambda_c^*, \theta_c^*) = 0$ and $V^u(p_c^*, \lambda_c^*, \theta_c^*) = \bar{V}^u$, and the following first-order condition.

$$e^{-\theta_c^*} p_c^* = \left(1 - \frac{\left[1 - e^{-\theta_c^*} - \theta_c^* e^{-\theta_c^*}\right] v - x}{(1-\lambda_c^*)\theta_c^*} \frac{1}{\bar{V}^u - \bar{V}^c}\right)$$
$$\times \left(\frac{1 - e^{-(1-\lambda_c^*)\theta_c^*} - (1-\lambda_c^*)\theta_c^* e^{-(1-\lambda_c^*)\theta_c^*}}{(1-\lambda_c^*)\theta_c^*}(v-u) + (1-\lambda_c^*)\lambda_c^*\theta_c^* e^{-(1-\lambda_c^*)\theta_c^*}(u-c)\right)$$

where $\bar{V}^c = V^c(p_c^*, \lambda_c^*, \theta_c^*)$ and $\bar{V}^u$ is set equal to the maximized objective of problem P_0. Now taking into account the constraint imposed by bidding limit c, the solution is $p_1 = \min\{c, p_c^*\}$ with λ_1 and θ_1 satisfying $V^s(p_1, \lambda_1, \theta_1) = 0$ and $V^u(p_1, \lambda_1, \theta_1) = \bar{V}^u$.

Algorithm: If $0 < \Lambda \leq \lambda_1$, set $\mathbb{P} = \{p_0, p_1\}$, $\lambda(p_0) = 0$, $\theta(p_0) = \theta_0$, $\lambda(p_1) = \lambda_1$, $\theta(p_1) = \theta_1$, $\sigma(p_0) = (\lambda_1 - \Lambda)\mathcal{B}/(\lambda_1\theta_0)$ and $\sigma(p_1) = \Lambda\mathcal{B}/\lambda_1\theta_1$. The equilibrium values are $\bar{V}^u = V^u(p_0, 0, \theta_0) = V^u(p_1, \lambda_1, \theta_1)$ and $\bar{V}^c = V^c(p_1, \lambda_1, \theta_1)$. For $p \leq c$, set λ and θ to satisfy

$\bar{V}^u = V^u(p, \lambda(p), \theta(p))$ and $\bar{V}^c = V^c(p, \lambda(p), \theta(p))$. If there is no solution to these equations with $\lambda(p) > 0$, set $\lambda(p) = 0$ and θ to satisfy $\bar{V}^u = V^u(p, 0, \theta(p))$; or if there is no solution to these equations with $\lambda(p) < 1$, set $\lambda(p) = 1$ and θ to satisfy $\bar{V}^c = V^c(p, 1, \theta(p))$. If there is still no solution with $\lambda(p) \in [0, 1]$ and $\theta(p) \geq 0$, set $\lambda(p)$ arbitrarily and set $\theta(p) = 0$. For $p \in (c, u]$, set $\lambda(p) = 0$ and θ to satisfy $\bar{V}^u = V^u(p, 0, \theta(p))$ or, if there is no solution to this equation, set $\theta(p) = 0$. Finally, for $p > u$, set $\lambda(p) = 0$ and $\theta(p) = 0$.

A.4 Omitted Proofs

Proof of Proposition 1. Construct a DSE as per the algorithms in Appendix A.2. Conditions 1(ii) and 2 of Definition 1 hold by construction. Condition 1(i) also holds for all $p > u$ because $V^s(p > u, \lambda, \theta) = -x$. To show that condition 1(i) holds for all $p \leq u$, suppose (FSOC) that there exists $p \leq u$ such that $V^s(p, 0, \theta(p)) > 0$, or

$$\theta(p)e^{-\theta(p)}p + \left[1 - e^{-\theta(p)} - \theta(p)e^{-\theta(p)}\right]u > x. \tag{A.7}$$

There exists $p' < p$ such that $V^s(p', 0, \theta(p)) = 0$, or

$$\theta(p)e^{-\theta(p)}p' + \left[1 - e^{-\theta(p)} - \theta(p)e^{-\theta(p)}\right]u = x.$$

Note, however, that

$$\bar{V}^u = \underbrace{\frac{1 - e^{-\theta(p)}}{\theta(p)}(v - u) + e^{-\theta(p)}(u - p)}_{V^u(p,0,\theta(p))} < \underbrace{\frac{1 - e^{-\theta(p)}}{\theta(p)}(v - u) + e^{-\theta(p)}(u - p')}_{V^u(p',0,\theta(p))}. \tag{A.8}$$

The equality follows by construction since inequality (A.7) requires $\theta(p) > 0$. The inequality follows from the fact that V^u is decreasing in the asking price and $p' < p$. The pair $\{p', \theta(p)\}$ therefore satisfies the constraint set of problem (P_0) and, according to (A.8), achieves a higher value of the objective than $\{p_0, \theta_0\}$: a contradiction. □

Proof of Proposition 2. Construct a DSE as per the algorithm in Appendix A.3. Conditions 1(ii), 1(iii) and 2 of Definition 1 hold by construction. Condition 1(i) also holds for all $p > u$ because $V^s(p > u, \lambda, \theta) = -x$. To show that condition 1(i) holds for all $p \leq u$, suppose (FSOC) that there exists a profitable deviation: either (1) there exists $p \leq u$ such that $\lambda(p) = 0$ and $V^s(p, \lambda(p), \theta(p)) > 0$, or (2) there exists $p \leq c$ such that $\lambda(p) > 0$ and $V^s(p, \lambda(p), \theta(p)) > 0$.

For case (1), the contradiction can be derived in the same manner as in the proof of Proposition 1. For case (2), the profitable deviation under consideration is $V^s(p \leq c, \lambda(p), \theta(p)) > 0$, or

$$\theta e^{-\theta}p + \left[1 - e^{-\theta} - \theta e^{-\theta}\right]c + \left[1 - e^{-(1-\lambda)\theta} - (1 - \lambda)\theta e^{-(1-\lambda)\theta}\right](u - c) > x, \tag{A.9}$$

where, for notational convenience, λ and θ refer to $\lambda(p)$ and $\theta(p)$. There exists $p'' < p$ such that $V^s(p'', \lambda, \theta) = 0$, or

$$\theta e^{-\theta} p'' + \left[1 - e^{-\theta} - \theta e^{-\theta}\right] c + \left[1 - e^{-(1-\lambda)\theta} - (1-\lambda)\theta e^{-(1-\lambda)\theta}\right](u - c) = x.$$

Note, however, that

$$\bar{V}^c = \underbrace{\frac{e^{-(1-\lambda)\theta} - e^{-\theta}}{\lambda\theta}(v - c) + e^{-\theta}(c - p)}_{V^c(p,\lambda,\theta)} < \underbrace{\frac{e^{-(1-\lambda)\theta} - e^{-\theta}}{\lambda\theta}(v - c) + e^{-\theta}(c - p'')}_{V^c(p'',\lambda,\theta)} \qquad \text{(A.10)}$$

The equality follows by construction since inequality (A.9) requires $\theta > 0$ and, by assumption, $\lambda > 0$. The inequality follows from the fact that V^c is decreasing in the asking price and $p'' < p$. Similarly, $\bar{V}^u = V^u(p, \lambda, \theta) < V^u(p'', \lambda, \theta)$. The triple $\{p'', \lambda, \theta\}$ therefore satisfies the constraint set of problem (P_1) and, according to (A.10), achieves a higher value of the objective than $\{p_1, \lambda_1, \theta_1\}$: a contradiction. $\square$