The Million Dollar Question: Can Lending Constraints Cool a Housing Boom?

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September 19, 2016

Abstract

In this paper we seek to understand the role of lending restrictions in the housing market. We exploit a natural experiment arising from the 2012 Canadian law change that restricts access to mortgage insurance (MI) whenever the purchase price of the home is 1 million Canadian dollars or more. Our empirical approach is motivated by a directed search model that features auction mechanisms and financially constrained bidders. We model the introduction of the Canadian MI regulation of 2012 as a tightening of the financial constraint faced by a subset of prospective buyers. This prompts some or all participating sellers to reduce their asking price in order to elicit bids from both constrained and unconstrained buyers. Competition between bidders intensifies, which dampens the impact of the policy on sales prices. Using transaction data from the Toronto housing market, we employ a distribution regression approach combined with a regression discontinuity design to test the model’s predictions. We find that the limitation of MI causes a 0.69 percent decline in the annual growth of houses listed above $1M and a 0.18 percent decline in the annual growth of houses sold above $1M. In addition, the policy causes a sharp rise in the incidence of both shorter-than-average listing times and sales above asking in the under million dollar segment, consistent with an increase in bidding war intensity. Overall, our findings provide evidence that financing constraints do play an important role in the housing market, but that macroprudential policies designed to manipulate them should take into account strategic and market equilibrium considerations.

Keywords: macroprudential regulation, directed search, financial constraints, regression discontinuity

JEL classification:
1 Introduction

This paper examines how the financial constraints faced by prospective home buyers affect housing market outcomes. Financial constraints are a fundamental feature of the housing market. On the demand side of the market, a buyer’s bidding limit on a desirable property may depend on both income constraints (e.g., debt-service constraint) and wealth constraints (e.g., loan-to-value ratio). On the supply side, the decision to list a house for sale and the choice of asking price may depend on the perceived ability to pay among potential buyers. Moreover, the central role of financial constraints makes them an appealing vehicle to influence housing market conditions. Since the crash of global financial markets caused by the great housing bubble in the 2000s, the tightening of mortgage financing rules has become one of the primary macroprudential tools aimed at limiting the risks associated with potential housing market imbalances during a house price boom.\(^1\)

This paper exploits one such macroprudential regulation that was implemented in Canada in 2012 which restricts access to mortgage insurance (the transfer of mortgage default risk from lenders to insurers; henceforth MI) when the purchase price of a home exceeds 1 million Canadian dollars. Under the new rules, a home buyer paying $1M or more must contribute at least 20 percent to a down payment to secure a mortgage.\(^2\) Designed by Jim Flaherty, the former Canadian Finance Minister, the policy was intended to restrain price appreciation in the higher-end segments of housing markets in major Canadian cities such as Toronto.\(^3\) Despite its clear intention, the consequences of this policy are not so clear-cut: on the one hand, the imposed financing constraint reduces the set of buyers able to afford million dollar homes; on the other hand, sellers of million dollar homes may respond with lower asking

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1In a 2014 IMF speech, macroprudential policies are deemed part of an appropriate policy response to a housing market boom to ensure that “shocks from the housing sector do not spill over and threaten economic and financial stability.” Source: “Managing House Price Boom: The Role of Macroprudential Policies.” December 2014, \url{https://www.imf.org/external/np/speeches/2014/121114.htm}.

2With a down payment of at least 20 percent, the buyer can still access low loan-to-value (LTV) mortgage insurance, or may even procure an uninsured mortgage.

3Jim Flaherty made the following statement in 2012 regarding house price appreciation and the corresponding policy reform: “I remain concerned about parts of the Canadian residential real estate market, particularly in Toronto...[and] we need to calm the...market in a few Canadian cities.” Source: “Canada Tightens Mortgage-Financing Rules.” \emph{Wall Street Journal}, June 21, 2012.
prices to attract both constrained and unconstrained buyers with the aim of stimulating bidding wars that ignite the market for homes listed just under $1M.\textsuperscript{4} We therefore propose an equilibrium search-theoretic model of a two-sided housing market to provide insight about the potential consequences of the MI policy.

The model is one of directed search, and features financial constraints on the buyer side and free entry on the seller side. Sellers pay a cost to list their house and post an asking price, and buyers allocate themselves across sellers subject to search/coordination frictions governed by a many-to-one meeting technology. A house is sold at the asking price when a single buyer arrives; when multiple buyers are matched with a single 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, 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.\textsuperscript{5} Sellers respond strategically to these financial constraints in terms of their entry decision and choice of asking price. To see this, consider first a setting without financial constraints. Competition for buyers drives each seller to post an asking price equal to their reservation value, and seller entry in equilibrium is efficient (Albrecht et al., 2014). With the introduction of a financial constraint, we demonstrate that seller entry in equilibrium is unaffected as long as the bidding limit is not too restrictive. The intuition is that sellers can make up for the reduction in expected sales revenue in multiple offer situations by increasing the asking price to extract a higher payment from the buyer in a bilateral situation. Once the financial constraint becomes sufficiently restrictive, sellers set the asking price at the buyers’ upper limit and capture less of the expected surplus. Consequently, fewer sellers participate in the market which reduces social welfare.

In the model, we assume that all buyers initially face a common income constraint that is not too restrictive. The introduction of a MI policy imposes a minimum wealth requirement that further constrains a subset of buyers. We show that the presence of heterogeneously


\textsuperscript{5}Others have studied auction mechanisms with financially constrained bidders (e.g., Che and Gale, 1996a,b, 1998; Kotowski, 2016), but to our knowledge this is the first paper to consider bidding limits in a model of competing auctions.
constrained buyers can bring about an equilibrium with fewer sellers and lower asking prices that attract both constrained and unconstrained buyers. Together, these lead to a higher buyer-seller ratio in the million dollar segment and hence a higher incidence of multiple offers. Since bidding wars often push the sales price above the asking price, the impact of the MI policy is mitigated by the auction mechanism and the endogenous participation of sellers. From a normative perspective, the tightening of financial constraints results in sub-optimal seller entry and thus reduces overall market activity. Although government intervention may be desirable from the point of view of preempting a price correction in the housing market and hence preventing spillovers to financial markets, the MI limitation is harmful in terms of the social welfare derived from housing market activity. Furthermore, while the MI policy does achieve the specific goal of cooling the high end of the housing market by reducing sales prices in the targeted segment, the policy’s effectiveness is diminished once we take into account the endogenous response on the part of sellers and their strategic interaction with heterogeneously constrained buyers.

Ultimately, determining the magnitudes of these effects is an empirical exercise. We test the model’s predictions and quantify the influence of the MI policy using 2011-2013 housing market transaction data for the single-family homes in the city of Toronto (Canada’s largest housing market). This provides a useful setting for studying the role of financing constraints in a housing market for two reasons. First, the MI 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 million dollar threshold. The market thus provides a natural experimental opportunity for examining the impact of a macroprudential mortgage-financing regulation on the housing market. Second, home sellers in Toronto typically initiate the search process by listing the property and specifying a particular date on which offers will be considered (often 5-7 days after listing). This institutional practice fits well with a model of competing auctions and enables us to explore the differential impact of the MI policy on asking prices and sales prices.

Estimating the MI policy’s impact on the Toronto housing market is complicated by
the fact that the implementation of the MI policy coincided with a number of accompanying government interventions\textsuperscript{6} as well as other general housing market trends. These confounding factors make it difficult to isolate the effects of the MI policy (Wachter et al., 2014). Moreover, despite the natural sources of variation generated by the policy along the price and time dimensions, the standard difference-in-difference approach cannot be implemented. Such an approach requires an exogenous distinction between the control and treatment groups, which is not feasible here since the MI policy affects house prices directly.

To overcome these problems, we implement a three-stage estimation procedure. First, we employ a distribution regression approach to estimate the before-after policy effects on the distribution of house prices. Unlike a standard difference-in-difference approach that would focus on a particular price point, the distribution approach models the impact of the MI policy on the proportion of houses listed/sold above any price in the support of the distribution. Thus, the distribution regression method examines not only the impact of the MI policy at the $1M threshold, but also potential spillover effects at other parts of the price distribution. In the second stage, we employ a regression discontinuity design and examine whether the before-after estimates exhibit a discontinuity at the $1M threshold. The key identifying assumption here is that the impact of all other contemporaneous macro and market forces on housing market transactions is continuous along the price distribution. Finally, to further isolate the effect of the MI policy from other potential sources of discontinuity at the $1M threshold,\textsuperscript{7} we perform a falsification test by repeating the same analysis as described above, but with data from before the implementation of the policy (specifically, between 2011 and 2012). We then combine the estimates from the falsification test with the before-after estimates to obtain a double-difference regression discontinuity estimate. Thus, to the extent that other potential sources of a discontinuity at the $1M threshold are constant over time,

\textsuperscript{6}The law that implemented the MI 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.

\textsuperscript{7}Other potential sources of discontinuity at the $1M threshold include psychological pricing (Foxall et al., 1998) and price filtering on online real estate marketing platforms.
our estimation procedure uncovers the causal effect of the MI policy on the joint distribution of house sales and prices.

We find that the limitation of MI insurance caused a 0.69 percent decline in the annual growth of houses listed above $1M and a 0.18 percent decline in the annual growth of houses sold above $1M. These estimates become 1.68 and 0.60, respectively, when we focus on central Toronto, where a million dollar home represents a median home. Both estimates are statistically significant. The smaller negative effect on sales prices relative to asking prices aligns with the predictions of the theoretical model and the intuition that sellers respond to the policy with lower asking prices to attract both constrained and unconstrained buyers. Consistent with this strategic response, we find that the MI policy generates not only a sharp decline in houses listed right above $1M, but also a spike in houses listed right below $1M. In the theory, the strategic reductions in asking price coincidentally with the increase in the ratio of buyers to sellers speed up housing sales and leads to bidding wars that sometimes push the sales price well above the asking price. Consistent with the notion of bidding wars, the aforementioned spike in homes listed just under $1M is accompanied by a higher fraction of sales over asking and a shorter selling times, both of which are associated with the MI policy. Together these results affirm the insights of our directed search model.

We next consider variation in the influence of the MI policy across markets and segments. According to the model, the consequences of the policy should be more dramatic when the MI limitation constrains a larger share of prospective buyers. We bring this to the data by comparing the MI policy effects across price segments and across geographic markets. Along the price dimension, there is good reason to believe that buyers searching for homes listed further from the $1M threshold face financial constraints that are unaffected by the MI policy. Consistent with this reasoning, we find that the MI policy has little impact on sales below $0.9M or above $1.1M. Across spatially separated markets, we find that the effects of the MI policy on prices are smaller (and sometimes not statistically significant) in suburban Toronto relative to central Toronto. This evidence, along with the observation that buyers of million dollar homes in Toronto’s periphery tend to be wealthier (and hence less likely
constrained by a 20% down payment requirement) than their counterparts in the urban core, again aligns with the theoretical predictions.\(^8\)

Mortgage insurance is a key component of housing finance systems in many countries, including the United States, the United Kingdom, the Netherlands, Hong Kong, France, and Australia. These countries share two important institutional features with Canada: (i) the requirement that most lenders insure high loan-to-value (LTV) mortgages, and (ii) the central role of the government in providing such insurance.\(^9\) These common features of mortgage markets make MI a potential macroprudential tool. It follows that the lessons learned from the 2012 MI policy in Canada are important and relevant not only for Canada, but also for many nations around the world. More specifically, this paper contributes to an ongoing debate\(^10\) about the effectiveness of macroprudential measures in moderating housing booms by characterizing and quantifying the effects of the MI policy on a housing market. Only recently has a literature emerged that aims to study the implications of macroprudential policies. One strand of literature relies on the low frequency, aggregate transaction data (e.g., Crowe et al. 2013, Elliott et al. 2013, Krznar and Morsink 2014). Another strand explores loan-level data to investigate the effects of macroprudential regulations on the market for mortgage loans (e.g., Allen et al. 2016). Our work differs from existing studies in two ways. First, we motivate our empirical strategy with a theoretical analysis of the strategic and equilibrium implications of the MI policy in a setting with competing auctions and financial constraints. Second, we use micro-level housing transaction data to directly examine how a macroprudential policy affects market interactions between buyers and sellers.

The paper proceeds as follows. In Section 2 we provide an overview of the Canadian housing market and the institutional details of the mortgage insurance market. In section

\(^8\) Finding an effect of the MI policy in a non-targeted segment of the housing market would have indicated a possible source of spurious correlation and called into question the interpretation of our main estimates. Our cross-segment and cross-market comparisons therefore lend further credibility to our results.

\(^9\) The MI market in the U.S., for example, is dominated by a large government-backed entity, the Federal Housing Administration (FHA), and MI is required for all loans with a LTV ratio greater than 80 percent.

\(^10\) Despite attracting considerable attention around the world, macroprudential policies are quite controversial because there is limited evidence as to their effectiveness. As noted by Crowe et al. (2013), the fact that macroprudential efforts often coincide with other housing market policy interventions contributes to the difficulty in isolating and assessing the consequences of each specific macroprudential tool.
3 we develop a theoretical model, characterize the directed search equilibrium, and derive a set of empirical implications. In sections 4 and 5 we discuss the data, outline our empirical strategy, and present our results on the impact of the MI policy. Section 6 concludes.

2 Background

Since 2000 Canada has experienced one of the world’s largest modern house price booms, with prices surging 150 percent between 2000 and 2014. Moreover, in contrast to other large housing markets like those in the U.S., homes in Canada suffered only minor price depreciation during the Great Recession. Figure 1 plots the national house price indices for Canada and the U.S.11 As home prices in Canada continued to escalate post-financial crisis, the Canadian government and outside experts became increasingly concerned that rapid price appreciation would eventually lead to a severe housing market correction.12 To counter the potential risks associated with the house price boom, the Canadian government implemented four major rounds of housing market macroprudential regulation between July 2008 and July 2012.13 Interventions included increasing minimum down payment requirements (2008); reducing the maximum amortization period for new mortgage loans (2008, 2011, 2012); reducing the borrowing limit for mortgage refinancing (2010, 2011, 2012); increasing homeowner credit standards (2008, 2010, 2012); and limiting government-backed high-ratio14 MI to homes with a purchase price of less than $1M (the focus of this paper).

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11 These are monthly repeat-sales house price indices. Sources: Teranet (Canada) and S&P Case-Shiller (U.S.) downloaded from Datastream (series ID numbers: USCSHP20F and CNTNHPCMF).
12 In 2013, Jim Flaherty, Canada’s Minister of Finance from February 2006 to March 2014, stated: “We [the Canadian government] have to watch out for bubbles - always - . . . including [in] our own Canadian residential real estate market, which I keep a sharp eye on.” Further, Robert Shiller observed in 2012 that “what is happening in Canada is kind of a slow-motion version of what happened in the U.S.” Sources: “Jim Flaherty vows to intervene in housing market again if needed.” The Globe and Mail, November 12, 2013; and “Why a U.S.-style housing nightmare could hit Canada.” CBC News, September 21, 2012.
13 For a summary of the changes made to the MI rules in Canada, see Box 2 on page 24 of the Bank of Canada’s December 2012 Financial System Review.
14 A high-ratio mortgage loan is defined as one with a LTV ratio above 80 percent.
2.1 Mortgage Insurance in Canada

Mortgage insurance is a financial instrument used to transfer mortgage default risk from the lender to the insurer. For federally regulated financial institutions in Canada, insurance is legally required for any mortgage loan with an LTV ratio higher than 80 percent.\textsuperscript{15} Mortgage originators can purchase MI from private insurers, but the largest mortgage insurer in Canada is the government-owned Canada Mortgage and Housing Corporation (CMHC). The Canadian government provides guarantees for both publicly and privately insured mortgages, and therefore all mortgage insurers are subject to financial market regulation through the Canadian Office of the Superintendent of Financial Institutions (OFSI). The MI requirement for high LTV mortgage loans and the influence of the government in the market for MI make it a potentially effective macroprudential tool.

\textsuperscript{15}Most provincially regulated institutions are subject to this same requirement. Unregulated institutions, in contrast, are not required to purchase MI. The unregulated housing finance sector in Canada, however, accounts for only five percent of all Canadian mortgage loans (Crawford et al., 2013).
2.2 The Canadian Mortgage Insurance Regulation of 2012

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

3 Theory

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

3.1 Environment

\textbf{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).

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

\textsuperscript{17}See “High-end mortgage changes seen as return to CMHC’s roots.” The Globe and Mail, June 23, 2012
MI policy. The introduction of the MI policy causes some buyers to become more severely financially constrained. Post-policy, a fraction $\Lambda$ of buyers are unable to pay more than $c$, where $0 < c < u$. 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. From the point of view of a seller, the number of buyers she will meet is a random variable that follows a Poisson distribution. The probability that a seller meets exactly $k = 0, 1, \ldots$ buyers is

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

where $\theta$ 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

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

which is the probability mass function for the binomial distribution with parameters $k$ and $1 - \lambda$, where $\lambda$ 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, $\theta$ and $\lambda$ are endogenous variables specific to the group of buyers and sellers searching for and asking price $p$.

Price determination. The price is determined by a second-price auction. The seller’s asking price, $p \in \mathbb{R}_+$, is interpreted as the binding reserve price. 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. Supply side participation in the market requires payment of a fixed cost, \( x < c \). It is worthwhile to enter the market as a seller if and only if the expected revenue exceeds the listing cost.

3.2 Equilibrium

3.2.1 The Auction

When a seller meets \( k \) buyers, the auction mechanism described above determines a game of incomplete information because 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 (unconstrained) buyers from submitting an offer.

3.2.2 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 \( \theta \) and buyer composition \( \lambda \), let \( V^*(p, \lambda, \theta) \) 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. Closed-form solutions are derived in Appendix A.1.

3.2.3 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 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 \( P \subset \mathbb{R}_+ \); a distribution of sellers \( \sigma \) on \( \mathbb{R}_+ \) with support \( P \), a function for market tightness \( \theta : \mathbb{R}_+ \rightarrow \mathbb{R}_+ \cup +\infty \), a function for the composition of buyers \( \lambda : \mathbb{R}_+ \rightarrow [0, 1] \), 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 \( p \in P \));
   
   (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 \( \bar{V}^i = \max_{p \in P} V^i(p) \) for \( i \in \{u, c\} \); and

2. market clearing:

\[
\int_P \theta(p) \, d\sigma(p) = B \quad \text{and} \quad \int_P \lambda(p) \theta(p) \, d\sigma(p) = \Lambda B.\]

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 \( \theta \) is derived from the free entry of sellers for active submarkets (i.e., for all \( p \in P \)). Similarly, parts 1(ii) and 1(iii) require that, for active submarkets, \( \lambda \) 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 \( \theta \) and \( \lambda \) 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 \( p \not\in P \), and buyers optimally sort among submarkets \( p \cup P \), 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 \( p \not\in \mathbb{P} \) guarantees that no deviation to an off-equilibrium asking price is worthwhile from a seller’s perspective. Part 2 of the definition makes certain that all buyers search.

3.2.4 Pre-Policy Directed Search Equilibrium

We first consider the initial setting with identically unconstrained buyers by setting \( \Lambda = 0 \).\(^{18} \) Sellers in this environment set an asking price to maximize their payoff subject to buyers achieving their market utility, \( \bar{V}^u \). The seller must also take into account buyers’ bidding limit \( u \). The seller’s asking price setting problem is therefore

\[
\max_{p,\theta} V^s(p, 0, \theta) \quad \text{s.t.} \quad p \leq u \quad \text{and} \quad V^u(p, 0, \theta) = \bar{V}^u. \quad (3)
\]

If the first constraint is ignored, the solution is a pair \( \{p^*_u, \theta^*\} \) satisfying the following first-order condition:

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

If \( p^*_u \) is in the set of equilibrium asking prices, \( p^*_u \) and \( \theta^* \) must also satisfy the free entry condition \( V^s(p^*_u, 0, \theta^*) = 0 \). If \( p^*_u > u \), then the proposed solution violates the first constraint of the problem in (3). The constrained solution is then \( \{u, \theta_u\} \), which must satisfy the free entry condition \( V^s(u, 0, \theta_u) = 0 \).

We can link the asking price to the entry cost by defining the function \( x \mapsto p^*_u(x) \) using equation (4) with \( \theta^* \) satisfying the free entry condition. The following lemma uses this function to determine exactly when the \( p \leq u \) constraint in the seller’s asking price setting problem binds.

**Lemma 1.** There exists a threshold \( \bar{x} \) such that \( p^*_u \leq u \) if and only if \( x \leq \bar{x} \).

\(^{18} \)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).
The next proposition provides a partial characterization of a DSE with identical buyers.

**Proposition 1.** If \( x \leq \bar{x} \), there is an equilibrium with \( P = \{ p^*_u \} \) and \( \theta(p^*_u) = \theta^* \). If instead \( x > \bar{x} \), there is an equilibrium with \( P = \{ u \} \) and \( \theta(u) = \theta_u > \theta^* \).

When buyers are not at all constrained (i.e., \( u = v \)), the equilibrium asking price is equal to zero, 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., \( p^*_u(x) \leq u < v \)), sellers set a higher asking price to capture more of the surplus in a bilateral match. This makes up for limited sales revenue when two or more buyers submit offers but are unable to pay their full valuation because of the common income constraint. When buyers are more severely constrained (i.e., \( u < p^*_u(x) \)), the seller’s choice of asking price is limited by buyers’ ability to pay. 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., \( \theta_u > \theta^* \)).

To address welfare considerations, we consider a constrained social planner\(^{19}\) that chooses seller entry (or, equivalently, overall market tightness) to maximize the welfare of market participants (i.e., total social surplus net of listing costs). By normalizing the social planner’s objective function by dividing by the fixed measure of buyers, \( B \), the optimization problem can be written

\[
\begin{align*}
\max_{\theta} & \quad \frac{1 - e^{-\theta}}{\theta} v - x \\
\text{s.t.} & \quad \theta u \geq x.
\end{align*}
\]

The constraint ensures that buyers’ ability to pay is enough to cover the cost of sellers’ market participation. The solution is \( \max\{\theta^*, x/u\} \).

**Corollary 1.** The DSE is constrained efficient if and only if \( x \leq \bar{x} \). Seller entry is inefficiently low when \( x > \bar{x} \).

\(^{19}\)The social planner is constrained by the search and matching frictions and by a financial resource constraint.
3.2.5 Post-Policy Directed Search Equilibrium

We now suppose that the implementation of the MI policy affects a subset of buyers by letting \( \Lambda \) take a value between 0 and 1. The interesting case is when \( p_u^* \leq u \) and \( c < p_u^* \), where

\[
p_u^* = \frac{1 - e^{-\theta^*} - \theta^* e^{-\theta^*}}{\theta^* e^{-\theta^*}} (v - c).
\]  

(6)

Since \( p_u^* < p_c^* \), there are still two possible scenarios: \( c < p_u^* \) and \( p_u^* \leq c \). We show in this section that the presence of financially constrained buyers triggers activity in submarket \( c \) in the first case. The following lemma uses the property that \( p_u^* \) is increasing in \( \theta^* \), which in turn is increasing in \( x \), to establish parameter restrictions that imply \( p_u^* \leq u \) and \( c < p_u^* < p_c^* \).

**Lemma 2.** There exist thresholds \( x \) and \( \overline{x} \) such that \( p_u^* \in (c, u] \) if and only if \( x \in (x, \overline{x}] \).

Recall from Section 3.2.4 that if there are only unconstrained buyers (i.e., \( \Lambda = 0 \)), then \( x \leq \overline{x} \) means that buyers’ spending limit \( u \) does not affect expected payoffs in equilibrium. Sellers can set an appropriately high asking price (namely \( p_u^* \)) to attain the same expected revenue from the sale of their home as they would if buyers were willing/able to pay their full valuation, \( v \). If there are financially constrained buyers (i.e., \( \Lambda > 0 \)), then \( x > x \) implies that the none of them will direct their search to a seller listing price \( p_u^* \).

Consider the possibility that all buyers (both constrained and unconstrained types) participate in a single submarket with sellers asking price \( c \). Market tightness in this case, denoted \( \Theta \), satisfies the free entry condition \( V^s(c, \Lambda, \Theta) = 0 \). Finally, denote by \( \lambda_p \) and \( \theta_p \) the unique solution to \( V^s(c, \lambda_p, \theta_p) = 0 \) and \( V^u(c, \lambda_p, \theta_p) = V^u(p_u^*, 0, \theta^*) \). In words, the free entry of sellers into submarkets \( c \) and \( p_u^* \) imply indifference on the part of unconstrained buyers between the two submarkets if the composition of buyers in submarket \( c \) is exactly \( \lambda_p \).

The following proposition uses the above defined \( p_u^*, \theta^*, \theta_p, \lambda_p \) and \( \Theta \) to characterize a DSE.
Proposition 2. Suppose $x \in (\underline{x}, \overline{x}]$. If $\Lambda < \lambda_p$, there is an equilibrium with $P = \{c, p^*_u\}$, $\lambda(p^*_u) = 0$, $\theta(p^*_u) = \theta^*$, $\lambda(c) = \lambda_p$ and $\theta(c) = \theta_p > \theta^*$. If instead $\Lambda \geq \lambda_p$, there is an equilibrium with $P = \{c\}$, $\lambda(c) = \Lambda$ and $\theta(c) = \Theta \geq \theta_p > \theta^*$.

With constrained buyers present in the market, it is worthwhile for some sellers to post an asking price less than or equal to $c$ in order to attract and elicit offers from constrained buyers. The assumption that $c < p^*_c$ means that the financial constraint is severe enough that the best asking price for targeting constrained buyers is the upper limit, $c$. Because unconstrained bidders can out-bid constrained ones, some or all of them search alongside constrained buyers for houses listed at $c$ instead of $p^*_u$. In other words, the presence of constrained buyers prompts a reduction in asking prices that whips buyers into a frenzy.

### 3.3 Empirical Predictions

This section summarizes the consequences of the MI policy by comparing the pre- and post-policy directed search equilibria under the assumption that $x \in (\underline{x}, \overline{x}]$.

**Prediction 1.** The MI policy causes a reduction in the set of equilibrium asking prices with both the increase of homes listed at $c$ and a reduction in the measure of homes listed strictly above $c$. The corresponding reduction in the set of equilibrium sales prices is partly neutralized by the auction mechanism and the pooling of buyers in submarket $c$, which escalate the price up to $u$ whenever the seller receives offers from at least two unconstrained bidders.

Post-policy, at least some sellers find it optimal to target buyers of either type by setting a low asking price of $c$. Otherwise, market tightness associated with asking price $c$ would be infinite, yielding a payoff of $c$ with certainty: a profitable deviation. As per Propositions 1 and 2, the set of asking prices falls from $P = \{p^*_u\}$ pre-policy to either $P = \{c, p^*_u\}$ (if $\Lambda < \lambda_p$) or $P = \{c\}$ (if $\Lambda \geq \lambda_p$) post-policy.

The financial constraints imposed by the MI policy cause some homes to sell for only $c$ when pre-policy they might have sold for $p^*_u$ or more. However, some sellers asking price
c still succeed in selling at the highest possible price, \( u \). The probability associated with this outcome (from the perspective of a seller in submarket \( c \)) is equal to the probability of meeting two or more unconstrained buyers:

\[
\text{Prob}\{\text{sales price} = u|p = c\} = \begin{cases} 
1 - e^{-(1-\lambda_p)\theta_p} - (1 - \lambda_p)\theta_p e^{-(1-\lambda_p)\theta_p} & \text{if } \Lambda < \lambda_p \\
1 - e^{-(1-\Lambda)\Theta} - (1 - \Lambda)\Theta e^{-(1-\Lambda)\Theta} & \text{if } \Lambda \geq \lambda_p
\end{cases}
\]

In fact, price escalation up to \( u \) is even more likely in submarket \( c \) than in submarket \( p^*_u \) if \( \Lambda \) is not too high (e.g., if \( \Lambda \leq \lambda_p \)).\(^{20}\) Consequently, the MI policy can potentially increase the overall share of listed homes selling for \( u \), thus undermining the MI policy’s influence on sales prices.

**Prediction 2.** The MI policy causes an increase in the ratio of buyers to participating sellers. Consequently, the policy induces a higher incidence of multiple offer situations and a lower probability of failing to sell a house (a proxy for time-on-the-market).

Because \( c < p^*_u \), the financial constraint limits the final price in the event that the seller matches with at most one unconstrained buyer. Free entry therefore implies that fewer sellers find it worthwhile to enter the market post-policy, resulting in a higher ratio of buyers to sellers. This result is embedded in Proposition 2, which states that \( \theta_p > \theta^* \) and, when \( \Lambda \geq \lambda_p \), \( \Theta \geq \theta_p > \theta^* \). It follows that the MI policy improves sellers’ matching probabilities and increases the incidence of bidding wars.

**Prediction 3.** Both the measure of sellers posting asking price \( c \) and the fraction of listed homes selling for price \( c \) are increasing in \( \Lambda \).

\(^{20}\) An implication of the indifference condition for unconstrained buyers between submarkets \( c \) and \( p^*_u \) when \( \Lambda \leq \lambda_p \) is \( \theta^* < (1 - \lambda_p)\theta_p \). It follows that the probability associated with selling at price \( u \) in submarket \( c \) exceeds that in submarket \( p^*_u \):

\[
1 - e^{-(1-\lambda_p)\theta_p} - (1 - \lambda_p)\theta_p e^{-(1-\lambda_p)\theta_p} > 1 - e^{-\theta^*} - \theta^* e^{-\theta^*}.
\]
The measures of sellers participating in submarkets $c$ and $p_u^*$ are

$$
\sigma(c) = \begin{cases} 
\frac{\Lambda B}{\lambda_p \theta_p} & \text{if } \Lambda < \lambda_p \\
\frac{\theta_p}{\Theta} & \text{if } \Lambda \geq \lambda_p
\end{cases}
$$

and

$$
\sigma(p_u^*) = \begin{cases} 
\frac{(\lambda_p - \Lambda) E}{\lambda_p \theta^*} & \text{if } \Lambda < \lambda_p \\
0 & \text{if } \Lambda \geq \lambda_p
\end{cases}
$$

Given the free entry conditions that pin down $\theta_p$ and $\Theta$, $\sigma(c)$ is continuous and increasing in $\Lambda$. In contrast, $\sigma(p_u^*)$ is continuous and decreasing in $\Lambda$. It follows that higher values of $\Lambda$ are associated with a higher relative share of activity in submarket $c$ wherein the probability of selling at price $c$ is

$$
\text{Prob}\{\text{sales price } = c | p = c\} = \begin{cases} 
[1 + (1 - \lambda_p) \theta_p] e^{-(1 - \lambda_p) \theta_p} - e^{-\theta_p} & \text{if } \Lambda < \lambda_p \\
[1 + (1 - \Lambda) \theta] e^{-(1 - \Lambda) \theta} - e^{-\Theta} & \text{if } \Lambda \geq \lambda_p
\end{cases}
$$

which is continuous and increasing in $\Lambda$ (given that $\Theta$ is continuous and increasing in $\Lambda$).

Prediction 3 therefore implies a more dramatic impact of the the MI policy on asking and sales prices if it constrains a large fraction of potential buyers.

### 3.4 Welfare Discussion

To explore the normative implications of the MI policy, we compare the pre- and post-policy social surplus generated by housing market activity. As described in section 2, the MI policy was introduced to counter the potential risks associated with a house price boom. Characterizing these potential benefits is beyond the scope of the model. The normative analysis that follows should instead be viewed as a description of the direct welfare implications of the MI policy on housing market participants that may undermine the intended potential benefits of the macroprudential regulation.

Given that $x \leq \bar{x}$, the welfare maximizing level of market activity is implemented when the ratio of buyers to sellers is $\theta^*$, which is achieved in the pre-policy DSE (see Corollary 1). The Post-policy DSE, however, features a reduction in the total number of sales as $\theta_p > \theta^*$ and, when $\Lambda > \lambda_p$, $\Theta \geq \theta_p > \theta^*$ (see Proposition 2). The decline in overall market activity
implies a reduction in the welfare of market participants (i.e., a decline in total social surplus net of listing costs). With free-entry on the supply side, these welfare costs are borne by the share of buyers that are financially constrained by the MI policy.

**Corollary 2.** Suppose \( x \in (x_\ell, x]\). The MI policy reduces the social welfare derived from housing market transactions.

**4 Data**

Our data set includes all transactions of single-family houses in the city of Toronto from January 1 2011 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, we focus on transactions during the first six months of each calendar year. More specifically, the *pre-policy period* is defined as January to June in 2012 and the *post-policy period* consists of those same months in 2013. We take this approach for two reasons: (i) due to seasonality in housing sales, we aim to compare the same calendar months pre- and post-policy; and (ii) the six month interval enables us to use January-June in 2011 and 2012 (both pre-policy) to perform a falsification test.\(^{21}\) For the purposes of assigning a home to a pre- or post-policy date, we use the date the house was listed.

Table 4 contains summary statistics for detached, single-family homes in Toronto. Our data include 7,715 observations in the pre-policy period and 6,733 observations in the post-policy period. The mean sales price in Toronto was $801,134 in the pre-policy period and $849,001 in the post-policy period, reflecting continued rapid price growth for detached homes. Our focus is on homes near the $1M threshold, which corresponds to approximately the 80th percentile of the pre-policy price distribution. There were 570 homes sold within $100,000 of $1M in the pre-policy period, and 576 in the post-policy period. Table 4 reports

\(^{21}\)We have assessed the sensitivity of our main results by repeating the analysis with eleven month pre- and post-policy periods. This alternative approach yields very similar results, which are available upon request.
the same statistics for central Toronto. Homes in the central district were substantially more expensive; a million dollar home represents the median home in Central Toronto. In sharp contrast, a million dollar home lies at the top 5th percentile of the house price distribution in suburban Toronto (not shown). Nearly 60 percent of all homes sold pre-policy in Toronto for a price within $100,000 of $1M are located in central Toronto.

Table 1: Summary Statistics for City of Toronto

<table>
<thead>
<tr>
<th></th>
<th>Pre-Policy</th>
<th>Post-Policy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Asking Sales</td>
<td>Asking Sales</td>
</tr>
<tr>
<td>All Homes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>796216.93</td>
<td>801134.05</td>
</tr>
<tr>
<td>25th Pct</td>
<td>449900.00</td>
<td>460000.00</td>
</tr>
<tr>
<td>50th Pct</td>
<td>599900.00</td>
<td>624800.00</td>
</tr>
<tr>
<td>75th Pct</td>
<td>895000.00</td>
<td>911000.00</td>
</tr>
<tr>
<td>N</td>
<td>7715.00</td>
<td>7715.00</td>
</tr>
<tr>
<td>Median Duration</td>
<td>9.00</td>
<td>9.00</td>
</tr>
<tr>
<td>1M Percentile</td>
<td>0.81</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Homes 0.9-1M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median Duration</td>
<td>8.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Mean Price</td>
<td>967238.01</td>
<td>943364.95</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Homes 1-1.1M</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median Duration</td>
<td>8.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Mean Price</td>
<td>1074683.47</td>
<td>1044466.87</td>
</tr>
</tbody>
</table>

5 Empirical Evidence

In this section, we take the predictions of the directed search model to the data. We first outline our estimation strategy, then present empirical results corresponding to predictions 1-3 from Section 3.3.

5.1 Estimation

Our three-stage estimation procedure combines a distribution regression approach with a regression discontinuity design. Using a distribution regression method, we first estimate the
Table 2: Summary Statistics for the Central District

<table>
<thead>
<tr>
<th></th>
<th>Pre-Policy</th>
<th>Sales</th>
<th>Post-Policy</th>
<th>Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Asking</td>
<td>Asking</td>
<td>Asking</td>
<td>Asking</td>
</tr>
<tr>
<td>All Homes</td>
<td>1231652.18</td>
<td>1235718.45</td>
<td>1340144.65</td>
<td>1315926.08</td>
</tr>
<tr>
<td>25th Pct</td>
<td>749000.00</td>
<td>761000.00</td>
<td>799900.00</td>
<td>828000.00</td>
</tr>
<tr>
<td>50th Pct</td>
<td>959900.00</td>
<td>1010000.00</td>
<td>1078000.00</td>
<td>1088500.00</td>
</tr>
<tr>
<td>75th Pct</td>
<td>1455000.00</td>
<td>1465000.00</td>
<td>1585000.00</td>
<td>1539000.00</td>
</tr>
<tr>
<td>N</td>
<td>2485.00</td>
<td>2485.00</td>
<td>2150.00</td>
<td>2150.00</td>
</tr>
<tr>
<td>Median Duration</td>
<td>9.00</td>
<td>9.00</td>
<td>11.00</td>
<td>11.00</td>
</tr>
<tr>
<td>1M Percentile</td>
<td>0.54</td>
<td>0.50</td>
<td>0.47</td>
<td>0.45</td>
</tr>
<tr>
<td>Homes 0.9-1M</td>
<td>N</td>
<td>180.00</td>
<td>206.00</td>
<td>215.00</td>
</tr>
<tr>
<td></td>
<td>Median Duration</td>
<td>8.00</td>
<td>8.00</td>
<td>8.00</td>
</tr>
<tr>
<td></td>
<td>Mean Price</td>
<td>966512.46</td>
<td>941320.81</td>
<td>968061.39</td>
</tr>
<tr>
<td>Homes 1-1.1M</td>
<td>N</td>
<td>98.00</td>
<td>140.00</td>
<td>111.00</td>
</tr>
<tr>
<td></td>
<td>Median Duration</td>
<td>7.00</td>
<td>7.50</td>
<td>9.00</td>
</tr>
<tr>
<td></td>
<td>Mean Price</td>
<td>1071199.88</td>
<td>1044509.06</td>
<td>1071978.05</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1044045.15</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

before-after policy effects on the distribution of house prices (both asking and sales price). Second, we examine whether these estimates have a discontinuity at the $1M threshold using a regression discontinuity design. Third, we further isolate the effects of the MI policy from other potential sources of discontinuity at the $1M threshold by performing a falsification test. More specifically, we repeat the same analysis using only data from before the implementation of the MI policy. We then combine the estimates from the falsification test with the before-after estimates of the impact of the MI policy to obtain a double-difference regression discontinuity estimate. Thus, our estimation strategy relies on two identifying assumptions: first, the influence of other macro and market forces on house sales is continuous along the price distribution; and second, other potential sources of a discontinuity at $1M are constant over time. Under these assumptions, any evidence of discontinuity at the $1M threshold represents a causal effect of the MI policy on the distribution of house prices.

The distribution regression approach was originally developed by Foresi and Peracchi (1995) to estimate the conditional distribution of excess returns. More recently, properties of this methodology have been examined by Chernozhukov et al. (2013), Koenker et al. (2013) and Rothe and Wied (2013), among others. We implement the distribution regression
technique to estimate the impact of the MI policy on the distributions of asking prices and sales prices. In particular, define the survivor function, $S(p|\mathbf{x}) = \text{Prob}\{\text{price} > p|\mathbf{x}\}$, as the probability that a house is sold/listed above price $p$ conditional on a vector $\mathbf{x}$, which includes year, month, and district dummies, as well as house characteristics. To estimate this, we first evaluate the empirical survivor function, $S_{itm}$, at a set of cut-off prices, $\{p_1, \ldots, p_J\}$, for each year $t$, month $m$, and district $i$. We define cut-off prices using a grid with intervals of $5,000.22$ Next, we use the computed values of $S_{itm}(p_j)$ for each $p_j \in \{p_1, \ldots, p_J\}$ to estimate the following:

$$S_{itm}(p_j) = \beta_0(p_j) + \alpha_i(p_j) + \mu(p_j) + \delta_m(p_j) + \tau(p_j)\mathbf{x}_{itm} + \epsilon_{itm}(p_j), \quad (7)$$

where $\mathbf{x}_{itm}$ is a vector of house characteristics; $\mu(p_j)$ indicates the post-policy year, and $\delta_m(p_j)$ and $\alpha_i(p_j)$ indicate month and district. By normalizing district coefficients to have mean zero and omitting June from the set of month dummy variables, the estimated constant term $\hat{\beta}_0(p_j)$ can be interpreted as an estimate of the survivor function at price $p_j$ for an average home in an average district in June prior to the implementation of the MI policy. Equivalently, $1 - \hat{\beta}_0(p_j)$ is an estimate of the house price cumulative distribution function (CDF) evaluated at price $p_j$. An appealing feature of this approach is that all coefficients are allowed to vary at each cut-off price, which provides considerable flexibility in fitting the underlying house price distribution.

Of particular interest is the vector of parameter estimates $\hat{\mu} = [\hat{\mu}(p_1) \cdots \hat{\mu}(p_J)]$. Given that (7) is estimated with data from one pre-policy period and one post-policy period, these estimates capture the MI policy’s impact on the house price distribution. The before-after approach obviously confounds policy effects with other common (to district) macro and market forces that may affect housing market outcomes between the two time periods.

---

22 The empirical survivor function at price $p$, denoted $S_{itm}(p)$, is defined as the number of prices in district $i$ in year $t$ and month $m$ greater than or equal to $p$ divided by the total sample size for that same district, year and month.

23 Smaller price bins allow more flexibility in estimating the underlying house price distribution, while larger bins allow for more precise estimates. All of our results are robust to reasonable deviations from the $5,000 interval.
To disentangle the MI policy effect from other potential factors, we employ a regression discontinuity design in the second stage and examine whether the before-after estimates along the housing price distribution have a discontinuity at the $1M threshold. More specifically, we model the set of estimates in $\hat{\mu}$ as a smooth function of the price except for the possibility of a discontinuity at $1M:

$$\hat{\mu}(p_j) = \gamma_0 + f_l(p_j - $1M) + D_{$1M} [\gamma + f_r(p_j - $1M)] + \varepsilon(p_j),$$

(8)

where $D_{$1M} = 1$ if $p_j \geq$ $1M$ and 0 otherwise, and the functions $f_l(\cdot)$ and $f_r(\cdot)$ are smooth functions that we approximate with low-order polynomials. We restrict attention to house prices near $1M by selecting various bandwidths centered at $1M. We estimate a variety of specifications with different bandwidths and orders of the polynomial functions. We also undertake a cross-validation method of bandwidth selection, and determine the optimal order of polynomial (given a fixed bandwidth) by minimizing the Akaike’s Information Criterion (AIC) (Lee and Lemieux, 2010). The coefficient of interest here is $\gamma$, which captures the possibility of a jump discontinuity in the before-after estimates obtained from the distribution regressions. This represents our estimate of the effect of the MI policy.

There remains the possibility that a discontinuity at $1M merely picks up some threshold effect arising from, for example, psychological pricing or fixed price bins embedded in the online marketing platforms for real estate. In order to attribute evidence of discontinuity to the MI policy, we perform the same first stage analysis using data from two six-month time periods before the implementation of the policy. Then, to complete this third stage of our empirical strategy, we combine the results from this falsification test, $\hat{\mu}_{pre}$, with our stage two before-after estimates, $\hat{\mu}_{post}$. Specifically, we estimate equation (8) using the difference, $\hat{\mu}_{post} - \hat{\mu}_{pre}$, as the dependent variable. The resulting estimate of coefficient $\gamma$ (termed double-

---

24We first set the largest possible bandwidth to 20 (corresponding to prices within $100,000 of $1M), and then choose the cross-validation minimizing bandwidth. This procedure is implemented using the \texttt{bwsselect} STATA code provided by Calonico et al. (2014).

25To avoid overfitting the models, we estimate (8) using only low-order polynomials to preserve at least 60% of the degrees of freedom, given the bandwidth. For example, when the bandwidth is set to 5, we report only the results for a local linear regression (i.e., order one).
difference regression discontinuity estimate) reveals any remaining discontinuity at $1M. To the extent that other potential sources of discontinuity are constant over time, the resulting double-difference regression discontinuity estimate represents a clean estimate of the impact of the MI policy on the housing market.

5.2 Results

5.2.1 Prediction 1: Asking Prices and Sales Prices

The main prediction of the model is that the implementation of the MI policy decreases both asking and sales prices in the million dollar segment, but that the latter effect can appear weaker because a home listed at a reduced price can still sell at a high final price when the seller receives multiple offers from unconstrained bidders. Empirically, we examine how the MI policy shifts the entire distribution of house prices. Since the policy specifically targets the $1M price point, Prediction 1 points to a reduction in the fraction of homes sold just above the $1M threshold, and an even more pronounced reduction in the fraction of homes listed just above $1M.

Figures 2 and 3 represent a graphical test of Prediction 1 based on the estimates from equation (7). Figure 2 examines the distribution of asking prices ranging from $500,000 to $1.4M. In panel A, we plot the estimated survivor function for the pre- and post-policy periods. The post-policy survivor function (solid line) lies everywhere above the pre-policy survivor function (dashed line) indicating an increase in the share of housing market transactions for homes listed above any given asking price. This reflects a general improvement (from sellers’ perspective) in the Toronto housing market between the first six months of 2012 and these same months in 2013. In panel B, we plot the difference between the two survivor functions, which is simply the vector of parameter estimates \( \hat{\mu} \) from equation (7). This difference generally falls smoothly with asking price except for a discrete jump down at the $1M threshold. This jump forms the basis for our regression discontinuity investigation.
Figure 3 examines the distribution of sales prices ranging from $500,000 to $1.4M. One key difference between the vector \( \hat{\mu} \) derived from asking prices (panel B of Figure 2) and that derived from sales prices (panel B of Figure 3) is that the magnitude of the jump at the $1M threshold is smaller in the case of sales prices. Drawing from the insights of the model presented in Section 3, a less dramatic discontinuity at $1M for sales prices could be attributed to an auction-type mechanism and market participants’ strategic response to the MI policy.

Figure 2: Estimates of the Survivor function and \( \hat{\mu}(p) \)

Note: The sample includes all detached homes. Panel A shows the pre- and post-period survivor function in asking price corresponding to the first six months in 2011 and 2013, respectively. Panel B shows the difference in the post- and pre-treatment period survivor functions.

To more formally test Prediction 1, we obtain the regression discontinuity estimates
Figure 3: Estimates of the Survivor function and $\hat{\mu}(p)$

*Note:* See the notes for 2. Here, we plot the survivor functions in sales price.

Based on equation (8). Table 3 contains the results of interest (i.e., the estimated $\hat{\gamma}$) from this exercise. The first panel shows the results when the asking price is the running variable, while the second panel is for the sales price. The columns of the table show the estimates for various price bandwidths around $1M, whereas the rows show the results from regressions with functions $f_l(\cdot)$ and $f_r(\cdot)$ approximated under different orders of polynomial.

In column (1), the bandwidth is set to include 5 price intervals of $5,000 on either side of $1M. The estimated coefficient in the first row of column (1) is based on a local linear regression for houses listed within $25,000 of $1M. The estimate of $-0.64$ indicates a decrease of nearly two thirds of a percentage point in the share of sales attributed to homes listed.
above $1M.\textsuperscript{26} This estimate is fairly robust to different bandwidth windows and orders of polynomial. We consider bandwidths of 5, 10, and 20 price bins in columns (1), (2) and (4), and present the cross-validation minimizing bandwidth in column (3). In the last row of the table, we report the optimal choice of polynomial order according to the AIC. The estimated coefficients from specifications with optimal order range from $-0.62$ to $-0.67$. The last four columns of Table 3 show the estimates when the sales price is the running variable. The estimates of $\hat{\gamma}$ are again fairly robust to bandwidth selection and polynomial order. For specifications with optimal order, the estimates range from $-0.18$ to $-0.24$. These results indicate that the share of transactions over $1M fell by approximately one fifth of a percentage point. These estimates are statistically significant at conventional levels. Figure 4 provides a graphical representation of the results from the fourth row of Table 3, columns (4) and (8). As can be seen by inspection of this figure, the fourth order polynomial functions fit the data quite well and reveal a marked discontinuity at the $1M threshold for both asking and sales prices.

Table 3: Regression Discontinuity Estimates: Policy Period

<table>
<thead>
<tr>
<th></th>
<th>Asking Price</th>
<th></th>
<th>Sales Price</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) bw(5)</td>
<td>(2) bw(10)</td>
<td>(3) bw(13)</td>
<td>(4) bw(20)</td>
</tr>
<tr>
<td>One</td>
<td>-0.64\textsuperscript{*} (0.027)</td>
<td>-0.62\textsuperscript{*} (0.018)</td>
<td>-0.57\textsuperscript{*} (0.035)</td>
<td>-0.44\textsuperscript{*} (0.042)</td>
</tr>
<tr>
<td>Two</td>
<td>-0.67\textsuperscript{*} (0.020)</td>
<td>-0.69\textsuperscript{*} (0.026)</td>
<td>-0.63\textsuperscript{*} (0.035)</td>
<td>-0.24\textsuperscript{*} (0.071)</td>
</tr>
<tr>
<td>Three</td>
<td>-0.66\textsuperscript{*} (0.027)</td>
<td>-0.64\textsuperscript{*} (0.038)</td>
<td>-0.74\textsuperscript{*} (0.034)</td>
<td>-0.18\textsuperscript{*} (0.074)</td>
</tr>
<tr>
<td>Four</td>
<td>-0.69\textsuperscript{*} (0.032)</td>
<td>-0.62\textsuperscript{*} (0.037)</td>
<td>-0.30\textsuperscript{*} (0.068)</td>
<td></td>
</tr>
<tr>
<td>Optimal Order</td>
<td>1 2 4 4</td>
<td>1 3 3 3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Standard errors in parentheses
\textsuperscript{*} $p < 0.05$

\textsuperscript{26} For ease of presentation, we multiply $\mu$ by 100 and report the results in terms of percentage points.
Figure 4: Estimates of $\hat{\mu}(p)$

**Note:** The sample includes all detached homes. The left panel shows the asking price estimates for $\hat{\mu}_p$, the difference in the survivor functions for the post- and pre-treatment periods using 20 price bins and fourth order polynomials in $f_l(·)$ and $f_r(·)$. Similarly, the right panel uses sale prices.

To address concerns about other pricing effects at the $1M threshold, Table 4 and Figure 5 show results obtained using only pre-policy data as a falsification test. The table is formatted in the same way as Table 3. For the asking price, there are a few specifications that reveal a significant discontinuity in the pre-program period, but for the most part the estimates are small and insignificant. In terms of sales price, the results do not at all indicate a significant negative threshold effect at $1M. Next, we take the difference, $\hat{\mu}_{post} - \hat{\mu}_{pre}$, as the dependent variable in the estimations of equation (8). Table 5 presents the resulting double-difference regression discontinuity estimates. The results are remarkably similar to those in Table 3,
indicating that our results are robust to permanent threshold effects at $1M.

Table 4: Regression Discontinuity Estimates: Pre Policy Period

<table>
<thead>
<tr>
<th></th>
<th>Asking Price</th>
<th></th>
<th></th>
<th></th>
<th>Sales Price</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) bw(5)</td>
<td>(2) bw(10)</td>
<td>(3) bw(10)</td>
<td>(4) bw(20)</td>
<td></td>
<td>(5) bw(5)</td>
<td>(6) bw(10)</td>
<td>(7) bw(10)</td>
</tr>
<tr>
<td>One</td>
<td>0.071*</td>
<td>0.11*</td>
<td>0.11*</td>
<td>0.071</td>
<td>0.066</td>
<td>0.083</td>
<td>0.083</td>
<td>0.12*</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.030)</td>
<td>(0.030)</td>
<td>(0.037)</td>
<td>(0.062)</td>
<td>(0.057)</td>
<td>(0.057)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>Two</td>
<td>0.073*</td>
<td>0.073*</td>
<td>0.075*</td>
<td>0.082</td>
<td>0.082</td>
<td>0.035</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.033)</td>
<td>(0.035)</td>
<td>(0.051)</td>
<td>(0.051)</td>
<td>(0.077)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Three</td>
<td>-0.0053</td>
<td>-0.0053</td>
<td>0.14*</td>
<td>0.011</td>
<td>0.011</td>
<td>0.12*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.051)</td>
<td>(0.046)</td>
<td>(0.046)</td>
<td>(0.057)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Four</td>
<td>0.032</td>
<td></td>
<td></td>
<td>0.048</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td></td>
<td></td>
<td>(0.045)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Optimal Order | 1 | 3 | 3 | 4 | 1 | 3 | 3 | 4

Standard errors in parentheses
* $p < 0.05$

5.2.2 Prediction 2: Bidding Wars

To interpret the above features of the house price data from the perspective of the theoretical model, we should also expect the MI policy to be linked to the incidence of multiple offers. More specifically, Prediction 2 states that the MI policy should increase the ratio of buyers to sellers in the million dollar segment, triggering more frequent bidding wars and reducing time-on-the-market for sellers. To empirically capture the incidence of bidding wars, we focus on transactions with sales price greater than or equal to the asking price. The intuition is straightforward. In a bilateral situation, it is quite common for the buyer and seller to negotiate a final price slightly below the asking price. Observing a sales price greater than or equal to the asking price typically requires competition between bidders, or at least the possibility of competing offers.\textsuperscript{27} A higher proportion of sales above asking could plausibly

\textsuperscript{27}The determination of prices thus differs in some ways from the simple auction mechanism modeled in Section 3. See Albrecht et al. (2016) and Han and Strange (2016) for more sophisticated pricing protocols that can account for sales prices both above and below the asking price.
Table 5: Regression Discontinuity Estimates: Double Difference

<table>
<thead>
<tr>
<th></th>
<th>Asking Price</th>
<th>Sales Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) bw(5)</td>
<td>(2) bw(10)</td>
</tr>
<tr>
<td>One</td>
<td>-0.71* (0.013)</td>
<td>-0.74* (0.022)</td>
</tr>
<tr>
<td>Two</td>
<td>-0.74* (0.028)</td>
<td>-0.81* (0.043)</td>
</tr>
<tr>
<td>Three</td>
<td>-0.66* (0.028)</td>
<td>-0.78* (0.066)</td>
</tr>
<tr>
<td>Four</td>
<td>-0.62* (0.047)</td>
<td>-0.66* (0.044)</td>
</tr>
</tbody>
</table>

Optimal Order: 1 3 4 4 1 3 3 3

Standard errors in parentheses
* p < 0.05

be indicative of hotter markets with a higher incidence of bidding wars and shorter selling times.

We now extend the distribution regression approach to examine the impact of the MI policy on the likelihood that a home is sold at a price above or equal to the asking price, conditional on being listed below $1M. We first evaluate a rescaled empirical survivor function from asking prices, $RS_{itm}$, at a set of cut-off prices, $\{p_1, \ldots, p_J\}$, for each year $t$, month $m$ and district $i$. This survivor function is rescaled by assigning a weight of zero to asking prices of homes that sell below asking. We then estimate the following distribution regression for each $p_j \in \{p_1, \ldots, p_J\}$:

$$RS_{itm}(p_j) = \beta_0(p_j) + \alpha_i'(p_j) + \mu'(p_j) + \delta_m'(p_j) + \tau'(p_j)x_{itm} + \epsilon_{itm}'(p_j).$$

(9)

District and month fixed effects are captured by $\alpha_i'(p_j)$ and $\delta_m'(p_j)$, while coefficient $\mu'(p_j)$

28 The rescaled empirical survivor function at price $p$, denoted $RS_{itm}(p)$, is defined as the number of sales in district $i$ in year $t$ and month $m$ with both a sales price greater than or equal to the asking price and an asking price greater than or equal to $p$, divided by the total sample size for the same district, year and month.
Note: See the notes from figure 4. Here, we use the pre-treatment 2011 and 2012 data.

measures any shift in the distribution over time. Shifts in both the marginal asking price distribution and the conditional sales price distribution (i.e., conditional on selling over asking) are possible. Given that equation (7) was used to estimate the marginal asking price distribution, combining both sets of results allows us to investigate the MI policy’s impact on the incidence of house sales above asking. Backing out estimates of the conditional sales

29Specifically, (9) estimates the (rescaled) distribution of asking prices for the sample of transactions at or above the asking price.
price distribution is an application of the chain rule of probability theory:

\[ \hat{\beta}_0'(p_j) = \text{Prob}\{p^s \geq p^a, p^a \geq p_j | \bar{x}\} = \text{Prob}\{p^s \geq p^a | p^a \geq p_j, \bar{x}\} \times \text{Prob}\{p^a \geq p_j | \bar{x}\}, \]

where \( \hat{\beta}_0(p) \) is obtained from estimating equation (7) with asking price data. Thus, the set of pre-policy period conditional estimates are derived from the estimated constant terms in (7) and (9). Similarly, with coefficients \( \hat{\mu} \) and \( \hat{\mu}' \), we obtain the before-after estimates of the conditional distribution of sales prices:

\[ \text{Prob}\{p^s \geq p^a | p^a \geq p_j, \bar{x}\}_{\text{post}} - \text{Prob}\{p^s \geq p^a | p^a \geq p_j, \bar{x}\}_{\text{pre}} = \frac{\hat{\beta}_0(p_j)\hat{\mu}'(p_j) - \hat{\beta}_0'(p_j)\hat{\mu}(p_j)}{\hat{\beta}_0(p_j) + \hat{\mu}(p_j)} \equiv \hat{\nu}(p_j). \]

We model the set of estimates \( \hat{\nu} = \{\hat{\nu}(p_1), \ldots, \hat{\nu}(p_J)\} \) as a smooth function of the asking price with a possible discontinuity around $1M as per equation (8), but with \( \hat{\nu}(p_j) \) on the left hand side. The coefficient of interest is again \( \gamma \), which captures any discontinuity at $1M in the before-after estimates of the conditional distribution of sales prices, conditional on asking at least \( p_j \).

Prediction 2 of the model implies a corresponding reduction in sellers’ expected time-on-the-market in the million dollar submarket. To test this, we construct a second rescaled empirical survivor function for asking price by assigning a weight of zero to asking prices of homes that take longer than the median time to sell (namely, 14 days).

The results related to sales over asking and days on the market are presented in Table 6. For the sake of brevity, we present the corresponding falsification tests and compare only the six month post-policy period in 2013 to the pre-policy period in 2012. The left panel contains the estimates for the incidence of sales above asking, and the right panel contains estimates related to days-on-the-market. Altogether, the results are consistent with Prediction 2. The incidence of sales above asking fell sharply by 1.28 percentage points just above $1M (see row four of column (3), where bandwidth and polynomial order are selected
optimally). Similarly, the incidence of longer than average selling times increased by 1.58 percentage points (see row two of column (7)). All coefficients have the expected signs and are statistically significant. Finally, the before-after estimates are presented graphically in Figure 6. The discrete jumps observed at the $1M threshold after the implementation of the MI policy provide strong support for the bidding war perspective established by our directed search model featuring auctions, financially constrained buyers and seller entry.

<table>
<thead>
<tr>
<th></th>
<th>Spread</th>
<th>Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>bw(5)</td>
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<tr>
<td>One</td>
<td>-1.34*</td>
<td>-1.55*</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>Two</td>
<td>-1.33*</td>
<td>-1.58*</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.100)</td>
</tr>
<tr>
<td>Three</td>
<td>-1.22*</td>
<td>-1.57*</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>Four</td>
<td>-1.28*</td>
<td>-1.32*</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.099)</td>
</tr>
<tr>
<td>Optimal Order</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* p < 0.05

5.2.3 Prediction 3: Cross-Market Analysis

The MI policy’s effects on asking and sales prices should, according to Prediction 3, be larger when the new policy affects a larger share of prospective buyers. We test this prediction in two ways: across price segments and across geographically separated markets.

Along the price dimension, we compare the MI policy’s impact on house prices around the $1M threshold and house prices well below or above $1M. The idea is that since the MI policy specifically targets the $1M price point, it should not affect non-adjacent price segments because the financial constraints faced by prospective buyers in those segments
Figure 6: Estimates of the Survivor function and $\hat{\mu}(p)$

Note: The sample includes all ...

Table 7 displays the results. The bottom row repeats our estimates for the $1M$ threshold for ease of reference. Each entry in the table is from a separate regression. The leftmost column displays the price threshold. The bandwidth is selected as per the data-driven cross-validation procedure and the order of the polynomial smoothing functions is chosen optimally by the AIC procedure, referenced above. As expected, most of the estimates are statistically
insignificant. There are some economically large and statistically significant estimates (e.g., at the $850,000 threshold for asking price), however, for the most part the results support the MI policy-based interpretation of the estimates reported at the $1M threshold.

We next compare two spatially-separated housing markets within of the Greater Toronto Area: central Toronto and suburban Toronto. Unfortunately, we do not have information about buyers’ wealth and borrowing limits to test Prediction 3 directly. Nevertheless, we collect information at the district level related to income and age for these two markets. As noted in section 4, a million dollar home is at the median of the house price distribution in central Toronto. In contrast, a million dollar home corresponds to the 95th percentile of the house price distribution in suburban Toronto. It seems reasonable to assume, therefore, that the average buyer of a million dollar home in central Toronto is a household of median income/wealth for the region, whereas a buyer of a million dollar home in suburban Toronto has income/wealth near the 95th percentile of the relevant suburban Toronto distributions. Table ? reveals the the former income level is smaller than the latter, which hints at a higher share of buyers in central Toronto with binding financial constraints. All this is to say that we suspect a more pervasive impact of the MI policy on prospective buyers in central Toronto than in suburban Toronto.

Tables 8 and 9 display the double difference regression discontinuity estimates for central and suburban Toronto. The estimates are consistent with Prediction 3 and the argument presented in the preceding paragraph. For central Toronto, the optimal order estimates of $\hat{\gamma}$ are statistically significant and range from $-1.44$ to $-1.68$ for asking price and $-0.60$ to $-1.22$ for sales price. By themselves, these effects align perfectly with Prediction 1. Turning to suburban Toronto, we find that these effects are economically small and less often statistically significant. This confirms the hypothesis that in suburban markets, where fewer buyers participating in the million dollar segment of the housing market are likely constrained by the 20% minimum down payment constraint and hence less affected by the MI restriction, the MI policy has a tempered impact on listing strategies and transaction outcomes.
Overall, variation in the influence of the MI policy across markets and segments are consistent with both the expected transaction outcomes described in Prediction 1 and the comparative statics summarized in Prediction 3.

Table 7: Regression Discontinuity Estimates: Alternative Cut-offs

<table>
<thead>
<tr>
<th>Policy</th>
<th>Pre-Policy</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asking</td>
<td>Selling</td>
<td>Asking</td>
</tr>
<tr>
<td>700000</td>
<td>-0.095*</td>
<td>-0.088</td>
</tr>
<tr>
<td>725000</td>
<td>0.010</td>
<td>-0.17</td>
</tr>
<tr>
<td>750000</td>
<td>-0.090</td>
<td>-0.21</td>
</tr>
<tr>
<td>775000</td>
<td>-0.071</td>
<td>0.042</td>
</tr>
<tr>
<td>800000</td>
<td>0.084</td>
<td>0.090</td>
</tr>
<tr>
<td>825000</td>
<td>-0.090</td>
<td>-0.093</td>
</tr>
<tr>
<td>850000</td>
<td>-0.32*</td>
<td>-0.14</td>
</tr>
<tr>
<td>875000</td>
<td>-0.049</td>
<td>-0.070</td>
</tr>
<tr>
<td>900000</td>
<td>0.0080</td>
<td>-0.14</td>
</tr>
<tr>
<td>1000000</td>
<td>-0.69*</td>
<td>-0.18*</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* p < 0.05
Table 8: Regression Discontinuity Estimates for the Central District: Double Difference

<table>
<thead>
<tr>
<th></th>
<th>Asking Price</th>
<th></th>
<th>Sales Price</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>(1) (2) (3) (4)</td>
<td>(5) (6) (7) (8)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>bw(5) bw(10) bw(10) bw(20)</td>
<td>bw(5) bw(10) bw(10) bw(20)</td>
<td></td>
</tr>
<tr>
<td>One</td>
<td>-1.78* 1.96* -1.96* -1.57*</td>
<td>-0.80* -0.49* -0.49* -0.58*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.044) (0.099) (0.099) (0.092)</td>
<td>(0.12) (0.18) (0.18) (0.18)</td>
<td></td>
</tr>
<tr>
<td>Two</td>
<td>-1.79* -1.79* -2.02*</td>
<td>-0.99* -0.99* -0.046</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.064) (0.064) (0.12)</td>
<td>(0.29) (0.29) (0.28)</td>
<td></td>
</tr>
<tr>
<td>Three</td>
<td>-1.68* -1.68* -2.09*</td>
<td>-0.60* -0.60* -1.02*</td>
<td></td>
</tr>
<tr>
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<td>(0.080) (0.080) (0.18)</td>
<td>(0.16) (0.16) (0.23)</td>
<td></td>
</tr>
<tr>
<td>Four</td>
<td>-1.44*</td>
<td>-1.22*</td>
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</tr>
<tr>
<td></td>
<td>(0.16)</td>
<td>(0.41)</td>
<td></td>
</tr>
</tbody>
</table>

Optimal Order: 1 3 3 4 1 3 3 4

Standard errors in parentheses

* $p < 0.05$

Table 9: Regression Discontinuity Estimates for the GTA outside of Toronto: Double Difference

<table>
<thead>
<tr>
<th></th>
<th>Asking Price</th>
<th></th>
<th>Sales Price</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>(1) (2) (3) (4)</td>
<td>(5) (6) (7) (8)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>bw(5) bw(10) bw(10) bw(20)</td>
<td>bw(5) bw(10) bw(10) bw(20)</td>
<td></td>
</tr>
<tr>
<td>One</td>
<td>-0.083* -0.14* -0.14* -0.22*</td>
<td>0.065 0.080* 0.080* -0.049</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.040) (0.039) (0.039) (0.032)</td>
<td>(0.039) (0.034) (0.034) (0.049)</td>
<td></td>
</tr>
<tr>
<td>Two</td>
<td>-0.088* -0.088* -0.14*</td>
<td>0.069* 0.069* 0.12*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.040) (0.040) (0.045)</td>
<td>(0.027) (0.027) (0.056)</td>
<td></td>
</tr>
<tr>
<td>Three</td>
<td>0.0023 0.0023 -0.047</td>
<td>0.052 0.052 0.11</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.031) (0.031) (0.031)</td>
<td>(0.030) (0.030) (0.061)</td>
<td></td>
</tr>
<tr>
<td>Four</td>
<td>-0.071</td>
<td>0.016</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.030)</td>
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</tr>
</tbody>
</table>

Optimal Order: 1 3 3 3 1 2 2 4

Standard errors in parentheses

* $p < 0.05$
6 Conclusion

In this paper we explore the price implications of financial constraints or lending restrictions 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 MI for homes purchased at a price of $1M or more. We exploit the policy’s $1M threshold by combining distribution regression and regression discontinuity methods to estimate the effects of the policy on prices and other housing market outcomes.

To guide our analysis and interpretation, we first characterize a directed search equilibrium in a setting with competing auctions and exogenous bidding limits. We model the introduction of the Canadian MI policy of 2012 as an additional financial constraint affecting a subset of prospective buyers. We show that sellers respond strategically to the policy by reducing their asking prices. Consequently, the policy’s impact on final sales prices is dampened by the heightened competition between constrained and unconstrained bidders.

Using housing transaction data from the city of Toronto, we find that the MI policy resulted in relatively fewer housing market transactions above the $1M threshold. Our estimate of discontinuity at $1M is 0.18 percentage points. Consistent with the model, the MI policy’s effect on asking prices is even more striking at 0.69 percentage points. We also find evidence that the incidence of bidding wars and below average time-on-the-market are relatively higher for homes listed just below the $1M threshold, which agrees with the theoretical results. Overall, the MI policy appears to have cooled the housing market just above the $1M threshold and at the same time heated up the market just below.

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A Theory: Details and Derivations

A.1 Expected Payoffs

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

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

\[
V^*_T(p, \lambda, \theta) = -x + \pi(1)p + \sum_{k=2}^{\infty} \pi(k) \left\{ [p_k(0) + p_k(1)]c + \sum_{j=2}^{k} p_k(j)u \right\}.
\]
Substituting expressions for $\pi(k)$ and $p_k(j)$ and recognizing the power series expansion of the exponential function, the closed-form expression is

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

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

The unconstrained buyer’s expected payoff is

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

The closed-form expression is

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

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

The constrained buyer’s expected payoff is

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

The closed-form expression is

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

The first term is the expected surplus when competing for the house with other constrained bidders; the last term reflects the possibility of being the only buyer.
Case II: \( c < p \leq u \). The seller’s expected net payoff is

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

The closed-form expression is

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

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

The unconstrained buyer’s expected payoff is

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

The closed-form expression is

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

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

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

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

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

\[
V^s_{III}(p, \lambda, \theta) = -x, \quad V^u_{III}(p, \lambda, \theta) = 0 \quad \text{and} \quad V^c_{III}(p, \lambda, \theta) = 0.
\]  

(A.7)

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

\[
V^i(p, \lambda, \theta) = \begin{cases} 
V^i_{III}(p, \lambda, \theta) & \text{if } p > u, \\
V^i_{II}(p, \lambda, \theta) & \text{if } c < p \leq u, \\
V^i_I(p, \lambda, \theta) & \text{if } p < c.
\end{cases}
\]  

(A.8)

### A.2 Algorithms for Constructing DSE

If \(\Lambda = 0\) and \(x \leq x\), set \(P = p^*_u\), \(\theta(p^*_u) = \theta^\ast\), \(\sigma(p^*_u) = B/\theta^\ast\) and \(\bar{V}^u = V^u(p^*_u, 0, \theta^\ast) = e^{-\theta^\ast}v\).

For \(p \leq u\), set \(\theta\) to satisfy \(\bar{V}^u = V^u(p, 0, \theta)\), or if there is no solution to this equation, set \(\theta(p) = 0\). For \(p > u\) set \(\theta(p) = 0\).

If \(\Lambda = 0\) and \(x > x\), set \(P = u\), \(\theta(u) = \theta_u\), \(\sigma(u) = B/\theta_u\) and \(\bar{V}^u = V^u(u, 0, \theta_u)\). For \(p \neq u\), set \(\theta\) as above.

If \(\Lambda \geq \lambda_p\) and \(x \in (x, \bar{x}]\), set \(P = \{c\}\), \(\lambda(c) = \Lambda\), \(\theta(c) = \Theta\), and \(\sigma(c) = B/\Theta\). The equilibrium values are \(\bar{V}^u = V^u(c, \Lambda, \Theta)\) and \(\bar{V}^c = V^c(c, \Lambda, \Theta)\). For \(p \leq c\), set \(\lambda\) and \(\theta\) 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 \(\theta\) to satisfy \(\bar{V}^u = V^u(p, 0, \theta(p))\). For \(p \in (c, u]\), set \(\lambda(p) = 0\) and \(\theta\) 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 \(\theta(p) = 0\).

If \(\Lambda < \lambda_p\) and \(x \in (x, \bar{x}]\), set \(P = \{c, p^*_u\}\), \(\lambda(p^*_u) = 0\), \(\theta(p^*_u) = \theta^\ast\), \(\lambda(c) = \lambda_p\), \(\theta(c) = \theta_p\), \(\sigma(p^*_u) = (\lambda_p - \Lambda)B/(\lambda_p \theta^\ast)\) and \(\sigma(c) = \Lambda B/\lambda_p \theta_p\). The equilibrium values are \(\bar{V}^u = V^u(p^*_u, 0, \theta^\ast)\) and \(\bar{V}^c = V^c(c, \lambda_p, \theta_p)\). For \(p \notin P\), set \(\lambda\) and \(\theta\) as above.
A.3 Omitted Proofs

Proof of Lemma 1. See proof of Lemma 2. 

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 $\theta(p) = 0$ implies $V^*(p,0,\theta(p)) = 0$. To show that condition 1(i) holds for all $p \leq u$, suppose (FSOC) that there exists $p' \leq u$ such that $V^*(p',0,\theta(p')) > 0$. This requires $\theta(p') > 0$. Then, by construction, $V^u(p',0,\theta(p')) = V^u$. The pair $\{p',\theta(p')\}$ satisfies the constraint set of Problem 3 and achieves a higher value of the objective than $\{p^*_u,\theta^*\}$ if $x \leq \bar{x}$ or $\{u,\theta_u\}$ if $x > \bar{x}$: a contradiction.

To prove that $\theta_u > \theta^*$, recall that $x > \bar{x}$ implies $u < p^*_u$ (by Lemma 1). Using the definition of $p^*_u$ using (4) and the the free entry condition $V^*(p^*_u,0,\theta^*) = 0$, inequality $u < p^*_u$ can be written

$$[1 - e^{-\theta^*}] u < x. \quad (A.9)$$

Moreover, the free entry condition $V^*(u,0,\theta_u) = 0$ can be written

$$[1 - e^{-\theta_u}] u = x \quad (A.10)$$

Combining inequality (A.9) and equality (A.10) yields $\theta_u > \theta^*$.

Proof of Corollary 1. If $x \leq \bar{x}$, market tightness in equilibrium is $\theta^* > x/u$. The inequality follows from Lemma 1, the definition of $p^*_u$ in equation (4), the free entry condition $V^*(p^*_u,0,\theta^*) = 0$, and the following property of the exponential function: $1 - e^{-\theta^*} < \theta^*$ for $\theta^* \geq 0$.

If $x > \bar{x}$, market tightness in equilibrium is $\theta_u > \theta^*$ (see Proposition 1). The free entry condition, $V^*(u,0,\theta_u) = 0$ and the above property of the exponential function also imply $\theta_u > x/u$. Hence, $\theta_u > \max\{\theta^*, x/u\}$.

Proof of Lemma 2. As $x \rightarrow 0$, $\theta^* \rightarrow 0$ and hence $\lim_{x \rightarrow 0} p^*_u(x) = 0$. As $x \rightarrow v$, $\theta^* \rightarrow \infty$ and hence $\lim_{x \rightarrow v} p^*_u(x) = \infty$. By the intermediate value theorem, there exist $\bar{x} \in (0,v)$ and
\( \bar{x} \in (0, v) \) such that \( p_u^*(x) = c \) and \( p_u^*(\bar{x}) = u \). Differentiating \( p_u^* \) with respect to \( x \) yields

\[
\frac{\partial p_u^*}{\partial x} = \frac{v - u}{\theta^* e^{-\theta^*}} \left[ 1 - \frac{1 - e^{-\theta^*}}{\theta^*} \right] \frac{\partial \theta^*}{\partial x} = \frac{v - u}{v} \left( \frac{1}{\theta^* e^{-\theta^*}} \right) \left[ 1 - \frac{1 - e^{-\theta^*}}{\theta^*} \right] > 0.
\]

This monotonicity implies uniqueness of both \( x \) and \( \bar{x} \). It also implies \( p_u^* \in (c, u] \) if and only if \( x \in (x, \bar{x}) \).

**Proof of Proposition 2.** Proof of existence goes here.

To prove that \( \theta_p > \theta^* \), recall that \( x > x \) implies \( c < p_u^* \) (by Lemma 2). Using the definition of \( p_u^* \) using (4) and the the free entry condition \( V^s(p_u^*, 0, \theta^*) = 0 \), inequality \( c < p_u^* \) can be written

\[
[1 - e^{-\theta^*}] c + [1 - e^{-\theta^*} - \theta^* e^{-\theta^*}] (u - c) < x \quad (A.11)
\]

Moreover, the free entry condition \( V^s(c, \lambda_p, \theta_p) = 0 \) can be written

\[
[1 - e^{-\theta_p}] c + [1 - e^{-(1 - \lambda_p)\theta_p} - (1 - \lambda_p)\theta_p e^{-(1 - \lambda_p)\theta_p}] (u - c) = x \quad (A.12)
\]

which implies

\[
[1 - e^{-\theta_p}] c + [1 - e^{-\theta_p} - \theta_p e^{-\theta_p}] (u - c) \geq x \quad (A.13)
\]

Combining inequalities (A.11) and (A.13) yields \( \theta_p > \theta^* \).

Finally, to prove that \( \Theta \geq \theta_p \) when \( \Lambda \geq \lambda_p \), note the free-entry condition \( V^s(c, \Lambda, \Theta) = 0 \) can be written

\[
[1 - e^{-\Theta}] c + [1 - e^{-(1 - \Lambda)\Theta} - (1 - \Lambda)\Theta e^{-(1 - \Lambda)\Theta}] (u - c) = x
\]

which, when \( \Lambda \geq \lambda_p \), implies

\[
[1 - e^{-\Theta}] c + [1 - e^{-(1 - \lambda_p)\Theta} - (1 - \lambda_p)\Theta e^{-(1 - \lambda_p)\Theta}] (u - c) \geq x \quad (A.14)
\]

Combining equality (A.12) and inequality (A.14) yields \( \Theta \geq \theta_p \) (when \( \Lambda \geq \lambda_p \)).