Do Financial Constraints Cool a Housing Boom? Theory and Evidence from a Macroprudential Policy on Million Dollar Homes

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March 20, 2017

Abstract

In this paper we seek to understand the role of financial constraints in the housing market and their effectiveness as a macroprudential policy tool aimed at cooling a housing boom. We exploit a natural experiment arising from the 2012 Canadian law change that restricts access to mortgage insurance (MI) 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 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 1.05 percent increase in the annual growth of houses *listed* just under \$1M and a 0.33 percent increase in the annual growth of houses *sold* just below \$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 \$1M segment, consistent with the model's predictions. Overall, our analysis points to the importance of strategic and equilibrium considerations in assessing the effectiveness of macroprudential policies.

Keywords: macroprudential regulation, directed search, financial constraints, 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 (Stein, 1995; Genesove and Mayer, 1997; Ortalo-Magne and Rady, 2006; Favilukis et al., 2017). On the buyer side, the required downpayment (e.g. loan-to-value ratio) and mortgage payment (e.g. debt-to-income ratio) reflect the two underwriting constraints, on wealth and income respectively, that limit how much a buyer can bid on a property. On the seller side, the decision to list a house for sale and the choice of asking price depend on the perceived ability to pay among potential buyers. Thus, the central role of financial constraints makes them an appealing vehicle for policymakers to intervene housing markets.[1] Since the global financial crisis of 2008, tightening financial constraints has become one of the primary macroprudential tools that aim to create a buffer in a boom to ensure that "shocks from the housing sector do not spill over and threaten economic and financial stability" (IMF Speech, 2014).[2] Despite the enormous importance and dramatic controversy surrounding such interventions,[3] "the macroprudential approach remains unproven" (Bernanke, 2015), partly because the core question how financial constraints affect housing markets has not been well answered. This paper aims to fill this gap by providing a search theoretical analysis to explore strategic and equilibrium implications of financial constraints in housing markets, and by empirically exploiting a natural experiment arising from a macroprudential policy implemented in Canada in 2012.

The macroprudential regulation that we focus on restricts access to mortgage insurance (the transfer of mortgage default risk from lenders to insurers; henceforth MI) when the

[1]For example, Kuttner and Shim (2016) document 94 policy actions on the loan-to-value ratio and 45 actions on the debt-service-to-income ratio in 60 countries between 1990–2012. Also see Elliott et al. (2013) for a comprehensive survey of the history of cyclical macroprudential policies in the U.S.

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

[3]For example, the Bank of International Settlements (BIS) suggested in 2014 that central banks need to use tighter monetary policy to counter domestic financial booms. In marked contrast, Janet Yellen, the Chair of the Federal Reserve, responded by contending that macroprudential regulation, and not monetary policy, should be used to control the risks associated with large asset price expansions.

purchase price of a home exceeds1 million Canadian dollars. Given that Canadian lenders, like those in the US and other developed countries, are required to insure mortgages with over 80% loan-to-value ratio, the MI policy effectively imposes a 20% minimum downpayment constraint for buyers of homes of $1M or more.[4] Designed by Jim Flaherty, the former Canadian Finance Minister, the aim of the policy was twofold: (i) to restrain price appreciation in the higher-end segments of housing markets,[5] and (ii) to improve borrower creditworthiness. Despite its clear intentions, the housing market consequences of this policy are challenging to assess in two aspects. Conceptually, understanding the impact of the MI policy requires an equilibrium analysis of a two-sided housing market. 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 lower the asking price to attract both constrained and unconstrained buyers, resulting in bidding wars that "create a 'red hot' market for homes under $999,999" (Financial Post, 2013). Empirically, as noted in Wachter et al. (2014), the macroprudential policies are "typically used in combination with macroeconomic policy and direct interventions, complicating the challenge to attribute outcomes to specific tools."

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

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

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

the model is the financial constraints faced by buyers which limit how much they can bid on a house.[6] We assume that buyers initially face a common income constraint that is not too restrictive, but that the introduction of the MI limitation imposes a minimum wealth requirement that further constrains a subset of buyers.

We characterize the pre- and post-policy equilibria and derive a set of empirical predictions. Under appropriate parameter restrictions, the post-policy equilibrium features lower asking prices and fewer sellers. The former effect is a strategic response among participating sellers; some sellers respond to the policy by setting their asking price just low enough to attract both constrained and unconstrained buyers. The latter effect is an extensive margin response; some home-owners that would have listed their house for sale absent the MI policy no longer find it worthwhile to participate in the market. Together, these increase the ratio of buyers to sellers, prompting a higher incidence of multiple offers. Heightened bidding war intensity sometimes pushes the sales price above the asking price, leading to a less severe reduction in sales prices. As a final empirical prediction for the purpose of cross-market comparisons, we show that the consequences of the policy should be more dramatic when a larger share of prospective buyers are constrained.

We test the model's predictions using the 2011-2013 housing market transaction data for single-family homes in the Greater Toronto Area, Canada's largest housing market. The Toronto market provides a particularly suitable setting for this study for two reasons. First, home sellers in Toronto typically initiate the search process by listing the property and specifying a particular date on which offers will be considered (often 5-7 days after listing). This institutional practice fits well with our model of competing auctions and hence enables us to explore the model's implications about the strategic interactions between buyers and sellers. Second, the 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 $1M threshold. This is apparent from Figure 1 where we plot smoothed

[6] 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.

percentage changes in sales volume before and after the change in MI policy by sale price.[7] Thus the market provides a natural experimental opportunity for examining the impact of a macroprudential policy on the housing market.

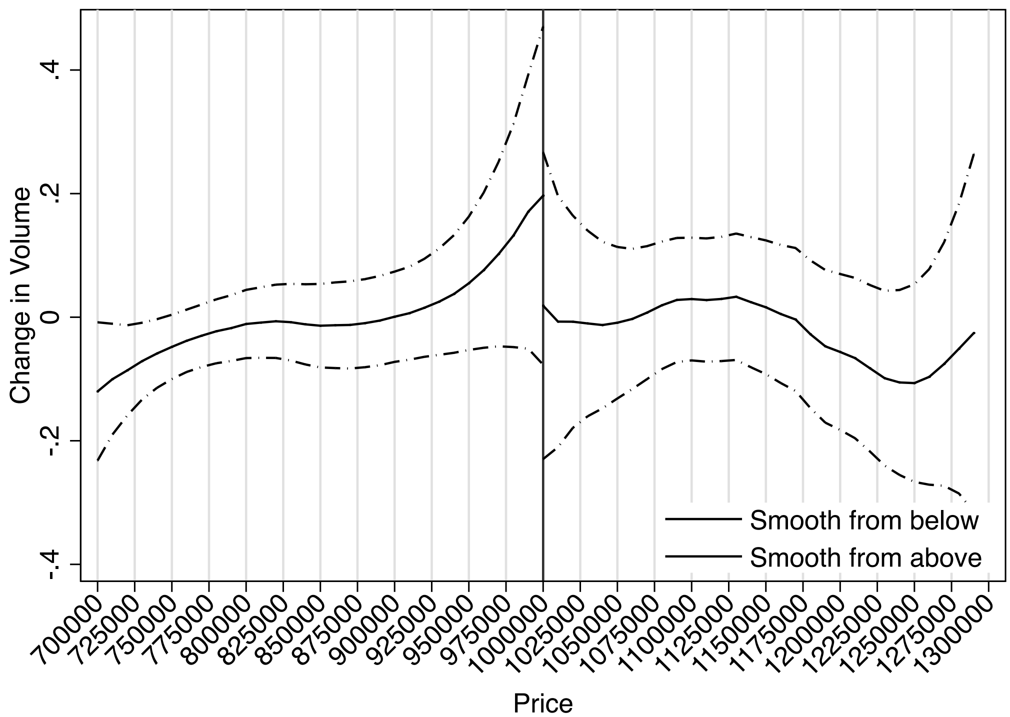

Figure 1: Smoothed Change in Sales Volume between 2012-2013 by Price

Despite the appealing setting, estimating the MI's impact is complicated by the fact that the implementation of the policy coincided with a number of accompanying government interventions[8] as well as other general housing market trends. These confounding factors make it difficult to isolate the effects of the MI policy. The standard differences-in-differences

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

[8]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.

approach requires an exogenous distinction between the *control* and *treatment* groups, which is difficult to implement here since the MI policy affects not only house prices but also the composition of housing stock in segments nearby $1M.

Our solution relies on a two-stage estimation procedure. First, we employ a distribution regression approach to estimate the before-after policy effects on listings and sales along the entire distribution of house price. 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 all other contemporaneous macro and market forces influence listings and transactions in a manner that is either continuous along the price distribution or discontinuous in a time-invariant way. Under this assumption, The two-stage estimation procedure uncovers the effects of the MI policy on listings and sales around the $1M threshold. Our specification ensures that these estimated effects are not driven by changes in housing stock compositions. To tease out other potential sources of discontinuity at the $1M threshold, such as psychological pricing (Foxall et al., 1998) or focus points in marketing and bargaining (Pope et al., 2015), we repeat the same analysis described above, but with either price thresholds further away from $1M[9] or with data from before the implementation of the policy. The small and insignificant estimates obtained from these falsification tests support the validity of our identifying assumption.

Overall, the empirical findings are remarkably consistent with the model. First, the MI restriction causes a 1.05 percent increase in the annual growth of houses listed just under $1M. This aligns with the prediction and the intuition that sellers respond to the policy with asking prices that are just low enough to attract both constrained and unconstrained buyers. The theory also predicts that an increase in the ratio of buyers to sellers speeds up housing sales and leads to bidding wars that sometimes push the sales price well above the asking

[9]There is good reason to believe that buyers and sellers participating in market segments further from the $1M threshold are less affected by the MI policy. By the very nature of the MI policy, listings and transactions at prices well below the $1M threshold are not likely affected by the new regulation. Buyers searching among homes listed far above the $1M cutoff likely have sufficient wealth to circumvent the MI limitation. It follows that sellers asking prices far above the $1M cutoff face less or no incentive to alter their listing strategies in response to the MI policy. Changes in listings and transactions at prices far from $1M should therefore be less influenced by the MI policy.

price. In line with this, we find that the aforementioned spike in homes listed just under \$1M is accompanied by a higher fraction of sales over asking price and a shorter selling time, both of which are attributed to the MI policy. A further implication of the theory is that escalation to prices above \$1M in situations with multiple offers from unconstrained bidders mitigates the policy's direct dampening impact, leading to a less dramatic effect on sales prices. Correspondingly, we find that the MI restriction causes a 0.33 percent increase in the annual growth of houses sold just under \$1M, much smaller than its effect on the asking price.

We next consider variation in the influence of the MI policy across geographic markets. The MI policy contributes to a 1.68 percent increase in the annual growth in listings in the under \$1M segment (equivalent to approximately 40 listings in six months) in central Toronto and a 0.60 percent increase (equivalent to approximately 15 listings in six months) in suburban Toronto. This evidence, along with the observation that buyers of million dollar homes in Toronto's periphery are wealthier and hence less likely constrained by a 20% down payment requirement than their counterparts in the urban core, align well with the theoretical prediction.

Our findings have two sets of policy implications. First, the model clarifies the conditions under which financial constraints affect aggregate transaction volume. With sufficient number of buyers constrained, the MI policy results in less than optimal seller entry. Thus lending restrictions may be efficient from the point of view of preventing a correction in the housing market and hence spillovers to the financial markets, although not always from the point of view of aggregate welfare of housing markets. Second, turning to the specific goal of cooling the high end of housing markets, we find that the MI policy has desired effects by lowering sales price in the targeted segment; however the policy's effectiveness in this regard is attenuated by the strategic response in sellers' listing decision and buyers' search decision. Everything considered, the analysis points to the importance of designing macroprudential policies that recognize potential strategic and equilibrium implications.

Finally we emphasize that mortgage insurance is a key component of housing finance systems in many countries, including the United States, the United Kingdom, the Netherlands, Hong Kong, France, and Australia. These countries share two important institutional features with Canada: (i) the requirement that most lenders insure high loan-to-value (LTV) mortgages, and (ii) the central role of the government in providing such insurance.[10] These features give policymakers "exceptional power to affect housing finance through the key role of government-backed mortgage insurance" (Krznar and Morsink, 2014). Thus the lessons learned in this paper are important not only for Canada, but also for many nations around the world.

In the next versions of this paper we are working to improve the empirical methodology in two ways. First, one potential concern is that the characteristics of the houses themselves shift differentially around the policy threshold. For example, our results suggest that houses which would have demanded a price over \$1M lowered their asking price to attract constrained buyers. It could be the case, however, that the type of home that lowered their asking price was low quality. To address this concern, we use our distribution regression approach to decompose the observed changes in the distribution of house sales into a component related to house characteristics and a component that isolates the shifts in the price structure using methods from Chernozhukov et al. (2013). We perform our analysis on both components, interpreting shifts related to the price structure around the \$1M threshold as being policy induced effects with composition held constant. We find that nearly all of the shifts in the observed distribution of house sales are related to price structure effects, and so composition concerns are minimal. Second, we show that our RD estimates can be thought of as a 'total' effect of the policy in terms of seller behaviour. We then combine our approach with methods borrowed from the literature on 'bunching' estimators Chetty et al. (2011); Slemrod et al. (2015); Best et al. (2015) and illustrate how the total effect we estimate can

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

be decomposed into two types of seller behaviour buy constructing 'missing masses' on either side of the cut-off; some sellers that would be in price bins below \$1M relocate upwards to the threshold and some sellers who would be in price bins above \$1M relocate downward toward the threshold. While preliminary, our results suggest nearly half of the total effect we estimate in terms of asking behaviour comes from sellers below the \$1M threshold relocating upward, but this behavioural effect is essentially zero for sales prices indicating that the total effect we estimate comes entirely from those who would have sold their home for more than \$1M in the absence of the policy.

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

2 Literature Review

Financial constraints (sometimes called "credit" or "borrowing" or "collateral" or "financing" or "liquidity" constraints) are an old and recurring theme of the literature on the housing markets. While much of the literature has focused on the impact of financial constraints on individual households' consumption-savings decision (Hayashi, 1985; Hurst and Lusardi, 2004; Lehnert, 2004) and rent versus buy choice (Linneman and Wachter, 1989; Gyourko et al., 1999), less work examines the macro consequences of financial constraints on house price, trading volume, and price volatility. Our paper is closely linked to the latter. On the theory front, a typical form of financial constraints that has been modelled is down-payment requirements. Focusing on repeated homebuyers, Stein (1995) demonstrates that tight down-payment constraints can result in lower house prices and fewer transactions. Extending Stein's idea into a dynamic setting, Ortalo-Magne and Rady (2006) show that down-payment constraints delay some households' first home purchase and force other to buy a house smaller than they would like, resulting in a lower house price. Both Stein (1995) and Ortalo-Magne and Rady (2006) take a partial equilibrium approach as they assume fixed housing supply. Favilukis et al. (2017) are among the first that explicitly incorporates housing production response in modelling the impact of financial constraints. In dong so, they show that in a general equilibrium setting the only way that a relaxation of financial constraints could lead to a housing boom is through a reduction in the housing risk premium. Our paper adds to this literature by taking an alternative approach to the general equilibrium analysis. In particular, we provide a search theoretical analysis to model buyers and sellers' search and listing decisions in a two-sided housing market. In this regard, our work is also close to a line of literature on search and matching in housing (e.g., Wheaton 1990, Krainer 2001 Williams 1995, Genesove and Han 2012). Unlike the current paper, none of these search papers incorporates credit market imperfections. In this sense, the theoretical analysis in our paper is the first search theoretical analysis that models the role of financial constraints in housing markets.[11]

Turning to the empirical literature, financial constraints are defined much more broadly.[12] In understanding the recent financial crisis, much focus has been placed on examining the role of financial constraints in explaining housing booms and busts. For example, Vigdor (2006), Duca et al. (2011), Berkovec et al. (2012) show that a relaxation of financial constraints results in a boom in house prices; Mian and Sufi (2009) link the expansion of mortgage credit to higher initial house prices and subsequent elevated default rates, which further lead to price declines; and Demyanyk and Van Hemert (2011) demonstrate that extreme credit constraints can result in a lower housing prices and fewer transactions because negative equity prevents some households from moving. Our empirical work differs from this body of work in the form of financial constraints, the level of the data, and the nature of the outcomes. As we emphasize above, the micro-level of the transaction data, combined with the natural

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

[12]They take the form of downpayment constraints (Lamont and Stein, 1999; Genesove and Mayer, 2001), debt-to-income ratio (Demyanyk and Van Hemert, 2011), borrowing against existing housing equity (Mian and Sufi, 2009), mortgage contract terms (Berkovec et al., 2012), and innovations in easing the access to mortgages (Vigdor, 2006).

experimental opportunity arising from the mortgage insurance restriction, greatly helps us in isolating the casual effect of the MI policy on the asking price, sales price and time on the market. We also exploit the geographical variation in the effects of the MI policy and linked that to the share of constrained households.

Finally, our paper contributes to a small but growing empirical literature on macroprudential policies. One strand of work relies on the low-frequency, aggregate transaction data (e.g., Dell'Ariccia et al. 2011; Crowe et al. 2013; Elliott et al. 2013; DellAriccia et al. 2012; Lim et al. 2013; Krznar and Morsink 2014). The other strand explores the loan-level data to analyze the impact of macro prudential policy on mortgage contract characteristics and mortgage demand. A pioneering work in this direction is Allen et al. (2016). Unlike these papers, our paper examines the policy impact on housing market outcomes. Such analysis requires micro-level house transaction data, which is a key advantage of our paper. In addition, benefiting from a search theoretic analysis, we illustrate the importance of strategic and equilibrium considerations in assessing the effectiveness of macroprudential policies.

3 Background

Since 2000 Canada has experienced one of the world's largest modern house price booms, with prices surging 150 percent between 2000 and 2014. Moreover, in contrast to other large housing markets like those in the U.S., homes in Canada suffered only minor price depreciation during the Great Recession. Figure 2 plots the national house price indices for Canada and the U.S.[13] 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.[14] To

[13]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).

[14]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.

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.[15] Interventions included increasing minimum down payment requirements (2008); reducing the maximum amortization period for new mortgage loans (2008, 2011, 2012); reducing the borrowing limit for mortgage refinancing (2010, 2011, 2012); increasing homeowner credit standards (2008, 2010, 2012); and limiting government-backed high-ratio[16] MI to homes with a purchase price of less than $1M (the focus of this paper).

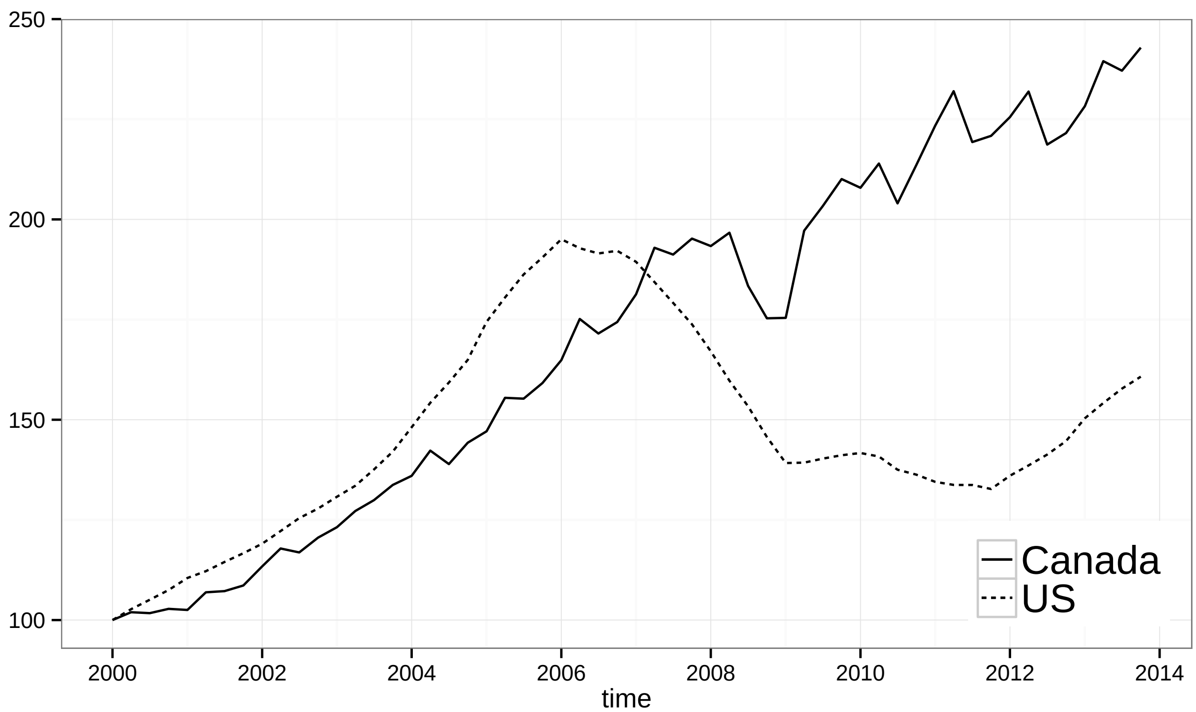

Figure 2: House Price Indices for Canada and the U.S.

3.1 Mortgage Insurance in Canada

Mortgage insurance is a financial instrument used to transfer mortgage default risk from the lender to the insurer. For federally regulated financial institutions in Canada, insurance is

[15]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.

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

legally required for any mortgage loan with an LTV ratio higher than 80 percent.[17] 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.

3.2 The Canadian Mortgage Insurance Regulation of 2012

In June of 2012, the Canadian federal government passed a law that limited the availability of government-back MI for high LTV mortgage loans to homes with a purchase price of less than one million Canadian dollars. To purchase a home for $1M or more, the 2012 regulation effectively imposes a minimum down payment requirement of 20 percent.[18] 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.[19]

4 Theory

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

[17] 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).

[18] 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 **?**).

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

4.1 Environment

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

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

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

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

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

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

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

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

Price determination. The price is determined in a second-price 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, where $0 < x < u$. It is worthwhile to enter the market as a seller if and only if the expected revenue exceeds the listing cost.

4.2 Equilibrium

4.2.1 The Auction

When a seller meets k buyers, the auction mechanism described above determines a game of incomplete information because 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 sensible offers.

4.2.2 Expected payoffs

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

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

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

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

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

The second term reflects the surplus from a transaction if she meets only one buyer. The third and fourth terms reflect the surplus when matched with two or more buyers, where the last term is specifically the additional surplus when two or more bidders are unconstrained. The expected payoff for an unconstrained buyer can be similarly derived to obtain

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

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

4.2.3 Directed Search

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

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

1. optimization:

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

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

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

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

2. market clearing:

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

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

4.2.4 Pre-Policy Directed Search Equilibrium

We first consider the initial setting with identically unconstrained buyers by setting $\Lambda = 0$.[20] Sellers in this environment set an asking price to maximize their payoff subject to buyers achieving their market value, $\bar{V}^u$. The seller must also take into account buyers' bidding limit u. The seller's asking price setting problem is therefore

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

If the first constraint is slack, the solution is a pair $\{p^*, \theta^*\}$ satisfying the following first-order condition:

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

With the aim of constructing a DSE, restrict attention to the pair that also satisfies the free entry condition $V^s(p, 0, \theta) = 0$ or, equivalently,

$$[1 - e^{-\theta} - \theta e^{-\theta}]v = x. \tag{5}$$

[20] 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).

We can link both market tightness and the asking price to the entry cost by defining the functions $x \mapsto \theta^*(x)$ using equation (5) and $x \mapsto p^*(x)$ using equation (4) with market tightness set according to function θ^*. The following lemma uses these functions to determine whether the proposed solution violates the first constraint in the seller's asking price setting problem in (3).

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

If $x > \overline{x}$ and hence $p^*(x) > u$, the constrained seller sets an asking price equal to u.

The next proposition provides a partial characterization of a DSE with identical buyers. For convenience we omit the argument x when it is clear we are referring to $p^*(x)$ and $\theta^*(x)$.

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

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., $p^* \leq u < v$), sellers set a higher asking price to capture more of the surplus in a bilateral match. The optimal asking price is such that the additional bilateral sales revenue (the left-hand side of equation 4) exactly compensates for the unseized portion of the match surplus when two or more buyers submit offers but are unable to pay their full valuation because of the common income constraint (the right-hand size of equation 4). Equilibrium expected payoffs in this case are independent of u. When buyers are more severely constrained (i.e., $u < p^*$), 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.

4.2.5 Post-Policy Directed Search Equilibrium

We now suppose that the implementation of the MI policy affects a subset of buyers by letting Λ take a value between 0 and 1. We are interested in parameter values for x, c, u and v that yield the following relationships:

$$0 < c < p^* \leq u.$$

A compelling strategic response by sellers to the presence of constrained buyers requires willingness to sell at price c. With the seller's reservation value normalized to zero, this requires $c > 0$. Under the assumption that $c < p^*$, however, financially constrained buyers cannot afford to direct their search to a seller asking price p^*. We show in this section that the presence of financially constrained buyers triggers activity in submarket c under the two aforementioned parameter restrictions. Finally, for convenience we impose that $p^* \leq u$ so that unconstrained buyers can afford p^* and consequently the MI policy is the only potential source of inefficiency.[21] The following lemma uses the property that p^* is increasing θ^*, which in turn is increasing in x to establish parameter restrictions that imply $c < p^* \leq u$.

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

To provide some intuition behind the equilibrium interactions between buyers and sellers, we first establish two interesting features of the post-policy DSE: the active participation of constrained buyers and the pooling of unconstrained buyers with constrained ones.

Lemma 3. *In any post-policy DSE with $x \in (\underline{x}, \overline{x}]$, (i) there exists $p \in \mathbb{P}$ such that $p \leq c$, and (ii) $\lambda(p) < 1$ for all $p \in \mathbb{P}$.*

In words, part (i) of Lemma 3 states that constrained buyers are not priced out of the market. Otherwise, $\bar{V}^c = 0$ and hence market tightness associated with any asking price $p \leq c$ would be infinite (by part 1(iii) of Definition 1). The payoff to a seller entering any submarket

[21] In other words, spending limit u is not restrictive enough to affect expected payoffs and seller entry in the pre-policy equilibrium.

$p \leq c$ would then be c with certainty: a violation of free entry (part 1(i) of Definition 1). Part (ii) of Lemma 3 precludes the possibility of a fully-revealing DSE wherein constrained and unconstrained buyers search in separate submarkets. Because unconstrained buyers can out-bid constrained ones, some or all of them prefer to search alongside constrained buyers.

It has been established that a post-policy DSE features a *pooling submarket* with asking price $p \leq c$. For the purposes of introducing useful notation, consider first 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 Θ, satisfies the free entry condition $V^s(c, \Lambda, \Theta) = 0$. Next, denote by λ^p and θ^p the unique solution to $V^s(c, \lambda^p, \theta^p) = 0$ and $V^u(c, \lambda^p, \theta^p) = V^u(p^*, 0, \theta^*)$. In words, the free entry of sellers into submarkets c and p^* imply indifference on the part of unconstrained buyers between the two submarkets if the composition of buyers in submarket c is exactly λ^p. The following proposition uses the above defined p^*, θ^*, θ^p, λ^p and Θ to characterize a DSE.

Proposition 2. *Suppose $x \in (\underline{x}, \overline{x}]$. If $\Lambda < \lambda^p$, there is an equilibrium with $\mathbb{P} = \{c, p^*\}$, $\lambda(p^*) = 0$, $\theta(p^*) = \theta^*$, $\lambda(c) = \lambda^p$ and $\theta(c) = \theta^p > \theta^*$. If instead $\Lambda \geq \lambda^p$, there is an equilibrium with $\mathbb{P} = \{c\}$, $\lambda(c) = \Lambda$ and $\theta(c) = \Theta \geq \theta^p > \theta^*$.*

The financial constraint imposed by the MI policy is sufficiently restrictive that the optimal asking price for targeting constrained buyers is the upper limit, c. Instead of searching for homes listed at price p^*, some or all unconstrained buyers compete with constrained buyers for houses listed at c. If the fraction of constrained buyers is not too high (i.e., $\Lambda < \lambda^p$), the DSE features partial pooling (i.e., only some unconstrained buyers search for low-priced homes while the rest search in submarket p^*). Otherwise, if the MI policy constrains sufficiently many buyers (i.e., $\Lambda \geq \lambda^p$), submarket p^* shuts down completely and the DSE is one of full pooling.

4.3 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. Specifically, the presence of constrained buyers prompts some sellers to change their asking price from p^* to c.*

Post-policy, some or all sellers find it optimal to target buyers of both types by asking price c. As per Propositions 1 and 2, the set of asking prices changes from just $\mathbb{P} = \{p^*\}$ pre-policy to either $\mathbb{P} = \{c, p^*\}$ (if $\Lambda < \lambda^p$) or $\mathbb{P} = \{c\}$ (if $\Lambda \geq \lambda^p$) post-policy. The measure of sellers initially participating in submarket p^* is $\mathcal{B}/\theta^*$. Post-policy, the measures of sellers participating in submarkets c and p^* are

$$\sigma(c) = \begin{cases} \frac{\Lambda\mathcal{B}}{\lambda^p\theta^p} & \text{if } \Lambda < \lambda^p \\ \frac{\mathcal{B}}{\Theta} & \text{if } \Lambda \geq \lambda^p \end{cases} \quad \text{and} \quad \sigma(p^*) = \begin{cases} \frac{(\lambda^p - \Lambda)\mathcal{B}}{\lambda^p\theta^*} & \text{if } \Lambda < \lambda^p \\ 0 & \text{if } \Lambda \geq \lambda^p \end{cases} \tag{6}$$

Both the introduction of homes listed at c and the smaller measure of homes listed at p^* contribute to the reduction in the set of equilibrium asking prices.

Prediction 2. *The MI policy raises the ratio of buyers to participating sellers due to an extensive margin response, leading to 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 $c < p^*$, 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 evident from 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. *The MI policy causes a reduction in the set of equilibrium sales prices in that it results in some transactions at price c and fewer transactions at price p^*. Downward pressure on sales prices, however, is partly offset by price escalation up to price u, which may even become more frequent post-policy (e.g., if $\Lambda \leq \lambda^p$).*

The MI policy's effect on sales prices is mitigated by the auction mechanism, the pooling of buyers, and sellers' extensive margin response. From the perspective of a seller, the probability of selling at price u is equal to the probability of receiving offers from at least two unconstrained bidders:

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

and

$$\text{Prob}\{\text{sales price} = u | p = p^*\} = 1 - e^{-\theta^*} - \theta^* e^{-\theta^*}.$$

Price escalation up to u is therefore even more likely in submarket c than in submarket p^* if Λ is not too high (e.g., if $\Lambda \leq \lambda^p$).[22] 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 4. *Both the measure of sellers asking price c and the fraction of listed homes selling for price c are increasing in Λ.*

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

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

which is continuous and increasing in Λ (given that Θ is continuous and increasing in Λ).

[22] An implication of the indifference condition for unconstrained buyers between submarkets c and p^* 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^*:

$$1 - e^{-(1-\lambda^p)\theta^p} - (1-\lambda^p)\theta^p e^{-(1-\lambda^p)\theta^p} > 1 - e^{-\theta^*} - \theta^* e^{-\theta^*}.$$

Prediction 4 therefore implies a more dramatic impact of the the MI policy on asking and sales prices if it constrains a larger fraction of potential buyers.

4.4 Welfare Discussion

To explore the normative implications of the MI policy, we compare the pre- and post-policy social surplus generated by housing market activity. As described in section 3, the MI policy was introduced to counter the potential risks associated with a house price boom. Characterizing 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.

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

$$W(\theta) = \frac{\left[1 - e^{-\theta}\right] v - x}{\theta}. \tag{7}$$

The welfare maximizing level of market activity is implemented when the ratio of buyers to sellers is θ^*, which is achieved in the pre-policy DSE when $x \leq \overline{x}$ (see Proposition 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).

Corollary 1. *Suppose $x \in (\underline{x}, \overline{x}]$. The MI policy reduces the social welfare derived from housing market transactions.*

With free-entry on the supply side, these welfare costs are borne by the share of buyers that are financially constrained by the MI policy.[23]

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

5 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.[24] For the purposes of assigning a home to a pre- or post-policy date, we use the date the house was listed.

Table 5 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 5 reports 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.

[24] 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.

Table 1: Summary Statistics for City of Toronto

		Pre-Policy		Post-Policy	
		Asking	Sales	Asking	Sales
All Homes	Mean	796216.93	801134.05	857363.42	849001.41
	25th Pct	449900.00	460000.00	489900.00	490000.00
	50th Pct	599900.00	624800.00	650000.00	661000.00
	75th Pct	895000.00	911000.00	950000.00	968000.00
	N	7715.00	7715.00	6733.00	6733.00
	Median Duration	9.00	9.00	11.00	11.00
	1M Percentile	0.81	0.79	0.78	0.77
Homes 0.9-1M	N	300.00	345.00	343.00	359.00
	Median Duration	8.00	8.00	9.00	9.00
	Mean Price	967238.01	943364.95	967005.66	946245.01
Homes 1-1.1M	N	152.00	225.00	170.00	217.00
	Median Duration	8.00	8.00	9.00	9.00
	Mean Price	1074683.47	1044466.87	1073975.08	1043521.33

Table 2: Summary Statistics for the Central District

		Pre-Policy		Post-Policy	
		Asking	Sales	Asking	Sales
All Homes	Mean	1231652.18	1235718.45	1340144.65	1315926.08
	25th Pct	749000.00	761000.00	799900.00	828000.00
	50th Pct	959900.00	1010000.00	1078000.00	1088500.00
	75th Pct	1455000.00	1465000.00	1585000.00	1539000.00
	N	2485.00	2485.00	2150.00	2150.00
	Median Duration	9.00	9.00	11.00	11.00
	1M Percentile	0.54	0.50	0.47	0.45
Homes 0.9-1M	N	180.00	206.00	215.00	213.00
	Median Duration	8.00	8.00	8.00	8.00
	Mean Price	966512.46	941320.81	968061.39	945936.65
Homes 1-1.1M	N	98.00	140.00	111.00	136.00
	Median Duration	7.00	7.50	9.00	9.00
	Mean Price	1071199.88	1044509.06	1071978.05	1044045.15

6 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 4.3.

6.1 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 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*, $S(p|\boldsymbol{x}) = \text{Prob}\{\text{price} > p|\boldsymbol{x}\}$, as the probability that a house is sold/listed above price p conditional on a vector $\boldsymbol{x}$, which includes year, month, and district dummies, as well as house characteristics. To estimate this, we first evaluate the empirical survivor function,[25] 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.[26] 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:

$$S_{itm}(p_j) = \beta_0(p_j) + \alpha_i(p_j) + \mu(p_j) + \delta_m(p_j) + \tau(p_j)\boldsymbol{x}_{itm} + \epsilon_{itm}(p_j), \tag{8}$$

where $\boldsymbol{x}_{itm}$ 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 (8) 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. 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

[25]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.

[26]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.

of a discontinuity at \$1M:

$$\hat{\mu}(p_j) = \gamma_0 + f_l(p_j - \$1\text{M}) + D_{\$1\text{M}}\left[\gamma + f_r(p_j - \$1\text{M})\right] + \varepsilon(p_j), \tag{9}$$

where $D_{\$1\text{M}} = 1$ if $p_j \geq \$1\text{M}$ 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,[27] and determine the optimal order of polynomial (given a fixed bandwidth) by minimizing the Akaike's Information Criterion (AIC) (Lee and Lemieux, 2010).[28] The coefficient of interest here is γ, 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 (9) using the difference, $\hat{\mu}_{post} - \hat{\mu}_{pre}$, as the dependent variable. The resulting estimate of coefficient γ (termed *double-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.

[27]We 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 `bwselect` STATA code provided by Calonico et al. (2014).

[28]To avoid overfitting the models, we estimate (9) 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).

6.2 Results

6.2.1 Predictions 1 and 3: 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 3 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 3 and 4 represent a graphical test of predictions 1 and 3 based on the estimates from equation (8). Figure 3 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 (8). 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 4 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 3) and that derived from sales prices (panel B of Figure 4) 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 4, 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.

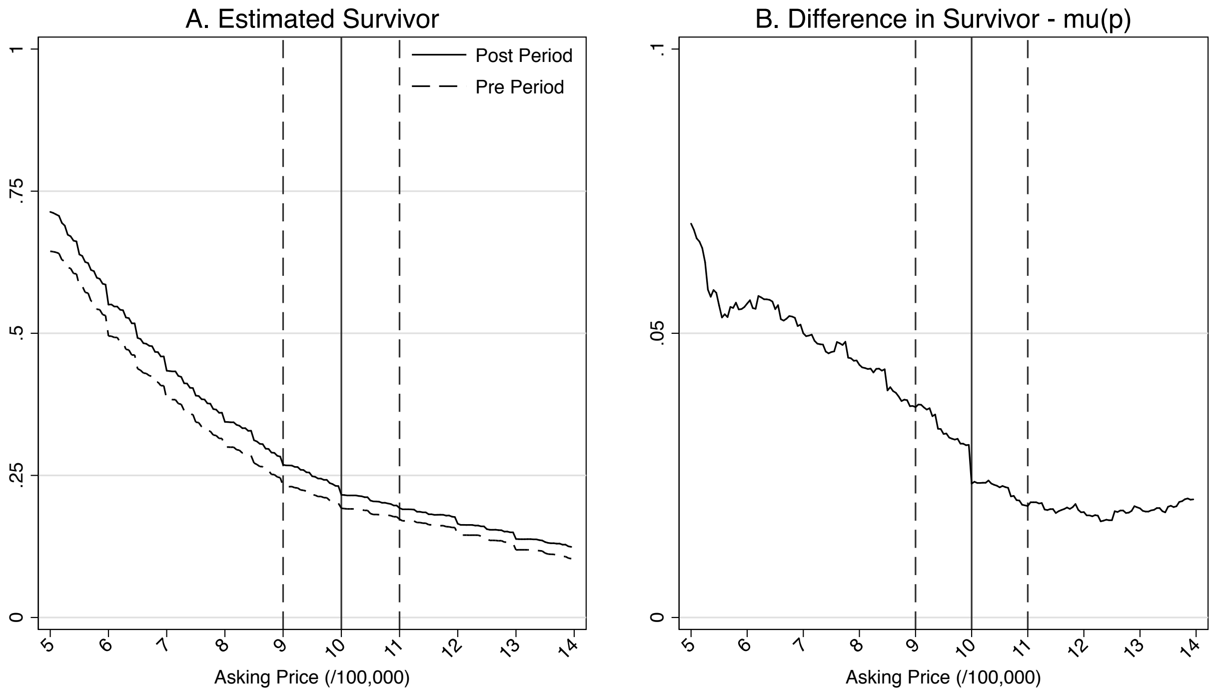

Figure 3: Estimates of the Survivor function and $\hat{\mu}(p)$

***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 these predictions, we obtain the regression discontinuity estimates based on equation (9). 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

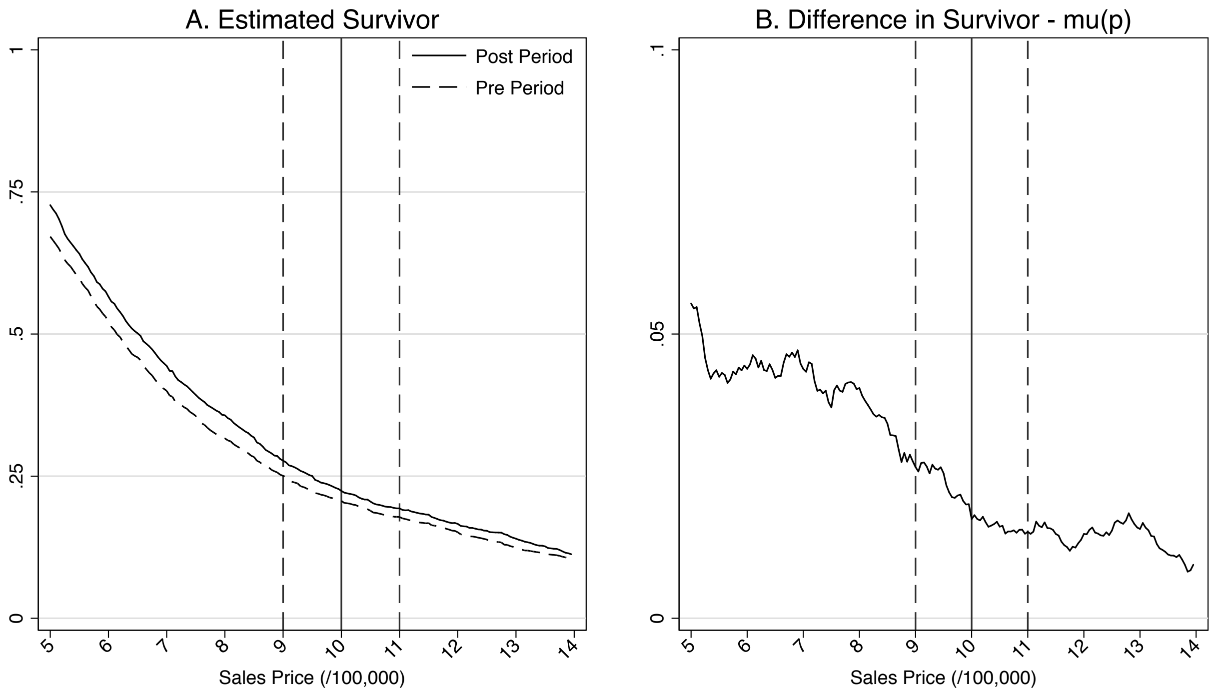

Figure 4: Estimates of the Survivor function and $\hat{\mu}(p)$

***Note*:** See the notes for 3. Here, we plot the survivor functions in sales price.

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.[29] 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.

[29]For ease of presentation, we multiply $\hat{\mu}$ by 100 and report the results in terms of percentage points.

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 5 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

	Asking Price				Sales Price			
	(1) bw(5)	(2) bw(10)	(3) bw(13)	(4) bw(20)	(5) bw(5)	(6) bw(10)	(7) bw(10)	(8) bw(20)
One	-0.64*	-0.62*	-0.57*	-0.44*	-0.20*	-0.15*	-0.15*	-0.21*
	(0.027)	(0.018)	(0.035)	(0.042)	(0.045)	(0.048)	(0.048)	(0.041)
Two		-0.67*	-0.69*	-0.63*		-0.24*	-0.24*	-0.058
		(0.020)	(0.026)	(0.035)		(0.071)	(0.071)	(0.063)
Three		-0.66*	-0.64*	-0.74*		-0.18*	-0.18*	-0.24*
		(0.027)	(0.038)	(0.034)		(0.074)	(0.074)	(0.051)
Four			-0.69*	-0.62*				-0.30*
			(0.032)	(0.037)				(0.068)
Optimal Order	1	2	4	4	1	3	3	3

Standard errors in parentheses

* $p < 0.05$

To address concerns about other pricing effects at the \$1M threshold, Table 4 and Figure 6 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

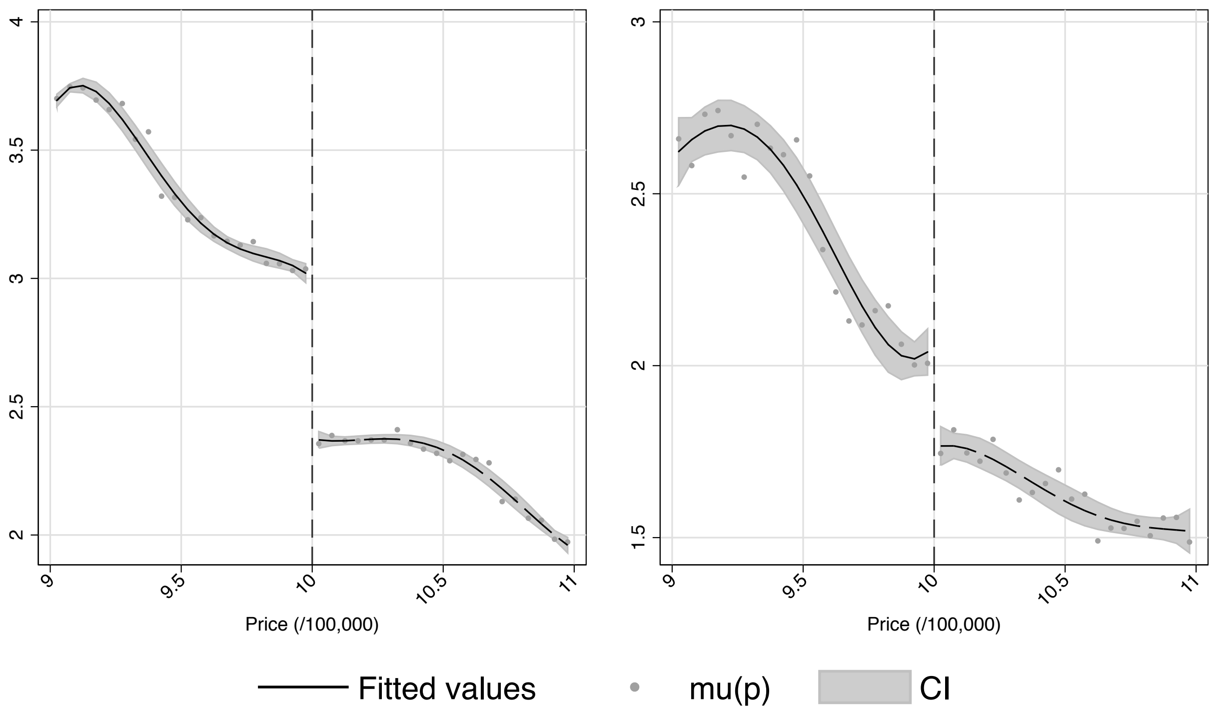

Figure 5: Estimates of $\hat{\mu}(p)$

***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 $f_l(\cdot)$ and $f_r(\cdot)$. Similarly, the right panel uses sale prices.

variable in the estimations of equation (9). 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.

6.2.2 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

Table 4: Regression Discontinuity Estimates: Pre Policy Period

	Asking Price				Sales Price			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	bw(5)	bw(10)	bw(10)	bw(20)	bw(5)	bw(10)	bw(10)	bw(20)
One	0.071*	0.11*	0.11*	0.071	0.066	0.083	0.083	0.12*
	(0.029)	(0.030)	(0.030)	(0.037)	(0.062)	(0.057)	(0.057)	(0.041)
Two		0.073*	0.073*	0.075*		0.082	0.082	0.035
		(0.033)	(0.033)	(0.035)		(0.051)	(0.051)	(0.077)
Three		-0.0053	-0.0053	0.14*		0.011	0.011	0.12*
		(0.019)	(0.019)	(0.051)		(0.046)	(0.046)	(0.057)
Four				0.032				0.048
				(0.038)				(0.045)
Optimal Order	1	3	3	4	1	3	3	4

Standard errors in parentheses
* $p < 0.05$

Table 5: Regression Discontinuity Estimates: Double Difference

	Asking Price				Sales Price			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	bw(5)	bw(10)	bw(17)	bw(20)	bw(5)	bw(10)	bw(10)	bw(20)
One	-0.71*	-0.74*	-0.53*	-0.51*	-0.26*	-0.24*	-0.24*	-0.33*
	(0.013)	(0.022)	(0.054)	(0.053)	(0.063)	(0.076)	(0.076)	(0.069)
Two		-0.74*	-0.81*	-0.71*		-0.32*	-0.32*	-0.091
		(0.028)	(0.043)	(0.040)		(0.062)	(0.062)	(0.11)
Three		-0.66*	-0.78*	-0.89*		-0.19*	-0.19*	-0.35*
		(0.028)	(0.066)	(0.078)		(0.096)	(0.096)	(0.063)
Four			-0.62*	-0.66*				-0.35*
			(0.047)	(0.044)				(0.078)
Optimal Order	1	3	4	4	1	3	3	3

Standard errors in parentheses
* $p < 0.05$

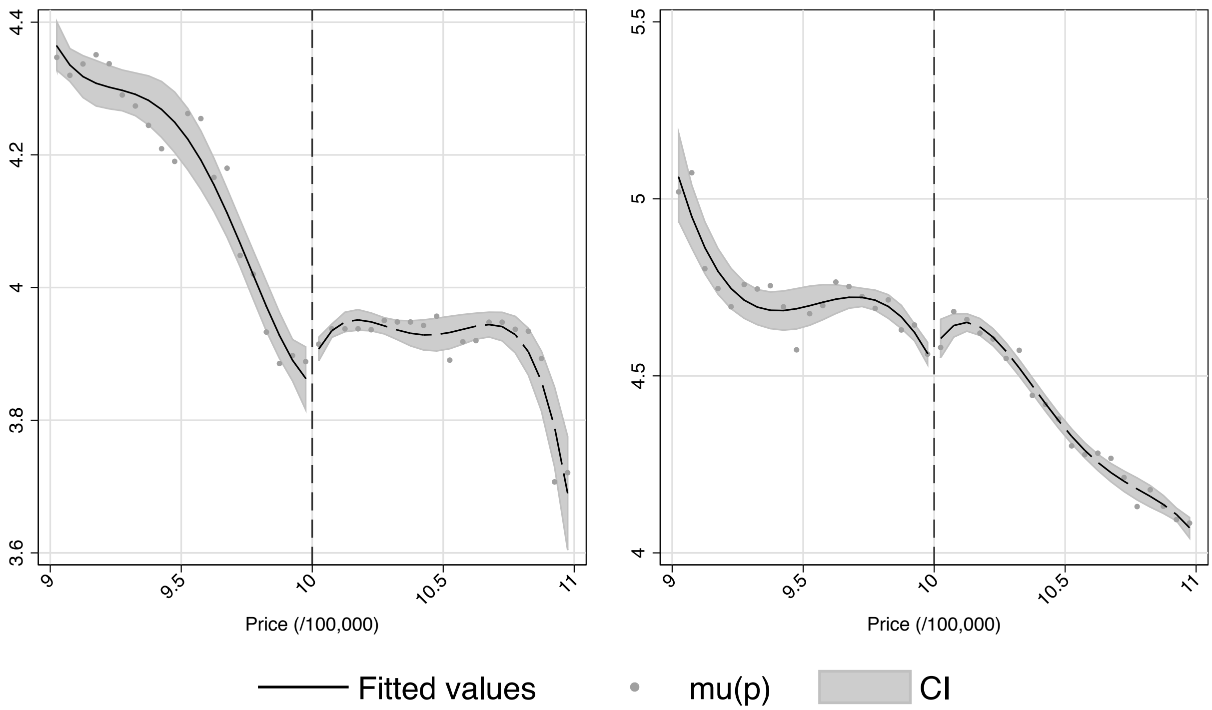

Figure 6: Estimates of $\hat{\mu}(p)_{pre}$

***Note*:** See the notes from figure 5. Here, we use the pre-treatment 2011 and 2012 data.

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.[30] A higher proportion of sales above asking could plausibly

[30]The determination of prices thus differs in some ways from the simple auction mechanism modeled in Section 4. 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.

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,[31] 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 $p_j \in \{p_1, \ldots, p_J\}$:

$$RS_{itm}(p_j) = \beta_0'(p_j) + \alpha_i'(p_j) + \mu'(p_j) + \delta_m'(p_j) + \tau'(p_j)\boldsymbol{x}_{itm} + \epsilon_{itm}'(p_j). \tag{10}$$

District and month fixed effects are captured by $\alpha_i'(p_j)$ and $\delta_m'(p_j)$, while coefficient $\mu'(p_j)$ measures any shift in the distribution[32] 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 (8) 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 price distribution is an application of the chain rule of probability theory:

$$\hat{\beta}_0'(p_j) = \text{Prob}\left\{p^s \geq p^a, p^a \geq p_j | \bar{\boldsymbol{x}}\right\} = \text{Prob}\left\{p^s \geq p^a | p^a \geq p_j, \bar{\boldsymbol{x}}\right\} \times \underbrace{\text{Prob}\left\{p^A \geq p_j | \bar{x}\right\}}_{\hat{\beta}_0(p_j)},$$

where $\hat{\beta}_0(p)$ is obtained from estimating equation (8) with asking price data. Thus, the set of pre-policy period conditional estimates are derived from the estimated constant terms in (8) and (10). Similarly, with coefficients $\hat{\mu}$ and $\hat{\mu}'$, we obtain the before-after estimates of

[31] 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.

[32] Specifically, (10) estimates the (rescaled) distribution of asking prices for the sample of transactions at or above the asking price.

the conditional distribution of sales prices:

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

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 (9), but with $\hat{\nu}(p_j)$ on the left hand side. The coefficient of interest is again γ, 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 7. 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 6: Regression Discontinuity Estimates: Pre vs Post Period

	Spread				Duration			
	(1) bw(5)	(2) bw(10)	(3) bw(19)	(4) bw(20)	(5) bw(5)	(6) bw(10)	(7) bw(15)	(8) bw(20)
One	-1.34* (0.041)	-1.55* (0.077)	-0.95* (0.16)	-0.90* (0.16)	1.58* (0.093)	1.46* (0.083)	1.24* (0.13)	1.16* (0.12)
Two		-1.33* (0.086)	-1.58* (0.100)	-1.56* (0.097)		1.57* (0.084)	1.58* (0.084)	1.42* (0.12)
Three		-1.22* (0.081)	-1.57* (0.15)	-1.60* (0.16)		1.72* (0.12)	1.65* (0.10)	1.68* (0.12)
Four			-1.28* (0.10)	-1.32* (0.099)			1.67* (0.11)	1.66* (0.097)
Optimal Order	1	3	4	4	1	1	2	4

Standard errors in parentheses

* $p < 0.05$

6.2.3 Prediction 4: Cross-Market Analysis

The MI policy's effects on asking and sales prices should, according to Prediction 4, 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 are likely unaffected by the policy. We proceed by re-estimating our regression discontinuity estimator using alternative price thresholds at $25,000 intervals from $700,000 to $900,000. These thresholds are far enough from $1M that we would not expect similar patterns to those documented in Section 6.2.1.

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

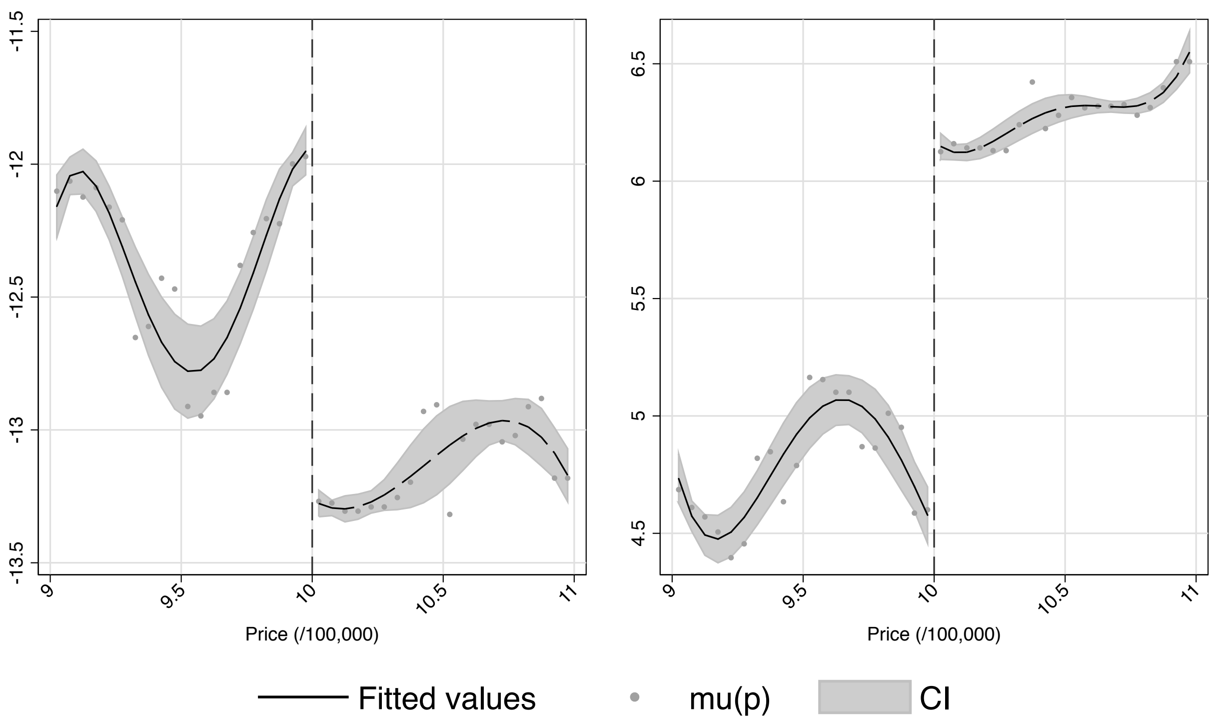

Figure 7: Estimates of the Survivor function and $\hat{\mu}(p)$

***Note*:** The sample includes all ...

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 4 directly. Nevertheless, we collect information at the district level related to income and age for these two markets. As noted in section 5, 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 5 reveals 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 4 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 predictions 1 and 3. 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 predictions 1 and 3, and the comparative statics summarized in Prediction 4.

Table 7: Regression Discontinuity Estimates: Alternative Cut-offs

	Policy		Pre-Policy		Difference	
	(1) Asking	(2) Selling	(3) Asking	(4) Selling	(5) Asking	(6) Selling
700000	-0.095*	-0.088	-0.092	0.15*	0.024	-0.23
	(0.041)	(0.099)	(0.096)	(0.067)	(0.11)	(0.13)
725000	0.010	-0.17	0.084	0.15	-0.089	-0.48*
	(0.052)	(0.14)	(0.14)	(0.14)	(0.22)	(0.14)
750000	-0.090	-0.21	-0.31*	0.033	0.22	-0.44
	(0.080)	(0.18)	(0.061)	(0.11)	(0.12)	(0.32)
775000	-0.071	0.042	-0.082	0.028	-0.078	-0.033
	(0.11)	(0.089)	(0.049)	(0.12)	(0.13)	(0.18)
800000	0.084	0.090	-0.40*	0.21*	0.35*	-0.16
	(0.13)	(0.050)	(0.059)	(0.11)	(0.089)	(0.16)
825000	-0.090	-0.093	0.13*	0.038	-0.054	-0.045
	(0.063)	(0.069)	(0.043)	(0.10)	(0.11)	(0.11)
850000	-0.32*	-0.14	-0.10*	-0.018	-0.24*	-0.024
	(0.049)	(0.084)	(0.029)	(0.11)	(0.049)	(0.12)
875000	-0.049	-0.070	-0.098	0.088	0.017	-0.22
	(0.071)	(0.11)	(0.097)	(0.061)	(0.15)	(0.16)
900000	0.0080	-0.14	-0.56*	0.27	0.57*	-0.51*
	(0.034)	(0.082)	(0.017)	(0.15)	(0.045)	(0.25)
1000000	-0.69*	-0.18*	-0.0053	0.011	-0.62*	-0.19*
	(0.032)	(0.074)	(0.019)	(0.046)	(0.047)	(0.096)

Standard errors in parentheses

* $p < 0.05$

Table 8: Regression Discontinuity Estimates for the Central District: Double Difference

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

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

Standard errors in parentheses

* $p < 0.05$

7 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 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

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

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

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

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

The unconstrained buyer's expected payoff is

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

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: $c < p \le u$. 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

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

The second term reflects the surplus from a transaction if she meets 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

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

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:

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

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

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