Do Financial Constraints Cool a Housing Boom?*

Lu Han[†]   Chandler Lutz[‡]   Benjamin Sand[§]   Derek Stacey[¶]

March 3, 2019

Abstract

We study the housing market implications of financial constraints by exploiting a regulatory change that withholds access to mortgage insurance when homes sell for $1 million or more, effectively increasing the downpayment requirement at the threshold. We motivate our listing and sales price analysis by advancing a model of competing auctions with constrained bidders. We model the regulation as a tightening of the financial constraint faced by a subset of prospective buyers. This prompts some sellers near the $1M segment to strategically adjust their asking price to $1M. This effect gets passed through to the sales price distribution, although competition among bidders and entry decisions on the supply side dampen the impact of the policy on sales prices. Using transaction data from the Toronto housing market, we find that the policy causes sharp excess bunching of homes listed at $1M. A muted bunching response in sales price coincides with an increase in bidding intensity for homes listed just below $1M. Everything considered, our analysis points to the importance of designing macroprudential policies that recognize the strategic responses of market participants.

JEL classification: R51, R28, D83, D44, C14

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

1 Introduction

This paper examines how the financial constraints faced by prospective home buyers affect buyers' and sellers' behavior and thereby housing market outcomes. On the buyer side, a buyer's bidding limit on a property may depend on both income and wealth constraints. On the seller side, the decision to list a house for sale and the choice of asking price may depend on the perceived ability to pay among potential buyers. The central role of financial constraints makes them an appealing vehicle for policymakers to intervene in housing markets. This is particularly so in the aftermath of the global financial crisis when tightening borrowers' financial constraints has become a primary macroprudential tool that governments use to create a buffer to "ensure that shocks from the housing sector do not spill over and threaten economic and financial stability" (IMF Speech, 2014).[1,2] In light of this, a large literature has emerged that studies how financial constraints affect house price growth through, for example, homeowner default and mobility.[3] There remains, however, no micro analyses of the links between financial constraints and the buying/selling strategies of housing market participants. This paper fills the gap in the literature by examining how financial constraints affect housing market outcomes via their influence on the interaction of buyers and sellers in a frictional market. Our empirical methodology exploits a natural experiment arising from a mortgage insurance policy change implemented in Canada in 2012, and the interpretation of our results is motivated by a search-theoretic model of sellers competing for financially constrained buyers.

Canada experienced one of the world's largest modern house price booms, with house prices more than doubling between 2000 and 2012. In an effort to cool this unprecedentedly long boom, the government tightened mortgage insurance rules eight times since 2008; mainly through stricter requirements on borrowers' downpayment or income. Our focus is on the

---

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

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

[3]See Mian and Sufi (2009), Demyanyk and Van Hemert (2011), and the papers cited below in our review of the literature.

so-called "million dollar" policy that restricts access to mortgage insurance (the transfer of mortgage default risk from lenders to insurers) when the purchase price of a home exceeds one million Canadian dollars ($1M).[4] Note that lenders are required to insure mortgages with loan-to-value ratios over 80%. As such, the minimum downpayment jumps from 5 to 20 percent of the entire transaction price at a threshold of $1M, creating an increase in the minimum downpayment of $150,000 for million dollar homes. The existence or absence of bunching around the threshold should provide compelling and transparent evidence about how home buyers and sellers respond to financial constraints. In this sense, although the focus in this paper is on downpayment discontinuity at a specific house price threshold, our analysis is broadly applicable to assessing the response of a frictional housing market to financing regulations and other related policies.

Understanding the mechanisms that generate bunching requires an equilibrium analysis of a two-sided market. To this end, we preface the empirical work with a search-theoretic model that features financial constraints on the buyer side. 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; but to the highest bidder when multiple buyers submit offers to purchase the same house. In that sense, our model draws from the competing auctions literature (e.g., McAfee 1993, Peters and Severinov 1997, Julien et al. 2000, Albrecht et al. 2014, Lester et al. 2015). The distinguishing feature of the model is the financial constraints faced by buyers that limit how much they can bid on a house.[5] We assume that buyers initially face a common income constraint that is not too restrictive, but that the introduction of the million dollar policy imposes a minimum wealth requirement that further constrains a subset of buyers.

---

[4]In July 2012, when the policy was implemented, the Canadian dollar was approximately at parity with the U.S. dollar.

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

We characterize the pre- and post-policy equilibria and derive a set of empirical predictions. Under appropriate parameter restrictions, the post-policy equilibrium features some sellers with asking prices exactly equal to the financial limit induced by the policy (i.e., the $1M threshold). Somewhat surprisingly, these price adjustments can come from either side of the threshold. In some circumstances, this represents a *reduction* in the set of equilibrium asking prices. Sellers lower their asking price to the threshold in order to attract offers from buyers genuinely constrained by the policy. At the same time, they continue to attract unconstrained buyers which sometimes pushes the sales price above the asking price. In other circumstances, this represents an *increase* in the set of equilibrium asking prices relative to the pre-policy equilibrium. While seemingly counterintuitive at first glance, it reflects sellers' initiative to extract a higher payment from the buyer in a bilateral situation by increasing the asking price in order to make up for the reduction in expected sales revenue in multiple offer situations. In both cases, the policy generates an excess mass (i.e., bunching) of homes listed at $1M. As the bunching response passes through to the sales price distribution, however, the effect on sales prices is dampened by the endogenous changes to bidding intensity arising from (1) the entry decisions of prospective sellers, (2) the pooling of constrained and unconstrained buyers searching for homes listed in the million dollar segment of the market, and (iii) the equilibrium trade-off between the asking price and the expected number of bidders.

Ultimately, the magnitude of the impact of the policy on prices is an empirical question. We test the model's predictions using the 2010-2013 housing market transaction data for single-family homes in the Greater Toronto Area, Canada's largest housing market. This market provides a particularly suitable setting for this study for two reasons. First, home sellers in Toronto typically initiate the search process by listing the property and specifying a particular date on which offers will be considered (often 5-7 days after listing). This institutional practice matches well with our model of competing auctions. Second, the million dollar policy was implemented in the midst of a housing boom in Toronto and caused two discrete changes in the market: one at the time the policy was implemented, and another

at the \$1M threshold. This provides a natural experimental opportunity for examining the price response to financial constraints.

Figure 1 presents motivating evidence that is consistent with the model's key implications. Panel A plots the distribution functions for the asking price between \$600,000 and \$1,400,000 in the pre- and post-policy years. The post-policy CDF lies everywhere below the pre-policy CDF, indicating that all housing market segments experienced a boom. Panel B plots the difference between the two CDFs.[6] The discrete jump at \$1M could reflect excess bunching in terms of listings, which would align with the intuition derived from the model. Turning to the sales prices, Panels C and D plot the distribution functions of sales price in the pre- and post-policy years and their difference, respectively. A jump in the sales price at the \$1M threshold is hardly apparent, supporting the notion that buyers' non-trivial search and bidding activities disentangle sales prices from asking prices, potentially mitigating the overall impact of the policy.

Despite the appealing first-cut evidence presented in Figure 1, netting out the million dollar policy's impact on the asking and sales price is difficult for two reasons. First, the implementation of the policy coincided with a number of accompanying government interventions as well as a booming market.[7] These confounding factors make it difficult to isolate the effects of the policy. Second, housing composition may have shifted around the time the policy was implemented. As a result, changes to the distributions of prices between pre- and post-policy periods may simply reflect the changing characteristics of houses listed/sold rather than buyers' and sellers' responses to the policy.

Our solution relies on a two-stage estimation procedure. First, using the well-known

---

[6]If the CDFs were the same pre- and post-policy for a given bin, the difference would show up as a zero in the figure. The displayed difference in CDFs is always below zero, indicating that houses in general are becoming more expensive over time.

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

reweighting approach introduced by DiNardo et al. (1996) and leveraging the richness of our data on house characteristics, we decompose the observed before-after-policy change in the distribution of house prices (both asking and sales) into: (1) a component that is due to changes in house characteristics; and (2) a component that is due to changes in the price structure (i.e., the assignment of prices to houses). The latter yields a quality-adjusted distribution of house prices that would have prevailed in the post-policy period if the characteristics of houses stayed the same as in the pre-policy period. Next, we measure the effects of the policy by comparing the composition-constant post-policy price distributions to the observed pre-policy distributions, separately for asking and sales prices, adopting a recently developed bunching estimation approach (e.g., Chetty et al. 2011a, Kleven and Waseem 2013, DeFusco et al. 2017). Working with differences in price distributions over-time means that our identification comes from *differential* bunching around the $1M threshold between the pre- and post-policy period. Time-invariant threshold price effects unrelated to the policy are therefore differenced out in our estimation.

Our main findings are the following. The asking price distribution features a large and sharp excess bunching pattern right at the $1M threshold with corresponding holes both above and below $1M. In particular, the policy adds 86 homes to *listings* in the million dollar bin (from $995,000 to $999,999) in the post-policy year for the city of Toronto, which represents about a 38% increase relative to the number of homes that would have been listed in this $5,000 bin in the absence of the policy. Among these, half would have otherwise been listed below $995,000; the other half above $1M. Both are consistent with the intuition developed in the theory. In contrast, the policy adds only about 11 homes to *sales* in the million dollar bin in this market, which is economically small and statistically insignificant. The lack of bunching in the sales price, together the with the sharp bunching in the asking price, suggests that the intended cooling impact of the policy is mitigated by sellers' listing decisions and buyers' search and bidding behavior. Consistent with this interpretation, we also find non-parametric evidence that housing segments right below the $1M threshold experience a shorter time on the market and a higher incidence of sales above asking.

Our empirical methodology exploits a discrete change in the required downpayment at the $1M threshold. Bunching around the threshold represents intensive margin responses induced by the policy notch in financial constraints. Such a policy, however, could produce both intensive and extensive margin responses since all homes over $1M are potentially affected by the higher downpayment. We are concerned with these price responses for two reasons; first, extensive margin responses could potentially bias our bunching estimates because they rely on an estimated counterfactual price distribution constructed using data above and below $1M. To mitigate these concerns, we construct counterfactual post-policy price distributions that use only data below $1M (Kleven, 2016). Our results are similar when we use this method, suggesting that our main estimates reflect only intensive margin responses. Second, we are interested in intensive and extensive margin responses on their own right, since they represent potential policy outcomes. Unfortunately, identifying such effects by comparing pre- and post-policy listings/sales above the policy threshold is difficult because it does not necessarily disentangle the effects of the specific macroprudential policy from other macro forces affecting the housing market. Nevertheless, we investigate potential intensive/extensive margin responses under the admittedly strong assumption that a rescaled pre-policy price distribution can be used to make pre/post comparisons in terms of listings/sales in price segments above the $1M threshold. We find little evidence that the policy had a marked impact on listings/transactions above the threshold.

All together, these results offer a useful lesson for macruprudential policy. We find that the mortgage insurance restriction did not achieve the specific goal of cooling the housing boom in the million dollar segment of the Toronto market. This is not because market participants did not respond to the financial constraints imposed by the policy. In fact, quite the opposite appears to be true: it is precisely the strategic responses of home sellers (in terms of listing decisions) and home buyers (in terms of search/bidding behavior) that interact to undermine the intended impact of the policy on sales prices. Everything considered, our analysis points to the importance of designing macroprudential policies that recognize the endogenous responses of buyers and sellers in terms of listing strategies, search decisions and

bidding behavior.

It is worth noting that the aim of the policy was twofold: (i) to curb house price appreciation in high segments of the market,[8] and (ii) to improve borrower creditworthiness. Our study focuses on the house price-related consequences of the policy in terms of the strategic responses of buyers and sellers in market segments around the $1M threshold. Despite failing to curb house price appreciation in these segments, the policy may have nonetheless succeeded in improving the creditworthiness of home buyers. In particular, our search model suggests that the post-policy allocation of homes favors less financially constrained buyers (i.e., those with sufficient wealth to meet the stricter downpayment requirement) since they outbid constrained ones in the post-policy equilibrium. This should be viewed as a desirable outcome in that it improves the stability of financial markets. We do not test this implication due to the lack of available Canadian micro-level data on borrower creditworthiness.[9] Nevertheless, in aggregate we observe that Canada exhibits a decrease in the fraction of new mortgage holders with a credit score below 660 after 2012,[10] which is consistent with the reallocation of houses to less constrained buyers as in our model and, more broadly, the objectives of the macroprudential policies.

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 Section 5 we discuss the data and outline our empirical strategy. Section 6 presents our results on the

---

[8]Canada's Minister of Finance from February 2006 to March 2014, 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.

[9]Nor do we examine the policy consequences on default rates (as in Mian and Sufi 2009 and Agarwal et al. 2017) due to the lack of data. In contrast to the U.S. market which has often been examined in this line of the literature, default is less widespread in Canada due to its highly regulated and very conservative financial system. Panel B of Figure A1 shows the difference in the delinquency rates (defined as overdue on a payment by 90 days or more) between Canada and the U.S. over time. In 2012, the fraction of all mortgages with delinquencies was 7.14% in the U.S., but only 0.32% in Canada (and 0.23% in Toronto in particular). The default rate in Canada stayed low in the subsequent years.

[10]See Panel A of Figure A1 in Appendix A.

impact of the million dollar policy. Section 7 concludes.

2   Literature Review

Financial constraints (e.g., credit limits, collateral/liquidity constraints and budget sets) represent a recurring theme in the housing literature. Some of this literature focuses on household decisions such as consumption-saving behavior (Hurst and Lusardi, 2004; Lehnert, 2004) and the choice between renting and buying (Linneman and Wachter, 1989; Gyourko et al., 1999). Other strands of the literature examine the implications of financial constraints for market-level or aggregate outcomes such as the price of housing and trading volume (Stein, 1995; Ortalo-Magne and Rady, 2006; Favilukis et al., 2017). We focus on the effects of financial constraints on house prices via their influence on the strategic behavior of buyers and sellers in a frictional market. In this regard, our work is related to a line of literature on search and matching frictions in housing markets (e.g., Wheaton 1990, Williams 1995, Krainer 2001, Genesove and Han 2012, Diaz and Jerez 2013, Head et al. 2014, and Head et al. 2018). An important departure from these papers is the interaction between search and financial frictions.

Turning to the empirical literature, financial constraints are defined much more broadly. They take the form of downpayment constraints (Genesove and Mayer, 1997; Lamont and Stein, 1999), debt-to-income ratios (Demyanyk and Van Hemert, 2011), borrowing against existing housing equity (Mian and Sufi, 2011), mortgage contract terms (Berkovec et al., 2012), and innovations in easing the access to mortgages (Vigdor, 2006). In understanding the recent financial crisis, much focus has been placed on examining the role of financial constraints in explaining housing booms and busts through borrower creditworthiness. Our paper differs from this body of work in that we examine how the mortgage insurance restriction affects sellers' listing decisions and buyers' search strategies and bidding behavior, thereby affecting market outcomes such as sales price and time on the market.

On the methodology side, our empirical work follows a recent and emerging literature that exploits the bunching behavior of agents faced with non-linear choice sets, often the

product of the tax system. Bunching estimators were first developed in the context of tax *kinks* by Saez (2010) and Chetty et al. (2011a) and then extended to the analysis of tax *notches*[11] by Kleven and Waseem (2013). The policy analyzed in this paper corresponds to a notch: that is, a discrete change in the required downpayment at the $1M threshold. In the context of real estate, Kopczuk and Munroe (2015) and Slemrod et al. (2017) analyse bunching behavior in sales volume induced by discontinuities in real-estate transfer taxes; Best et al. (2018) exploit variation in interest rates that produce notches in the loan-to-value ratio at various thresholds; and DeFusco et al. (2017) estimate leverage responses to a notch created by the conforming loan limit in the U.S. Our empirical design differs from these related studies along two dimensions. First, we propose a two-step approach that combines a bunching approach and a standard reweighting method to account for changes in the distribution of housing characteristics between the pre-and post-policy periods. Second, we consider a two-sided bunching estimator to accommodate both possibilities explored in our theoretical framework.

Finally, our paper contributes to work on macroprudential policies. In the aftermath of the Great Recession, with the emergence of macroprudential policies, a growing literature developed to investigate their consequences and effectiveness. For example, Allen et al. (2016) use loan-level data to examine the influence of macroprudential policies on mortgage contract characteristics and mortgage demand. In contrast, our paper examines the impact of a macroprudential policy on housing market outcomes.

3 Background

3.1 Mortgage Insurance

Mortgage insurance is an instrument used to transfer mortgage default risk from the lender to the insurer, which has been a key component of housing finance systems in many countries, including the United States, the United Kingdom, the Netherlands, Hong Kong, France, and

---

[11]Notches occur when there are discrete changes in agents' choice sets induced by policy.

Australia. These countries share two common features with Canada: (i) the need insure high loan-to-value (LTV) mortgages, and (ii) the central role of the government in providing such insurance. The combination of these two requirements gives the central government the ability to influence the financial constraints in the housing market and hence market outcomes.

In Canada, all financial institutions regulated by the Office of the Superintendent of Financial Institutions (OSFI) are required to purchase mortgage insurance for any mortgage loan with an LTV above 80 percent. The mortgage insurance market is comprised of the government-owned Canada Mortgage and Housing Corporation (CMHC) as well as private insurers. Both CMHC and private mortgage insurance is backed by the government. In practice, while it is possible for buyers to obtain uninsured residential mortgages with a loan-to-value ratio greater than 80% from unregulated lenders, we find that such mortgages accounted for only 0.11% of total residential mortgage loans in 2012 and further reduced to 0.01% in 2013.[12] In addition, anecdote evidence suggests that it is generally difficult for a borrower to obtain a second mortgage at the time of origination to reduce the downpayment of the primary loan below 20 percent in Canada, making this strategic circumvention of macroprudential regulation less of a concern. The pervasiveness of government-backed mortgage insurance within the housing finance system makes it an appealing macroprudential policy tool for influencing housing finance and housing market outcomes.

3.2 The Million Dollar Policy

Figure 2 plots the national house price indices for Canada and the U.S. reflecting Robert Shiller's observation in 2012 that "what is happening in Canada is kind of a slow-motion version of what happened in the U.S."[13] As home prices in Canada continued to escalate post-

---

[12]See the 2018 report from Canada Mortgage and Housing Corporation. Note that the unregulated loans are largely issued by Mortgage Finance Companies and cannot be securitized into either Canada Mortgage Bonds or National Housing Act mortgage-backed bonds. Anecdotal evidence suggests that the interest rates on unregulated mortgages are 3–6 times higher than conventional mortgage rates. See "Ordinary Canadians turn bankers as shadow mortgage lending rises," *Reuters.* July 9, 2015.

[13]"Why a U.S.-style housing nightmare could hit Canada." *CBCNews.* September 21, 2012.

financial crisis, the Canadian government became increasingly concerned that rapid price appreciation would eventually lead to a severe housing market correction.[14] To counter the potential risks associated with this house price boom, the Canadian government implemented several rounds of housing market macroprudential regulation – all through changes to the mortgage insurance rules. This paper examines the impact of the so-called "million dollar" policy that prevents regulated lenders from offering mortgage loans with loan-to-value ratios above 80% when the purchase price is $1M or more. The objective of the regulation was to curb house price appreciation in high price segments of the market and at the same time improve borrower creditworthiness. The law was announced on June 21, 2012, and effected July 9, 2012. Anecdotal evidence suggests that the announcement of the policy was largely unexpected by market participants.[15]

4   Theory

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

---

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

[15]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).

Million dollar policy. The introduction of the million dollar policy causes some buyers to become more severely *financially constrained*. Post-policy, a fraction Λ of buyers are unable to pay more than c, where $c < u$. Parameter restrictions $c < u \leq v$ can be interpreted as follows: all buyers may be limited by their budget sets, but some are further financially constrained by a binding wealth constraint (i.e., minimum downpayment constraint) following the implementation of the policy.[16] Buyers with financial constraint c are hereinafter referred to as *constrained* buyers, whereas buyers willing and able to pay up to u are termed *unconstrained*.

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

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

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

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

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

---

[16]We model the implied bidding limit rather than the downpayment constraint explicitly. The interpretation is as follows: the discontinuous downpayment requirement at \$1M effected by the mortgage insurance policy means that buyers with wealth levels between \$50,000 and \$200,000 must bid less than \$1M.

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

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

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

4.2 Equilibrium

4.2.1 The Auction

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

4.2.2 Expected payoffs

Expected payoffs are computed taking into account the matching probabilities in (1) and (2). These payoffs, however, are markedly different depending on whether the asking price, p, is above or below a buyer's ability to pay. Each case is considered separately in Appendix

B.1. In the *submarket* associated with asking price p and characterized by market tightness θ and buyer composition λ, let $V^s(p, \lambda, \theta)$ denote the sellers' expected net payoff. Similarly, let $V^c(p, \lambda, \theta)$ and $V^u(p, \lambda, \theta)$ denote the expected payoffs for constrained and unconstrained buyers.

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

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

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

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

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

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

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

and the closed-form expression is

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

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

14

unconstrained buyer visits the same seller, the constrained buyer is outbid with certainty and loses the opportunity to purchase the house. Finally, the expected payoff for an unconstrained buyer can be similarly derived to obtain

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

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

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

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

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 $\Lambda = 0$.[17] Buyers in this environment direct their search by targeting the asking price that maximizes their expected payoff. Because the buyer correctly anticipates the free entry of sellers, the

---

[17] 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).

search problem can be written

$$\bar{V}^u = \max_{p,\theta} V^u(p, 0, \theta) \quad \text{s.t.} \quad V^s(p, 0, \theta) = 0. \tag{P_0}$$

We construct a DSE with a single active submarket with asking price and market tightness determined by the solution to problem P_0, denoted $\{p_0, 0, \theta_0\}$.[18] Given the auction mechanism and the role of the asking price, a strictly positive expected surplus from searching requires $p \leq u$. If the solution is interior it satisfies the following first-order condition and the constraint:

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

$$\theta_u^* e^{-\theta_u^*} p_u^* = [1 - e^{-\theta_u^*} - \theta_u^* e^{-\theta_u^*}](v - u). \tag{4}$$

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

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

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

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

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

As buyers' ability to pay approaches their willingness to pay (i.e., as $u \to v$), the equilibrium asking price tends to zero (i.e., $p_0 = p_u^* \to 0$), which is the seller's reservation value.

---

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

$$\max_{p,\theta} V^s(p, 0, \theta) \quad \text{s.t.} \quad V^u(p, 0, \theta) = \bar{V}^u. \tag{P_0'}$$

This aligns with standard results in the competing auctions literature in the absence of bidding limits (McAfee, 1993; Peters and Severinov, 1997; Albrecht et al., 2014; Lester et al., 2015). When buyers' bidding strategies are somewhat limited (i.e., $p_0 = p_u^* \leq u < v$), sellers set a higher asking price to capture more of the surplus in a bilateral match. The equilibrium asking price is such that the additional bilateral sales revenue (the left-hand side of equation (4)) exactly compensates for the unseized portion of the match surplus when two or more buyers submit offers but are unable to bid up to their full valuation (the right-hand side of equation (4)). When buyers' bidding strategies are too severely restricted (i.e., $p_0 = u < p_u^*$), the seller's choice of asking price is constrained by the limited financial means of prospective buyers. Asking prices in equilibrium are then set to the maximum amount, namely u. In this case, a seller's expected share of the match surplus is diminished, and consequently fewer sellers choose to participate in the market (i.e., $\theta_u > \theta_u^*$).[19]

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

4.2.5 Post-Policy Directed Search Equilibrium

As in the previous section, an active submarket with $p \leq c$ is determined by an optimal search strategy. The search problem of a constrained buyer takes into account the participation of

---

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

both sellers and unconstrained buyers:

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

Let $\{p_1, \lambda_1, \theta_1\}$ denote the solution to problem P_1 when $\bar{V}^u$ is set equal to the maximized objective of problem P_0. The bidding limit once again limits the set of worthwhile submarkets. In particular, the optimal submarket for constrained buyers must feature an asking price less than or equal to c. If the solution is interior, it satisfies the two constraints with equality and a first-order condition derived in Appendix B.3. This interior solution is denoted $\{p_c^*, \lambda_c^*, \theta_c^*\}$. The corner solution is denoted $\{c, \lambda_c, \theta_c\}$, where λ_c and θ_c satisfy the free entry condition $V^s(c, \lambda_c, \theta_c) = 0$ and an indifference condition for unconstrained buyers $V^u(c, \lambda_c, \theta_c) = \bar{V}^u$. In summary, the solution to problem P_1 is $p_1 = \min\{p_c^*, c\}$ with λ_1 and θ_1 satisfying $V^s(p_1, \lambda_1, \theta_1) = 0$ and $V^u(p_1, \lambda_1, \theta_1) = \bar{V}^u$.

As long as the aggregate share of constrained buyers, Λ, does not exceed λ_1, we can construct an equilibrium with two active submarkets associated with the asking prices obtained by solving problems P_0 and P_1 in the manner described above.

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

Intuitively, constrained buyers would prefer to avoid competition from unconstrained buyers because they can out-bid them. For the same reason, some unconstrained buyers prefer to search alongside constrained buyers. The equilibrium search decisions of constrained buyers takes into account the unavoidable competition from unconstrained buyers to achieve the optimal balance between price, market tightness, and the bidding limits of potential auction participants.

If the fraction of constrained buyers is not too high (i.e., $\Lambda < \lambda_1$), the DSE features partial pooling (i.e., only some unconstrained buyers search for homes priced at p_1 while the rest search in submarket p_0). As $\Lambda \to \lambda_1$, it can be shown that $\sigma(p_0) \to 0$ and the DSE converges to one of full pooling (i.e., all buyers and sellers participate in submarket p_1).

19

Finally, if $\Lambda > \lambda_1$, market clearing (part 2 of Definition 1) is incompatible with unconstrained buyer indifference between these two submarkets, which begets the possibility of full pooling with unconstrained buyers strictly preferring to pool with constrained buyers. We restrict attention to settings with $\Lambda \leq \lambda_1$ for the analytical characterization of equilibrium and rely on numerical results for settings with $\Lambda > \lambda_1$.[20]

The pooling of buyer types in submarket p_1 of the post-policy equilibrium means that constrained buyers lose the auction whenever the seller receives an offer from at least one unconstrained bidder. It follows that the post-policy equilibrium allocation of houses among buyers favors the unconstrained. From a macroprudential policy perspective, this could be viewed as a desirable outcome if it improves the overall creditworthiness of home buyers and thus supports a healthy housing finance system in a broad sense. While we think this is an interesting result that could be relevant for assessing the mortgage market implications of macroprudential policies that impose tighter financial constraints on prospective home buyers, we focus hereinafter on the housing market consequences of the policy.

4.3   Empirical Predictions

This section summarizes the housing market implications of the million dollar policy by comparing the pre- and post-policy directed search equilibria. There are four possible cases to consider depending on whether financial constraints u and c lead to corner solutions to problems P_0 and P_1. In this section we focus on the most empirically relevant case where the financial constraint is slack in problem P_0 but binds in problem P_1. In other words, we consider the possibility that pre-existing financial constraints are mild (i.e., not restrictive enough to affect expected payoffs and seller entry in the pre-policy equilibrium), but that the additional financial constraint imposed by the policy is sufficiently severe (i.e., restrictive

---

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

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

Under the restrictions discussed above, the model has several testable predictions that we bring to the data in Section 5.2. Some of these predictions rely on additional analytical results, which are summarized in the following lemma:

Lemma 1.

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

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

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

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

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

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

Prediction 1 suggests that the million dollar policy can induce a strategic response among sellers in market segments near the newly imposed financial constraint. Some sellers who would have otherwise listed below c might respond to the policy by increasing their asking price to the threshold. The intuition for *bunching from below* is the following: as buyers become more constrained, the distribution of possible sales prices features fewer extreme

21

prices at the high end. Sellers respond by raising their asking price to effectively truncate the distribution of prices from below. The higher price in a bilateral situation can offset the unseized sales revenue in multiple offer situations arising from the additional financial constraint. Constrained buyers tolerate the higher asking price because they face less severe competition from unconstrained bidders in submarket c. The policy may also induce some sellers who would have otherwise listed above c to drop their asking price to exactly equal the threshold. In the case of *bunching from above*, the reduction in asking prices is designed to attract constrained buyers. Because there is pooling of both buyer types in submarket p_1, these sellers may still match with unconstrained buyers and sell for a price above c.

To illustrate the predictions of the theory, we simulate two parameterized versions of the model. Example 1 features *bunching from below* using parameter values $\mathcal{B} = 1$, $v = 1$, $x = 0.18$, $c = 0.40$, $u = 0.50$ and $\Lambda = 0.05$. The second example features *bunching from above* using the same set of parameter values except $x = 0.10$, $c = 0.15$, and $u = 0.30$. Figure 3 provides a graphical illustration of Prediction 1 by plotting the pre- and post-policy distributions of asking prices. The plot on the left corresponds to Example 1 (bunching from below) and the plot on the right corresponds to Example 2 (bunching from above).

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

Prediction 2 is related to the ratio of unconstrained buyers to sellers (see parts (ii) and (iii) of Lemma 1) and relies on the indifference condition for unconstrained buyers between submarkets, p_0 and p_1. If $p_1 < p_0$, this ratio is higher in submarket p_1 (i.e., $\theta_0 < (1 - \lambda_1)\theta_1$), which shifts the Poisson distribution that governs the random number of unconstrained buyers meeting each particular seller in the sense of first-order stochastic dominance. The policy therefore increases the probability of multiple offers from unconstrained buyers and the overall share of listed homes selling for u. The intuition for this is that unconstrained buyers enter the pooling submarket until the lower sales price when not competing against other unconstrained bidders (that is, p_1 instead of p_0) is exactly offset by the higher incidence of

22

price escalation, resulting in indifference between the two submarkets. If instead $p_0 < p_1$, the indifference condition for unconstrained buyers implies the opposite, namely $\theta_0 \geq (1 - \lambda_1)\theta_1$. In that case, the policy lowers the probability of multiple offers from unconstrained buyers.

Figure 4 presents graphical illustrations of Prediction 2 by plotting market tightness, θ, for asking prices in $[x, u]$. In both cases, market tightness is only affected by the presence of constrained buyers for a subset of asking prices. Submarkets that attract both constrained and unconstrained buyers post-policy feature higher market tightness because unconstrained buyers have an advantage when competing bidders face tighter financial constraints. Following the implementation of the policy, unconstrained buyers are therefore willing to tolerate a higher ratio of buyers to sellers. The ratio of unconstrained buyers to sellers, $(1 - \lambda)\theta$, is nearly unaffected by the policy, and remains completely unchanged at asking price $p_1 = c$. Since this ratio must be decreasing in the asking price to satisfy the indifference condition for unconstrained buyers, it follows that an increase (decrease) in asking price from p_0 to p_1 is associated with a lower (higher) probability of selling at price u.

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

The frictional matching process and the auction mechanism imply a smaller mass of sales relative to listings at price c. Figure 5 plots the distributions of sales prices for the two numerical examples. In both cases, the post-policy share of sales at price c is less than the corresponding share of listings at price c in Figure 3. The policy's effect on sales prices is further mitigated by the post-policy equilibrium search and bidding strategies of buyers. Specifically, upward (downward) pressure on sales prices resulting from sellers' adjustments to price-posting strategies is partly offset by the lower (higher) incidence of price escalation up to u. For example, the CDF plotted on the left of Figure 5 (Example 1: bunching from below) reveals relatively fewer transactions at p_0, but also fewer transactions at price u. Similarly, the plot on the right (Example 2: bunching from above) reveals the introduction of sales at price $c < p_0$, but also more transactions escalating up to price u. In both cases, the effect of the policy on sales prices via sellers' revised listing strategies (Prediction 1) is

partly neutralized by the endogenous change in bidding intensity (Prediction 2). We should therefore expect a more dramatic impact of the million dollar policy on asking prices than sales prices.

4.4   Caveats

A brief discussion of some of the features of the model is in order. First, since financial constraint c is intended to represent the maximum ability to pay among buyers affected by the million dollar policy, parameter c corresponds to the \$1M threshold (relative to the seller's reservation value) and Λ reflects the share of potential buyers with insufficient wealth from which to draw a 20 percent downpayment.[21] If the parameter values for v, u and c are small (i.e., close to the seller's reservation value, which is normalized to zero), the scope of the model shrinks to a narrow segment of the market around \$1M. As such, the model can address price and bidding intensity effects at the threshold, but misses interactions between market segments resulting from, for example, constrained buyers targeting lower quality homes or sellers pricing to attract a different group of buyers from another segment.

Second, the determination of prices in practice differs in some ways from the simple auction mechanism modeled here. For instance, privacy and/or ethical concerns may prevent sellers from disclosing details of competing offers thereby precluding the use of escalation clauses when submitting offers. A first-price sealed-bid auction is arguably a better representation of the observed bidding process. Replacing the second-price auction with a first-price auction in the model would change the distribution of sales prices but would leave expected payoffs and therefore the strategic implications of the theory unchanged. In a bilateral meeting, on the other hand, it is quite common for the buyer and seller to negotiate a final transaction price slightly below the asking price. In contrast, we assume that the asking price effectively represents a firm commitment to a minimum price. We rely on this assumption for deriving meaningful implications about the effect of the policy on asking prices.

---

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

Embellishing the price determination mechanism[22] may allow for transaction prices below asking prices without compromising the asking price-related implications of the theory. Such extensions, however, would add considerably to the analytical complexity of the model.

Finally, entry on the supply side of the market is a common approach to endogenizing housing market tightness in directed search models with auctions (e.g., Albrecht et al., 2016 and Arefeva, 2016). This assumption equates the seller's expected surplus with the listing cost. Keeping instead the measure of sellers constant pre- and post-policy would further reduce the seller's expected payoff and hence sales prices. A third alternative is to allow entry on the demand side, as in Stacey (2016). Buyer entry would be less straightforward in our context given that the demand side of the market is homogeneous pre-policy but heterogeneous thereafter. With post-policy entry decisions on the demand side, buyers would self-select into the market in such a way that the effects of the policy would be mitigated or even non-existent. More specifically, suppose for a moment that both types of buyers face entry decisions subject to an entry fee or search cost. Provided there are sufficiently many unconstrained potential market participants, unconstrained buyers would enter the market until they reach indifference about market participation: their expected payoff would equal the participation cost. Because constrained buyers are outbid by unconstrained buyers, the expected payoff for a constrained buyer would be strictly less than the cost of market participation. It follows that constrained buyers would optimally choose not to participate in this segment of the housing market and consequently the post-policy equilibrium would be indistinguishable from the pre-policy equilibrium with identically unconstrained buyers. In contrast, we have shown in the preceding analysis that the policy does affect equilibrium strategies and outcomes when entry decisions are imposed on the supply side of the market.

---

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

5 Data and Methodology

5.1 Data

Our data set includes all transactions of single-family detached and semi-detached houses in the Greater Toronto Area from January 1st, 2010 to December 31st, 2013. For each transaction, we observe asking price, sales price, days on the market, transaction date, location, as well as detailed housing characteristics, which we discuss in more detail below. For the purpose of our analysis, we split our data into two mutually exclusive time periods. We define a *post-policy period* from July 15th, 2012, to June 15th, 2013. Our *pre-policy period* is similarly defined as July 15th, 2011, to June 15th, 2012. That is, we choose one year around the policy implementation date, but we omit a month covering the pre-implementation announcement of the policy. For the purposes of assigning a home to the pre- or post-policy period, we use the date the house was listed. We assess the sensitivity of our results to these choices in a later robustness section.

Table 1 contains summary statistics for single-family homes in the city of Toronto.[23] Panel (a), containing information on all districts, includes 22,244 observations in the pre-policy period and 19,061 observations in the post-policy period. The mean sales price in Toronto was \$723,396.82 in the pre-policy period and \$760,598.15 in the post-policy period, reflecting continued rapid price growth for single family houses (all figures in Canadian Dollars). Our focus is on homes near the \$1M threshold, which corresponds to approximately the 86th percentile of the pre-policy price distribution. There were 1,448 homes sold within \$100,000 of \$1M in the pre-policy period and 1,423 in the post-policy period. Panel (b) of Table 1 shows summary statistics for the Central district only. The Central district of Toronto is more expensive than suburban markets in general; in the post-policy period, a \$1M home is at the 56th percentile of the sales price distribution in the Central district. The Central district contains nearly 40 percent of the homes sold within the \$0.9M-1.1M price range. In

---

[23]The geographic area of our study includes the city of Toronto and the immediate boarding municipalities of Vaughan, Richmond Hill, and Markham. We do not include the municipalities to the west (Mississauga and Brampton) or east (Pickering) because there are very few million dollar homes. Our main results (available on request) are very similar when we include them.

the empirical analysis below, we will examine the policy impact separately for the city of Toronto, central Toronto and suburban Toronto.

Our data contain information on housing characteristics. In order to control for these characteristics, we define a number of variables. We create an indicator variable for whether the house is detached or semi-detached. Houses in our data are coded in 16 different styles. We condense this information into three housing styles (2-story ($\approx$65%), bungalow ($\approx$25%), other ($\approx$10%)), where the style 'other' includes 1-1/2 story, split-level, backsplit, and multi-level. We observe the depth and width of the lot in meters, which we convert to the total size of the lot by taking their product. We create a categorical variable for the number of rooms in a house that has 7 categories, from a minimum of 5 to >11, and another for the number of bedrooms that has 5 categories from 1 to >5. We create an indicator for the geographic district of the house listing. For our main sample of the city of Toronto, this district variable identifies 43 districts corresponding to the MLS district code.

5.2   Empirical Methodology

We now present empirical tests of the predictions derived in Section 4. To measure price responses, we use a bunching approach recently developed in the public finance literature (e.g., Saez 2010, Chetty et al. 2011b, and Kleven and Waseem 2013). Our theoretical model established that the downpayment discontinuity can create incentives for bunching at the $1M threshold in terms of listings, but less so in terms of sales. The key idea is to use the price segments which are not subject to the policy's threshold effects to form a valid counterfactual near the $1M threshold. The two underlying assumptions are that (1) the policy-induced incentives for bunching occur locally in segments near the $1M threshold, leaving other parts of the price distributions unaffected by threshold consequences; and (2) the counterfactual is smooth and can be estimated using these other parts of the price distributions. In forming the counterfactual, we use a two-step approach: first constructing counterfactual price distributions that would have prevailed if there were no changes in the composition of the housing stock using a common reweighting method; then applying the

bunching approach to the difference between each composition-constant post-policy price distribution and the observed pre-policy distribution.

5.2.1 First step: controlling for housing composition

If houses listed/sold in the million dollar segment in the post-policy year differ in terms of quality from those listed/sold in the previous year, then the difference between price distributions in the two periods could simply reflect the changes in the composition of housing rather than the effect of the policy. We alleviate this concern by leveraging the richness of our data to flexibly control for a set of observed house characteristics to back out a counterfactual distribution of house prices that would have prevailed if the characteristics of houses in the post-policy period were the same as in the pre-policy period.

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

$$\underbrace{F_{Y\langle 1|1\rangle} - F_{Y\langle 0|0\rangle}}_{\Delta_O=\text{Observed}} = \underbrace{\left[F_{Y\langle 1|1\rangle} - F_{Y\langle 1|0\rangle}\right]}_{\Delta_X=\text{Composition}} + \underbrace{\left[F_{Y\langle 1|0\rangle} - F_{Y\langle 0|0\rangle}\right]}_{\Delta_S=\text{Price Structure}}. \tag{6}$$

Since the counterfactual is not observed, it must be estimated. We use a simple reweighting method proposed by DiNardo et al. (1996) based on the following relation:

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

where $\Psi(x) = dF_{X_0}/dF_{X_1}$ is a reweighting factor that can be easily estimated using a logit model (for details, see Fortin et al. 2011). In our implementation of this method, we obtain

the weighting function by pooling pre- and post-policy data and estimating a logit model where the dependent variable is a pre-policy period dummy. The covariate vector contains indicators for district, month, the number of rooms, the number of bedrooms, whether the house is detached or semi-detached, the lot size and its square, and the housing style (2-story, bungalow, other).[24] The estimated counterfactual distribution is given by $\hat{F}_{Y\langle 1|0\rangle} = \int \hat{F}_{Y_1|X_1}(y|x) \cdot \hat{\Psi}(x) \cdot d\hat{F}_{X_1}(x)$, where $\hat{F}$ denotes a distribution function estimated using grid intervals of \$5,000. The result is a reweighted version of the observed price distribution in the post-policy period; that is, $\hat{F}_{Y\langle 1|0\rangle}$ is the price distribution that would prevail if the characteristics of homes were the same as in the pre-policy period.

5.2.2 Second step: bunching estimation

Set-up. With the estimated $\hat{\Delta}_S(y_j) = \hat{F}_{Y\langle 1|0\rangle}(y_j) - \hat{F}_{Y\langle 0|0\rangle}(y_j)$ in hand, we are now ready to estimate the policy effects on asking and sales price using a bunching estimation procedure. This procedure requires separation of the observed $\hat{\Delta}_S(y_j)$ into two parts: the price segments near \$1M that are subject to the policy's threshold effects, and the segments that are not. The affected segment is known as the 'excluded' region in the bunching literature. Since knowledge of this region is not known *a priori*, it must also be estimated and we develop a procedure below to do so. Once this region around \$1M is determined, we use standard methods to estimate the counterfactual difference in distributions by fitting a flexible polynomial to the estimated $\hat{\Delta}_S(y_j)$ outside the excluded region. We use the estimated polynomial to predict or 'fill in' the excluded region which forms our counterfactual. Our estimates of the policy effect are given by the difference between the observed $\hat{\Delta}_S(y_j)$ and the estimated counterfactual.

---

[24]The weighting function is $\Psi(x) = \frac{p(x)}{1-p(x)} \cdot \frac{1-P(t=1)}{P(t=0)}$, where $p(x)$ is the propensity score: i.e., the probability that $t = 0$ given x.

In particular, consider the equation:

$$\hat{\Delta}_S(y_j) = \sum_{i=0}^{p} \beta_i \cdot y_j^i + \beta_A \cdot 1[y_j = \$1\text{M}] + \beta_B \cdot 1[y_j = \$1\text{M} - h]$$

$$+ \sum_{l=1}^{L} \gamma_l \cdot 1[y_j = \$1\text{M} - h \cdot (1+l)] + \sum_{r=1}^{R} \alpha_r \cdot 1[y_j = \$1\text{M} + h \cdot r] + \epsilon_j \quad (7)$$

where p is the order of the polynomial, L is the excluded region to the left of the cut-off, R is the excluded region to the right of the cut-off, and h is the bin size.[25]

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

$$\underbrace{\hat{\Delta}_S(\$1\text{M}) - \hat{\Delta}_S(\$1\text{M} - h)}_{\text{Jump at threshold}} = \underbrace{\sum_{i=0}^{p} \hat{\beta}_i \cdot y_{\$1\text{M}}^i - \sum_{i=0}^{p} \hat{\beta}_i \cdot y_{\$1\text{M}-h}^i}_{\text{Counterfactual}} + \underbrace{\hat{\beta}_A - \hat{\beta}_B}_{\text{Total Policy Response}} \quad (8)$$

It is important to note that the interpretation of the total jump at the threshold, as shown in the left-hand-side of equation (8), is not all causal. Since there was more pronounced house price appreciation in lower-price segments, we expect the difference in the CDFs between the two periods to be upward sloping, even in the absence of the million dollar policy. This shape should be captured by our polynomial estimates as a counterfactual. Specifically, the first two terms on the right-hand-side of equation (8) reflect the counterfactual difference at the \$1M threshold.

After netting out the counterfactual, we are left with $\hat{\beta}_A - \hat{\beta}_B$, which is the policy response we aim to measure. A finding of $\hat{\beta}_A > 0$ is consistent with *bunching from above* since it indicates that sellers that would have otherwise located in bins above \$1M instead locate in the \$1M bin. A finding of $\hat{\beta}_B < 0$, on the other hand, is consistent with *bunching from below* since it indicates that sellers that would otherwise locate below the \$1M bin now move up to locate in the \$1M bin. Both are responses to the million dollar policy.

In the absence of an extensive margin response, the two sources of response described

---

[25]Note that there is no residual component in equation (7) since, through the excluded region, every bin has its own dummy and the fit is exact. We observe the population of house sales during this time, thus, the error term in (7) reflects specification error in our polynomial fit rather than sampling variation. We discuss the computation of our standard errors of our estimates in more detail below.

above imply two adding up constraints. First, sellers locating from adjacent bins below the threshold come from bins in the region L. The excess mass in the distribution at \$1M resulting from *bunching from below* should equal the the responses from lower adjacent bins, implying

$$R^B \equiv \beta_B - \sum_{l=1}^{L} \gamma_l \cdot 1[y_j = \$1M - h \cdot (1+l)] = 0. \tag{9}$$

Similarly, for those sellers coming from above the threshold,

$$R^A \equiv \beta_A - \sum_{r=1}^{R} \alpha_r \cdot 1[y_j = \$1M + h \cdot r] = 0. \tag{10}$$

Estimation. In order to implement our estimator, several decisions must be made about unknown parameters, as is the case for all bunching approaches. In particular, the number of excluded bins to the left, L, and right, R, are unknown, as is the order of the polynomial, p. In addition to these we choose to limit our estimation to a range of price bins around the \$1M threshold. We do this because the success of our estimation procedure requires estimation of the counterfactual in the region local to the policy threshold (Kleven, 2016). Using data points that are far away from the excluded region to predict values within the excluded region can be sensitive to polynomial choice and implicitly place very high weights on observations far from the threshold (Gelman and Imbens, 2014; Lee and Lemieux, 2010). Thus, we focus on a more narrow range, or estimation window, W, of house prices around the policy threshold. Since we are fitting polynomial functions, this can be thought of as a bandwidth choice for local polynomial regression with rectangular weights (Imbens and Lemieux, 2008). Thus, the parameters we require for estimation of the regression coefficients are (L, R, W, p).

We use a data-driven approach to select these parameters. The procedure we implement is a 5-fold cross-validation procedure, described fully in Appendix C.1. Briefly, we split our individual-level data into 5 equally sized groups and carry out both step 1 and 2 of our estimation procedure using 4 of the groups (i.e., holding out the last group), and then

obtain predicted squared residuals from equation (7) for the hold-out group. We repeat this procedure 5 times, holding out a different group each time, and average the predicted squared residuals across each repetition. This is the cross-validated Mean Squared Error (MSE) for a particular choice of (L, R, W, p). We perform a grid search over several values of each parameter, and choose the specification which minimizes the MSE.[26]

One legitimate concern is that our bunching estimates pick up threshold effects in pricing that are caused by, for example, marketing convention or psychological bias surrounding $1M, or other macro forces that affected the housing market at the same time as the implementation of the million dollar policy. Our estimation methodology addresses this concern in two ways. First, we examine the the post-policy CDF relative to the CDF in the pre-policy period. Time-invariant threshold price effects unrelated to the policy are therefore differenced out in our estimation. Second, we allow for round number fixed effects to capture potential rounding in the price data. Thus, all estimates reported below include a dummy variable for prices in $25,000 increments, and another for prices in $50,000 increments.

6   Empirical Evidence

The core estimation is presented in Section 6.1 with an aim to test Predictions 1 and 3. We then explore Prediction 2 related to market tightness and bidding intensity in Section 6.2.

---

[26]We do not claim that this method for model selection is necessarily optimal. In the literature on bunching estimation, the excluded region is sometimes selected by visual inspection (Saez, 2010; Chetty et al., 2011b) in combination with an iterative procedure (Kleven and Waseem, 2013; DeFusco et al., 2017) that selects the smallest width consistent with adding-up constraints. Often, high-order global polynomials are used in estimation and robustness to alternative polynomial orders are shown. In the closely related regression discontinuity literature, free parameters are sometimes chosen by cross-validation (Lee and Lemieux, 2010). In a recent paper by Diamond and Persson (2016), there are many different regions and time periods where bunching occurs, and so visual inspection is impractical. They develop a k-fold cross-validation procedure to choose the width of the manipulation region and polynomial order. Our approach closely follows theirs. However, we additionally consider a series of robustness checks to assess the sensitivity of our estimates to the choice of parameters L, R, W, and p. In practice, we find that our estimates are quite robust to reasonable deviations from the parameter values selected by our cross-validation procedure.

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

Recall from the main predictions of the model in Section 4.3 that the million dollar policy leads to sellers adjusting their asking prices in the million dollar segment (Prediction 1). This, along with the strategic response among buyers, result in changes in sales prices in the million dollar segment (Prediction 3).

The top panel of Figure 6 replicates the top panel of Figure 1 and presents the asking price distributions between \$600,000 and \$1,400,000 in the pre- and post-policy years and their differences. Following equation (6), we then decompose the difference in CDFs into two components: (i) price difference due to shifting housing characteristics in each segment (Panel C); and (ii) price difference due to changes in sellers' listing strategies (Panel D). The latter is the market response that we aim to measure at the \$1M threshold. As shown in Panel C, the price change caused by shifting housing characteristics is small in magnitude and relatively flat. In contrast, Panel D shows that the price difference caused by sellers' listing strategies generally changes smoothly with price, with a relatively large jump at \$1M. Given the minimal composition effect, nearly all of the differences in the observed distribution of asking prices are driven by sellers' listing behavior.

The top panel of Figure 7 replicates the bottom panel of Figure 1 and presents the sales price distributions for the two periods and their differences. The bottom panel of Figure 7 shows that even after accounting for the composition effect, a jump in the sales price at the \$1M threshold is less obvious. Evidently, the observed jump in the asking price distribution does not completely pass through to the sales price distribution.

The descriptive findings presented in Figures 6 and 7 are consistent with the model. However, this evidence alone does not distinguish the policy effects from the impact of other contemporaneous macro forces. To isolate the million dollar policy's effects on the price distributions, we now turn to the results obtained from bunching estimation.

Figure 8a shows a graphical test of Prediction 1 based on the estimation of equation (7). In particular, we plot both the changes in CDFs of the asking price, $\hat{\Delta}_S(y_j) =$

$\hat{F}_{Y\langle 1|0\rangle}(y_j) - \hat{F}_{Y\langle 0|0\rangle}(y_j)$, after controlling for house characteristics and the estimated counterfactual changes. The solid line plots the quality-adjusted changes, with each dot representing the difference in the CDFs before and after the policy for each $5,000 price bin indicated on the horizontal axis. The dashed line plots the counterfactual, while the vertical dashed lines mark the lower and upper limits of the bunching region ($975,000 and $1,025,000). Note that the width of the estimation widow ($100,000 dollars around the threshold), the order of the polynomial (cubic), and the width of the excluded region were chosen based on the cross-validation procedure outlined above.

The pattern shown in Figure 8a is striking. Consistent with Prediction 1, the empirical distribution of asking price exhibits a sharp discontinuity at the $1M threshold. After the policy, 0.45% listings were added to the $1M bin, out of which the counterfactual increase accounted for only 0.06%. Thus much of the excess bunching in the asking price at the $1M threshold is attributable to the million dollar policy.

Figure 8b further presents a graphical test of Prediction 1 based on the difference in densities. The spike in homes listed at the $1M is accompanied by dips in homes listed to the right and left of $1M. The spike reflects the excess mass of homes listed between $995,000 and $1M after the implementation of the policy. The dips reflect missing homes that would have been listed at prices further from the $1M in the absence of the policy.

Column (1) of Table 2 reports our baseline bunching estimates. The specification used is chosen by the cross-validation procedure outlined above. Standard errors are calculated via bootstrap.[27] Overall, we find that approximately 86 homes that would have otherwise been listed away from $1M were shifted to the $1M bin. In other words, the policy increased the number of homes listed in the million dollar price bin by 38.3% compared to the counterfactual. Among these additional listings, about half are shifted from below $995,000; the remaining half come from above $1M. Both estimates are significant at the five percent level. Interpreting these estimates in the context of our model, this means that the con-

---

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

straint imposed on prospective buyers by the million dollar policy induces some sellers, who would have otherwise listed homes below $1M, to increase their asking prices towards the $1M mark. By doing so, these sellers demand a higher price in a bilateral situation, which makes up for the lower amount they might receive in a multiple offer situation once the policy is effected. At the same time, the policy also induces some other sellers who would have otherwise listed homes above $1M to lower their asking price to just below the cut-off. Such a strategic response allows these sellers to attract both constrained and unconstrained buyers.

Columns (2)-(7) provide a variety of robustness checks. Columns (2) and (3) use alternative excluded regions. These regions are based by the cross-validation "plus one-standard error rule" outlined in Appendix C.1, where we choose the widest and narrowest excluded region specifications whose MSE is no more than one standard error above the minimum MSE obtained from the model in Column (1). Column (2) adds one excluded bin to the left of the threshold, whereas Column (3) subtracts one bin from the left and the right of the excluded region. These two specifications yield nearly identical results. Column (4) extends the estimation window by $25,000. Column (5) includes a fourth-order, rather than third-order polynomial used in the baseline specification. Column (6) imposes the constraints in equations (9) and (10) during estimation. Reassuringly, the bunching estimates are extremely robust, suggesting that our results are not driven by the selection of the size of the estimation window, order of the polynomial, or the width of the excluded region. We discuss column (7) in Section 6.1.2 below.

Turning to Prediction 3, we report the bunching estimates for the sales price in Table 3, with a visualization of the estimates shown in Figures 9a and 9b. Despite sharp excess bunching of the asking price, we do not find evidence of bunching of the sales price at the $1M price bin; the estimated total response attributable to the million dollar policy is small and statistically insignificant. The evidence is robust across different specifications. In keeping with the model (specifically, Prediction 3), the finding here suggests that the policy's impact on sales prices is mitigated and perhaps obfuscated by the auction mechanism, the listing

35

decisions of sellers, and the endogenous changes in bidding intensity among unconstrained buyers. To further explore this interpretation, we directly estimate the policy effect on bidding intensity in Section 6.2.

6.1.1 Robustness Checks

In this section, we assess the robustness of our main results to alternative choices of the pre- and post-policy period and we present two *placebo tests* as an additional check on our identification strategy. For our pacebo tests, we first designate two years prior to the implementation of the million dollar policy as 'placebo' years. Specifically, we estimate our baseline specification for asking and sales prices (column (1) of Tables 2 and 3) to compare the distribution of house prices between the period from July 15th, 2011, to June 15th, 2012, and the period from July 15th, 2010, and June 15th, 2011. We refer to this comparison as the 'pre-policy difference' below. Between and during these time periods, there were no changes to policies specifically affecting houses around the $1M threshold, and so we would not expect to find patterns of excess bunching. The middle row of Table 4 presents the results. The total observed jump at $1M is 0.0008 for the asking price and 0.0001 for the sales price. Neither are statistically significant, as expected.

Second, we designate alternative 'placebo' cut-offs at prices well below or above the $1M threshold, and again estimate our baseline specification at each of these points. The idea is straightforward: since the million dollar policy generates a notch in the downpayment required of buyers at precisely $1M, house prices in market segments well below or well above the $1M cut-off should not be affected by the policy in a discontinuous manner. Excess bunching at selected 'placebo' thresholds (multiples of $25,000 between $800,000 and $1,150,000) would thus thus represent contradictory evidence.

Table 4 contains 50 'placebo' estimates: 24 during the years overlapping the implementation of the policy for alternative price thresholds (the estimates excluding the $1M threshold), and 26 during the pre-policy years. Out of the 50 bunching estimates, only 4 are statistically significant and only 1 is economically large. Most of estimates are statistically insignificant

and economically small. Taken individually, each estimate alone may not be sufficient to alleviate concerns regarding marketing convention, psychology bias or other threshold factors unrelated to mortgage insurance regulation. But all together, these estimates provide compelling evidence that the bunching results presented in Section 6.1 provide an accurate measure of the price effects of the million dollar policy.

Our baseline empirical work uses data from transactions occurring one year before and after the implementation of the million dollar policy, but omits the few weeks following the announcement of the policy but before its implementation. In Table 5 we assess the robustness of our asking price related results to this choice. Column (1) uses the entire year, including the announcement period. This gives results that are very similar to our baseline. Column (2) takes the post-policy period to be the six months following implementation and the pre-policy period to be the six months prior to implementation. The results using this timing choice are slightly greater in magnitude compared to our baseline results. One issue with column (2) is that it compares two different sets of months within the same year, and so one might worry about seasonality of housing sales. Column (3) addresses this by again taking a six month window, but using as a pre-policy period the same six calendar months in the prior year. The results are very similar to column (2) which suggests that the degree of excess bunching perhaps dissipated slightly over time. Table 6 repeats this exercise using sales prices. Overall, we find that our main results are not sensitive to the choice of the pre- and post-policy time periods.

Columns (4) and (5) of Tables 5 and 6 contain additional falsification tests. First, we compare the last six months of 2011 with the first six months of 2012. Both periods pre-date the million dollar policy and there were no other policy changes occurring contemporaneously that specifically targeted million dollar homes. Second, we compare two six month periods *following* the implementation of the policy: the last six months of 2012 and the first six months of 2013. Again, these time periods do not correspond to other changes in policy specifically affecting the $1M segment of the market. As expected, we find no evidence of excess bunching in asking or sales prices around the $1M threshold.

6.1.2 Policy Responses Above $1M

So far our estimation has focused on examining the policy effects on homes with the sales price around $1M, i.e. ($975,000, $1,025,000). We choose this segment for two reasons. First, by the design of the policy, homes below $1M are unaffected by the 20% downpayment requirement. Second, homes far above $1M represent a very high-end segment in the Toronto market in 2012. Buyers in this segment belong to the most wealthy class in Canada and are unlikely to be constrained by the 20% downpayment constraint. To see whether this is the case, we now consider possible policy consequences in the above $1M segment including fewer listings (extensive margin response) and reduced prices (intensive margin). We first show that the bunching estimates remain robust when we rely on a counterfactual estimated using only data below $1M, suggesting that price responses above $1M are minimal. We then empirically assess the the discrepancies between the counterfactual and observed post-policy price distributions. Once again, the results do not point to marked price responses in markets segments above $1M, consistent with the observation that buyers in the high-end housing market segment are unlikely to be financially constrained.

Our first empirical exercise deals with the concern that the bunching estimates from the main analysis may be altered by the possible responses above the $1M segment. For example, if the introduction of the policy hindered potential listings/transactions above $1M, our counterfactual distribution, estimated by fitting a flexible polynomial through the empirical distribution excluding an area around the $1M threshold, would not accurately reflect the distribution that would have occurred in the absence of the policy. Note that this is also a common issue in the bunching literature (Kopczuk and Munroe, 2015; Best et al., 2018; Best and Kleven, 2018). As suggested by Kleven (2016), we construct the counterfactual using only data below $1M under the assumption that the distribution below the threshold is not affected by the policy. These results are presented in column (7) of of Tables 2 and 3, where we use the same excluded region and polynomial order as in column (1), and extend the estimation window leftward in order to maintain the same number of

bins despite only using data below $1M.[28] These results are similar to the other columns of the tables, suggesting that our main bunching estimates are quite robust and that the policy effects in the above the $1M segment are minimal.

We now examine the possible price responses above the $1M threshold. An extensive margin response in this segment would imply that some of the sales above the $1M did not take place due to the notch in financial constraints, rather than a simple relocation of sales around the policy threshold. An intensive responsive margin response would imply that some of the sales prices above the $1M are dampened. Together these responses should manifest as a systematic discrepancy between the counterfactual post-policy distributions and the observed post-policy distributions for price bins above the $1M threshold.

In order to empirically assess this, we require a counterfactual of what the post-policy sales distribution in the above $1M segment would have looked like in the absence of the MI policy. Estimating such a counterfactual is challenging, because a simple comparison of sales above $1M between the post- and pre-policy period would not capture a policy effect in the presence of trends or other macro forces affecting the housing market. Recall that our bunching approach at the million dollar segment addresses such identification challenge by comparing differential bunching around the threshold before and after the policy, where within-year bunching comparisons eliminate macro shocks that are smooth through the policy threshold.[29] Lacking such treatment thresholds in the above $1M segment, we can no longer rely on the bunching approach.

Instead, we form a counterfactual post-period sales distribution in the following way. We estimate composition adjusted sales distributions for the pre- and post-period, and invert them to obtain pre- and post-quantile functions. These functions map sales prices into the

---

[28]In implementing this specification, we add additional constraints to the estimating procedure. In particular, to avoid unstable behavior of polynomial estimates near boundary points, we restrict the coefficients within the excluded region to be positive to the left of $1M and positive in the excluded region in the bins above $1M. The idea behind these constraints are similar to natural splines that place shape restrictions near boundary values. Note that these constraints do not impose the adding up conditions in (9) or (10), but simply restrict the extrapolated polynomial counterfactual to lie within the excluded region.

[29]Our differenced bunching estimator works like a difference-in-differences design, where the first difference compares the distribution of sales above and below the threshold to a parametric counterfactual, and then differences this between the pre- and post-policy periods. This is similar in spirit to the first-differenced, regression discontinuity estimates in ?.

probability of house being sold for less than or equal to a given price. We first regress the post-period quantile function on the pre-period quantile function, using only data below $900K, and then then use the estimated intercept and slope coefficients from this regression to form a counterfactual quantile function for the post-period distribution above the threshold. Thus, our identification assumption is that that any trends in house price distribution in the absence of the policy can be represented by an intercept and slope shift in the quantile functions which we estimated from the the the below $900K segment. We then invert the counterfactual quantile function back into a distribution function to obtain a post-period counterfactual sales distribution. We compare this counterfactual distribution to the observed post-period sales distribution to make inferences about the policy effects on the above $1M segment.[30]

Panel A of Figure 10 shows the observed sales distribution functions for the pre- and post-policy periods as well as the counterfactual distribution function from the procedure outlined above. Two patterns emerge. First, the pre-period quantile function always lies below the post-period quantile function, reflecting the fact that the housing market experienced a boom during the sample period. Second, the counterfactual distribution is nearly visibly indistinguishable from the observed post-policy distribution, suggesting that the policy effects in the above $1M segment is minimal.

Panel B of Figure 10 further plots the differences between the observed and counterfactual post-policy distributions along with a confidence interval.[31] We also plot the difference in the observed distributions for reference. Had the MI policy caused fewer sales or dampened the sales price in the above $1M segment, we should expect a systematic negative difference in the distribution above the $1M threshold. However, given the standard errors, we are unable to reject that hypothesis that the difference between the counterfactual and observed post-policy distributions is zero.

Putting all this evidence together, we do not find that the million dollar policy has any substantial impact on home sales above the $1M segment. The finding is not only consistent

---

[30]The advantage of re-scaling quantile function to form the counterfactual rather than re-scaling the distribution function directly comes from the fact that the distribution function is bounded.

[31]The standard errors used to construct the confidence interval are obtained by bootstrapping our procedure 199 times.

with the conjecture that buyers in the highest-end housing market segment are financially unconstrained but also further reassures the robustness of our main bunching estimates in the million dollar segment.

6.2 Prediction 2: The Policy Effects on Sales above Asking and Time on the Market

As revealed in the context of the search model presented in Section 4, sales price effects can be dampened by increased competition between buyers and heightened bidding intensity among unconstrained buyers in the million dollar segment. Recall from Prediction 2 that the introduction of a financial constraint such as the one imposed by the million dollar policy drives up market tightness just below \$1M (recall Figure 4) and, in the case of bunching from above, increases the incidence of price escalation above \$1M (Prediction 2). We might therefore expect the million dollar policy to create a hotter market for houses listed just under \$1M, as reflected by a higher probability of selling above asking and a shorter time on the market.

We bring this interpretation to the data by employing a regression discontinuity design. The variables of interest are (1) the probability that a house sold above the asking price conditional on being listed at $p \geq y_j^A$; and (2) the probability that a house stayed on the market for more than two weeks conditional on being listed at $p \geq y_j^A$, where two weeks is roughly the median time on the market in the sample. We construct these two variables in three steps.

First, using the approach described in Section 5.2.1, we estimate the complementary CDF, $\hat{S}_{Y\langle 1|1\rangle}(y_j^A) = 1 - \hat{F}_{Y\langle 1|1\rangle}(y_j^A)$, which represents the probability of a house being listed for at least y_j^A. Holding the distribution of housing characteristics the same as the pre-policy period using the reweighting method, we then estimate the counterfactual probability $\hat{S}_{Y\langle 1|0\rangle}(y_j^A) = 1 - \hat{F}_{Y\langle 1|0\rangle}(y_j^A)$.

Second, we estimate the rescaled complementary CDF, $RS_{Y\langle 1|1\rangle}(y_j^A, y^S \geq y^A)$, which gives the joint probability of a house being listed for at least y_j^A and selling above asking price.

Similarly, we estimate $\hat{RS}_{Y\langle 1|0\rangle}(y_j^A, y^S \geq y^A)$, the counterfactual rescaled complementary CDF, holding the distribution of housing characteristics the same as the pre-policy period.

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

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

and the corresponding counterfactual post-policy conditional probabilities,

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

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

We plot each of the two constructed variables above as a function of the asking price, along with third order polynomials which are fit separately to each side of \$1M. Figures 10a and 10b display the results and provide further opportunity to explore the implications of the theory. Recall that market tightness falls at the threshold in Figure 4 because constrained buyers do not search in more expensive submarkets. Moreover, in the case of bunching from above, the ratio of unconstrained buyers to sellers is higher for homes listed at the cut-off than for homes listed at their pre-policy asking price (Prediction 2). We therefore expect shorter selling times and, in the case of bunching from above, a higher incidence of price escalation above the asking price for homes listed just below \$1M post-policy. Turning now to Figure 10a, the probability of being sold above asking exhibits a discrete downward jump at \$1M, with an upward sloping curve to the left of the \$1M. The probability of staying on

the market for more than two weeks is plotted in Figure 10b and exhibits a discrete upward jump at the \$1M, with a downward sloping curve to the left of the \$1M. When viewed through the lens of the theoretical model, these patterns reflect the pooling of constrained and unconstrained buyers along with heightened competition among unconstrained bidders for homes listed just under \$1M: both consequences of the million dollar policy.

6.3 Cross-Market Analysis

So far our main analysis has focused on the city of Toronto. In this section, we explore heterogeneity in policy response by comparing two geographical submarkets: central Toronto and suburban Toronto. Table 7 presents estimates of excess bunching at \$1M in terms of asking price and sales price in both central and suburban Toronto. The asking price response to the policy in suburban Toronto is about 40% of that in central Toronto, while the sales price response in both markets is small and insignificant.

The relative larger asking price response in central Toronto than in suburban Toronto is interesting. One possible explanation is that households in the former market are more constrained than those in the latter market. In this case, sellers in central Toronto would have more incentive to bunch their asking price at the \$1M threshold to attract both constrained and unconstrained buyers, as illustrated by part (i) of Lemma 1. This conjecture is not entirely implausible. A million dollar home lies at the top 5th percentile of the house price distribution in suburban Toronto, but represents roughly the median house price in central Toronto, as reported in Table 1. On the other hand, the wealth level at the top 5th percentile of the wealth distribution for households in suburban Toronto is much higher than the median wealth level in central Toronto. Since household wealth is positively correlated with home purchase price, the evidence here together suggests that prospective buyers of million dollar homes in suburban Toronto are less constrained than those in central Toronto, which would explain the sharper excess bunching in asking price at \$1M in central Toronto. A formal test of how the policy response varies with the severity or pervasiveness of the imposed financial constraint requires household-level data on borrower income and wealth, which we view as

a fruitful avenue for future research.

7 Conclusion

In this paper we derive and test the theoretical implications of financial constraints in the market for housing, with an empirical methodology that exploits a natural experiment arising from mortgage insurance regulation in Canada. The macroprudential regulation that we focus on withholds access to high LTV mortgage insurance when the purchase price of a home exceeds \$1M. This so-called million dollar policy effectively imposes a 20 percent minimum downpayment requirement on home buyers paying \$1M or more. We study the consequences of this policy in terms of the strategic responses of buyers and sellers in market segments around the \$1M threshold.

We first advance a directed search model of the \$1M segment of the market to provide insight about the potential consequences of the policy. We model the million dollar policy as a strict financial constraint affecting a subset of prospective buyers. We show that sellers respond strategically by adjusting their asking prices to \$1M, which attracts both constrained and unconstrained buyers. Somewhat surprisingly, these price adjustments can come from either side of the \$1M threshold. Because of bidding wars and the search/listing strategies of buyers and sellers, asking price effects translate into milder sales price effects.

We exploit the policy's \$1M threshold to isolate the effects of the policy on prices and other housing market outcomes. Specifically, we implement an estimation procedure that combines a decomposition method with bunching estimation. Using housing market transaction-level data from the city of Toronto, we find that the million dollar policy results in excess bunching at \$1M for asking prices but not for sales prices. These results, together with evidence that the incidence of bidding wars and below average time-on-the-market are relatively higher for homes listed just below the \$1M threshold, agree well with the intuition from the theory.

A brief sketch of a normative argument in favor of the million dollar policy is in order. In the theory, the policy influences market tightness via the free entry condition, which distorts

the number of housing market transactions and hence the total social surplus derived from housing market activity. At the same time, the policy results in an allocation of homes to buyers that favors less financially constrained buyers (i.e., those with sufficient wealth to meet the stricter downpayment requirement). It follows that the million dollar policy could be justified from a social welfare perspective if the welfare costs to housing market participants are more than offset by the welfare gains derived from enhanced stability of the financial system owing to improved creditworthiness of home buyers and downward pressure on house prices (if any).

When designing or evaluating macroprudentical policy, the findings in this study point to the importance of considering the market microstructure and anticipating how all market participants might respond. This is of particular interest and has broad applicability because mortgage financing is a channel through which policymakers in many countries are implementing macroprudential regulation.

References

Agarwal, S., G. Amromin, I. Ben-David, S. Chomsisengphet, T. Piskorski, and A. Seru (2017). Policy Intervention in Debt Renegotiation: Evidence from the Home Affordable Modification Program. *Journal of Political Economy*.

Albrecht, J., P. A. Gautier, and S. Vroman (2014). Efficient entry in competing auctions. *The American Economic Review 104*(10), 3288–3296.

Albrecht, J., P. A. Gautier, and S. Vroman (2016). Directed search in the housing market. *Review of Economic Dynamics 19*, 218–231.

Allen, J., T. Grieder, B. Peterson, and T. Roberts (2016). The impact of macroprudential housing finance tools in canada: 2005-2010.

Arefeva, A. (2016). How auctions amplify house-price fluctuations. *Mimeo*.

Berkovec, J., Y. Chang, and D. A. McManus (2012). Alternative lending channels and the crisis in u.s. housing markets. *Real Estate Economics 40*, S8–S31.

Best, M. C., J. Cloyne, E. Ilzetzki, and H. Kleven (2018, August). Estimating the elasticity of intertemporal substitution using mortgage notches. Working Paper 24948, National Bureau of Economic Research.

Best, M. C. and H. J. Kleven (2018). Housing market responses to transaction taxes: Evidence from notches and stimulus in the uk. *The Review of Economic Studies 85*(1), 157–193.

Che, Y.-K. and I. Gale (1996a). Expected revenue of all-pay auctions and first-price sealed-bid auctions with budget constraints. *Economics Letters 50*(3), 373–379.

Che, Y.-K. and I. Gale (1996b). Financial constraints in auctions: effects and antidotes. In M. Baye (Ed.), *Advances in Applied Microeconomics, Volume 6*, pp. 97–120. JAI Press Inc.

Che, Y.-K. and I. Gale (1998). Standard auctions with financially constrained bidders. *The Review of Economic Studies 65*(1), 1–21.

Chetty, R., J. N. Friedman, T. Olsen, and L. Pistaferri (2011a). Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records. *The Quarterly Journal of Economics 126*(2), 749–804.

Chetty, R., J. N. Friedman, T. Olsen, and L. Pistaferri (2011b). Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records. *Quarterly Journal of Economics 126*(2), 749–804.

DeFusco, A. A., S. Johnson, and J. Mondragon (2017, March). Regulating Household Leverage. Work in progress, Kellogg School of Management.

Demyanyk, Y. and O. Van Hemert (2011). Understanding the subprime mortgage crisis. *The Review of Financial Studies 24*(6), 1848.

Diamond, R. and P. Persson (2016, April). The long-term consequences of teacher discretion in grading of high-stakes tests. Working Paper 22207, National Bureau of Economic Research.

Diaz, A. and B. Jerez (2013). House prices, sales, and time on the market: A search-theoretic framework. *International Economic Review 54*(3), 837–872.

DiNardo, J., N. M. Fortin, and T. Lemieux (1996, September). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica 64*(5), 1001–1044.

Elliott, D. J., G. Feldberg, and A. Lehnert (2013). The history of cyclical macroprudential policy in the United States. Finance and Economics Discussion Series 2013-29, Board of Governors of the Federal Reserve System (U.S.).

Favilukis, J., S. C. Ludvigson, and S. V. Nieuwerburgh (2017). The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium. *Journal of Political Economy 125*(1), 140–223.

Fortin, N., T. Lemieux, and S. Firpo (2011). *Decomposition Methods in Economics*, Volume 4 of *Handbook of Labor Economics*, Chapter 1, pp. 1–102. Elsevier.

Gelman, A. and G. Imbens (2014, August). Why high-order polynomials should not be used in regression discontinuity designs. Working Paper 20405, National Bureau of Economic Research.

Genesove, D. and L. Han (2012). Search and matching in the housing market. *Journal of Urban Economics 72*(1), 31 – 45.

Genesove, D. and C. J. Mayer (1997). Equity and time to sale in the real estate market. *The American Economic Review 87*(3), 255–269.

Gyourko, J., P. Linneman, and S. Wachter (1999). Analyzing the relationships among race, wealth, and home ownership in america. *Journal of Housing Economics 8*(2), 63 – 89.

Han, L. and W. C. Strange (2016). What is the role of the asking price for a house? *Journal of Urban Economics 93*, 115–130.

Head, A., H. Lloyd-Ellis, and D. Stacey (2018, October). Heterogeneity, frictional assignment and home-ownership. Working papers, Queen's University, Department of Economics.

Head, A., H. Lloyd-Ellis, and H. Sun (2014). Search, liquidity, and the dynamics of house prices and construction. *American Economic Review 104*(4), 1172–1210.

Hurst, E. and A. Lusardi (2004). Liquidity constraints, household wealth, and entrepreneurship. *Journal of Political Economy 112*(2), 319–347.

Imbens, G. W. and T. Lemieux (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics 142*(2), 615 – 635. The regression discontinuity design: Theory and applications.

Julien, B., J. Kennes, and I. King (2000). Bidding for labor. *Review of Economic Dynamics 3*(4), 619–649.

Kleven, H. J. (2016). Bunching. *Annual Review of Economics 8*(1), 435–464.

Kleven, H. J. and M. Waseem (2013). Using notches to uncover optimization frictions and structural elasticities: Theory and evidence from pakistan. *The Quarterly Journal of Economics*, qjt004.

Kopczuk, W. and D. Munroe (2015, May). Mansion Tax: The Effect of Transfer Taxes on the Residential Real Estate Market. *American Economic Journal: Economic Policy 7*(2), 214–257.

Kotowski, M. H. (2016). First-price auctions with budget constraints.

Krainer, J. (2001, January). A Theory of Liquidity in Residential Real Estate Markets. *Journal of Urban Economics 49*(1), 32–53.

Kuttner, K. N. and I. Shim (2016). Can non-interest rate policies stabilize housing markets? Evidence from a panel of 57 economies. *Journal of Financial Stability 26*(C), 31–44.

Lamont, O. and J. C. Stein (1999, Autumn). Leverage and House-Price Dynamics in U.S. Cities. *RAND Journal of Economics 30*(3), 498–514.

Lee, D. S. and T. Lemieux (2010, June). Regression discontinuity designs in economics. *Journal of Economic Literature 48*, 281–355.

Lehnert, A. (2004). Housing, consumption, and credit constraints. Finance and Economics Discussion Series 2004-63, Board of Governors of the Federal Reserve System (U.S.).

Lester, B., L. Visschers, and R. Wolthoff (2015). Meeting technologies and optimal trading mechanisms in competitive search markets. *Journal of Economic Theory 155*, 1–15.

Linneman, P. and S. Wachter (1989). The impacts of borrowing constraints on homeownership. *Real Estate Economics 17*(4), 389–402.

McAfee, R. P. (1993). Mechanism design by competing sellers. *Econometrica*, 1281–1312.

Mian, A. and A. Sufi (2009). The consequences of mortgage credit expansion: Evidence from the u.s. mortgage default crisis*. *The Quarterly Journal of Economics 124*(4), 1449.

Mian, A. and A. Sufi (2011). House prices, home equity–based borrowing, and the us household leverage crisis. *The American Economic Review 101*(5), 2132–2156.

Ortalo-Magne, F. and S. Rady (2006). Housing market dynamics: On the contribution of income shocks and credit constraints. *The Review of Economic Studies 73*(2), 459–485.

Peters, M. and S. Severinov (1997). Competition among sellers who offer auctions instead of prices. *Journal of Economic Theory 75*(1), 141–179.

Saez, E. (2010). Do Taxpayers Bunch at Kink Points? *American Economic Journal: Economic Policy 2*(3), 180–212.

Slemrod, J., C. Weber, and H. Shan (2017). The behavioral response to housing transfer taxes: Evidence from a notched change in D.C. policy. *Journal of Urban Economics 100*(C), 137–153.

Stacey, D. (2016, November). Commitment and costly signaling in decentralized markets. *International Economic Review 57*(4), 1507–1533.

Stein, J. C. (1995). Prices and trading volume in the housing market: A model with down-payment effects. *The Quarterly Journal of Economics 110*(2), 379–406.

Vigdor, J. L. (2006). Liquidity constraints and housing prices: Theory and evidence from the {VA} mortgage program. *Journal of Public Economics 90*(8–9), 1579 – 1600.

Wachter, S., M. Cho, and M. J. Tcha (Eds.) (2014). *The Global Financial Crisis and Housing: A New Policy Paradigm.* KDI series in Economic Policy and Development.

Wheaton, W. C. (1990, December). Vacancy, Search, and Prices in a Housing Market Matching Model. *Journal of Political Economy 98*(6), 1270–1292.

Williams, J. T. (1995). Pricing Real Assets with Costly Search. *Review of Financial Studies 8*(1), 55–90.
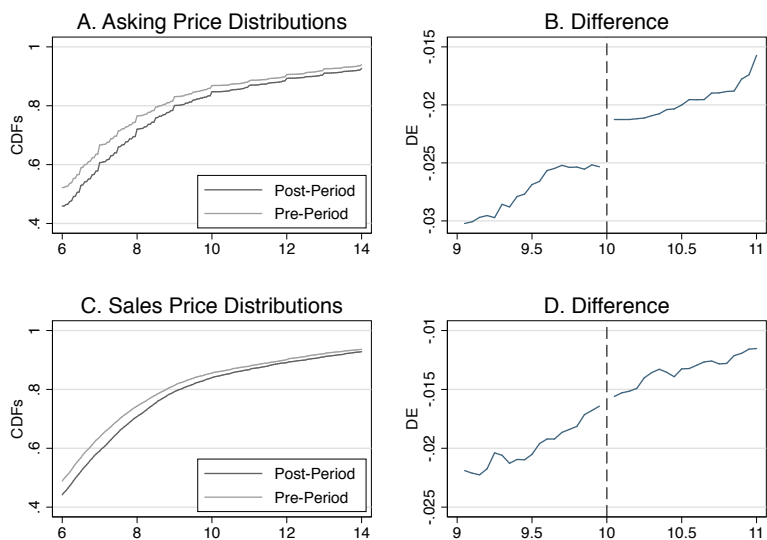
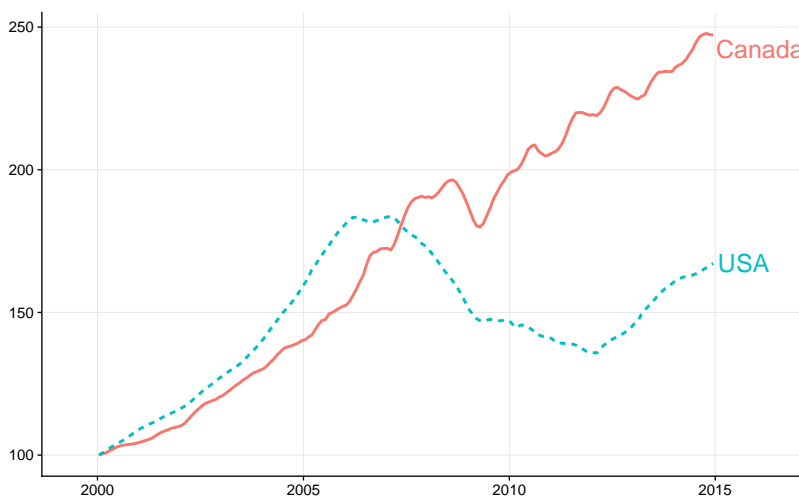Figure 1: Observed Distribution and Decomposition of Asking and Sales Prices

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

Notes: Monthly house price indices from S\&P Case-Shiller (US) and Teranet (Canada). All series downloaded from Datastream and are indexed to 100 in 2000. Series ID numbers: USCSHP20F and CNTNH-PCMF.
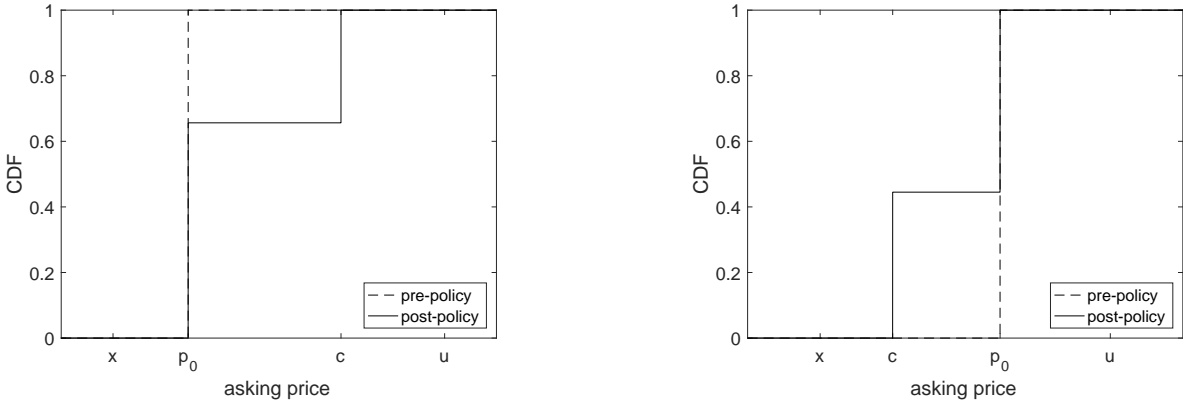
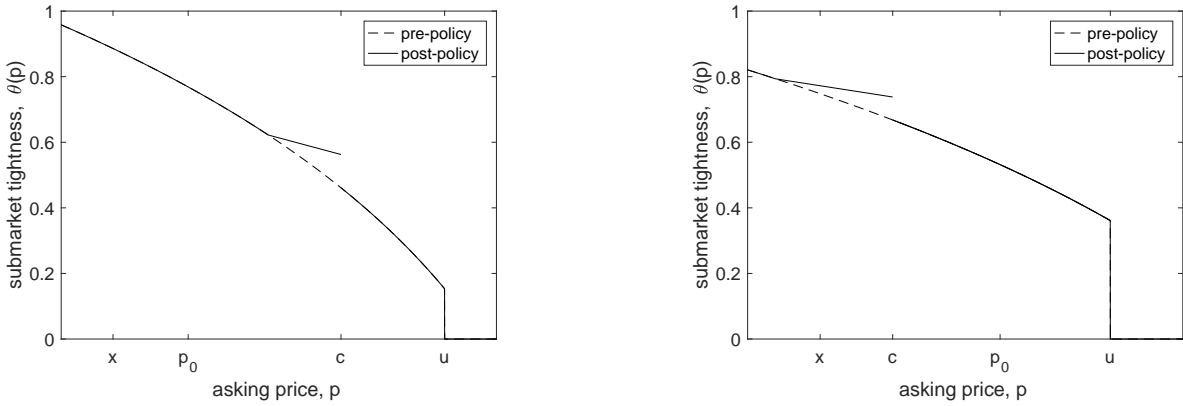Figure 3: Distributions of Asking Prices, Examples 1 (left) and 2 (right)

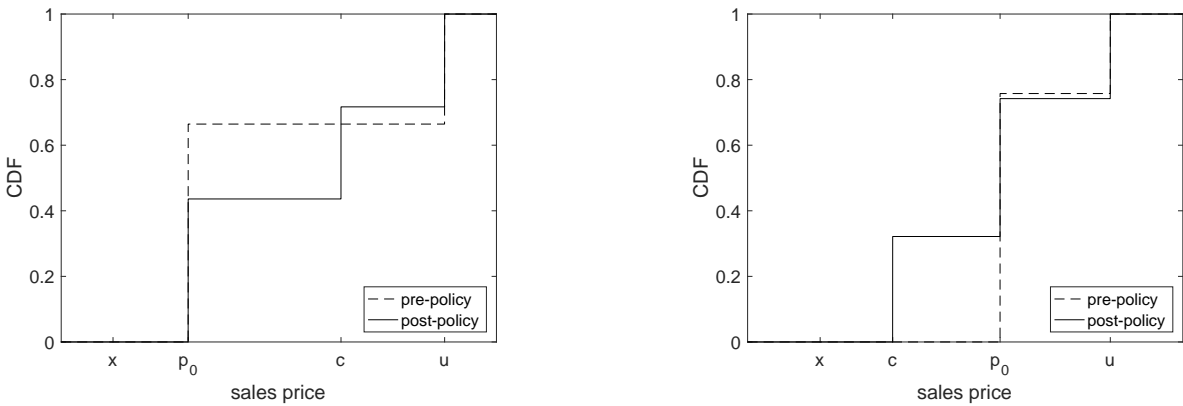Figure 4: Tightness as a Function of the Asking Price, Examples 1 (left) and 2 (right)

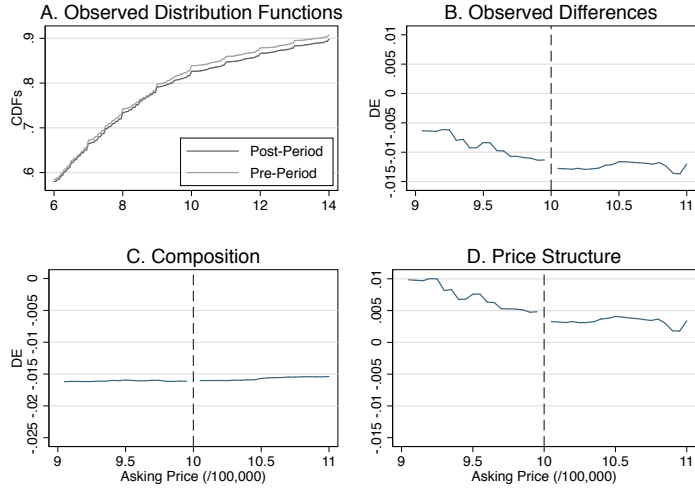Figure 5: Distributions of Sales Prices, Examples 1 (left) and 2 (right)

Figure 6: Observed Distribution and Decomposition of Asking Prices

Notes: The figure uses data on asking prices for the city of Toronto in the year before (pre-period) and after (post-period) the implementation of the million dollar policy. Panel A plots the empirical CDF of asking prices for each year. Panels B through D decomposes the difference in the CDFs according to equation 6. Panel B plots the observed difference in the CDFs, Δ_O. Panel C plots the difference in the CDFs due to composition, Δ_X. Panel D plots the difference due to the change in the price structure, Δ_S.
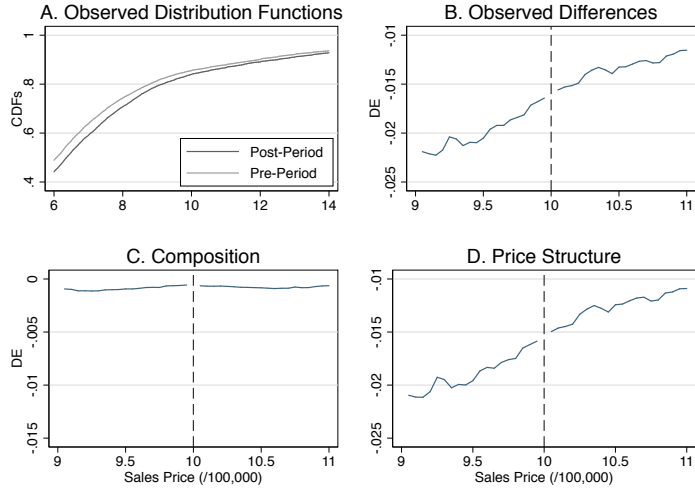
Figure 7: Observed Distribution and Decomposition of Sales Prices

Notes: The figure uses data on sales prices for the city of Toronto in the year before (pre-period) and after (post-period) the implementation of the million dollar policy. Panel A plots the empirical CDF of asking prices for each year. Panels B through D decomposes the difference in the CDFs according to equation 6. Panel B plots the observed difference in the CDFs, Δ_O. Panel C plots the difference in the CDFs due to composition, Δ_X. Panel D plots the difference due to the change in the price structure, Δ_S.
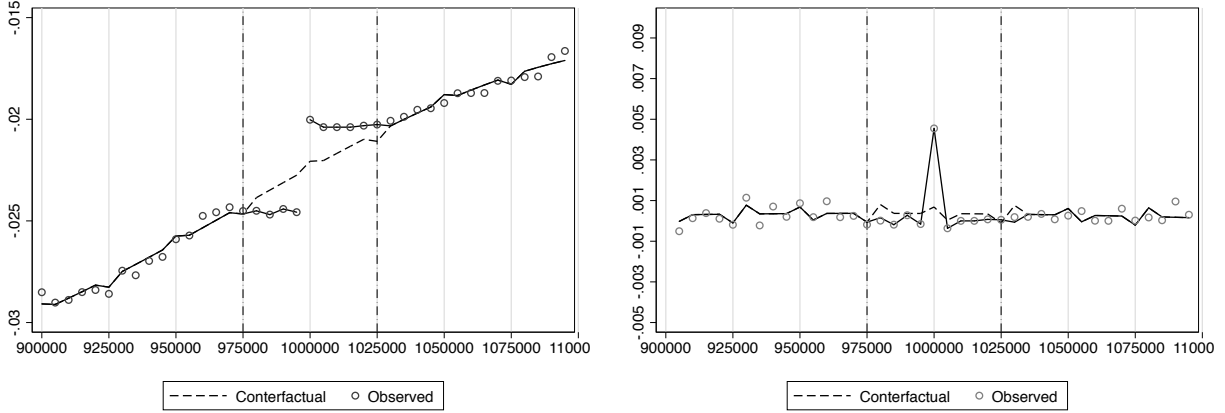
(a) $\hat{\Delta}_S(y_j)$ and counterfactual estimate

(b) $\hat{\Delta}_{S'}(y_j)$ and counterfactual estimate

Figure 8: Visual representation of column (1) in Table 2

Notes: Panel (a) of the figure shows a visual representation of the bunching specification in Column 1 of Table 2 which uses data on asking prices for the city of Toronto. The dots indicate the before-after policy differences in the CDFs, $\hat{\Delta}_S(y_j)$. Vertical dashed lines in the figure indicate the excluded region. The solid line is the fitted polynomial from equation (7) outside the excluded region and the fitted dummies within it. The dashed line, formed from predicted values of the polynomial within the excluded region, indicates the counterfactual estimate of the CDF difference that would have prevailed in the absence of the policy. Panel (b) represents the same specification in terms of differences in PDFs.
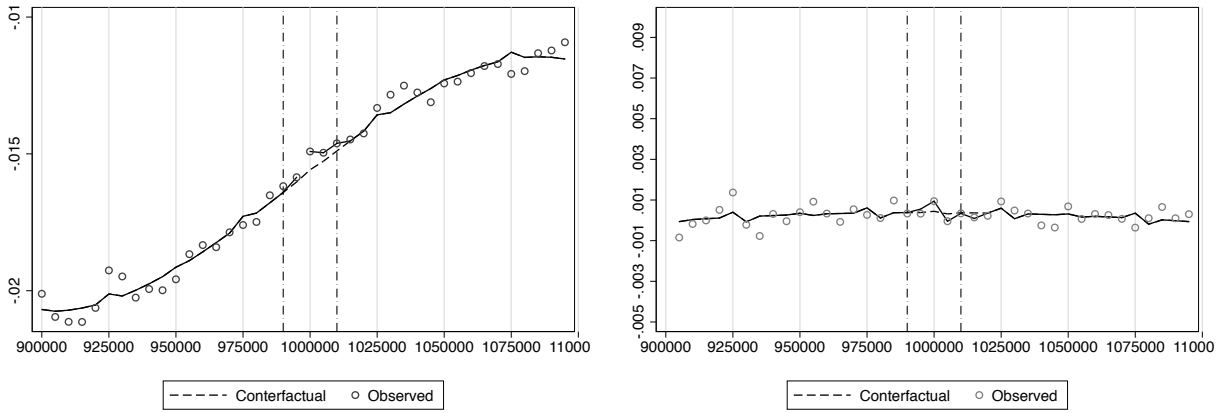

(a) $\hat{\Delta}_S(y_j)$ and counterfactual estimate

(b) $\hat{\Delta}_{S'}(y_j)$ and counterfactual estimate

Figure 9: Visual representation of column (1) in Table 3

Notes: Panel (a) of the figure shows a visual representation of the bunching specification in Column 1 of Table 2 which uses data on sales prices for the city of Toronto. The dots indicate the before-after policy differences in the CDFs, $\hat{\Delta}_S(y_j)$. Vertical dashed lines in the figure indicate the excluded region. The solid line is the fitted polynomial from equation (7) outside the excluded region and the fitted dummies within it. The dashed line, formed from predicted values of the polynomial within the excluded region, indicates the counterfactual estimate of the CDF difference that would have prevailed in the absence of the policy. Panel (b) represents the same specification in terms of differences in PDFs.

53
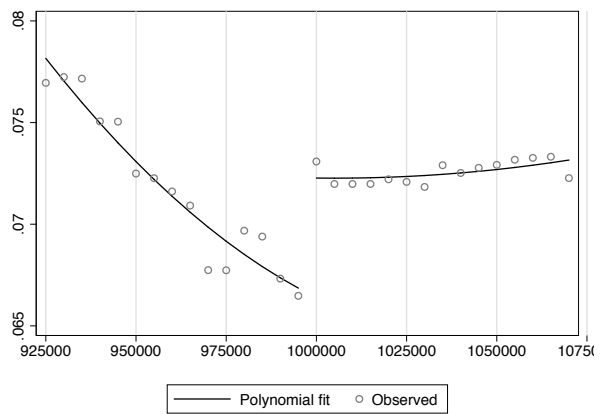
(a) Sales above Asking   (b) Duration on Market

Figure 10: Policy Effects on Sales above Asking and Time on the Market

Notes: Panel (a) of the figure plots the change in the probability that a home is sold above asking, conditional on the asking price. Panel (b) plots the change in the probability that a home is on the market for a duration longer than two weeks, conditional on the asking price. Each dot represents the observed change in probability, while the solid line plots the predicted values from a third-order polynomial fit separately to either side of \$1M.

Table 1: Summary Statistics: City of Toronto

(a) All Districts

		Pre-Policy		Post-Policy	
		Asking	Sales	Asking	Sales
All Homes	Mean	722430.15	723396.82	770836.16	760598.15
	25th Pct	459900.00	465000.00	499000.00	491000.00
	50th Pct	599000.00	605000.00	639000.00	635000.00
	75th Pct	799000.00	807500.00	849000.00	845000.00
	N	22244.00	22244.00	19061.00	19061.00
	Median Duration	10.00	10.00	13.00	13.00
	1M Percentile	0.87	0.86	0.85	0.84
Homes 0.9-1M	N	840.00	934.00	888.00	907.00
	Median Duration	9.00	8.00	13.00	12.00
	Mean Price	964427.90	942427.89	966120.77	946257.88
Homes 1-1.1M	N	364.00	514.00	410.00	516.00
	Median Duration	10.00	9.00	13.00	12.00
	Mean Price	1071802.41	1043508.98	1073840.91	1044025.97

(b) Central District

		Pre-Policy		Post-Policy	
		Asking	Sales	Asking	Sales
All Homes	Mean	1082210.56	1087206.62	1172612.53	1153957.65
	25th Pct	649000.00	665000.00	699900.00	718000.00
	50th Pct	849000.00	875000.00	899900.00	925000.00
	75th Pct	1288000.00	1295000.00	1395000.00	1362500.00
	N	4943.00	4943.00	4065.00	4065.00
	Median Duration	9.00	9.00	11.00	11.00
	1M Percentile	0.64	0.60	0.58	0.56
Homes 0.9-1M	N	334.00	363.00	336.00	335.00
	Median Duration	8.00	8.00	8.00	8.00
	Mean Price	966559.71	943206.85	968328.73	945389.72
Homes 1-1.1M	N	163.00	228.00	186.00	226.00
	Median Duration	8.00	8.00	10.00	10.00
	Mean Price	1073393.17	1044304.37	1074523.94	1045802.38

Notes: This table displays summary statistics for the city of Toronto for single family homes (attached and detached). The pre-policy period is defined as July 15th, 2011, to June 15th, 2012, and the post-policy period is defined as July 15th, 2012, to June 15th, 2013. The columns labeled Asking refers to the asking price and the columns labeled Sales refers to sales prices. Duration refers to the number of days a home is on the market.

Table 2: Regression Bunching Estimates: City of Toronto

	Asking Price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Jump at cut-off	0.0045*	0.0045*	0.0045*	0.0045*	0.0045*	0.0045*	0.0045*
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Total Response	0.0039*	0.0039*	0.0039*	0.0035*	0.0040*	0.0049*	0.0041*
	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0011)	(0.0014)	(0.0011)
From Below	-0.0018*	-0.0018*	-0.0018*	-0.0018*	-0.0024*	-0.0022*	-0.0019*
	(0.00074)	(0.00075)	(0.00070)	(0.00079)	(0.00075)	(0.00089)	(0.00088)
From Above	0.0020*	0.0021*	0.0021*	0.0017	0.0016	0.0027*	0.0022
	(0.00090)	(0.00089)	(0.00089)	(0.00089)	(0.00096)	(0.00098)	(0.0014)
Observations	41305	41305	41305	41305	41305	41305	41305
Excluded Bins:							
L	4	5	3	4	4	4	4
R	5	5	4	5	5	5	5
Tests of Fit:							
$B - \sum_l^L \beta_B^l$	-.0013	-.0011	-.00063	-.0016	-.0023	6.9e-18	-.0012
	(.0014)	(.002)	(.00064)	(.0016)	(.0012)	(8.3e-12)	(.00097)
$A - \sum_r^R \beta_A^r$	.0025	.0025	.0018	.0032	.00093	-2.8e-17*	.00049
	(.0017)	(.0017)	(.0011)	(.002)	(.0018)	(.)	(.0066)
Joint p-val.	0.22	0.29	0.21	0.16	0.18	.	0.46
Impact:							
Δ Houses at cutoff	85.9	86.0	85.7	77.7	88.9	108.5	91.4
%Δ at cutoff	38.3	38.4	38.2	33.4	40.2	49.9	41.8
Specifications:							
Poly. Order	3	3	3	3	4	3	3
Window	20	20	20	25	20	20	20
Other	CV Opt.	CV Wide	CV Narrow			Constrained	Extensive

Notes: This table displays the bunching estimates of the MI policy for the City of Toronto. The dependent variable is $\hat{\Delta}_S(y_j)$ constructed using asking prices. The rows of the table correspond to the components of (8). The first row shows the total jump at the million dollar threshold, the second row shows the total response due to the policy $(\hat{\beta}_A - \hat{\beta}_B)$, and the last two rows show the response from above $(\hat{\beta}_A)$ and below $(\hat{\beta}_B)$ the threshold, respectively. Standard errors, in parentheses, are constructed via bootstrap discussed in the main text. (*) denotes significance at the 5% level.

Table 3: Regression Bunching Estimates: City of Toronto

	Sales Price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Jump at cut-off	0.00094*	0.00094*	0.00094*	0.00094*	0.00094*	0.00094*	0.00094*
	(0.00040)	(0.00040)	(0.00040)	(0.00040)	(0.00040)	(0.00040)	(0.00040)
Total Response	0.00050	0.00035	0.00051	0.00048	0.00054	0.00035	0.00032
	(0.00053)	(0.00051)	(0.00054)	(0.00045)	(0.00053)	(0.00046)	(0.00050)
From Below	0.00017	0.00051	0.00015	0.00016	-0.0000099	0.00013	-5.3e-38
	(0.00061)	(0.00079)	(0.00062)	(0.00069)	(0.00048)	(0.00062)	(0.00022)
From Above	0.00067	0.00086	0.00065	0.00065	0.00053	0.00048	0.00032
	(0.00076)	(0.00088)	(0.00075)	(0.00078)	(0.00068)	(0.00056)	(0.00055)
Observations	41305	41305	41305	41305	41305	41305	41305
Excluded Bins:							
L	1	3	2	1	1	1	1
R	2	8	1	2	2	2	2
Tests of Fit:							
$B - \sum_l^L \beta_B^l$	.00017	.00058	.000058	.00016	-9.9e-06	.00013	-5.3e-38
	(.00061)	(.0009)	(.00037)	(.00069)	(.00048)	(.00062)	(.00022)
$A - \sum_r^R \beta_A^r$	-.00036	.0043	.00065	-.00027	-.00039	0*	-.00032
	(.00057)	(.0038)	(.00075)	(.00055)	(.00058)	(0)	(.00033)
Joint p-val.	0.82	0.51	0.66	0.88	0.76	0.83	0.61
Impact:							
Δ Houses at cutoff	11.1	7.83	11.3	10.8	11.9	7.75	7.03
%Δ at cutoff	25.8	17.0	26.5	24.9	28.4	18.7	14.9
Specifications:							
Poly. Order	3	3	3	3	4	3	3
Window	20	20	20	25	20	20	20
Other	CV Opt.	CV Wide	CV Narrow			Constrained	Extensive

Notes: This table displays the bunching estimates of the MI policy for the City of Toronto. The dependent variable is $\hat{\Delta}_S(y_j)$ constructed using sales prices. The rows of the table correspond to the components of (8). The first row shows the total jump at the million dollar threshold, the second row shows the total response due to the policy $(\hat{\beta}_A - \hat{\beta}_B)$, and the last two rows show the response from above $(\hat{\beta}_A)$ and below $(\hat{\beta}_B)$ the threshold, respectively. Standard errors, in parentheses, are constructed via bootstrap discussed in the main text. $(^*)$ denotes significance at the 5% level.

Table 4: Regression Bunching Estimates: Alternative Cut-offs and Period

	Post-Policy Difference		Pre-Policy Difference	
	(1)	(2)	(3)	(4)
	Asking	Sales	Asking	Sales
800000	0.0017	-0.0015*	0.0018	-0.0000097
	(0.0015)	(0.00077)	(0.0014)	(0.00074)
825000	-0.00015	-0.000038	-0.00023	0.00032
	(0.00056)	(0.00077)	(0.00047)	(0.00071)
850000	0.00100	0.00068	0.00088	-0.000087
	(0.0013)	(0.00078)	(0.0012)	(0.00069)
875000	0.00011	-0.000064	0.00030	0.00034
	(0.00045)	(0.00069)	(0.00039)	(0.00063)
900000	0.00037	-0.00059	0.0030*	0.00039
	(0.0013)	(0.00072)	(0.0012)	(0.00059)
925000	-0.00055	0.00099	-0.00016	0.00033
	(0.00042)	(0.00066)	(0.00035)	(0.00059)
950000	-0.00098	-0.00022	-0.0015	-0.00085
	(0.00090)	(0.00062)	(0.00080)	(0.00051)
1000000	0.0039*	0.00051	0.00062	0.00013
	(0.0011)	(0.00054)	(0.00093)	(0.00043)
1050000	-0.0015*	0.00030	-0.00027	-0.000018
	(0.00066)	(0.00044)	(0.00058)	(0.00037)
1075000	-0.00038	-0.00055	0.00011	0.00026
	(0.00023)	(0.00043)	(0.00022)	(0.00041)
1100000	0.0012	-0.00011	0.00088	-0.00045
	(0.00073)	(0.00036)	(0.00066)	(0.00031)
1125000	-0.000066	-0.00062	0.00020	0.00041
	(0.00025)	(0.00036)	(0.00020)	(0.00036)
1150000	-0.00056	0.00055	-0.0012*	-0.00064
	(0.00061)	(0.00040)	(0.00060)	(0.00033)

Notes: This table displays the bunching estimates at various price thresholds for the City of Toronto. The dependent variable is $\hat{\Delta}_S(y_j)$ constructed using either asking prices (columns 1 and 3) or sales prices (columns 2 and 4). Each row of the table shows the total policy component of equation (8) using price thresholds indicated in the left-side panel. The post-policy difference (columns 1 and 2) use data on sales one year before and after the MI policy. The pre-policy difference (columns 3 and 4) compares the two years prior to the implementation. Standard errors, in parentheses, are constructed via bootstrap discussed in the main text. (*) denotes significance at the 5% level.

Table 5: Assessing Robustness to Alternative Time Choices

	Asking Price				
	(1)	(2)	(3)	(4)	(5)
Jump at cut-off	0.0044*	0.0049*	0.0057*	0.0011	-0.00047
	(0.00093)	(0.0015)	(0.0016)	(0.0011)	(0.0018)
Total Response	0.0037*	0.0051*	0.0050*	0.00026	-0.0014
	(0.00100)	(0.0016)	(0.0016)	(0.0012)	(0.0018)
From Below	-0.0018*	-0.0026*	-0.0027*	-0.00018	0.0010
	(0.00065)	(0.0011)	(0.0011)	(0.00090)	(0.0012)
From Above	0.0019*	0.0024*	0.0023	0.000084	-0.00032
	(0.00088)	(0.0012)	(0.0014)	(0.0011)	(0.0013)
Observations	44766	22257	17071	24068	19061
Excluded Bins:					
L	4	4	4	4	4
R	5	5	5	5	5
Tests of Fit:					
$B - \sum_l^L \beta_B^l$	-.0014	-.0037	-.0013	.0024	.0018
	(.0012)	(.002)	(.0019)	(.0017)	(.002)
$A - \sum_r^R \beta_A^r$	.0023	.0027	.0015	-.0012	.00082
	(.0014)	(.002)	(.0023)	(.002)	(.0022)
Joint p-val.	0.12	0.085	0.67	0.30	0.62
Impact:					
Δ Houses at cutoff	87.6	73.8	46.4	2.46	-10.1
%Δ at cutoff	36.6	52.6	54.2	2.84	-9.48
Specifications:					
Poly. Order	3	3	3	3	3
Window	20	20	20	20	20
Timing	Include Announcement	6 Months Before and After	July - Dec. 2012 VS. July - Dec. 2011	Jan. - Jun. 2012 VS. July - Dec. 2011	July . - Dec. 2012 VS. Jan - June 2013

Notes: This table displays the bunching estimates of the MI policy for the City of Toronto. The dependent variable is $\hat{\Delta}_S(y_j)$ constructed using asking prices. The rows of the table correspond to the components of (8). The first row shows the total jump at the million dollar threshold, the second row shows the total response due to the policy ($\hat{\beta}_A - \hat{\beta}_B$), and the last two rows show the response from above ($\hat{\beta}_A$) and below ($\hat{\beta}_B$) the threshold, respectively. Standard errors, in parentheses, are constructed via bootstrap discussed in the main text. (*) denotes significance at the 5% level.

Table 6: Assessing Robustness to Alternative Time Choices

	Sales Price				
	(1)	(2)	(3)	(4)	(5)
Jump at cut-off	0.00095*	0.00095	0.0011	0.00023	0.000022
	(0.00044)	(0.00064)	(0.00065)	(0.00050)	(0.00079)
Total Response	0.00035	0.00089	0.00024	-0.00053	-0.00054
	(0.00052)	(0.00078)	(0.00082)	(0.00068)	(0.00086)
From Below	0.00013	0.00030	0.00011	-0.000060	-0.00043
	(0.00053)	(0.00089)	(0.00094)	(0.00067)	(0.00100)
From Above	0.00049	0.0012	0.00035	-0.00059	-0.00097
	(0.00069)	(0.0011)	(0.0012)	(0.00091)	(0.0011)
Observations	44766	22257	17071	24068	19061
Excluded Bins:					
L	1	1	1	1	1
R	2	2	2	2	2
Tests of Fit:					
$B - \sum_l^L \beta_B^l$	.00013	.0003	.00011	-.00006	-.00043
	(.00053)	(.00089)	(.00094)	(.00067)	(.001)
$A - \sum_r^R \beta_A^r$	-.00014	-.00021	.00044	.00077	.00012
	(.00051)	(.00087)	(.00086)	(.00072)	(.00074)
Joint p-val.	0.95	0.94	0.82	0.53	0.91
Impact:					
Δ Houses at cutoff	8.45	13.0	2.25	-5.00	-4.00
$\%\Delta$ at cutoff	17.5	57.2	11.4	-26.1	-18.9
Specifications:					
Poly. Order	3	3	3	3	3
Window	20	20	20	20	20
Timing	Include Announcement	6 Months Before and After	July - Dec. 2012 VS. July - Dec. 2011	Jan. - Jun. 2012 VS. July - Dec. 2011	July . - Dec. 2012 VS. Jan - June 2013

Notes: This table displays the bunching estimates of the MI policy for the City of Toronto. The dependent variable is $\hat{\Delta}_S(y_j)$ constructed using sales prices. The rows of the table correspond to the components of (8). The first row shows the total jump at the million dollar threshold, the second row shows the total response due to the policy ($\hat{\beta}_A - \hat{\beta}_B$), and the last two rows show the response from above ($\hat{\beta}_A$) and below ($\hat{\beta}_B$) the threshold, respectively. Standard errors, in parentheses, are constructed via bootstrap discussed in the main text. (*) denotes significance at the 5% level.
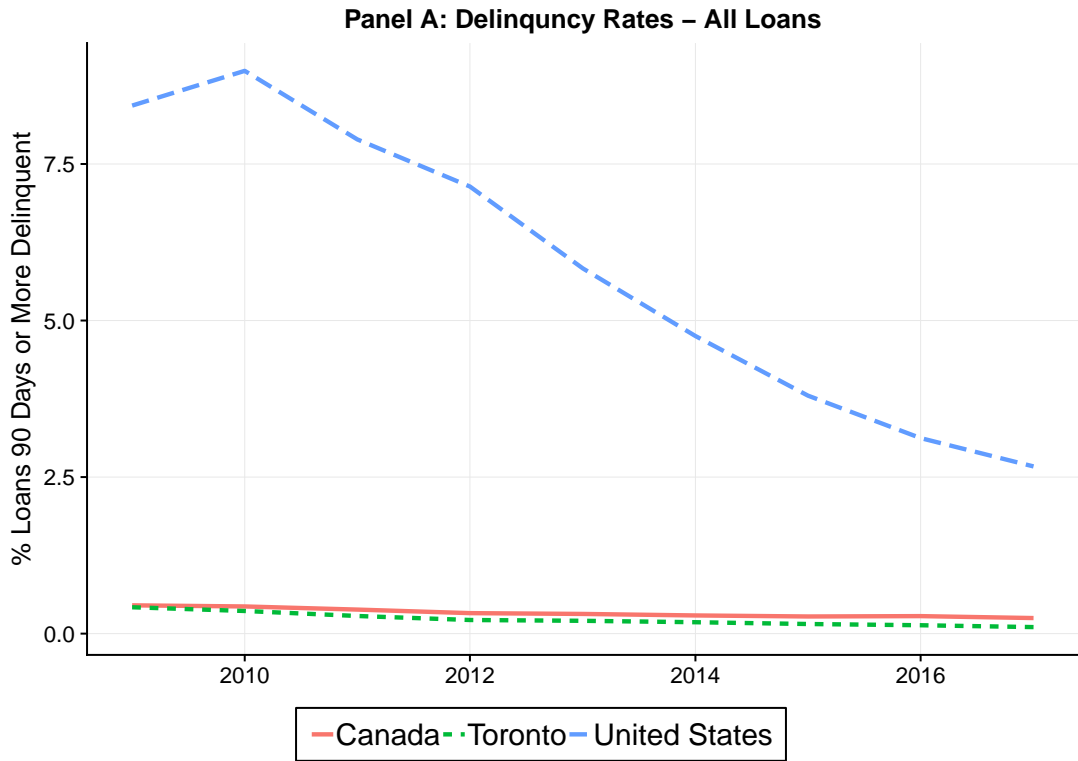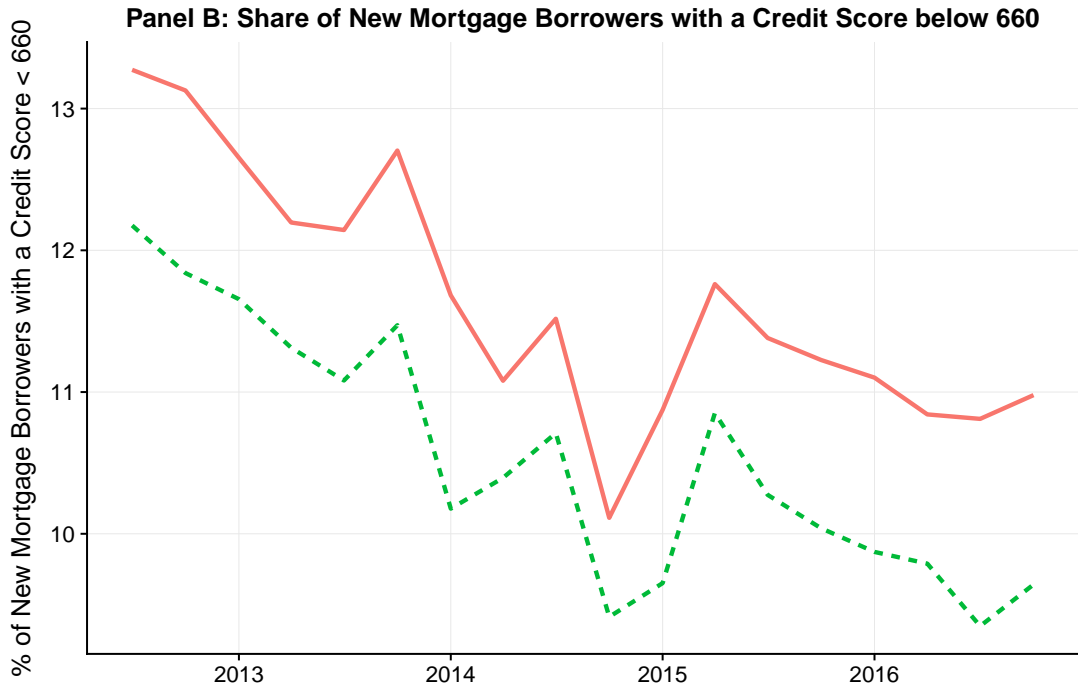
Table 7: Regression Bunching Estimates: Central vs Suburbs

	Central		Suburbs	
	(1) Asking	(2) Sales	(3) Asking	(4) Sales
Jump at cut-off	0.0094*	0.0032*	0.0031*	0.00032
	(0.0032)	(0.0014)	(0.0011)	(0.00040)
Total Response	0.0068*	0.0028	0.0029*	-0.00010
	(0.0031)	(0.0016)	(0.0011)	(0.00051)
From Below	-0.0049*	-0.0013	-0.00077	0.00054
	(0.0023)	(0.0020)	(0.00073)	(0.00061)
From Above	0.0020	0.0014	0.0021*	0.00044
	(0.0024)	(0.0023)	(0.00097)	(0.00073)
Observations	9008	9008	32297	32297
Excluded Bins:				
L	3	1	3	1
R	4	2	5	1
Tests of Fit:				
$B - \sum_l^L \beta_B^l$	-.00045	-.0013	-.00052	.00054
	(.0023)	(.002)	(.00061)	(.00061)
$A - \sum_r^R \beta_A^r$	.0048	-.0012	.0017	.00044
	(.0041)	(.0019)	(.0017)	(.00073)
Joint p-val.	0.51	0.46	0.48	0.67
Impact:				
Δ Houses at cutoff	33.8	13.7	49.6	-1.76
$\%\Delta$ at cutoff	32.0	96.6	41.4	-6.21
Specifications:				
Poly. Order	2	2	3	3
Window	25	20	20	20

Notes: This table displays the bunching estimates of the MI policy for Central Toronto and the Toronto Suburbs. The dependent variable is $\hat{\Delta}_S(y_j)$ constructed using either asking prices (columns 1 and 3) or sales prices (columns 2 and 4). The rows of the table correspond to the components of (8). The first row shows the total jump at the million dollar threshold, the second row shows the total response due to the policy ($\hat{\beta}_A - \hat{\beta}_B$), and the last two rows show the response from above ($\hat{\beta}_A$) and below ($\hat{\beta}_B$) the threshold, respectively. Standard errors, in parentheses, are constructed via bootstrap discussed in the main text. (*) denotes significance at the 5% level.

A Delinquency and Credit Score Metrics

Figure A1: Delinquency Rates and Origination Credit Scores

Panel B: Share of New Mortgage Borrowers with a Credit Score below 660

Panel A: Delinquncy Rates – All Loans

Canada · · Toronto — United States

Notes: Data from Canada Mortgage and Housing Corporation (CMHC)

B   Theory: Details and Derivations

B.1   Expected Payoffs

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

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

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

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

The closed-form expression is

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

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

The unconstrained buyer's expected payoff is

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

The closed-form expression is

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

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

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

$$V_{II}^c(p, \lambda, \theta) = 0. \qquad \text{(B.3)}$$

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

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

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

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

B.2 Algorithm for Constructing Pre-Policy DSE

Solution to Problem $\mathbf{P}_0$: Assuming (for the moment) an interior solution, the solution to problem $\mathbf{P}_0$ satisfies the following first-order condition with respect to θ and the free-entry condition:

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

which combine to yield

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

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

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

B.3 Algorithm for Constructing Post-Policy DSE

Solution to Problem $\mathbf{P}_1$: Assuming (for the moment) an interior solution, the solution to problem $\mathbf{P}_1$ satisfies the two constraints with equality, $V^s(p_c^*, \lambda_c^*, \theta_c^*) = 0$ and $V^u(p_c^*, \lambda_c^*, \theta_c^*) = \bar{V}^u$, and the following first-order condition.

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

where $\bar{V}^c = V^c(p_c^*, \lambda_c^*, \theta_c^*)$ and $\bar{V}^u$ is set equal to the maximized objective of problem $\mathbf{P}_0$. Now taking into account the constraint imposed by bidding limit c, the solution is $p_1 = \min\{c, p_c^*\}$ with λ_1 and θ_1 satisfying $V^s(p_1, \lambda_1, \theta_1) = 0$ and $V^u(p_1, \lambda_1, \theta_1) = \bar{V}^u$.

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

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

B.4 Omitted Proofs

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

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

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

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

Note, however, that

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

The equality follows by construction since inequality (B.7) requires $\theta(p) > 0$. The inequality follows from the fact that V^u is decreasing in the asking price and $p' < p$. The pair $\{p', \theta(p)\}$ therefore satisfies the constraint set of problem (P$_0$) and, according to (B.8), achieves a higher value of the objective than $\{p_0, \theta_0\}$: a contradiction. $\qquad \square$

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

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

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

where, for notational convenience, λ and θ refer to $\lambda(p)$ and $\theta(p)$. There exists $p'' < p$ such

that $V^s(p'', \lambda, \theta) = 0$, or

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

Note, however, that

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

The equality follows by construction since inequality (B.9) requires $\theta > 0$ and, by assumption, $\lambda > 0$. The inequality follows from the fact that V^c is decreasing in the asking price and $p'' < p$. Similarly, $\bar{V}^u = V^u(p, \lambda, \theta) < V^u(p'', \lambda, \theta)$. The triple $\{p'', \lambda, \theta\}$ therefore satisfies the constraint set of problem (P$_1$) and, according to (B.10), achieves a higher value of the objective than $\{p_1, \lambda_1, \theta_1\}$: a contradiction. □

C Estimation Details

C.1 Cross Validation

We use a 5-fold cross validation procedure to select unknown hyperparameter involved in our estimation procedure. In particular, we aim to select the number of excluded bins to the left, L, and right R, the order of polynomial, p, and the estimation window, W, that determines how many house price bins are used in the estimation procedure. The latter can be thought of as a bandwidth choice for a local polynomial regression with rectangular weights (Imbens and Lemieux, 2008). In order to select the quadruple $\theta \equiv \{L, R, p, W\}$ we use a minimum mean squared error criterion.

We begin our procedure by splitting the microdata on houses into 5 groups in a structured way. We cross validate both steps of our estimating procedure, first constructing the reweighted distribution functions and then estimating the bunching regression. Since the construction of the CDFs depend on ordered data, we respect this by sorting the data in increasing order of house price. We construct fold 1 by taking the observations $n_1 \in \{1, k+1, 2k+1, ...\}$, the 2nd fold by taking observations $n_2 \in \{2, k+2, 2k+2, ...\}$, and so on, where $k = 5$ in our implementation.

We estimate both steps of our empirical procedure using observations in $n_1, \ldots, n_4$ and the only the first step of our procedure (the construction of the empirical distribution) using observations in the 5th fold. We iterate the second step of our empirical procedure over a grid of potential hyperparameter values in the set $L, R \in \{1, 2, \ldots, 8\}$, $p \in \{2, 3\}$, and $W \in \{20, 25, 30\}$. For each combination of these values, we fit the bunching estimator on folds $n_1, \ldots, n_4$ and using the estimated coefficients, predict the residuals on n_5. When estimating our bunching estimator, we impose the adding up constraints given in (9) and (10) to assist in regularization. These restrictions are not imposed in our estimation in our main text. We repeat this procedure five times, holding out a different fold each time. For

each choice of θ the cross-validation error is:

$$CV(\theta) = \frac{1}{W \cdot 5} \sum_k^5 \sum_j^W \left(\hat{\Delta}_S(y_j)_{n_k} - \widehat{\Delta_S(y_j)}_{\theta, n_{-k}} \right)^2$$

Where $\widehat{\Delta_S(y_j)}_{\theta, n_{-k}}$ are fitted values for the k fold from the bunching estimator estimated on folds n_{-k} with parameter values θ, W is the estimation window (the number of observations used in the bunching estimation). We choose as our optimal hyperparameters:

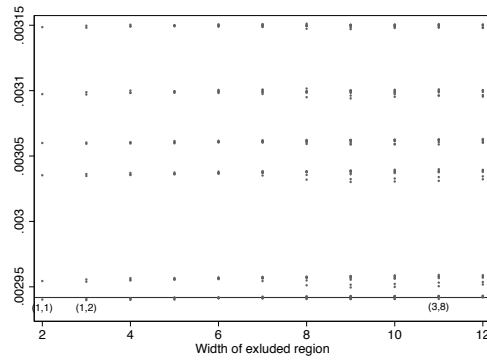$$\theta_{Opt.} = \mathrm{argmin}_{\theta \in \{\theta_1, \ldots, \theta_V\}} CV(\theta)$$

where V is the total number of combinations of parameter values in $\{L, R, p, W\}$. We also compute the standard error for the cross-validation, letting

$$CV_k(\theta) = \frac{1}{W} \sum_j^W \left(\hat{\Delta}_S(y_j)_{n_k} - \widehat{\Delta_S(y_j)}_{\theta, n_{-k}} \right)^2$$

we compute $SD(\theta) = \sqrt{\mathrm{Var}\,(CV_1(\theta), \ldots, CV_5)}$ and $SE = SD(\theta)/\sqrt{5}$ as the standard error of $CV(\theta)$. We use a 'one standard error rule': $CV(\theta) \leq CV(\theta_{opt.}) \pm SE(\theta_{Opt.})$ to find the widest and narrowest excluded region that is within one standard error of the optimum chosen $\theta_{Opt.}$. A graphical representation of this procedure is given in Figure A2. In the Panel (a), the root-mean squared error for each θ is plotted against the width of the excluded region (given by $L + R$) for asking price. Each dot on the figure represents one iteration of our procedure. The solid line gives the 'one standard error' rule. The points chosen by our procedure are labelled as (L, R). For instance, in panel (a), the optimum excluded region is given by $(4, 5)$, the narrowest by $(3, 4)$, and the widest by $(5, 5)$. Panel (b) shows the results for the sales prices. Notice that the CV values are much flatter and that no excluded region $(1, 1)$ is not rejected by the one standard error rule.
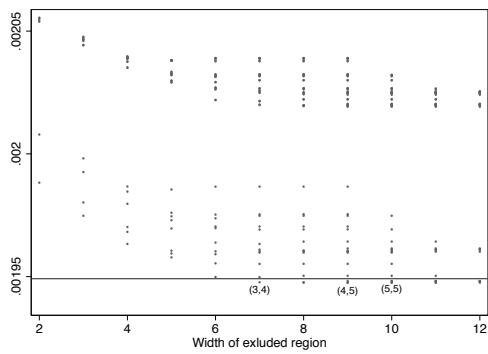
(a) Cross-Validation for Asking Prices   (b) Cross-Validation for Sales Prices

Figure A2: Cross-Validation Procedure

Notes: Panel (a) plots the root-mean squared error of each iteration of the cross-validation procedure for a given θ against the width of the excluded region for the city of Toronto using asking prices. Panel (b) plots the root-mean squared error of each iteration of the cross-validation procedure for a given θ against the width of the excluded region for the city of Toronto using sales prices. The chosen width of the excluded region is labelled on each panel.

C.2 Extensive Margin
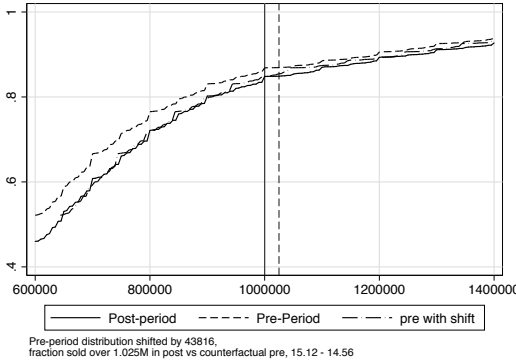
(a) CDFs for Asking Prices
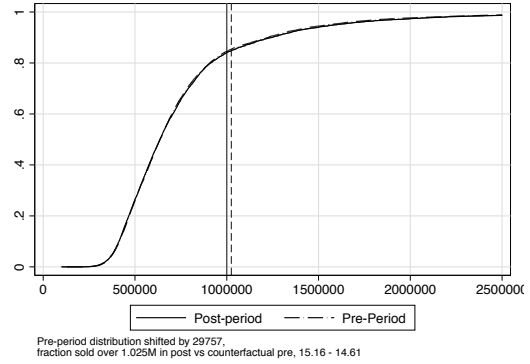
(b) CDFs for Sales Prices

Figure A3: Examining Extensive Margin Responses

Notes: Panel (a) Plots the CDF of asking prices for the pre- and post-policy period, along with a counterfactual leftward shifted pre-period CDF. Panel (b) plots the CDF of sales prices for the pre- and post-policy period, along with a counterfactual leftward shifted pre-period CDF.