The Effects of a Targeted Financial Constraint on the Housing Market*

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Abstract

We study the housing market implications of financial constraints by exploiting a regulatory change that increases the downpayment requirement for homes that sell for $1M or more. Using Toronto data, we find that the policy causes excess bunching of homes listed at $1M, heightened bidding intensity for these homes, but only a muted response in sales. While difficult to reconcile in a frictionless market, these findings are consistent with the implications derived from an equilibrium search model with auctions and financial constraints. Our analysis points to the importance of designing macroprudential policies that recognize the strategic responses of market participants.

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1 Introduction

This paper examines how financial constraints targeting a specific housing market segment impact house price formation. A growing class of "targeted" policies aim to cool a red-hot housing segment rather than the overall market. In Toronto and Vancouver, a higher downpayment has been required for homes purchased for over $1M. In New York and London, so-called "mansion taxes" have been imposed on purchases of all homes valued over $1M (USD) (since 1989) and over £1.5M (GBP) (since 2014), respectively.[1] While varied in their design, these policies impose additional financial constraints on prospective homebuyers in a particular segment relative to those in other segments, which in turn can affect a seller's decision to list a house and the choice of asking price. The central role of financial constraints makes them an appealing macroprudential vehicle for policymakers to intervene in housing markets, often for the purpose of "[ensuring] that shocks from the housing sector do not spill over and threaten economic and financial stability" (IMF Speech, 2014).[2] While financial constraints represent a recurring theme in the finance literature, there remains no micro analyses of the links between financial constraints and search behavior among housing market participants. Moreover, policies targeting a particular housing segment have just begun to attract serious attention from economists (e.g., Kopczuk and Munroe 2015). This paper fills the gap in the literature by examining how financial constraints affect price formation in the targeted segment of a frictional housing market. Our empirical methodology exploits a natural experiment arising from a mortgage insurance policy change implemented in Canada in 2012. 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

[1]Million dollar homes are not the mansions they used to be. In Toronto, a $1M (CAD) house represents the 86th percentile in 2012 but the 58th percentile in 2017. Furthermore, in 2019, a $1M (USD) home represents the 52nd percentile in San Francisco and the 33rd percentile in Manhattan among homes purchased with mortgages.

[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 1980–2012.

long boom, the government implemented the so-called "million dollar" policy that restricts access to mortgage insurance when the purchase price of a home exceeds one million Canadian dollars ($1M). Note that lenders are required to insure mortgages with loan-to-value ratios (LTV) over 80 percent. As such, the minimum downpayment jumps from 5 to 20 percent of the entire transaction price at a threshold of $1M, creating an increase of $150,000 in the minimum downpayment 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 a targeted financial constraint.

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 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 (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 that the million dollar policy tightens the financial constraints faced by a subset of buyers and limits how much they can bid on a house.[3]

We characterize the pre- and post-policy equilibria and derive a set of empirical predictions. The post-policy equilibrium features a mass of sellers with asking prices at the $1M threshold. These price adjustments can come from either side of $1M. In some circumstances, sellers lower the asking price from above $1M in order to attract both constrained and unconstrained buyers to compete for their homes. In other circumstances, sellers increase the asking price from below $1M to extract a higher payment when a bilateral situation arises. In both cases, the policy generates an excess mass of homes listed at $1M. As the bunching

[3] Others have studied auction mechanisms with financially constrained bidders (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.

response passes through to the sales price distribution, however, the effect on sales prices is mitigated by search frictions and bidding wars. For example, even though some sellers lower the asking price to $1M, the induced competition among constrained and unconstrained buyers creates a heated market just under $1M that both pushes the sales price above $1M and leads to shorter time-on-the market.

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 in the Greater Toronto Area, Canada's largest housing market. This market provides an ideal setting for this study for two reasons. First, home sellers in Toronto typically initiate the search process by listing the property and specifying a 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 caused two discrete changes in the market: one at the time the policy was implemented, and another at the $1M threshold. The market thus provides a natural experimental opportunity for examining the price response to targeted financial constraints.

Figure 1 presents the distribution of listings (left column) and sales (right column) in the segments around the $1M threshold. Panels A and B display frequency counts of asking prices in each $5,000 dollar bin during the pre- and post-policy periods, respectively.[4] In both periods, there is a substantial mass of listings right below $1M, possibly due to a psychological bias associated with the million dollar threshold. Panels C and F net out the time-invariant threshold effects by presenting the difference in the frequency of *listings* and *sales* between the post- and pre-policy periods, along with confidence interval bars.[5] The results are striking. First, there is a substantial and statistically significant positive jump in the number of *listings* in the $995,000 – $999,999 bin, suggesting that the policy induces excess bunching of listings at $1M. Second, this excess bunching appears to come from both

[4]The figure shows the raw frequency counts of Toronto homes for one year prior to the July 12th, 2012 policy implementation (the pre-policy period) and one year after the implementation (the post-policy period). The frequency counts were created by sorting the data by either asking or sales price and grouping into $5,000 dollar bins. The figure is restricted to within $100,000 dollars of the $1M policy threshold.

[5]Confidence bars were created by bootstrapping 399 random samples with replacement.

sides of the threshold, as reflected by the reduction in the number of homes listed in bins just to the left and right of the million dollar bin. Finally, the mass of *sales* in the million dollar segment is much less pronounced and statistically insignificant. Together, the evidence here, in its most descriptive form, lends support to the key implications of our model and forms the basis for our empirical estimation design.

Despite the appealing first-cut evidence presented in Figure 1, identifying the million dollar policy's impact on asking and sales prices is difficult for several reasons. First, 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. Second, the implementation of the policy coincided with a number of accompanying government interventions,[6] complicating the challenge of attributing any changes in the price distributions to the million dollar policy. In addition, while the overall market experienced a boom in our sample period, the boom was always larger in lower price segments. Thus a standard differences-in-differences approach that compares homes below \$1M with those above \$1M would not tease out the policy effect.

Our solution relies on a two-stage estimation procedure that examines changes in the price distribution. First, leveraging the richness of our data on house characteristics and using the well-known reweighting approach introduced by DiNardo et al. (1996), we decompose the observed before-after-policy change in the distribution of house prices 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. 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.

[6]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); lowered the maximum total debt service ratio (all housing expenses, credit card, and car loan payments relative to income) from 45% to 44% and fix the gross debt service (mortgage payments, property taxes, and heating costs relative to income) ratio at 39%. Source: "Harper Government Takes Further Action to Strengthen Canada's Housing Market." *Department of Finance Canada*, June 21, 2012.

Next, we measure the effects of the $1M policy by comparing the actual distribution of changes in the quality-adjusted price to a counterfactual distribution of changes in quality-adjusted price that would have prevailed in the absence of the policy, separately for asking and sales prices. Our approach employs a recently developed bunching estimation approach (Chetty et al. 2011, Kleven and Waseem 2013). The key idea is to use price segments that are not subject to the policy's threshold effects to form a counterfactual near the $1M threshold. By comparing the counterfactual distribution with the actual post-policy distribution around $1M, the bunching estimation allows us to difference out impacts of contemporaneous factors on house prices, such as other mortgage rule changes and market trends. Further, working with *changes* in price distributions over time allows us to net out any time-invariant threshold price effects unrelated to the policy, such as psychological bias.

Our main findings are the following. In the single-family-house market, the asking price distribution features large and sharp excess bunching 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 percent 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. In contrast, the policy adds only about 11 homes to *sales* in the million dollar bin, which is economically small and statistically insignificant. These findings are robust to an extensive set of specification checks, including a counterfactual constructed using only data below $1M, alternative functional forms, estimation windows and excluded regions, and different definitions of pre- and post-policy periods. We also find similar patterns in the condominium and townhouse markets.

The lack of excess bunching in the sales price, together 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' bidding behavior. Consistent with this interpretation, we find that housing segments right below the $1M threshold experience a shorter time on the market and a higher incidence of bidding wars, confirming the notion that the million dollar policy created a "red hot" market for home s listed just below $1M.[7]

While our main focus is on segments around $1M, we also go beyond the bunching estimation and examine the policy effects in segments far above $1M. An extensive margin response would imply that some transactions above $1M did not occur due to the additional financial constraint. An intensive margin response would imply a downward shift of the price distribution at least for some ranges in the above $1M segment. Either of these responses should manifest as a systematic discrepancy between the counterfactual post-policy price distribution and the observed post-policy price distribution for price bins above the $1M threshold. We do not find such discrepancies, which suggests that transactions well above $1M are not markedly affected by the policy, in line with the evidence that buyers at the high-end of this market are much less financially constrained.

Together, our findings contribute to a better understanding of policies that use a targeted financial constraints to temper a heated market segment. We find that the million dollar policy did not achieve the specific goal of cooling the housing boom in the million dollar segment. This is not because market participants did not respond to the policy. In fact, quite the opposite appears to be true: it is precisely the strategic responses of home sellers and home buyers that interact to undermine the intended impact of the policy on sales prices. Our analysis thus points to the importance of designing policies that recognize the endogenous responses of buyers and sellers in terms of listing strategies, search decisions and bidding behavior. Although the focus in this paper is on downpayment discontinuity at $1M, our analysis is broadly applicable to assessing the response of a frictional housing market to financial constraints targeted at any price threshold. With a larger share of constrained buyers, bunching at the targeted threshold increases.

Despite failing to curb house price appreciation, the policy may have nonetheless succeeded in improving the creditworthiness of home buyers. A key implication of the model is that when facing the $1M policy less constrained buyers have an advantage over constrained

[7] See "Ottawa's new rules creating 'red hot' market for homes under $999,999." Financial Post. July 3, 2013.

ones in multiple offer situations and hence have incentives to participate in the segment below \$1M. Consistent with this, we observe a reduced fraction of homebuyers with LTV above 80% even in the segment right below \$1M. Thus, the policy improves borrower creditworthiness not only for the segment above \$1M simply by its design, but also for the segment slightly below \$1M through influencing buyers' and sellers' search behaviors. More broadly, by reallocating million dollar homes from more constrained to less constrained homebuyers, the policy effectively prevents lenders from making more risky loans. As such, our analysis is also related to the recently advanced literature that finds the government-backed mortgages may create moral hazard for mortgage lenders to make more and riskier mortgage loans, thereby raising the likelihood of mortgage crises and compromising the stability of the financial system (Elenev et al. 2016). In this sense, the \$1M policy should be considered as one step toward "phasing out the GSEs," which may be welfare enhancing in the long run. Such benefits may be found in quantifying how the policy affects the mortgage market outcomes, which we view as an important area for future research.[8]

2 Literature Review

Financial constraints 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). Other strands of the literature examine the implications of financial constraints for market-level outcomes such as house price and trading volume (Stein, 1995; Ortalo-Magne and Rady, 2006; Favilukis et al., 2017). Turning to the empirical side, financial constraints have been examined in the form of downpayment constraints (Genesove and Mayer, 1997; Lamont and Stein, 1999), debt-to-income ratios (Demyanyk and Van Hemert,

[8] As preliminary evidence, we observe that in aggregate Canada exhibited a decrease in the fraction of new mortgage holders with a credit score below 660 after 2012. See Panel A of Figure A1 in Appendix A. We do not examine the policy effects on credit market outcomes for two reasons. First, we do not have micro-level mortgage data. Second, default is not widespread in Canada due to its highly regulated 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 percent in the U.S., but only 0.32 percent in Canada (and 0.23 percent in Toronto).

2011), existing home equity based borrowing (Mian and Sufi, 2011), mortgage contract terms (Berkovec et al., 2012), and innovations affecting the accessibility of mortgage credit (Vigdor, 2006). Our paper differs from this body of work in that we examine how a targeted financial constraint affects sellers' listing decisions and buyers' search bidding behavior, thereby affecting market outcomes such as sales price and time on the market. Our theoretical analysis 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 and an empirical setting permitted by a policy-induced natural experimental opportunity.

Financial constraints have also been a key element in the emerging literature on macroprudential policies. Significant contributions have been made towards our understanding how these policies affect financial stability and mortgage efficiency (Elenev et al., 2018; Acharya et al., 2018; Van Bekkum et al., 2017). In the Canadian context, Allen et al. (2016) examine the impact of macroprudential policies on mortgage contract characteristics and mortgage demand. In the U.S. context, by exploiting a sharp policy-induced discontinuity in the cost of originating high-leverage mortgages, DeFusco et al. (2019) find that the Dodd-Frank "ability-to-repay" rule, through affecting the income constraint, has modest effects on the interest rate but large effects on the quantity of borrowing. Our paper shares a similar spirit in that we exploit a sharp regulatory cut-off affecting the downpayment constraint, but differs in that we focus on *housing market outcomes*.

With respect to the empirical methodology, our work follows a recent and growing 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. (2011) and then extended to the analysis of tax *notches* by Kleven and Waseem (2013). 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 and Paciorek (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.

3 Background

3.1 Mortgage Insurance

Mortgage insurance is an instrument used to transfer mortgage default risk from the lender to the insurer and represents a key component of housing finance in many countries including the United States, the United Kingdom, the Netherlands, Hong Kong, France, and Australia. These countries share two common features with Canada: (i) the need to 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 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 two private insurers, Genworth Financial Mortgage Insurance Company Canada (Genworth) and Canada Guaranty. All three institutions benefit from guarantees provided by the Canadian government and therefore are subject to federal regulations through the OFSI.

In practice, while it is possible for buyers to obtain uninsured residential mortgages with a loan-to-value ratio greater than 80 percent from unregulated lenders, we find that private lending accounted for only 4% of all loans in the Greater Toronto Area in 2013 and this sector did not experience any noticeable growth around the $1M policy period. The reason is that, compared to traditional mortgages from regulated lenders, private mortgages on average have one-fifth duration, over three times higher interest rates, and loan amounts that are one-third of the size. Hence they operate in a small disparate niche corner of the Canadian mortgage market.[9] In addition, anecdotal 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."[10] As home prices in Canada continued to escalate post-financial crisis, the Canadian government became increasingly concerned that rapid price appreciation would eventually lead to a severe housing market correction.[11] To counter the potential risks associated with this house price boom, the Canadian government implemented several rounds of housing market macroprudential regulation, all through changes to the mortgage insurance rules.[12] This paper examines the impact of the so-called "million dollar" policy that prevents regulated lenders from offering mortgage loans with LTV ratios above

[9] See *Bank of Canada Financial System Review* (June 2018) for the statistics reported here and relevant discussions.

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

[11] In 2013, Jim Flaherty, Canada's Minister of Finance from February 2006 to March 2014, stated: "We [the Canadian government] have to watch out for bubbles - always - . . . including [in] our own Canadian residential real estate market, which I keep a sharp eye on." Sources: "Jim Flaherty vows to intervene in housing market again if needed." *The Globe and Mail*, November 12, 2013.

[12] These changes included increasing minimum down payment requirements (2008); reducing the maximum amortization period for new mortgage loans (2008, 2011, 2012); reducing the borrowing limit for mortgage refinancing (2010, 2011, 2012); increasing homeowner credit standards (2008, 2010, 2012); and limiting government backed mortgage insurance to homes with a purchase price of less than one million Canadian dollars (2012).

80 percent 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.[13]

4 Theory

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

4.1 Environment

Agents. There is a fixed measure $\mathcal{B}$ of buyers, and a measure of sellers determined by free entry. Buyers and sellers are risk neutral. Each seller owns one indivisible house, their value of which is normalized to zero. 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 or debt-service constraint.[14]

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 un-

[13] See "High-end mortgage changes seen as return to CMHC's roots." *The Globe and Mail*, June 23, 2012.
[14] A non-binding constraint (i.e., $u > v$) would have the same implications as the case where $u = v$ in the analysis that follows.

able 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 such as a minimum downpayment requirement following the implementation of the policy.[15] Buyers with financial constraint c are hereinafter referred to as *constrained* buyers, whereas buyers willing and able to pay up to u are termed *unconstrained*.

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

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

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

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

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

Price determination. The price is determined in a sealed-bid second-price auction. The seller's asking price, $p \in \mathbb{R}_+$, is interpreted as the binding reserve price. If a single bidder submits an offer at or above p, he pays only p. In multiple offer situations, the bidder

[15]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 policy means that buyers with wealth levels less than \$200,000 must bid less than \$1M.

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

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

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

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

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

and the closed-form expression is

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

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

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

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:*

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

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 $\Lambda = 0$.[16] 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

[16] 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 $\{p_0, 0, \theta_0\}$.[17] 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* $\mathbb{P} = \{p_0\}$, $\theta(p_0) = \theta_0$, $\sigma(p_0) = \mathcal{B}/\theta_0$ *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 equi-

[17] 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

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

librium asking price tends to zero (i.e., $p_0 = p_u^* \to 0$), which is the seller's reservation value. This aligns with standard results in the competing auctions literature in the absence of bidding limits (McAfee, 1993; Peters and Severinov, 1997; Albrecht et al., 2014; Lester et al., 2015). When buyers' bidding strategies are somewhat limited (i.e., $p_0 = p_u^* \leq u < v$), sellers set a higher asking price to capture more of the surplus in a bilateral match. The equilibrium asking price is such that the additional bilateral sales revenue 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. This the economic interpretation 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., $\theta_u > \theta_u^*$).

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 both sellers and unconstrained buyers:

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

Let $\{p_1, \lambda_1, \theta_1\}$ denote the solution to problem P_1 when $\bar{V}^u$ is set equal to the maximized objective of problem P_0. The bidding limit once again limits the set of worthwhile submarkets. In particular, the optimal submarket for constrained buyers must feature an asking price less than or equal to c. If the solution is interior, it satisfies the two constraints with equality and a first-order condition derived in Appendix 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 $\mathbb{P} = \{p_0, p_1\}$, $\lambda(p_0) = 0$, $\lambda(p_1) = \lambda_1$, $\theta(p_0) = \theta_0$, $\theta(p_1) = \theta_1$, $\sigma(p_0) = (\lambda_1 - \Lambda)\mathcal{B}/(\lambda_1\theta_0)$, $\sigma(p_1) = \Lambda\mathcal{B}/(\lambda_1\theta_1)$, $\bar{V}^c = V^c(p_1, \lambda_1, \theta_1)$ 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.

The incentive to search alongside constrained buyers in a submarket distorted by a binding financial constraint is increasing in the share of buyers constrained by the policy. If the fraction of constrained buyers is not too high (i.e., $\Lambda < \lambda_1$), the DSE features partial pooling.

That is, only some unconstrained buyers search for homes priced at p_1 while the rest search in submarket p_0.[18] As $\Lambda \to \lambda_1$, it can be shown that $\sigma(p_0) \to 0$ and the DSE converges to one of full pooling, with all buyers and sellers participating in submarket p_1. Finally, if $\Lambda > \lambda_1$, market clearing (part 2 of Definition 1) is incompatible with unconstrained buyer indifference between these two submarkets, which begets the possibility of full pooling with unconstrained buyers strictly preferring to pool with constrained buyers. We restrict attention to settings with $\Lambda \leq \lambda_1$ for the analytical characterization of equilibrium and rely on numerical results for settings with $\Lambda > \lambda_1$.[19]

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. 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 and Λ reflects the share of potential buyers with insufficient wealth from which to draw a 20 percent downpayment.[20]

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, but that the additional financial constraint imposed by the policy is sufficiently

[18] The partial separation of unconstrained buyers in this case arises because the source of heterogeneity is bidders' *ability to pay* and not their *willingness to pay*. A similar environment with heterogeneous valuations rather than financial means would not necessarily deliver more than one active submarket in equilibrium (Cai et al., 2017).

[19] 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 $\Lambda \leq \lambda_1$.

[20] 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 expressed relative to the seller's reservation value. So as to avoid awkward wording, we hereinafter use the \$1M threshold to refer to the price point *just under* \$1M.

severe. 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 derive several testable predictions that we bring to the data in Sections 6.1, 6.2 and 6.3.

Prediction 1. *The million dollar policy motivates some sellers to change their asking price to \$1M. This asking price response corresponds to "bunching from below" if $p_0 < p_1$, or "bunching from above" if $p_0 > p_1$.*

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 million dollar policy can thus induce a strategic response among sellers in market segments near the newly imposed financial constraint. If $p_0 < p_1$, some sellers who would have otherwise listed below c respond to the policy by increasing their asking price to the threshold. The intuition for *bunching from below* is the following: as buyers become more constrained, the distribution of possible sales prices features fewer extreme prices at the high end. Sellers respond by raising their asking price to effectively truncate the distribution of prices from below. The higher price in a bilateral situation can offset (in expectation) 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 p_1. If instead $p_0 > p_1$, the policy induces 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.

Prediction 2. *Bunching at \$1M in asking prices only partially passes through to the sales price distribution because of search frictions and bidding wars.*

The frictional matching process between buyers and sellers results in some homes failing to sell. With probability $e^{-\theta_1}$, a seller listing a home post-policy at price $p_1 = c$ does not meet even a single buyer. The auction mechanism further reduces the mass of sales relative to listings at price c. With probability $1 - e^{-(1-\lambda_1)\theta_1} - (1 - \lambda_1)\theta_1 e^{-(1-\lambda_1)\theta_1}$, competition among unconstrained bidders in submarket p_1 escalates the sales price up to u.

This bidding war effect intensifies (diminishes) in response to the million dollar policy if $p_0 > p_1$ ($p_0 \leq p_1$). This is related to the ratio of unconstrained buyers to sellers and relies on the indifference condition for unconstrained buyers between submarkets p_0 and p_1. If $p_1 < p_0$, the 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 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 raises asking prices but lowers the probability of multiple offers from unconstrained buyers.

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. We should therefore expect a more dramatic impact of the million dollar policy on asking prices than sales prices.

Prediction 3. *The million dollar policy increases the probability of selling above asking and shortens expected time-on-the-market for homes listed below \$1M. This results in discrete jumps in the probability of selling above asking (downward) and in expected time-on-the-market (upward) at asking price \$1M.*

At asking price $p_1 = c$, the presence of constrained buyers does not alter the payoff to an unconstrained buyer. This is because, in a second price auction with reserve price exactly equal to constrained buyers' ability to pay, offers from constrained buyers affect neither the probability of winning the auction nor the final sales price when an unconstrained buyer bids u. For submarkets priced above c, these constrained buyers cannot afford to participate. Given that $\bar{V}^u$ is unchanged by the policy, it follows that the ratio of unconstrained buyers to sellers is also unaffected by the policy in any submarket asking c or more. The policy, however, induces the participation of constrained buyers in submarket c and a range of inactive submarkets below c. Submarkets that attract both constrained and unconstrained buyers post-policy feature higher market tightness because the presence of constrained buyers does not deter unconstrained buyers. On the contrary, unconstrained buyers are drawn to these submarkets because they have an advantage when competing bidders face tighter financial constraints. The resulting discontinuous drop in market tightness at asking price c can be understood as discontinuous reductions in both the probability of selling and the probability of receiving multiple offers and hence selling above asking. The inverse of the probability of selling in the static model proxies for expected time-on-the-market in a dynamic setting. Prediction 3 therefore summarizes the implications for time-on-the market. Specifically, the million dollar policy causes homes listed just below \$1M to sell faster, as well as induces a discontinuous increase in average selling time at the threshold.

In Appendix B.5, we illustrate Predictions 1, 2 and 3 by simulating a parameterized version of the model that has been extended to incorporate a form of seller heterogeneity. Specifically, sellers with different reservation values implement different asking price strategies, which permits the characterization of equilibria featuring *bunching from both above and below* simultaneously. Figures A2 and A3 plot the asking and sales price distributions. These simulated distribution functions reveal an excess mass of listings at \$1M from both above and below the threshold (Prediction 1), and a much less pronounced excess mass of sales at \$1M (Prediction 2). Figures A4 and A5 present visualizations of Prediction 3 by plotting expected time-to-sell and the probability of selling above asking as functions of the asking price.

While the model is not designed to examine the impact of a targeted financial constraint on the *entire* house price distribution, it can, however, be used to assess the impact of a hypothetical financial constraint applied to *any* targeted segment, just with a reinterpretation of the threshold parameter c. A key difference between a policy that is targeted at $1M and a policy that is targeted at an alternative threshold, say $500,000, is that buyers in a lower price segment are typically more constrained than those in a higher price segment.[21] Motivated by this, we now examine the role of the fraction of constrained buyers in determining the policy effects. In this regard, the model implies a sharper bunching of asking and sales prices at bidding limit c if the constraint impacts a larger fraction of potential buyers of homes in the targeted segment. Intuitively, when more buyers are constrained (larger Λ), then more sellers optimally adjust their asking price to c to compete for a larger number of buyers in the pooling submarket. In the context of the $1M policy, this yields the following prediction.

Prediction 4. *The shares of listings and sales bunched at $1M increase with the share of buyers constrained by the million dollar policy.*

Given that λ_1 and θ_1 are independent of Λ, the post-policy measure of sellers in submarket p_1, $\sigma(p_1)$, increases linearly with Λ (see Proposition 2). In contrast, the post-policy $\sigma(p_0)$ decreases linearly with Λ. Conditional on being listed in submarket $p_1 = c$, the probability of selling for a price of c is one minus the probability of its complement:

$$1 - e^{-\theta_1} - \left[1 - e^{-(1-\lambda_1)\theta_1} - (1-\lambda_1)\theta_1 e^{-(1-\lambda_1)\theta_1}\right].$$

As it depends only on λ_1 and θ_1, the probability of selling at c is independent of Λ. It follows that the measure of transactions at price c is proportional to the measure of listings at price c, and hence proportional to Λ.

Our analysis so far has focused exclusively on housing market outcomes. On the normative side, the model implies that the policy reduces the social surplus derived from housing market activity, as it affects the entry decision of sellers and hence market tightness, distorting the total number of housing market transactions.[22] It is worth noting that the million

[21]Between 2011-2012, the fraction of mortgages with less than 20% downpayment is about 31% among those who purchase over $500,000 homes and about 9% among those who purchase over $1M in the city of Toronto.

[22]The welfare maximizing level of housing market activity is achieved in the pre-policy DSE, provided the

dollar policy was introduced not only to cool housing markets but also to improve financial stability and mortgage market efficiency. The latter is a central theme in the recent macro-finance literature on macroprudential policies.[23] Although the model is not designed to assess the policy's impact on borrowers' creditworthiness, it nevertheless offers an important insight in this regard. In particular, less constrained buyers have an advantage over constrained ones in multiple offer situations, and as such we would expect post-policy home buyers to be wealthier and hence more "creditworthy.[24]

Prediction 5. *An unconstrained buyer is more likely to purchase a house than a constrained buyer following the introduction of the million dollar policy.*

4.4 Caveats about Modeling Assumptions

Further discussion of some features of the model is in order. First, the asking price is assumed to represent a firm commitment to a minimum price, which results in a sales price either above or at the asking price. In practice, sales prices can be above, at, and below asking prices. Embellishing the price determination mechanism may allow for transaction prices below asking prices without compromising the asking price-related implications of the theory.[25] The theory of asking prices advanced in Khezr and Menezes (2018), for example, considers the situation wherein sellers learn their reservation value *after* setting an asking price and observing buyers' interest. As in our setting, transactions at the asking price arise

pre-existing financial constraint is slack in problem P_0.

[23]See Jeske et al. (2013), Clerc et al. (2015), Elenev et al. (2016), Elenev et al. (2018) and Begenau (2019).

[24]In the post-policy DSE, the buying probabilities for constrained and unconstrained buyers are

$$\pi(0) + \sum_{k=1}^{\infty} \pi(k)\phi_k(0)\frac{1}{k+1} = \frac{e^{-(1-\lambda_1)\theta_1} - e^{-\theta_1}}{\lambda_1\theta_1} \quad \text{and} \quad \pi(0) + \sum_{k=1}^{\infty} \pi(k)\sum_{j=0}^{k}\phi_k(j)\frac{1}{j+1} = \frac{1-e^{-(1-\lambda_1)\theta_1}}{(1-\lambda_1)\theta_1}.$$

The probability of success in purchasing a house for unconstrained buyers therefore exceeds that for constrained buyers by

$$\frac{1-e^{-(1-\lambda_1)\theta_1}}{(1-\lambda_1)\theta_1} - \frac{e^{-(1-\lambda_1)\theta_1} - e^{-\theta_1}}{\lambda_1\theta_1} = \frac{1}{\lambda_1}\left[\frac{1-e^{-(1-\lambda_1)\theta_1}}{(1-\lambda_1)\theta_1} - \frac{1-e^{-\theta_1}}{\theta_1}\right] > 0.$$

[25]See Albrecht et al. (2016) and Han and Strange (2016) for more sophisticated pricing protocols that can account for sales prices above, at, and below the asking price.

in bilateral meetings; but unlike our model, multilateral meetings can, in some circumstances, result in transactions below the asking price. Alternative price determination mechanisms would add considerably to the analytical complexity of the model. Such extensions, however, would not affect our theoretical results substantively as long as (i) the asking price remains meaningful (in expectation) for price determination in a bilateral match, and (ii) competition among bidders in a multilateral match tends to drive up the sales price. The former is to ensure the directing role of the asking price, which is key for establishing Prediction 1. The latter is to allow for price escalation in multilateral matches so that sellers can list at $1M in response to the policy but may still end up selling for more. This is important for Prediction 2.

Second, 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. 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.

Finally, the scope of the model shrinks to a narrow segment of the market around $1M if the parameter values for v, u and c are close to the seller's reservation value, which is normalized to zero. The 20% downpayment constraint also reduces the maximum affordable price for buyers in segments well above $1M. The model's implications for these segments are the same as the $1M segment, albeit with a reinterpretation of parameter c. In these segments well above $1M, however, the downpayment requirement is continuous in the sales price, which makes it empirically challenging to identify the policy effects on buyers' and sellers' strategies and price formation. In contrast, the policy creates a discrete change in the downpayment requirement at the $1M threshold. The degree of excess bunching at $1M in the data, which we turn to next, provides evidence on the extent to which buyers and sellers respond to this targeted financial constraint.

5 Data and Methodology

5.1 Data

Our dataset includes transactions of residential homes 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. In particular, we define a number of variables to control for house quality. We create indicator variable for whether the house is detached, semi-detached, condominium or townhouse. 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 $\geq$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.

We observe the final asking price posted in each listing, not the changes in the asking price. Overall, about 12.23% of listings experienced changes in the asking price. This number reduces to 2% when it comes to the estimation sample of properties around $1M. For 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 do so because a seller's list decision depends on the perceived ability to pay among potential buyers, which in turn depends on whether the policy is implemented. We assess the sensitivity of our results to different time windows of the pre- and post-policy periods in a later robustness section.

For the main analysis, we focus on single-family homes in the city of Toronto.[26] Table 1 contains summary statistics. 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 CAD). 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

[26]The geographic area of our study includes the city of Toronto and the immediate bordering 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.

in the Central district. The central district contains nearly 40 percent of the homes sold within the \$0.9M-1.1M price range. In the empirical analysis below, we will examine the policy impact separately for the city of Toronto, central Toronto and suburban Toronto.

5.2 Empirical Methodology

We now present empirical tests of Predictions 1 and 2 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. 2011, 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. To test this, we 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). To implement this, 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).[27] 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

[27] 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.

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.

In particular, consider the equation:

$$\begin{aligned}\hat{\Delta}_S(y_j) = \sum_{i=0}^{p} \beta_i \cdot y_j^i + \beta_A \cdot 1[y_j = \$1\text{M}] + \beta_B \cdot 1[y_j = \$1\text{M} - h] \\ + \sum_{l=1}^{L} \gamma_l \cdot 1[y_j = \$1\text{M} - h \cdot (1+l)] + \sum_{r=1}^{R} \alpha_r \cdot 1[y_j = \$1\text{M} + h \cdot r] + \epsilon_j \quad (7)\end{aligned}$$

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.[28]

[28] 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.

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

$$\underbrace{\hat{\Delta}_S(\$1\text{M}) - \hat{\Delta}_S(\$1\text{M} - h)}_{\text{Jump at threshold}} = \underbrace{\sum_{i=0}^{p} \hat{\beta}_i \cdot y^i_{\$1\text{M}} - \sum_{i=0}^{p} \hat{\beta}_i \cdot y^i_{\$1\text{M}-h}}_{\text{Counterfactual (C)}} + \underbrace{\underbrace{\hat{\beta}_A}_{\text{Bunching from above (A)}} - \underbrace{\hat{\beta}_B}_{\text{bunching from below (B)}}}_{\text{Total Policy Response}} \tag{8}$$

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 above imply the following two constraints. First, 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, 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.[29]

[29] 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., 2011)

Caveat. 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 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.

Another potential concern is that the million dollar policy is announced in combination with three other mortgage rule changes, which may complicate the challenge for identification. However, unlike the million dollar policy, these contemporaneous mortgage rule changes apply to the entire housing market.[30] Their housing market impacts are accounted for in the counterfactual price distribution that would have prevailed in the absence of the million dollar policy. By comparing the actual post-policy distribution of house prices to the counterfactual distribution, the bunching estimation teases out the effect of the million dollar policy from these confounding factors. To address the possibility where the impact of these rule changes on buyer and seller strategies may shift at some threshold or scale non-linearly in a way that is not reflected in the counterfactual distribution, we implement several placebo experiments that use alternative cut-offs in Section 6.1.1 and by using only data below $1M to construct the counterfactual distribution in Section 6.1.2.

In addition, our analysis hinges on the assumption that homes further below $1M are

in combination with an iterative procedure (Kleven and Waseem, 2013; DeFusco and Paciorek, 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.

[30] See footnote 6 for details.

unaffected by the policy. This is by design of the million dollar policy. One potential concern is that a seller of a below-$1M home is also a buyer for an above-$1M home. The seller may be constrained in that the proceeds from the sale of their current home must not compromise their ability to make a 20% downpayment on their next home. To that end, there may be an incentive to raise the asking price at the cost of a longer time-on-the-market. However, our counterfactual distribution is constructed from an estimation window that starts at $900,000. A seller/buyer hoping to trade up from a $900,000 home to a $1.2M home will likely be able to cover the downpayment required for the purchase of their next home using the net proceeds from the sale of their current home. For this reason, we do not believe the "trading-up" constraint poses a threat to our identification assumption.

Finally, it is worth comparing the bunching estimation approach with a differences-in-differences approach. While a standard differences-in-differences approach may allow us to consider broader market responses from segments above $1M, it cannot successfully isolate the policy effect in our sample market where lower price segments tended to experience a larger price boom.[31] Our bunching estimation is similar in spirit to the first-differenced, regression discontinuity design in Lemieux and Milligan (2008) in that the first difference compares sales between the pre- and post-policy periods, and the second difference compares the distribution of changes in sales across the threshold to a parametric counterfactual that would have prevailed in the absence of the $1M policy. Unlike a differences-in-differences approach, the narrow data-driven estimation window used in bunching estimation makes for a less stringent identification requirement.[32] Moreover, within this narrow estimation window, the non-$1M-policy-driven variation in house prices across segments is captured by the counterfactual. As a result, the bunching approach allows us to disentangle the effect of the million dollar policy from other macro forces that are continuous across the policy threshold.

[31] See page 35 for the discussion about the lack of parallel pre-trends as shown in Figures 3 and 4.

[32] For example, one would not expect the $295,000 homes to experience similar price growth as the $1,025,000 homes, but such assumption may not be too strong when we compare homes of $925,000 with homes of $975,000.

6 Empirical Evidence

Given that the strength of our data comes from the housing market rather than the mortgage market, our core estimation examines the policy effects on house market outcomes, including asking and sales price in Section 6.1 and time-on-the market in Section 6.2. Using limited information about borrowing, we present facts consistent with Predictions 4 and 5 in Section 6.3.

6.1 Predictions 1 and 2: The Policy Effects on Asking Price and Sales Price

The main predictions of the model are that the million dollar policy leads to an excess mass of homes listed at the $1M threshold (Prediction 1), which only partially passes through to the sales price distribution (Prediction 2).

Our main analysis focuses on single-family-house markets. Figures 3 and 4 present graphical results from the first step estimation of asking and sales price distributions based on equation (6). We first discuss asking prices. Panel A of Figure 3 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. 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, again indicating that houses in general are becoming more expensive over time. The *difference* in CDFs is upward sloping, indicating that the boom in lower price segments is larger than in higher ones, even among homes that are well below $1M. Thus a standard differences-in-differences analysis that compares homes above $1M with those below $1M would not be able to tease out the policy effect.

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' updated listing strategies generally changes smoothly with price, with a relatively large jump at $1M. Given the minimal composition effect, nearly all of the difference in the observed distribution of asking prices is driven by sellers' listing behavior.

Turning to the sales prices, the top panels of Figure 4 plot the distribution of sales price in the pre- and post-policy years and their differences. The bottom panels of Figure 4 show that after accounting for the composition effect, 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.

The descriptive findings presented in Figures 3 and 4 are consistent with the model. However, this evidence alone does not distinguish the policy effects from the impact of other contemporaneous macro forces. To isolate the million dollar policy's effects on the price distributions, we now turn to the second step estimation – bunching estimation. We choose to plot the bunching estimates in both the CDFs and the PDFs. While the latter is more standard in the bunching literature, the former allows us to visualize the decomposition of the estimated jump based on equation (8) in a more transparent way.

Figure 5a presents a graphical test of Prediction 1 based on the estimation of equation (7). In particular, we plot changes in the CDFs of the asking price, $\hat{\Delta}_S(y_j) = \hat{F}_{Y\langle 1|0\rangle}(y_j) - \hat{F}_{Y\langle 0|0\rangle}(y_j)$, holding housing characteristics constant. The solid line plots the quality-adjusted observed changes, with each dot representing the difference in the CDFs before and after the policy for each $5,000 price bin indicated on the horizontal axis. The dashed line plots the counterfactual changes in the absence of the policy, 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 on each side of 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 empirical distribution of asking prices exhibits a sharp discontinuity at the $1M threshold. After the policy, a total of 0.45 percent of listings were added to the $1M bin. Following equation (8), Figure 5a decomposes this total jump into three distinct components: 0.06 percent of listings reflect the counterfactual change in the absence of the million dollar policy (marked by C), 0.18 percent of listings bunched from below (marked by B) and 0.20 percent of listings bunched from above (marked by A). Thus, 87% (i.e., (A+B)/(A+B+C)) of the excess bunching in the asking price at the $1M threshold is attributed to the policy.

Figure 5b 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 underlying the above graphical presentation. The specification used is chosen by the cross-validation procedure outlined above. Standard errors are calculated via bootstrap.[33] Overall, we find that approximately 86 homes that would have otherwise been listed away from $1M were shifted to the $1M bin. While seemingly small, 86 additional homes represent a 38.3 percent increase relative to the number of homes that would have been listed in the million dollar bin in the absence of the policy. 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. When viewed through the lens of our search model, price adjustments from both sides of $1M are quite sensible. On the one hand, the 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 to

[33]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.

offset any price dampening effect of the policy in multilateral situations. On the other hand, the policy induces other sellers who would have otherwise listed homes above \$1M to lower their asking price to just below the cut-off, attracting both constrained and unconstrained buyers to compete their homes.

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.

Turning to Prediction 2, we report the bunching estimates for the sales price in Table 3, with a visualization of the estimates shown in Figures 6a and 6b. 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 and highly consistent with Prediction 2. In light of the model, the policy's intention to dampen sales price is mitigated by buyers' and sellers' strategic behavior in terms of listing and bidding in a frictional market with competing auctions. To test this interpretation, we estimate the policy effect on bidding intensity in Section 6.2.

It is worth noting again that we do not observe sellers' revisions to asking prices from the main data. With a one-time access to a local brokerage office's confidential database, we find that about 44 houses in the estimation sample (2% of all sold houses in [\$900,000,

$1,100,000]) were originally listed before the policy, pulled off the market, re-listed after the policy and then sold. Restricting the attention to these 44 houses, Figure 7 shows that 40% of them adjusted their asking price to [$975,000, $1,000,000]. These adjustment comes from two sides. In particular, out of 22 houses that were listed between [$1,000,000, $1,100,000] before the policy, 14 houses (64%) reduced their price to just under $1M after the policy, supporting the notion that some sellers lower the asking price to invite competition from both constrained and unconstrained buyers. These observed changes in the asking price complement the counterfactual results generated from our bunching estimation and further strengthen our main results.

So far our analysis has been on the single-family-house market. As shown in Table C.2, in the city of Toronto, condominiums and townhouses are an equally important sector with 21,768 transactions in the pre-policy period. While a $1M home corresponds to the 86th percentile in the single-family-house market, it corresponds to the 99th percentile in the condominium and townhouse market. We repeat the estimation above for this market and present the results in Table 4. The million dollar policy adds 19 listings at $1M and 12 sales at $1M, again confirming Predictions 1 and 2. Quantitatively, the degree of bunching in the condominium and townhouse market is much smaller than that in the single-family-house market, for both the asking and sales price. This is consistent with the fact that there are much fewer million dollar condominiums than houses. Given the small number of million dollar condominiums and townhouses, we focus the analysis hereafter on the single-family-house market.

6.1.1 Robustness Checks

In this section, we estimate an extensive set of specifications to assess the robustness of our main results. Our first empirical exercise deals with the concern that the bunching estimates may be altered by the possible responses above the $1M threshold. By design, the million dollar policy affects not only homes around the $1M threshold but also all homes above $1M. 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 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 unaffected by the policy. These results are presented in column (7) 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.[34] These results are similar to the other columns of the tables, reassuring the robustness of our main bunching estimates.

Our next empirical exercise involves two *placebo tests* as additional checks on our identification strategy. 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 5 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. In a similar spirit, in Table 6, we compare the last six months of 2011 with the first six months of 2012 in column (4) and the last six months of 2012 and the first six months of 2013 in column (5). The former are two periods before the million

[34] 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 negative to the left of $1M ($\gamma_l < 0$) and positive in the excluded region in the bins above $1M ($\alpha_r > 0$). 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 restricts the extrapolated polynomial counterfactual to lie between the observed $\hat{\Delta}_S(y_j)$ within the excluded region.

dollar policy, the latter are two periods after the policy. As expected, we find no evidence of excess bunching in asking or sales prices around the $1M threshold.

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 represent contradictory evidence.

Table 5 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 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.

Finally, we assess the robustness of our main results to alternative choices of the pre- and post-policy period. 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 column (1) of Table 6, we use 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. By leaving six months between the two periods out of estimation, we also tease out the impact of properties that may have been listed before the policy and sold after the policy. Across all these specifications, the bunching estimates are remarkably consistent, highlighting the robustness of the main findings. Table 7 repeats this exercise using sales prices. Again, we find that our main results are not sensitive to the choice of the pre- and post-policy time periods.

6.1.2 Policy Responses Above $1M

The million dollar policy affects not only homes around the $1M threshold but also all homes above $1M. Lacking a discrete change in the downpayment requirement in the segments far above $1M, the bunching approach cannot be used to estimate policy consequences there.

In this section, we design an alternative approach to examine the possible price responses above the $1M threshold. An extensive margin response in these segments would imply that some transactions above the $1M threshold did not transpire due to the additional financial constraint. An intensive margin response would occur if some prices above $1M are lower than they would have been in the absence of the policy. Either of these responses should manifest as a systematic discrepancy between the counterfactual post-policy price distribution that would have occurred in the absence of the million dollar policy and the observed post-policy price distribution for price segments above the $1M threshold.

Following Chernozhukov et al. (2013), we form a counterfactual post-policy sales price distribution as follows. We estimate composition-adjusted sales distributions for the pre- and post-policy periods, and invert them to obtain pre- and post-policy quantile functions. A quantile function in this context determines the sales price at which the probability of a house being sold for less than or equal to this price is equal to a given probability. We first regress the post-policy quantile function on the pre-policy quantile function, using only data below $900K. We 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 any trend affecting the 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 price segments below $900K. We then invert the counterfactual quantile function to recover a counterfactual post-policy sales price distribution.[35] Finally, we compare this counterfactual distribution to the observed post-policy sales price distribution to make inferences about the policy effects above $1M.

Panel (a) of Figure 8 displays the observed pre- and post-policy sales price distributions as well as the counterfactual distribution constructed according to the procedure outlined above. Two patterns emerge. First, the pre-policy quantile function lies everywhere below the post-policy 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 segments are minimal.

Panel (b) of Figure 8 further plots the differences between the observed and counterfactual post-policy distributions along with a confidence interval.[36] We also plot the difference between the observed distributions as a reference. Had the policy either inhibited sales or dampened prices in segments above $1M, we would expect a systematic difference between the observed and counterfactual post-policy price distributions above the 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.

In summary, we do not find evidence that the million dollar policy impacted home sales well above the $1M threshold. This may not be surprising given that $1M was at the 86th percentile of the house price distribution in 2012. Homes far above $1M thus represent very high-end segments. Buyers in these segments are among the wealthiest individuals in Canada and hence not likely financially constrained. Restricted-access Bank of Canada mortgage data show that, during the pre-policy year in our sample market, the fraction of

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

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

homebuyers with less than 20% downpayment was 18.33% for the million dollar segment but only 7.61% for segments above \$1.1M. The tightened downpayment constraint induced by the million dollar policy would therefore mostly hit buyers of homes priced around \$1M, rather than buyers of homes priced well above \$1M. This is consistent with our findings.

6.2 Prediction 3: The Policy Effects on Sales above Asking and Time on the Market

Turning to the policy effects on market liquidity, Prediction 3 states that the million dollar policy reduces expected time-on-the-market and increases the incidence of sales above asking for homes listed just under \$1M. The policy further triggers a discontinuous increase in the expected time-on-the-market and a discontinuous decrease in the probability of selling above asking price right at asking price \$1M.

We bring this prediction 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, 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 described in Section 5.2.1, 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. In Figure 9(a), changes in the probability of being sold above asking exhibit a discrete downward jump at \$1M, with an upward sloping curve to the left of \$1M. In 9(b), changes in the probability of staying on the market for more than two weeks exhibit a discrete upward jump at \$1M, with a downward sloping curve to the left of \$1M. The evident discontinuity at \$1M for time-on-the-market and sales above asking is highly aligned with Prediction 3, suggesting that the mitigated policy effects on sales price is at least partially achieved through heightened competition for homes listed just under \$1M. Moreover, Figures 9(c) and 9(d) display changes in these two variables during two years prior to the policy. It is clear that changes in sales-above-asking is a smooth function of asking price before the policy. Changes in time on the market still exhibit a discrete jump at \$1M even during the pre-policy periods, but the jump is statistically insignificant and much smaller in magnitude than during the policy periods. Together, these patterns are congruent with the finding that the policy caused a discrete jump in bidding intensity at the \$1M and a "red hot" market right under the \$1M.

6.3 Predictions 4 and 5: Relative Degree of Financial Constraints

Prediction 4 states that the million dollar policy induces a sharper bunching of homes listed and hence sold at \$1M when there is a larger fraction of constrained buyers in the million dollar segment. Prediction 5 implies that the million dollar policy reallocates million dollar homes from more constrained to less constrained homebuyers. Lacking the micro-level data on homebuyers' wealth and mortgage terms, we provide suggestive evidence that supports Prediction 4 and 5. Formal tests of these implications require household-level data on borrower wealth and mortgage terms, which we view as a fruitful area for future research.

We start with Prediction 4. To examine whether the policy effect is larger when a larger share of prospective buyers is constrained, we compare two geographical submarkets: central Toronto and suburban Toronto. 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 relatively fewer prospective buyers of million dollar homes in suburban Toronto are constrained than in central Toronto. Table 8 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 percent of that in central Toronto, while the sales price response in both markets is small and insignificant. Together, these patterns are consistent with the positive relationship between the magnitude of the policy's effect and the severity of financial constraints, as implied by the theory.

We then turn to Prediction 5 regarding the reallocation of million dollar homes. With a one-time-access to highly-restricted proprietary mortgage data, we impute the fraction of constrained buyers (LTV $\geq$ 80%) around the million dollar segment in our sample market during one year before and one year after the policy, respectively. For the segment slightly above \$1M, the fraction of constrained buyers is reduced to zero, which is not surprising given the nature of the policy. Notably, for the segment slightly below \$1M, the fraction of constrained buyers is also reduced by roughly 20% after the policy. This is consistent with the model's implication that less constrained buyers have an incentive to participate in the segment below \$1M because they can outbid constrained buyers in multiple offer situations. The policy hence improves borrower creditworthiness not only for the segment above \$1M simply by design, but also for the segment slightly below \$1M through influencing buyers' and sellers' search behavior. The latter emphasizes the importance of designing policies that take into account how buyers and sellers respond to them.

7 Conclusion

In this paper we assess the impact of a financial constraint on price formation in the targeted segment of a frictional housing market. Our empirical methodology exploits a natural experiment arising from a mortgage insurance policy change that effectively imposes a 20 percent minimum downpayment requirement on home buyers paying \$1M or more. The interpretation of our results is motivated by a search-theoretic model of sellers competing for financially constrained buyers.

We model the million dollar policy as a targeted financial constraint affecting a subset of prospective buyers in a directed search model of the \$1M housing market segment. We show that sellers respond strategically by adjusting their asking prices to \$1M, which attracts both constrained and unconstrained buyers. Because of the interactions of search, bidding and 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 homes listed just below the \$1M threshold sell faster with a higher incidence of above-asking sales price, match the intuition from the theory.

Overall, we find that the million dollar policy did not achieve the specific goal of cooling the housing boom in the million dollar segment, but instead created a heated market right below \$1M. These findings are difficult to reconcile in a frictionless market, but are fully consistent with an equilibrium model of financial constraints with search frictions and auction mechanisms. Our analysis thus points to the importance of designing macroprudential policies that consider the underlying market microstructure and recognize the strategic responses of market participants.

Finally, a brief sketch of a normative argument in favor of the million dollar policy is in order. In 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, by reallocating million dollar homes from financially constrained buyers to less financially constrained buyers, the policy effectively improves borrower creditworthiness and prevents lenders from making more risky loans. Such benefits may be found in how the policy affects mortgage market outcomes, which we view as an important area for future research.

References

Acharya, V. V., A. N. Berger, and R. Roman (2018). Lending Implications of U.S. Bank Stress Tests: Costs or Benefits? *The Journal of Financial Intermediation 34*, 58–90.

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*.

Begenau, J. (2019). Capital requirements, risk choice, and liquidity provision in a business-cycle model. *Journal of Financial Economics*.

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.

Cai, X., P. A. Gautier, and R. P. Wolthoff (2017). Search frictions, competing mechanisms and optimal market segmentation. *Journal of Economic Theory 169*, 453–473.

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.

Chernozhukov, V., I. Fernández-Val, and B. Melly (2013). Inference on counterfactual distributions. *Econometrica 81*(6), 2205–2268.

Chetty, R., J. N. Friedman, T. Olsen, and L. Pistaferri (2011). 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.

Clerc, L., A. Derviz, C. Mendicino, S. Moyen, K. Nikolov, L. Stracca, J. Suarez, and A. Vardoulakis (2015, July). Capital regulation in a macroeconomic model with three layers of default.

DeFusco, A., S. Johnson, and J. Mondragon (2019). Regulating household leverage. *Review of Economic Studies, Forthcoming*.

DeFusco, A. A. and A. Paciorek (2017). The interest rate elasticity of mortgage demand: Evidence from bunching at the conforming loan limit. *American Economic Journal: Economic Policy 9*(1), 210–40.

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.

Elenev, V., T. Landvoigt, and S. Van Nieuwerburgh (2016). Phasing out the gses. *Journal of Monetary Economics 81*, 111–132.

Elenev, V., T. Landvoigt, and S. Van Nieuwerburgh (2018). A macroeconomic model with financially constrained producers and intermediaries.

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.

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.

Jeske, K., D. Krueger, and K. Mitman (2013). Housing, mortgage bailout guarantees and the macro economy. *Journal of Monetary Economics 60*(8), 917–935.

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

Khezr, P. and F. Menezes (2018, November). Auctions with an asking price. *International Journal of Game Theory 47*(4), 1329–1350.

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.

Lemieux, T. and K. Milligan (2008, feb). Incentive effects of social assistance: A regression discontinuity approach. *Journal of Econometrics 142*(2), 807–828.

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.

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

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.

Van Bekkum, S., M. Gabarro, and R. M. Irani (2017). Does a larger menu increase appetite? collateral eligibility and credit supply. *The Review of Financial Studies 31*(3), 943–979.

Vigdor, J. L. (2006). Liquidity constraints and housing prices: Theory and evidence from the {VA} mortgage program. *Journal of Public Economics 90*(89), 1579 – 1600.

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.

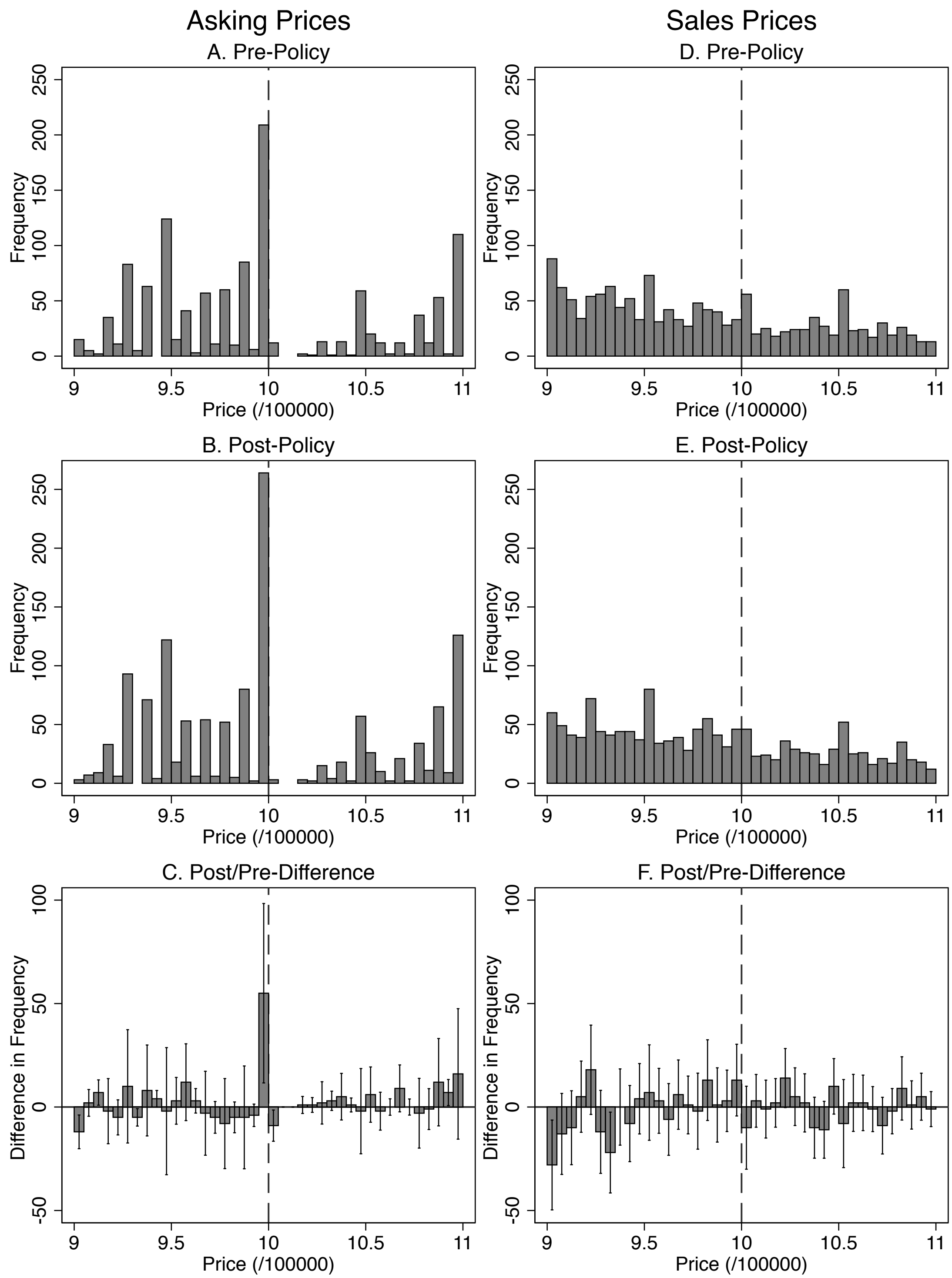


Figure 1: Frequency Counts of Asking and Sales Prices in the Pre- vs Post-policy Periods

Notes: The figure uses data on asking and sales prices for the city of Toronto in the year before (pre-period) and after (post-period) the implementation of the million dollar policy. Panels A, B, D, and E show frequency counts for $5,000 bins within $100,000 dollars of the policy threshold for the indicated period. Panels C and F show the difference in the frequency counts for the post- vs pre-periods in each bin. The confidence bars in Panels C and F are constructed via bootstrap for 399 random samples with replacement.

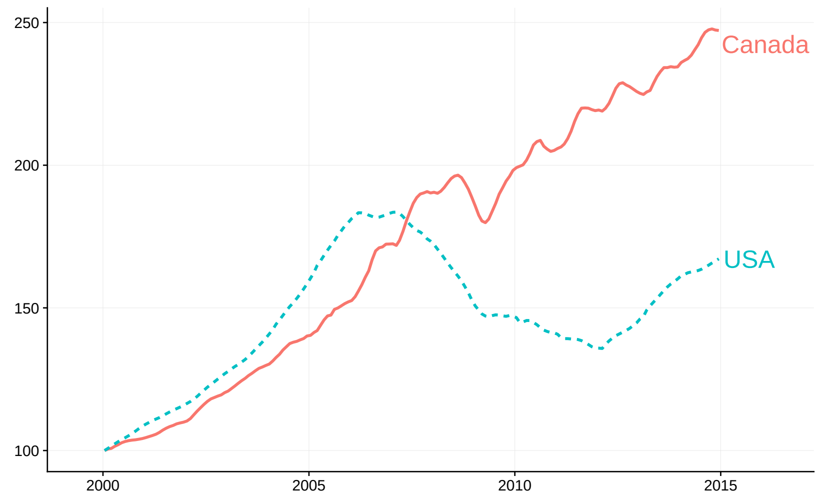


Figure 2: House Price Indices for Canada and the U.S.

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 CNTNHPCMF.

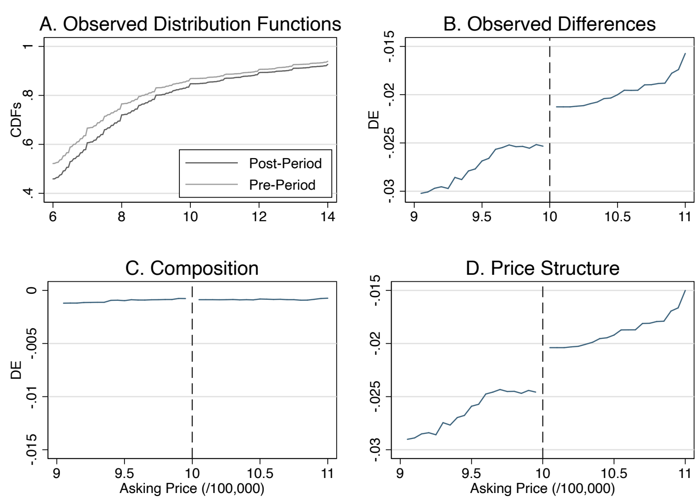


Figure 3: Observed Distribution and Decomposition of Asking Prices

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.

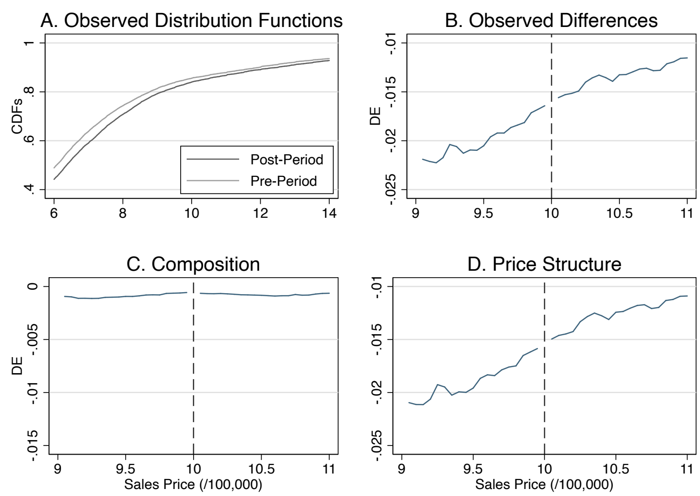
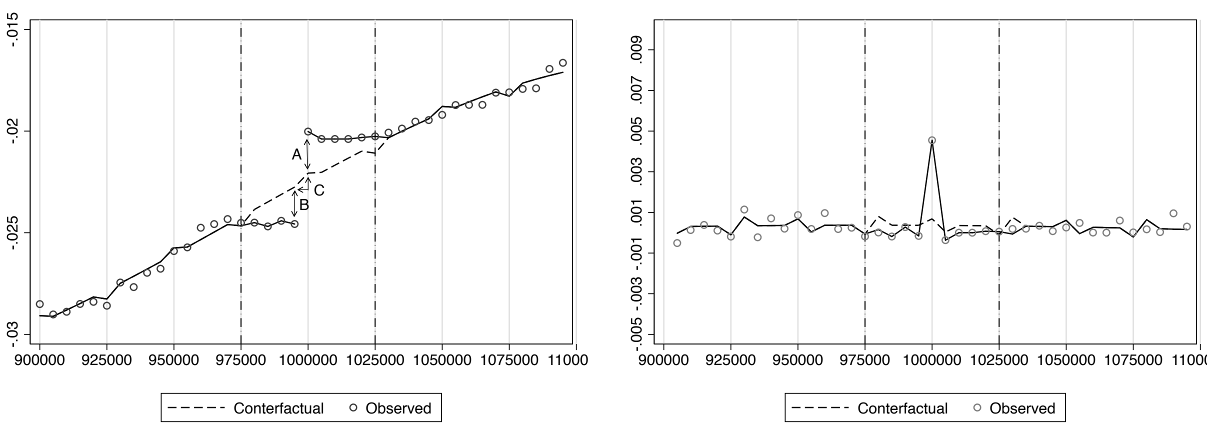


Figure 4: Observed Distribution and Decomposition of Sales Prices

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.

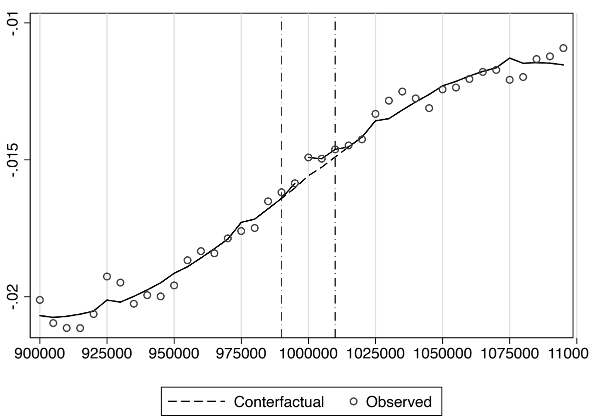


(a) $\hat{\Delta}_S(y_j)$ and counterfactual estimate

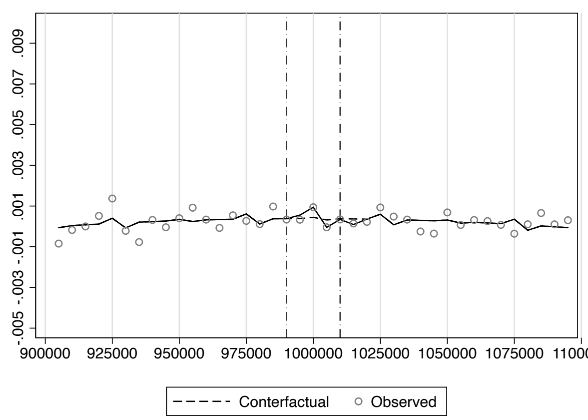
(b) $\hat{\Delta}_{S'}(y_j)$ and counterfactual estimate

Figure 5: 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. The figure labels correspond to those in equation (8) that decompose the vertical jump at the policy threshold, indicating the magnitude of bunching from above (A) and below (B), and the counterfactual estimate (C). 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 6: 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.

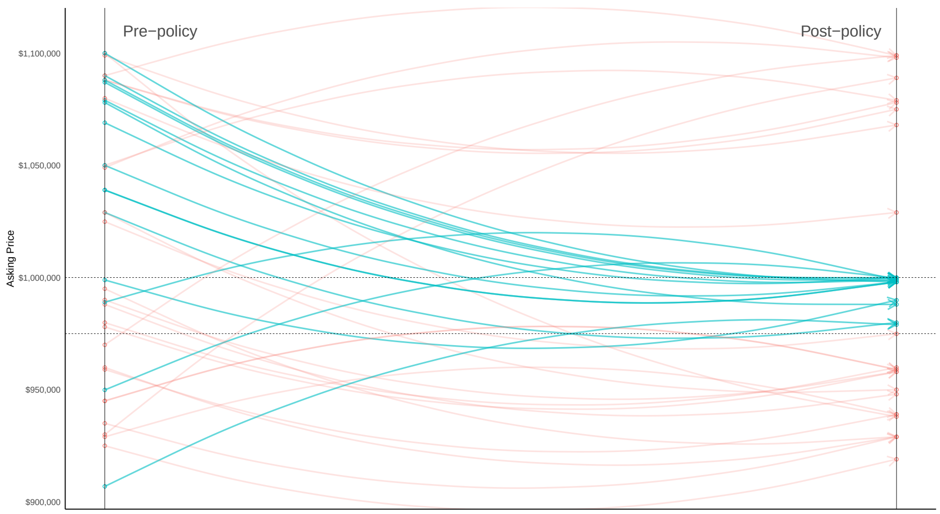
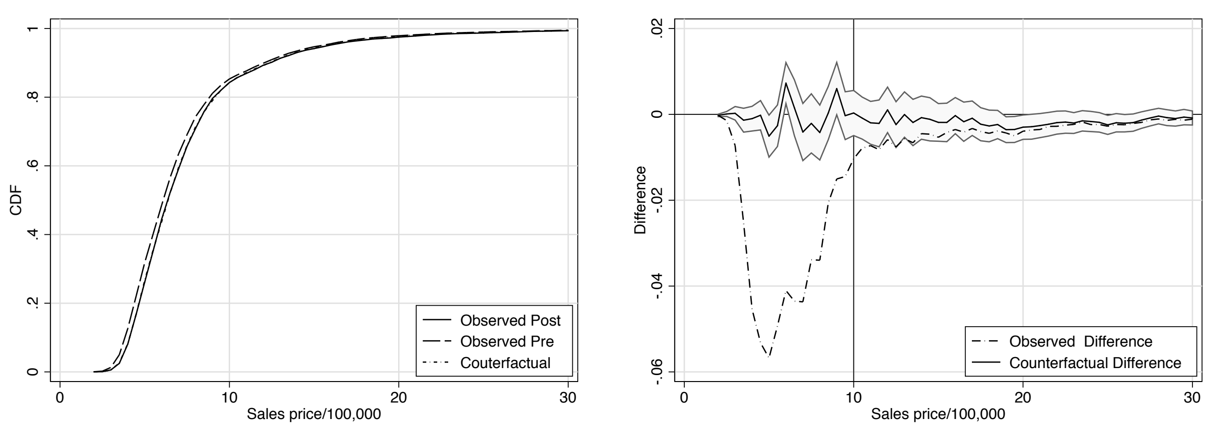


Figure 7: Observed Changes in Asking Price Among Re-Listed Properties

Notes: The figure uses data for a subset of houses that were listed prior to the implementation of the 1M policy that were withdrawn and listed again after the implementation of the policy. This subset includes only houses that had listing prices in the range of 900k-1M within 180 days of June 9th, 2012. The left vertical bar shows the a house's pre-policy asking price and the right vertical bar shows the house's post-policy asking price. Lines in green show pricing behaviour consistent with our bunching analysis; that is, these houses re-listed just below 1M in the segment [975k-1M) (indicated by dashed horizontal lines.).

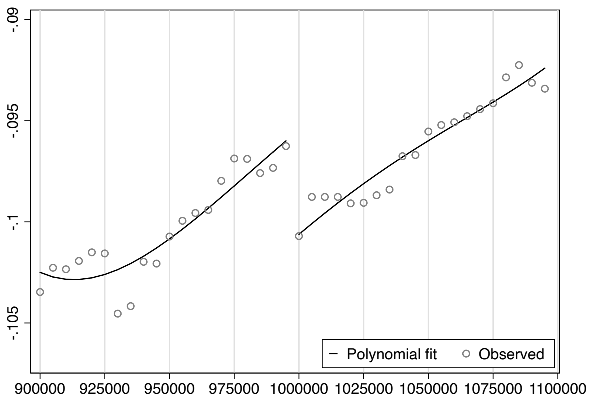


(a) Sales Price Distributions

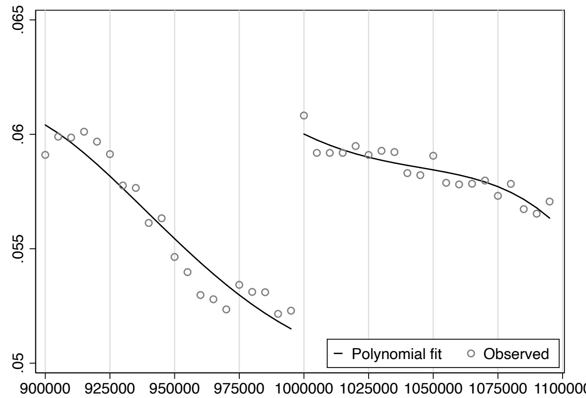
(b) Differences

Figure 8: Examining Policy Responses Above $1M

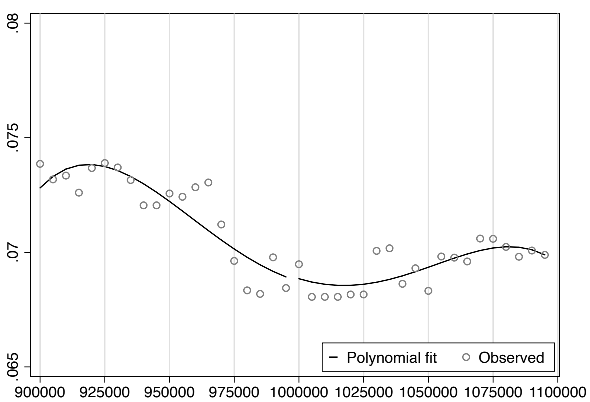
Notes: Panel (a) of the figure plots the composition adjusted sales price distribution for the pre- and post-policy periods, as well as the counterfactual sales price distribution. Panel (b) plots the differences in the pre- and counterfactual distributions relative to the post-policy distribution. The shaded area represents a 95% confidence interval, obtained via bootstrap.



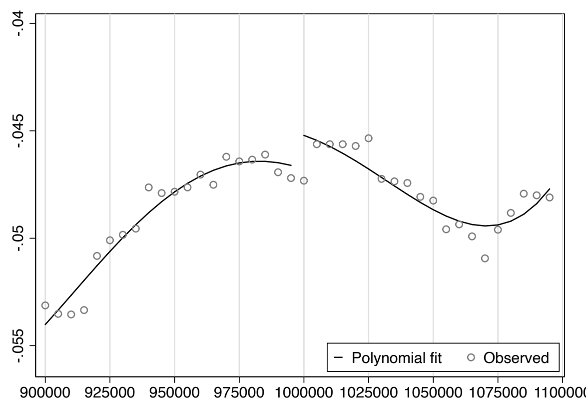
(a) Sales above Asking - Policy Period



(b) Duration on Market - Policy Period



(c) Sales above Asking - Pre-Policy Period



(d) Duration on Market - Pre-Policy Period

Figure 9: 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 during the policy period. 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 during the policy period. Panels (c) and (d) repeat the analysis in panels (a) and (b), respectively, for the pre-policy period. Each dot represents the observed change in probability, while the solid line plots the predicted values from a second-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
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
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: Assessing Robustness to Housing Types

	Condos/Townhouses		All Homes	
	(1) Asking	(2) Sales	(3) Asking	(4) Sales
Jump at cut-off	0.00077	0.00052*	0.0030*	0.00074*
	(0.00041)	(0.00018)	(0.00058)	(0.00025)
Total Response	0.00086*	0.00056*	0.0025*	0.00049
	(0.00041)	(0.00019)	(0.00059)	(0.00031)
From Below	-0.00012	-0.000076	-0.00097*	0.000076
	(0.00028)	(0.00021)	(0.00041)	(0.00032)
From Above	0.00074*	0.00049*	0.0016*	0.00057
	(0.00029)	(0.00023)	(0.00046)	(0.00041)
Observations	40025	40025	83058	83058
Excluded Bins:				
L	4	1	4	1
R	5	3	5	2
Tests of Fit:				
$B - \sum_l^L \beta_B^l$	.00016	-.000076	-.00048	.000076
	(.00055)	(.00021)	(.00078)	(.00032)
$A - \sum_r^R \beta_A^r$	.001	.00012	.0022*	-.00021
	(.00055)	(.00028)	(.00081)	(.00032)
Joint p-val.	0.19	0.86	0.031	0.80
Impact:				
Δ Houses at cutoff	18.7	12.2	114.4	22.1
Specifications:				
Poly. Order	3	3	3	3
Window	20	20	20	20

Notes: This table displays the bunching estimates of the MI policy for condominiums and townhouses and all housing types in Toronto. The dependent variable is $\hat{\Delta}_S(y_j)$ constructed using 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.

Table 5: Regression Bunching Estimates: Alternative Cut-offs and Period

	Post-Policy Difference		Pre-Policy Difference	
	(1) Asking	(2) Sales	(3) Asking	(4) 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 6: 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
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 7: 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
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.

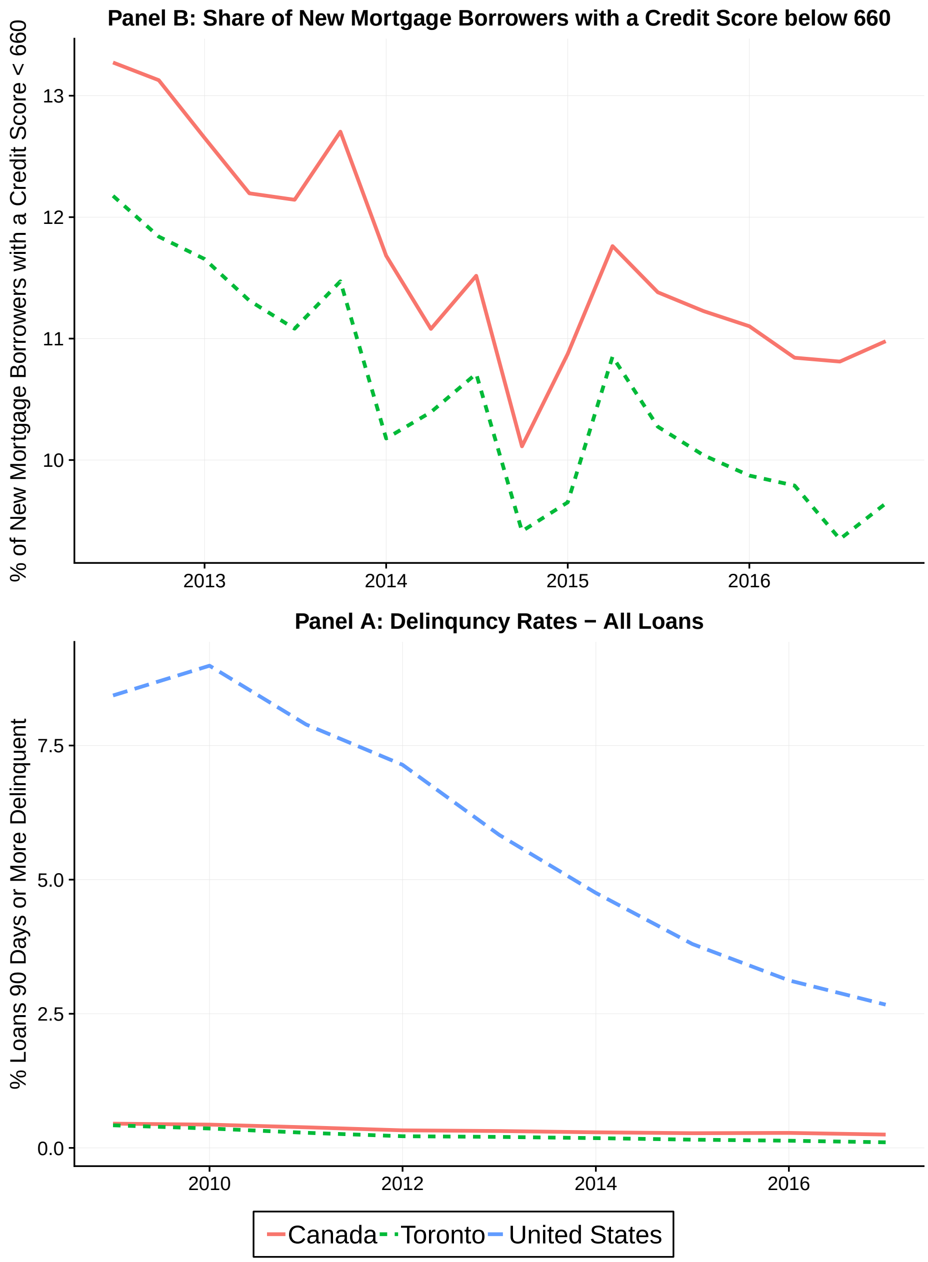
Table 8: Regression Bunching Estimates: Central vs Suburbs

	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
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



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

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

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

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

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:

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

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:

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

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

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

which combine to yield

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

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 P$_1$: Assuming (for the moment) an interior solution, the solution to problem P$_1$ satisfies the two constraints with equality, $V^s(p^*_c, \lambda^*_c, \theta^*_c) = 0$ and $V^u(p^*_c, \lambda^*_c, \theta^*_c) = \bar{V}^u$, and the following first-order condition.

$$e^{-\theta^*_c} p^*_c = \left(1 - \frac{\left[1 - e^{-\theta^*_c} - \theta^*_c e^{-\theta^*_c}\right] v - x}{(1 - \lambda^*_c)\theta^*_c} \frac{1}{\bar{V}^u - \bar{V}^c}\right)$$
$$\times \left(\frac{1 - e^{-(1-\lambda^*_c)\theta^*_c} - (1 - \lambda^*_c)\theta^*_c e^{-(1-\lambda^*_c)\theta^*_c}}{(1 - \lambda^*_c)\theta^*_c}(v - u) + (1 - \lambda^*_c)\lambda^*_c\theta^*_c e^{-(1-\lambda^*_c)\theta^*_c}(u - c)\right)$$

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

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

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

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. □

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

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

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. □

B.5 Numerical Simulation

To illustrate the predictions of the theory, we parameterize and simulate a version of the model that has been extended to incorporate a form of seller heterogeneity. Specifically, we assume that, upon listing their house for sale at cost x, a seller's reservation value is an idiosyncratic random variable that takes one of N possible values, $\{r_1, \ldots, r_N\}$ satisfying $r_1 < \cdots < r_N < u$, with equal probability.[37] The free entry condition on the supply side must now be satisfied in expectation. Modifying the model environment along this dimension does not affect the incentives facing buyers, but the expressions for sellers' expected net payoffs must be modified accordingly. For example, if the asking price is low enough to elicit bids from both unconstrained and constrained buyers, the expected net payoff for a seller with reservation value $r_n < c$ is

$$\begin{aligned} V_n^s(p \le c, \lambda, \theta) &= r_n - x + \pi(1)(p - r_n) + \sum_{k=2}^{\infty} \pi(k) \left\{ [\phi_k(0) + \phi_k(1)]\, c + \sum_{j=2}^{k} \phi_k(j) u - r_n \right\} \\ &= e^{-\theta} r_n - x + \theta e^{-\theta} p + \left[1 - e^{-\theta} - \theta e^{-\theta}\right] c \\ &\qquad + \left[1 - e^{-(1-\lambda)\theta} - (1-\lambda)\theta e^{-(1-\lambda)\theta}\right](u - c). \end{aligned}$$

Sellers with different ex post reservation values will implement different asking price strategies, which permits the characterization of equilibria featuring *bunching from both above and below* simultaneously.

For our parameterization we set $c = 1000$, $v = 1100$ and $x = 50$, so that the unit of measurement corresponds to \$1,000 (CAD). We then choose $N = 200$ equally spaced reservation values, $\{r_1, \ldots, r_{200}\} = \{900, \ldots, 1041\}$, and set $u = 1070$ so that the pre-policy

[37] The interpretation is that a seller may not be certain about their value of moving/staying in advance. Their precise reservation value is ascertained at some stage of the listing process.

equilibrium asking prices range from 950 to 1,050. Finally, we calibrate the overall fraction of constrained buyers to $\Lambda = 0.0061$, which means only 0.61 percent of prospective buyers in this segment are constrained by the policy in this particular parametrization of the model.

The simulated distributions of asking prices are plotted in Figure A2a. These distributions have been rescaled to accommodate (unmodeled) asking prices outside of $[950, 1050]$. Specifically, we apply scale factors 0.0300 and 0.0390 to the pre- and post-policy asking price distributions to match the shares of overall listings in this segment of the Toronto market. Next, the pre- and post-policy distributions are anchored at 0.87 and 0.85 at asking price $c = 1000$ to mimic the percentiles of the $1M home in the Toronto market in the two sample periods (see summary statistics in Table 1, discussed below in Section 5). Figure A2b plots the differences in the simulated distribution functions, along with a counterfactual obtained using the pre-policy asking price distribution, but shifted and rescaled to reflect the post-policy percentile at $c = 1000$ and measure of sellers in the $[950, 1050]$ segment. The discontinuity at the threshold is a visual representation of Prediction 1. Following the introduction of the policy, 25 out of the 200 seller types (12.5 percent of sellers) find it optimal to list at exactly price c. Of these sellers, roughly one third would have otherwise listed further below the threshold, the remaining two thirds would have listed above. Note that the excess mass of listings at policy threshold $c = 1000$ matches our estimates in Section 6. The share of constrained buyers, $\Lambda = 0.0061$, was chosen precisely to mimic this feature of the data.

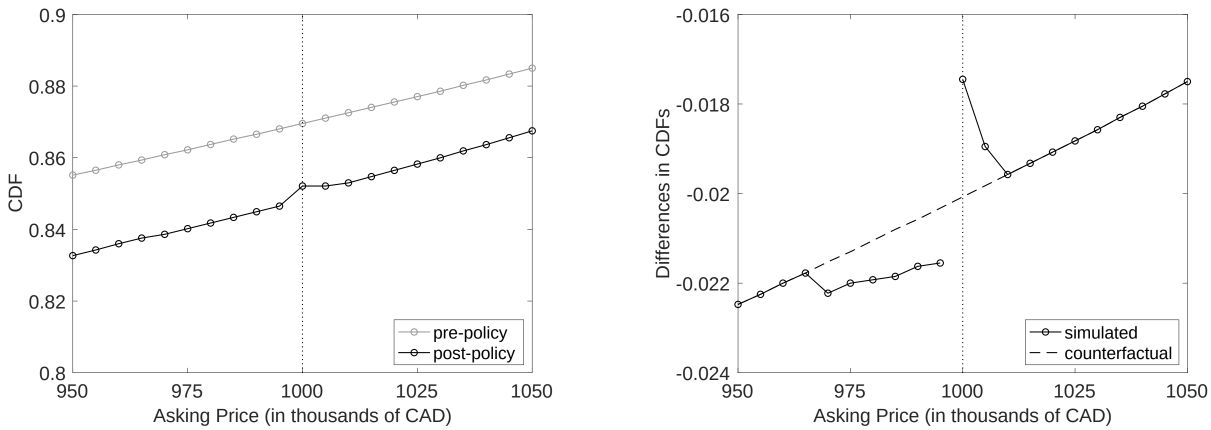
Figure A3a displays the simulated sales price distributions, and Figure A3b plots their differences. The pre- and post-policy distributions are anchored at 0.86 and 0.84 at sales price $c = 1000$ to again mimic the summary statistics in Table 1. The scale factors applied to the simulated sales price distributions, however, are the same as those applied to the asking price distributions. Notice that the discontinuity in Figure A3b is much less pronounced than the discontinuity in Figure A2b: an unmistakable illustration of Prediction 2. Many of the homes listed with asking price c sell for more than c in a bidding war involving multiple unconstrained buyers.

To illustrate Prediction 3, we plot the expected time to sell (i.e., the reciprocal of the probability of selling) as well as the probability of selling above asking, as functions of the asking price, in Figures A4a and A5. The pre- and post-policy differences are plotted in Figures A4b and A5b. As discussed above, the liquidity of homes listed above the threshold is unaffected by the policy.In contrast, homes listed below the threshold post-policy attract both constrained and unconstrained buyers and consequently sell with higher probability and are more likely to sell for more than the asking price. The threshold nature of the policy induces discrete changes in these liquidity measures at asking price $c = 1000$.

C Estimation Details

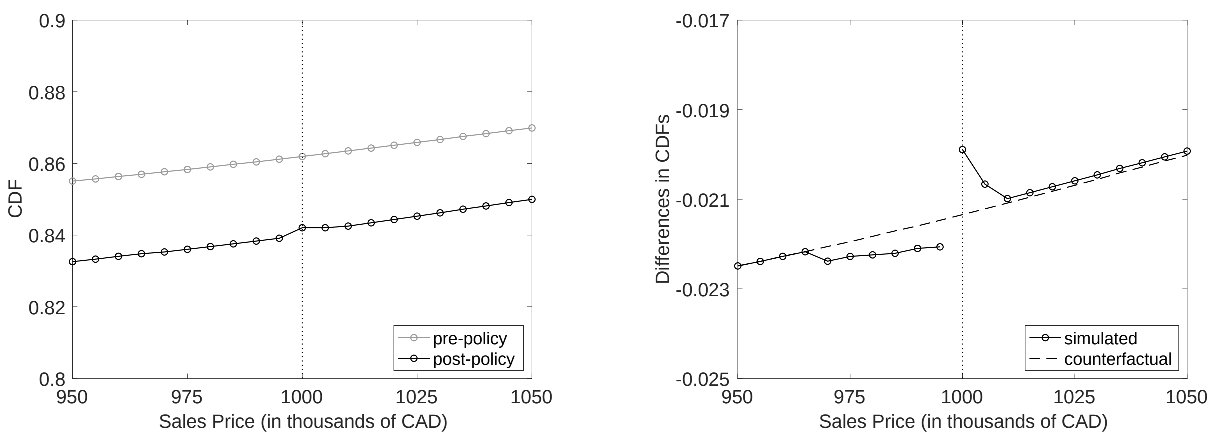
C.1 Cross Validation

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,



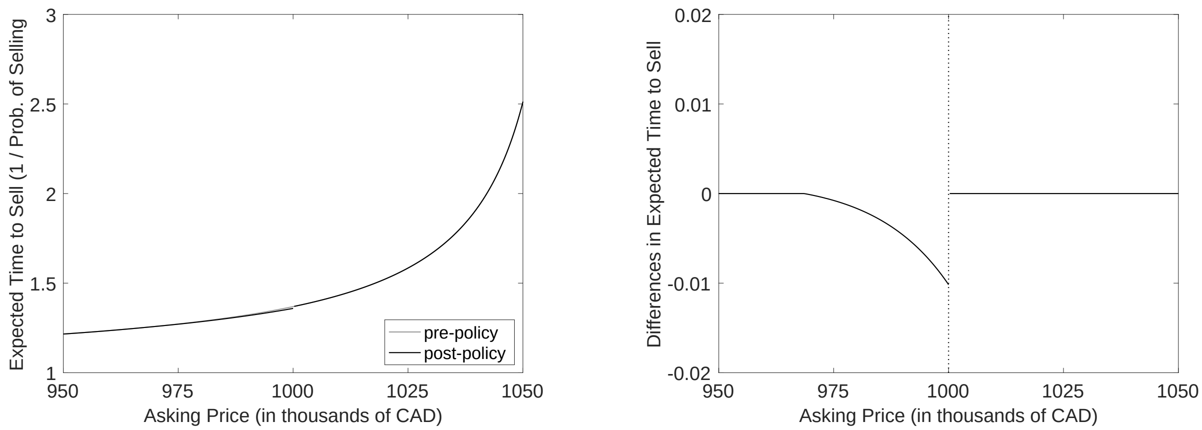
(a) distribution functions (b) differences

Figure A2: Asking prices



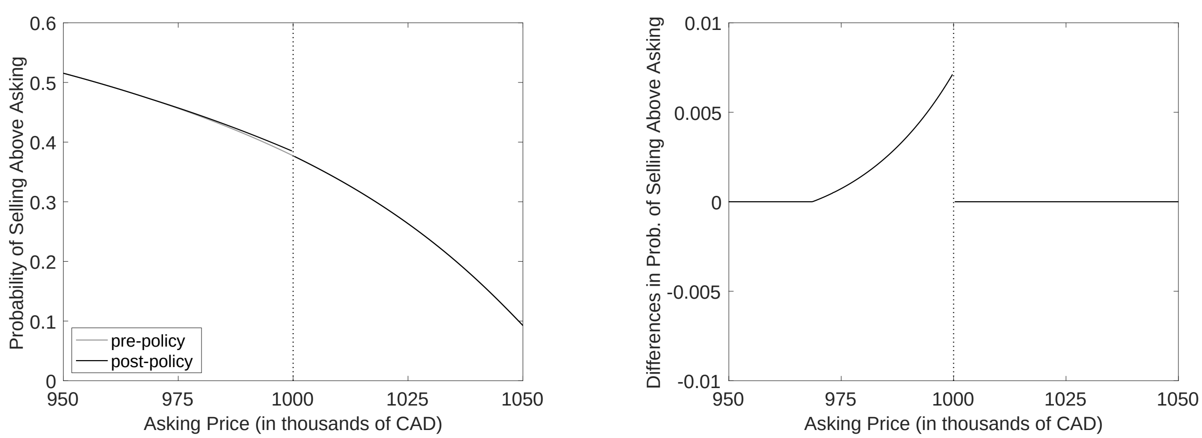
(a) distribution functions (b) differences

Figure A3: Sales prices



(a) expected time-to-sell (b) differences

Figure A4: Expected Time-to-Sell (Reciprocal of the Probability of Selling), by Asking Price



(a) probability of selling above asking (b) differences

Figure A5: Probability of Selling Above Asking, by Asking Price

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:

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

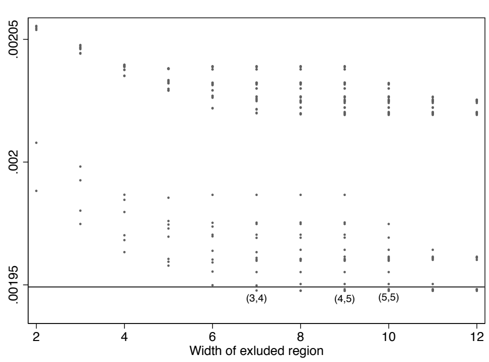
Where $\widehat{\hat{\Delta}_S(y_j)}_{\theta, n_{-k}}$ are fitted values for the k fold from the bunching estimator estimated on folds n_{-k} with parameter values θ, W is the estimation window (the number of observations used in the bunching estimation). We choose as our optimal hyperparameters:

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

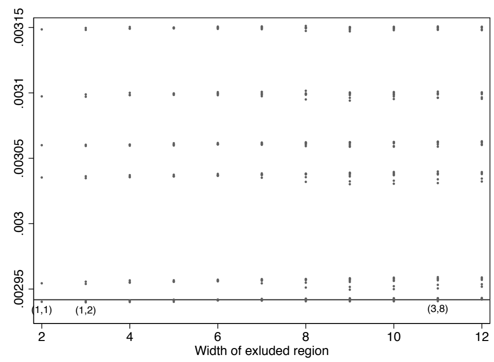
where V is the total number of combinations of parameter values in $\{L, R, p, W\}$. We also compute the standard error for the cross-validation, letting

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

we compute $SD(\theta) = \sqrt{\text{Var}\left(CV_1(\theta), \ldots, CV_5\right)}$ 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 A6. 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 A6: 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 Summary Statistics for Condominiums and Townhouses

		Pre-Policy		Post-Policy	
		Asking	Sales	Asking	Sales
All Condos/Townhouses	Mean	383058.22	377722.79	390153.40	381873.22
	25th Pct	275000.00	270000.00	278999.00	270000.00
	50th Pct	349000.00	343000.00	349900.00	345000.00
	75th Pct	439900.00	437000.00	454900.00	448000.00
	N	21768.00	21768.00	18257.00	18257.00
	Median Duration	20.00	20.00	24.00	24.00
	1M Percentile	0.99	0.99	0.99	0.99
Condos/Townhouses 0.9-1M	N	92.00	89.00	100.00	105.00
	Median Duration	22.50	17.00	18.50	18.00
	Mean Price	963255.20	943872.89	968476.07	949377.90
Condos /Townhouses 1-1.1M	N	50.00	71.00	46.00	47.00
	Median Duration	22.50	30.00	19.50	23.00
	Mean Price	1071297.66	1051929.44	1073844.09	1046271.06