Persistence of market conditions in real estate markets

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Abstract

We show how using commonly reported measures of real estate market conditions can improve the accuracy of price predictions. The standard model of competitive markets asserts that excess demand causes price(s) to adjust to an equilibrium with little delay. In an illiquid market, such as the market for real estate, attaining an equilibrium may take significantly more time. That fact implies that data on market conditions would be informative. A better understanding of the adjustment process in a real estate market could also lead to buying or selling strategies which are better informed.

This paper has two parts. The first part uses different types of models to focus on the conceptual distinction between an exogenous variable and an endogenous variable. Based on this distinction, we offer six hypotheses on why the effects of market conditions might differ between cities. The second part uses vector auto-regression to study the persistence of several variables, with a particular focus on an inflation-adjusted price index and two popular measures of excess demand (the ratio of sales to new listings and "Months of Inventory"). Using monthly data on residential real estate markets in 31 Canadian cities, we find that excess demand affects prices contemporaneously, that changes in measured excess demand persist for a significant period of time and that they affect prices with a lag. We also find evidence of a statistically significant feedback effect, in some cities, from changes in prices to the measures of excess demand.

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1. Introduction and Motivation

Many researchers offer evidence showing that the trends in the prices of real estate assets, such as residential homes, commercial properties and units in a REIT, are predictable using publicly available information for at least a short period of time (e.g., Broxterman, Gatzlaff, Letdin, Sirmans and Zhou, 2023; Shiller and Thompson, 2022; Letdin, Sirmans, Sirmans, and Zietz. 2019; Glaeser and Nathanson, 2017). Even so, economists generally agree that market forces are balanced in a long run sense, if only because buyers and sellers can adapt in so many ways that a persistent imbalance favoring one of the sides is almost unbelievable. Between these two positions, there is less agreement about the strength of market forces, about how long it takes to achieve an equilibrium and the relevant features of that equilibrium concept. This paper seeks to fill that gap.

Local real estate boards monitor market conditions and use administrative records to publish regular reports. These reports can provide information on a variety of indicators of market conditions, such as average transaction price, number of sales, total monetary value of all transactions, number of new listings, months of inventory (i.e., ratio of stock of listings to the flow of sales), average time on market, average selling price discount, or quality-controlled price indices.[1] Individuals may supplement these aggregate measures of market conditions with measures which focus on a subset of the market, such as a price range, a type of property, a neighborhood or a short period of time. Researchers have proposed other measures also, such as the exuberance index discussed in Coulter et al (2022) and in Shi and Phillips (2023), indexes of sentiment (e.g., Anastasiou, Kapopoulos and Zekente, 2023; Marcato and Nanda, 2016; Ling, Ooi and Le, 2015), the Buy/Rent Index (Beracha and Johnson, 2012), or the repeat time-on-the-market index (Carrillo and Williams, 2019). Miller and Sklarz (2012, Exhibit 15) list 15 types of drivers of market conditions and seven types of indicators that should be used when studying a real estate market.

[1] Anecdotally, reports on current market conditions published in different countries emphasize different subsets of these indicators.

The obvious challenges with applying this list in practice are that the list is very long, that the information is not always available for all levels of geography and that high quality recent information may not be available in time to make a decision. Even so, media and practitioners use some data when describing the current state of a residential market as a "buyers' market", a "sellers' market", a "balanced market", or as a "hot" vs. "cold". In theory, both the buyers' market condition and the sellers' market condition are temporary, as transitions to balanced market conditions. A challenge is whether the imbalance persists long enough to be relevant, especially when the data used in the descriptions emphasizes endogenous variables (also known as indicators).

Our paper offers three contributions. First, it confirms that changes in real prices are associated with two familiar indicators of excess demand (the ratio of sales to new listings (S/NL) and "months of inventory" (MoI; computed as the ratio of listings to sales). This finding is a significant contribution because the traditional equilibrium model of supply and demand would predict that prices adjust so quickly that evidence on a change in excess demand would *not* be useful. Further, we find that these effects persist for many months. We also provide evidence of feedback from prices to S/NL and to MoI which affect the time path of prices for many months later. These findings are a significant contribution because many researchers (e.g., Deng and Wong, 2023; Coulter, Grossman, Martínez-García, Phillips and Shi, 2022; Oikarinen, Bourassa, Hoesli and Engblom, 2023; Glaeser and Nathanson, 2017; Leung, 2014) have studied the persistence of price changes in isolation from other indicators of market conditions. We know of only one other paper (Carrillo, de Wit and Larson, 2015) which considers how to use evidence on market conditions when studying prices in a residential real estate market. Therefore, our paper offers a different perspective on the problem of classifying market conditions.

Our second contribution identifies similarities and differences in how prices and measures of excess demand adjust over time across 31 Canadian cities. We show that the contemporaneous correlation between measures of excess demand and prices is generally consistent with traditional theory but that the magnitude of that correlation can differ between cities by a factor of more than 10. We also find a two-way Granger-causality relationship between prices and S/NL or MoI or both for many cities, but not all. We find statistically significant differences between cities concerning three features: whether a city is big, whether it is geographically isolated from other cities and its supply elasticity. Thus, we show how the details of the equilibration process differ between cities quantitatively.

Our third contribution is motivated by a tension between theory and practice. Residential real estate markets display many features which seem consistent with a textbook example of a perfectly competitive market. Each buyer or seller is small relative to the set of its competitors. The facts that potential competitors can enter the market at any time and that there is a high rate of turnover are reminders that the decisions of active participants can adapt to new conditions easily. At the same time, transaction costs and heterogeneous offerings imply that, according to a buyer or a seller, market conditions cannot be summarized by a single price. In such situations, high quality information about additional measures of market conditions would be highly valued. The discussion above noted that many measures attempt to classify the state of a market and, in the near future, newer measures may claim to identify a “hot market” or “overlooked opportunities”. Our literature review summarizes the findings of two types of models (perfectly competitive vs. search, matching and bargaining) to highlight the conceptual differences between exogenous variables and any possible endogenous variables. These differences help to determine how long an effect might last.

The next section reviews the literature from several perspectives. The third section contains six hypotheses while the following section discusses the data set and the methods we use. We use monthly data from 31 Canadian cities to study the evolution of two popular and widely available measures of market conditions over time. The fifth section presents our results. The concluding section summarizes our findings and some of their implications.

2. Literature Review

This review contains two sections. The first part considers recent literature on estimate price trends, where almost all of them emphasize data on prices. Very few papers study the information value of additional measures, of which the most common are credit conditions and sentiment. Almost always, they ignore the usefulness of data on indicators of market conditions other than prices, even if such data are discussed frequently by practitioners. For example, Glaeser and Nathanson (2017) offer four stylized facts about housing markets, all of which focus on how prices evolve over time and ignore other variables endogenous to a market. The second part of this review builds on this theme by referring to two families of models to propose robust hypotheses.

2.1 Previous Research on Explaining Price Trends

Many papers have studied the determinants of prices in a real estate market from many perspectives, and we can discuss only a small fraction of it. For example, Duca, Muellbauer and Murphy (2021) review the literature with a focus on trends and cycles at a national level. Their work emphasizes macroeconomic determinants. Some papers argue that the effects from credit markets dominate (e.g., Duca, Muellbauer and Murphy, 2021; Cox and Ludvigson, 2021). Other recent papers argue that the effects of price expectations and sentiment dominate (e.g., Kaplan, Mitman and Violante, 2020). While the determinants of price expectations, their accuracy and their effects, have been discussed for many years (e.g., Shiller and Thompson, 2022; Bailey, Cao, Kuchler, and Stroebel. 2018; Glaeser and Nathanson, 2017; Case and Shiller, 1990), a growing literature considers sentiments (e.g., Anastasiou, Kapopoulos and Zekente, 2023; Aroul, Sabherwal and Saydometov, 2022; Kaplan, Mitman and Violante 2020; Ling, Ooi and Le, 2015). Our interpretation of this literature indicates that the concept of sentiment encompasses more aspects of a housing market than simply the expected future price of an average property in a city. Different papers propose different channels by which sentiments have an effect.

The issue of expectations has been widely studied. For example, rational expectations models or perfect foresight models (e.g., DiPasquale and Wheaton, 1995) find equilibrium solutions where expected prices are compatible with the exogenous variables. Other work, such as Shiller (2022), Ling, Ooi and Le (2015) and others, show that changes in expectations can have their own effect, at least temporarily. Glaeser and Nathanson (2017) and Case and Shiller (1988) provide evidence of backward-looking influences. Shiller and Thompson (2022) provide evidence that expectations underreact to recent information. On the other hand, Broxterman, Gatzlaff, Letdin, Sirmans and Zhou, (2023, p. 202) suggest "it is likely that market participants may overweight recent information and underweight historical information". Bailey, Cao, Kuchler, and Stroebel (2018) show that expectations are influenced by friends, including friends who live in areas where prices far away. A few papers (e.g., Strobel, Nguyen Thanh and Lee, 2020; Miller and Peng, 2006) study the effects of uncertainty in those expectations. DeFusco, Nathanson and Zwick (2022) and Fu and Qian (2014) provide evidence of how expectations are related to the activities of speculators and how those effects vary with the information efficiency of a market segment. Shiller and Thompson (2022) note that the short-term expectations, long-term expectations and actual price changes are synchronized sometimes. We do not add to this literature, specifically. We note that price expectations may depend on the ease or inability to transact at the current price and, if so, expectations would also vary with the measures of excess demand.

Papers which study price trends may include measures related to the determinants of the demand curve and determinants of the supply curve (e.g., Duca, Muellbauer and Murphy, 2021; Kaplan, Mitman and Violante, 2020; Bourassa, Hoesli and Oikarinen, 2019). Exogenous variables which affect the supply side may include construction costs or zoning regulations. Baum-Snow and Han (2024) argue, using US data, that about half of the supply response to a price change is new construction (if measured in terms of the number of units over a 10 year period). The fraction would be greater if the supply response were measured in terms of floor space. Exogenous variables which affect the demand side may include population, consumer income or the unemployment rate. Berkovec and Goodman (1996) study whether turnover (also known as sales) is a suitable proxy measure for demand.

Titman, Wang and Yang (2014) find that demand shocks are correlated over time, rather than changes in “demand” being evidence of adjustment.

A small number of papers consider the use of complementary data. Some older papers study the relationship between the rental rate and the vacancy rate for rented accommodation and the “natural” vacancy rate (e.g., Belski and Goodman, 1996; Igarashi, 1991; Rosen and Smith, 1983). There is also a literature on covariation in price and volume (e.g., DeFusco, Nathanson and Zwick, 2022; Lee, Wang and Zeng, 2017; Shi, Young and Hargreaves, 2010; Clayton, Miller and Peng, 2010). We suggest that this literature is motivated by curiosity about the sources and joint effects of various market imperfections since the volume of transactions is not a measure of excess demand.

The best example of using complementary data may be Carrillo, de Wit and Larson (2015). They study the determinants of prices while including measures constructed by the authors such as “market tightness”. We suggest that, in addition to investigating the relevance of such sophisticated measures, it would be useful to consider the relevance of less sophisticated measures which are published more regularly.

2.2 Robust Findings from Familiar Models

This subsection reviews two types of models often used to explain how real estate markets adjust to market forces. We start by discussing the familiar perfectly competitive model of supply and demand. This type of model highlights the ideas that excess demand determines whether prices are rising or falling and that it is a transitional phenomenon. More importantly, the discussion clarifies the differences between exogenous and endogenous variables and how constraints on decision makers affect the elasticities of supply and demand. Models of search, matching and bargaining (e.g., Han and Strange, 2015) offer additional margins of adjustment (such as time on market) and provide insight into the effects of introducing transaction costs. Because actions take time in this type of model, the equilibration process might be observable in real time. Both types of models have been studied intensively.

Supply, Demand and Perfect Competition

The standard model of perfect competition is a useful starting point, because it is well known and adaptable. It concludes that if there is excess demand for a good or service then its price would rise until what the marginal buyer is willing matches the price that the marginal seller is willing to accept. Books on real estate market analysis read by practitioners (e.g., Brett, 2019) often use the language of supply and demand to justify the relevance of different sources of data and to organize ideas.

Equilibrium conditions, of which the most famous is that quantity supplied equals quantity demanded at the equilibrium price, reveal which outcomes are compatible with the aggregated actions of both buyers and sellers simultaneously. Perhaps more importantly, stating these conditions precisely distinguishes the variables deemed to be endogenous to a market, and those taken as given by participant, from the exogenous variables. Sometimes these two types of variables are labeled as “indicators” and “drivers” of market conditions. This familiar model allows researchers to study the short run and long run effects of changes in exogenous variables (such as population, interest rates or local government policies) on endogenous variables (such as average selling price or the number of sales).

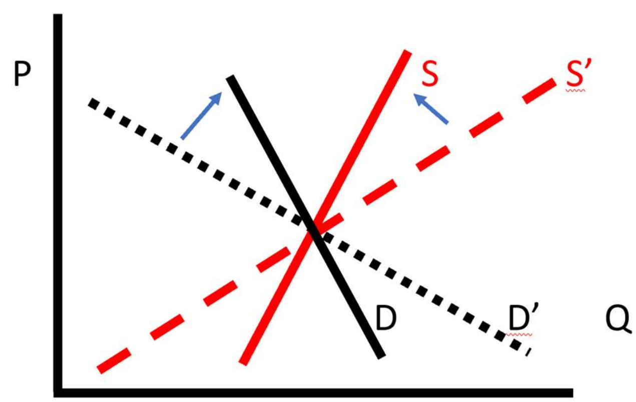
The familiar model of a perfectly competitive market also contains a well-known paradox: since buyers and sellers are assumed to take the price as given, but that price does not necessarily start at the equilibrium price, whose job is it to adjust the price and quantity the appropriately? Two answers are commonly offered to an undergraduate student in economics. One answer is that “the short side dominates” (e.g., Benassy, 1982; Fair, 1972).[2] A second answer is that a neutral “Walrasian auctioneer” adjusts prices as needed until everybody’s plans are compatible. Both of these answers are problematic given the

[2] Older editions of a popular econometrics textbook (Greene, 1990, section 21.4.4b) suggest using a regime switching model to account for the differences in the relevant “short side” between a buyers' market and a sellers' market.

question that we are studying. The first answer replaces a theory of supply *and* demand with a theory of supply *or* demand, where the relevant side depends on the arbitrarily given price. The second answer asserts that excess demand would not be observed using commonly available data, making it impossible to distinguish a buyers' market from a sellers' market. Regardless of this paradox, the perfectly competitive model or purely competitive model (Rosen, 1974) of markets has proven useful.

Le Chatelier's Principle[3] helps to find robust features. Its most familiar application may be the textbook discussion of the short-term and long-run decisions of a supplier: if the price is right then the short run solution equals the long run solution and if the price increases then the long run change in quantity is at least as big as the short run response. Figure 1 illustrates this logic, where ' denotes the situation with fewer endogenous variables. As discussed when developing the hypotheses, the generality of Le Chatelier's Principle is useful because constraints come in many other forms, such as when considering the consequences of treating a variable as endogenous variable as if it were fixed it arbitrarily.

Figure 1: Supply and Demand with Different Price Elasticities



As a matter of comparative statics analysis, the Principle shows that removing

[3] Le Chatelier's Principle also depends on some maintained assumptions, such as the assumption that the relevant functions are differentiable. We assume that these assumptions are satisfied, as seems reasonable in a large market with many small players.

restrictions tends to increase the magnitude of a response by an individual. When the researcher's perspective shifts from an individual decision maker to the market, the responses of different individual must become compatible. An exogenous shock to the market would create a mismatch between the intentions of buyers and of sellers for any given price and would lead to a price change. The Principle implies that fewer restrictions implies that a smaller price change is needed to remove a given mismatch.

A model which is perfectly competitive and dynamic includes more endogenous variables and specifies more equilibrium conditions. Stock-flow models, such as those popularized by DiPasquale and Wheaton (1995), blur the distinction between the short run and the long run while accounting for additional endogenous variables (e.g., new construction). The extra variables permit new types of solutions, including endogenous cycles and deterministic chaos. Still, a model with n endogenous variables requires exactly n independent equilibrium conditions.[4] Without careful attention to the differences between endogenous and exogenous variables, endogenous cycles can be hard to distinguish from cycles associated with changes in exogenous variables, such as income or macroeconomic[5] cycles. An endogenous cycle in prices can be compatible with equilibrium conditions, but a necessary condition for compatibility is that at least one other endogenous variable display a complementary cycle.[6]

Search, Matching and Bargaining Models[7]

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[4] While this result is well-known, there is some fine print which should not be overlooked. Please see a graduate textbook in microeconomics (e.g., Mas-Colell, Whinston and Green, 1995) for more details.

[5] Some papers, such as Davis and Haltiwanger (2024), study the possibility of feedback effects from housing to the macroeconomy. We assume that this effect is too small to affect our results for any single city.

[6] While it is not too hard to find constructive proofs of this statement (e.g., Stokey, Lucas and Prescott, 1989), a simpler proof by contradiction may suffice here: if the equilibrium solution is unique and if the exogenous variables are vary and if all of the endogenous variables *other than price* do not vary over time then the equilibrium conditions imply that the equilibrium price cannot vary over time. Note also that a steady state solution is always relevant in a dynamic model since it may represent the point to which a time-varying equilibrium path converges to or diverges from.

[7] These models are often used to study the trade off faced by sellers who must choose a selling strategy which balances a desire to sell for a high price and a desire to sell quickly (e.g., Han and Strange, 2015). Hence, much of the empirical work in this area is cross-sectional. A change in market conditions might change the decision

The existence of transaction costs and illiquidity means that a fundamental assumption of the perfectly competitive model is violated. Search, matching and bargaining models are widely used to incorporate these assumptions and explain significant features of a real estate market. Han and Strange (2015) summarize the literature. This subsection discusses how such models refine the concept of excess demand while retaining important features of the perfectly competitive model, at least as an approximation.

In a typical standard search and matching model, buyers and sellers search for an acceptable match. A match is acceptable to a pairing of buyers and seller if the quality of the match is high enough that they can agree on a mutually beneficial price. Changes in prices are determined by changes in the bargaining position of buyers and sellers which depend on the relative numbers of buyers and sellers. The bargaining process in these types of models is often specified by the Nash Bargaining Solution which assumes that the bargaining power of a buyer and a seller are fixed.

In a simple model, the matching process for buyers and sellers is governed by a matching function where

#matches per unit of time= m(#Active Buyers, #Active Sellers)

for some function m(.) which displays constant returns to scale in the number of active buyers and sellers. Of course, the number of sales per unit of time is some fraction of the number of matches per unit time. If

θ= (#Active Buyers)/(#Active Sellers)

then

(#matches per unit of time)/(#Active Sellers)= m(θ).

Since θ varies with the aggregated actions of buyers and sellers, it is often associated with an equilibrium condition. An increase in θ above that level may be considered as evidence of excess demand. This type of model is often used to study the choice of list price and how

or strategy of a single seller (e.g., Anglin, 2006) but the measured change in market condition represents the actions of many sellers and buyers.

long it takes for a house to sell.

These models have some features which look like perfect competition. Prices in a real estate market can adjust easily if there is a reason to change: list prices are easy to change and a bargaining process over the selling price makes list prices easy to ignore. In addition, the fact that there is a constant turnover[8] in participants means that new participants are not constrained by previous decisions. Therefore, the decisions of active buyers or sellers should vary smoothly and continuously with any measure of excess demand, such as θ.

The actual time needed to find an acceptable match is random and this randomness is interesting for two reasons. First, it represents a margin of adjustment which is omitted from the standard model of supply and demand. Because the reservation price (reservation utility) is a choice, it can vary with the exogenous variables and with the variables that a seller (buyer) takes as given. Secondly, this randomness avoids the paradox discussed above concerning a perfectly competitive market: rather than being aware of any excess demand or excess supply being rationed arbitrarily, no individual can know if the equilibrium conditions are satisfied at any point in time.

Using search, matching and bargaining models has an additional conceptual benefit. In the limit as the transaction costs go to zero (or, equivalently, as m(.) approaches infinity), the solution to these kinds of models often tends to the perfectly competitive solution (e.g., Satterthwaite and Shneyerov, 2007).[9] Hence, the predicted effect of a change in an

[8] This idea suggests an interesting hypothesis that we cannot test: since turnover in participants is related to the average time on market, an exogenous change in matching technology which reduces the average time on market, should cause selling prices to adapt faster to any new information, including information on excess demand.

[9] The intuition is simple. When transaction costs are very small, any buyer or any seller who is matched can find a nearly identical alternative trading partner at nearly no extra cost. Given that context, the equilibrium conditions imply that all of the acceptable matches are nearly ideal for both buyers and sellers and that there is little surplus to be divided in equilibrium. The same reasoning implies that the equilibrium negotiated price differs little from the perfectly competitive solution for an equilibrium price.

exogenous variable, such as consumer income or interest rates, on aggregate measures of the equilibrium outcome would differ little between this type of model and a model of perfect competition. The obvious exception is any exogenous change to the search and matching processes.

A small number of papers propose search models while relaxing the steady state assumption: e.g., Pissarides (2000, section 1.7 using a labor market context) and Akın and Platt (2022). They tend to not comment on a transition or to make strong assumptions about what is known during that transition.[10] Figure 1 of Carrillo, de Wit, and Larson (2015) shows how the time path of many variables (e.g., prices, matching probability and seller's bargaining power) can converge to a long-term compatible outcome following a simulated change in the buyer/seller ratio. Readers interested in an empirical model of search which estimates or infers expectations are encouraged to read Fowler, Fowler, Seagraves and Beauchamp (2018).

Other papers add useful insights. Novy-Marx (2009) distinguishes "hot" and "cold" markets based on a measure of "market tightness" (i.e., θ). He argues that illiquid markets are volatile for reasons which traditional search models overlook: sellers take advantage of favourable market conditions and are not replaced instantly. Allowing the rate of entry to vary with the expected value of entry amplifies the effect of a shock.[11] Krainer (2001) offers a simple Markov model to study how prices change with the state, especially if the transition probability between high and low is unequal (i.e., if the hot and cold phases of a market are asymmetric).

[10] This review has avoided discussing a learning process. That oversight is unfortunate since the perfectly competitive model often invokes the assumption that people agree on the market price. Search and matching models relax that assumption, slightly. Many dynamic models assert that participants make expectations about future prices while few consider whether those price expectations are consistent with finding a trading partner at that price. Discussing such issues is beyond the scope of this paper since, as Howitt (1990, Ch. 1) argues, the classic argument about a Walrasian auctioneer relies on heroic assumptions and the alternatives also rely on heroic assumptions.

[11] Some work on the Beveridge Curve which proposes that an increase in the number of listings is followed by an increase in the number of buyers (Piazzesi, Schneider and Stroebel, 2020; Gabrovski and Ortego-Marti, 2019). The data available to us does not allow us to investigate this effect.

This selective review emphasizes the intuition concerning the concepts of excess demand and market tightness, but we humbly suggest that no paper looks at our empirical specification. The perfectly competitive model asserts that prices respond to excess demand quickly, where the magnitude of the response depends on the price elasticities of supply and demand. Those elasticities vary with the constraints on decision markers. Dynamic models show that the observable variation of one endogenous variable over time requires a change in an exogenous variable or complementary changes in one or more endogenous variable(s). Models of search, matching and bargaining may display features of a real estate market realistically, especially by creating an internally consistent reason for the actions of buyers and sellers to be observable in real time. They reveal the importance of θ= (#Active Buyers)/(#active Sellers) as a relevant endogenous measure of current market conditions.

3. Hypotheses

The previous section focuses on how different models of the market process offer different perspectives on the meaning and effects of excess demand. The hypotheses we propose below do not refer to any specific theoretical model and use the robust characteristics of many models.[12]

Our first hypothesis focuses on a prediction which should be obvious but is rarely tested directly in a real estate market: that excess demand increases prices. The extra transaction costs and illiquidity of a real estate market make this hypothesis testable since, in a perfectly competitive model, prices are expected to adjust sufficiently quickly that the potential evidence of excess demand is not observed in real time.

Hypothesis 1: An increase in excess demand is associated with an increase in price

[12] We do not offer a new model which combines aspects of the different types of models because we expect any model which merges the different types would be complicated with no predictions that are not found in the original "special case" models. Our literature review emphasizes features which are robust.

contemporaneously.

The most obvious differences between cities are their size and relative location. Big cities have more buyers and more sellers. Therefore, the effects of random differences in matching on aggregated measures of market conditions should be smaller. Reports produced by real estate board in big cities should be more reliable, due to the effects of the law of large numbers. That increase in reliability should imply that buyers and sellers react faster to that evidence. In addition, we note that most conceptual models of search and matching assume that a very large number of buyers and an equally large number of sellers participate in the market. This assumption simplifies the algebra used to solve for a steady state equilibrium but it may be implausible in a smaller city where a buyer may be able to quickly decide that all of the existing listings are completely unacceptable and that there are no close substitutes. Therefore, buyers in a smaller city are more likely to be forced to wait because a certain type of house is not available at any price. Both of these reasons support a final hypothesis:

Hypothesis 2: In a big city, the effect of an increase in excess demand on price diminishes faster over time.

People living in isolated cities are more constrained since they cannot move to another city. As contrast, somebody who lives in a city which is not isolated can buy a home in a different city (through another real estate board) or they can find a job and a new home in a different city with relative ease. By Le Chatelier's Principle, constrained quantity decisions respond less to any change in excess demand. Hence, the required price change is greater. Hence,

Hypothesis 3A: In a city which is isolated from other cities, an increase in excess demand has a greater change in price contemporaneously.

Hypothesis 3B: In a city which is isolated from other cities, the effect of an increase in excess demand on price diminishes over time slower.

The following hypotheses focus on differences in the timing of that common process. Researchers (e.g., Glaeser and Nathanson, 2017; Paixão, 2021) suggest that differences in supply elasticity are relevant. As Figure 1 shows, an increase in supply elasticity implies a greater quantity response to any given change in price; sellers in that city change their decisions by more. Therefore, for a given shock to quantity, the change in price needed to reestablish an equilibrium is less. Hence, we expect the immediate response to be less and any later responses to be smaller.

Hypothesis 4A: In a city with a greater supply elasticity, an increase in excess demand has a smaller effect on price contemporaneously.

Hypothesis 4B: In a city with a greater supply elasticity, the effect of an increase in excess demand on price diminishes over time faster.

4. Data and Methods

Each of these hypotheses will be studied with two measures of excess demand: S/NL and MoI. The sign of an effect on prices should differ S/NL and MoI because an increase in S/NL tends to imply an increase in excess demand while an increase in MoI tends to imply an increase in excess supply. This section discusses the data that we use and the methods of analysis.

Data

The data on market conditions summarize activities in the real estate markets for 31 cities, and are provided by the Canadian Real Estate Association (CREA) and. The time period varies from city to city, with the boards in some cities providing data for nearly 25 years (January 2000- September 2024, although the data provided for most cities starts in

2005). The long time span offers some assurance that the data account for at least one complete cycle (peak to trough to peak) in each city. None of the variables are seasonally adjusted. Appendices 1 and 2 provide more detailed information.

One of our three dependent variables (DV) is the percentage change in CREA's Housing Price Index (HPI; Composite Home type) for a city deflated by Statistics Canada's national measure of the Consumer Price Index (CPI), excluding the eight most volatile components as defined by the Bank of Canada. We denote this variable as ΔPI. The HPI is estimated by a repeat sale methodology which accounts for differences in the quality of properties bought and sold in a given month.

The second dependent variable is the ratio of sales in a month to the number of new listings in a month (S/NL). It is widely used by practitioners in Canada when commenting on the state of the market in a location, such as demonstrated by monthly reports from CREA.[13] Intuitively, the number of new listings in a month is direct evidence on the number of sellers willing to sell and the number of sales in a month is direct evidence on the number of buyers willing and able to buy. Using the S/NL ratio to identify any imbalance has the advantage that it adjusts automatically for changes in the size of a city over the long period we consider.

Our third DV is "Months of Inventory" (MoI) which is computed as the ratio of the stock of listings on last day of a month divided by the number of sales during that month. It is similar to S/NL in the sense that the measure automatically adjusts for the size of a city. The key difference is that the number of listings measures a flow, in the case of S/NL, or a stock, in the case of MoI. The former measure is conceptually similar to the model of flows proposed in the typical model of supply and demand. When studying a transition, the difference may mean that using MoI introduces spurious effects from history.

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[13] Please see https://www.crea.ca/media-hub/news/ for examples.
The Canada Mortgage and Housing Corporation, a Crown corporation, offers examples with some similarities and some differences https://www.cmhc-schl.gc.ca/professionals/housing-markets-data-and-research/housing-research/surveys/methods/methodologies-housing-market-assessment.

We treat both S/NL and MoI as measures of excess demand, where an increase in S/NL or a decrease in MoI suggests that the number of buyers has increased relative to the number of sellers. Inspecting the data show that they are highly correlated for any given city. Both S/NL and MoI are closely related to the endogenous variable θ discussed above.[14]

Testing our hypotheses uses data on three characteristics of a city. A city is deemed to be Big if it is one of the 15 largest cities in Canada. A city is deemed to be Isolated if the city is relatively far from another city, in the opinion of the authors. Evidence on a city's supply elasticity is provided by Paixão (2021) who measures the "sensitivity of local house prices to regional house price cycles".

One potential concern with these measures is that the different sources define a city in slightly different ways. Data on real estate activity is provided by a local real estate board. Data on a city's population is defined by Statistics Canada. Paixão (2021) reports a city-wide measure by aggregating a localized measure. In most cases, the geographic overlap between the definitions is substantial.

Method

We account for any effects of exogenous variables simply. In an ideal world, it would be possible to study the determinants of a dependent variable (DV_{ct}) in city c by collecting data on a long list of time-varying exogenous variables ($e_{c1}(t)$, $e_{c2}(t)$, $e_{c3}(t)$, ...) and then estimate a regression equation such as

$$DV_{ct} = \alpha_{c0} + \alpha_{c1}\, e_{c1}(t) + \alpha_{c2}\, e_{c2}(t) + \alpha_{c3}\, e_{c3}(t) + \ldots + u_{ct}, \qquad (1)$$

where u_{ct} is a random variable. In this specification, the estimated coefficients could reveal an income elasticity for each city or the net effect of a local regulation. Our research has a

[14] The relative importance of using a stock measure of the number of sellers vs. using a flow measure could vary with the average time on market. Our data does not include such data. Changes in the search and matching processes over time may change the average time on market, which would change the steady state values of S/NL and MoI.

different objective. For this reason, we combine the effects of exogenous variables into a fourth-order time trend in order to emphasize the variation and co-variation in the endogenous variables. For each city, we estimate

$$DV_{ct} = \beta_{c0} + \beta_{c1}\, t + \beta_{c2}\, t^2 + \beta_{c3}\, t^3 + \beta_{c4}\, t^4 + u_{ct}. \qquad (2)$$

where t is a time trend. In this specification, the estimates for (β_{c0}, β_{c1}, β_{c2}, β_{c3}, β_{c4}) represent the combined effects of (α_{c0}, α_{c1}, α_{c2}, α_{c3}, ...) and ($e_{c1}(t)$, $e_{c2}(t)$, $e_{c3}(t)$, ...). In both specifications, the estimated residuals, $\hat{u}_{ct}$, represent changes in the DV which are not explained by the exogenous variables. In addition, we use 12 dummy variables to measure monthly seasonal effects.

This specification means that we cannot comment on, say, the effects of population growth or interest rates in a particular city and we are not trying to estimate a long-term relationship between the exogenous variables and the endogenous variables.[15] Relative to the changes in the endogenous variables, the exogenous variables should vary over time slowly. Therefore, a high-order polynomial time trend should be able to account for the effects of variables which govern the endogenous variables in a long run equilibrium.

We use a vector autoregression (VAR) model[16] to estimate the relationships for the

[15] There are a couple of reasons. We are confident that we cannot collect data on all of the relevant exogenous variables for all cities identified by Miller and Sklarz (2012). Further, we are confident that all of the high-quality information would not be available for market participants to use at the time that the participants need it. Our goal is to fill the gap concerning the persistence of indicators of market conditions and their implications for short term forecasting. Many other researchers have studied long term relationships in real estate markets (e.g., Oikarinen, Bourassa, Hoesli and Engblom, 2023; Lai and Van Order, 2017; Leung and Tang, 2020; Stevenson, 2008; Capozza, Hendershott and Mack, 2004).

[16] Other methods of analysis exist and have been applied to study questions related to ours. For example, a Markov model could account for the effects of a hidden state variable which evolves over time (e.g., Carstens and Freybote, 2021; Nneji, Brooks, and Ward, 2013). We prefer to not use such methods because using a small number of discrete categories (such as three: "buyers' market", "sellers' market" or "balanced" market conditions) for the state of the market may limit insights. It is also possible to study how market conditions evolve in a city by paying more attention to "ripple effects" from other cities (e.g., Payne and Sun, 2023; Zhang, Sun and Stengos, 2019; Meen, 1999). Papers which study localized contagion (e.g., Fischer, Füss and Stehle, 2021) also account for spatial effects but, because they use data on individual transactions, represent a different perspective. Since these methods are not nested, a preference for any one estimator may enhance certain features and diminish other features by assumption. Consideration of these other methods is beyond the scope of this paper.

three DVs in each city independently.[17] The resulting estimates are used to compute a contemporaneous correlation coefficient (CCC_{csr}) between residuals for any pair of regression equations (s and r) in any city c, and to estimate various impulse response functions. IR_{clsr} denotes the estimated impulse response of a change in variable s on variable r in city c on the l-th lag. These estimates are then used in an OLS regression to identify and estimate differences between cities.

We could test the hypotheses by estimating a model such as:

$$IR_{clsr}= \delta_0+ \delta_1 I\_(Lag= 2)+ \delta_2 I\_(Lag= 3)+ ... + \delta_{23} I\_(Lag= 24)+ \delta_{24} CCC_{csr}+ \delta_{25} (Lag\# \times Big_c)+ \delta_{26} (Lag\# \times Isolated_c)+ \delta_{27} (Lag\# \times Supply\ Elasticity_c)+ e_{clsr} \quad (3)$$

where I_(.) represents a dummy variable which equals 1 if the condition "." is True and 0 otherwise, Lag# is the lag length (i.e., from one to 24). The flexibility of this specification means that it can account for the shape of an arbitrary function. The disadvantages of this specification are that it requires that a large number of coefficients be estimated and it could lead to overfitting. The large number of coefficients also makes it harder to compute test statistics related to how any the rate of decay in an effect differs between cities. Estimating so many coefficients independently also seems inefficient statistically, since Figure 3 below shows that some impulse response functions display similarities amongst cities. For this reason, we use a flexible functional form which is also easier to interpret.

Our regression model is based on a spline function with five coefficients:

$$S(L)= b_1 I\_(Lag= 1)+ b_2 I\_(Lag= 2)+ b_3 I\_(Lag\geq 3)+ b_a \max(Lag- 3, 0)+ b_b \max(Lag- 12, 0). \quad (4)$$

The specification allows the value of IR_{clsr} to vary independently for the first three lags (i.e., months after the impulse). After the third lag and before the 13th lag, the increase or decrease in IR_{clsr} is assumed to be linear in the lag and is captured by the coefficient b_a. After the 12th lag, any additional increases or decreases in IR_{clsr} are also assumed to be linear and

[17] The number of lags used when estimating the regression model for each city was chosen after inspecting the output from a `varsoc` command in Stata. When different test statistics suggest different lag lengths, we pick the average with a small tendency to round up. Appendix 1 reports the number of lags used for each city.

are captured by the coefficient b_b. Stated more simply, the short-term effects of an impulse are summarized by b_1, b_2 and b_3 while medium- or longer-term effects are summarized by b_s and b_b.

This spline function offers a number of advantages when working with regressors which interact the lag length with city-specific variables. Our regression model is

$$IR_{clsr}= \gamma_0+ \gamma_1\, CCC_{csr}+ \gamma_2\, I\_(Lag= 2)+ \gamma_3\, I\_(Lag\geq 3)+ \gamma_4 \max(Lag- 3, 0)+ \gamma_5 \max(Lag- 12, 0)+$$
$$\gamma_6\, I\_(Lag= 2)\times Big_c+ \gamma_7\, I\_(Lag= 2)\times Big_c+ \gamma_8\, I\_(Lag\geq 3)\times Big_c+ \gamma_9 \max(Lag- 3, 0)\times Big_c+$$
$$\gamma_{10} \max(Lag- 12, 0)\times Big_c +$$
$$\gamma_{11}\, I\_(Lag= 2)\times Isolated_c+ \gamma_{12}\, I\_(Lag= 2)\times Isolated_c+ \gamma_{13}\, I\_(Lag\geq 3)\times Isolated_c+$$
$$\gamma_{14} \max(Lag- 3, 0)\times Isolated_c+ \gamma_{15} \max(Lag- 12, 0)\times Isolated_c+$$
$$\gamma_{16}\, I\_(Lag= 2)\times Elasticity_c+\gamma_{17}\, I\_(Lag= 2)\times Elasticity_c+ \gamma_{18}\, I\_(Lag\geq 3)\times Elasticity_c+$$
$$\gamma_{19} \max(Lag- 3, 0)\times Elasticity_c+ \gamma_{20} \max(Lag- 12, 0)\times Elasticity_c+ e_{clsr}. \qquad (5)$$

If s= r= ΔPI then both the contemporaneous correlation coefficients between S/NL and ΔPI and between MoI and ΔPI are included.

5. Results

This section reports on the similarities and differences amongst cities. We start by summarizing the data for four well-known Canadian cities before testing our hypotheses. We report on relationship. We report on the contemporaneous correlation between prices changes and changes in either the ratio of sales to new listings (S/NL) or months of inventory (MoI) across cities. "Contemporaneous" implies before participants see updated data on the state of the market). Then we test for differences between cities in this correlation. We then test for Granger-causality to find one- or two-way relationships between price changes and changes in either the ratio of sales to new listings (S/NL) or months of inventory (MoI). These tests confirm that these indicators of market conditions can be used to improve the accuracy of a price forecast. The last part of our discussion studies the determinants of impulse response functions to comment on the economic significance of the differences between cities.

To manage the length of the paper, Table 1 summarizes the data for three of Canada's four largest cities (Toronto, Vancouver and Calgary) plus the national capital (Ottawa). This table also summarizes the time trend variable used to construct the quartic equation which is intended to capture the net effects of any trends in exogenous variables and, to indicate that the data covers a longer span of time in some cities than in other cities, the number of observations for each city. Based on an Augmented Dickey-Fuller Test, each of these series rejects the hypothesis that they display a unit root. Additional results are available from the authors on request.

Table 1: Sample Summary of Data: Four Large Cities

	Mean	St.Dev.	25%ile	50%ile	75%ile	N
Time Trend	1.43	0.54	1.00	1.25	1.84	297
Ottawa						
Price Index	1.33	0.31	1.14	1.21	1.42	237
ΔPI	0.27	1.15	-0.34	0.24	0.86	236
Sales/New Listings	61.88	17.74	49.52	58.60	71.53	237
Months of Inventory	3.90	1.88	2.68	3.77	4.93	237
Greater Toronto						
Price Index	1.43	0.54	1.00	1.25	1.84	297
ΔPI	0.36	1.28	-0.14	0.38	0.89	296
Sales/New Listings	60.78	15.86	51.31	59.12	67.61	297
Months of Inventory	2.57	1.04	1.95	2.57	3.06	297
Calgary						
Price Index	1.41	0.31	1.26	1.51	1.61	297
ΔPI	0.28	1.17	-0.36	0.16	0.68	296
Sales/New Listings	64.12	17.79	51.67	63.58	74.56	297
Months of Inventory	3.61	1.82	2.33	3.23	4.93	297
Greater Vancouver						
Price Index	1.74	0.42	1.39	1.61	2.18	237
ΔPI	0.35	1.26	-0.41	0.42	1.15	236
Sales/New Listings	61.72	22.88	46.40	57.14	73.02	237
Months of Inventory	4.81	2.53	3.07	4.28	5.76	237

Source: Canadian Real Estate Association and authors' calculations
Note: "Price Index" refers to a House Price Index which has been adjusted for inflation. "ΔPI" refers to the monthly percentage change in inflation adjusted price index.

Table 1 demonstrates how the experiences of buyers and sellers in the different cities differed during the 20- 25 year period covered by our data. For example, the growth in the real price level in the Greater Toronto and the Greater Vancouver areas was much more than in Ottawa during this time. This fact suggests that there is a useful heterogeneity amongst the cities.

This table also shows how the average value of S/NL and MoI in different cities differ and, more relevant to our study, that the ranges differ. CMHC suggests a reference point for when market conditions are balanced: the upper bound is S/NL= 0.55 and lower bound is S/NL= 0.40. The 25th and the 75th percentiles listed in Table 1 suggest that these bounds are too low for most cities, which would make the market appear to be in a "sellers' market" condition for an extraordinarily long time. Identifying an appropriate reference point for "balanced market conditions" is complicated by an additional feature of the data. Inspecting the data directly show that S/NL and MoI display runs for extended periods of time. The significance of this concern can also be seen by comparing MoI during Jan. 1990 to Dec. 1994 and MoI during Jan 2019 to Dec. 2023. The five-year average was less during the latter period in all cities and the decrease was often dramatic: in more than half of the cities in the data set, the average MoI dropped by over 65 percent. Since this trend is evident in nearly every city in our data, we conclude that historic averages offer an imperfect guide to what is normal.

It is also possible to plot the relationship between S/NL and ΔPI or between MoI and ΔPI using either a monthly or annual periodicity. Such plots imply that the relationship is not as simple or as clear as the famous relationship between the unemployment rate and wage inflation associated with the Phillips Curve (Phillips, 1958).

To better understand the differences between cities, we estimate equation (2). Since we consider many cities and since the individual coefficient estimates are intended to be a reduced form of a more complicated process, we do not report them directly. (Interested readers can contact the authors for more details.) We consider its implications: we compute the residuals to each equation and compute the contemporaneous correlation coefficients between them for each city independently. These are reported in Table 2.

Table 2: Distribution of Contemporaneous Correlation Coefficients across Cities

Panel A: S/NL and ΔPI

Range	<0.0	0.0 to 0.1	0.1 to 0.2	0.2 to 0.3	0.3 to 0.4	Total
Number of Cities	1	5	11	7	7	31

Panel B: MoI and ΔPI

Range	-0.4 to -0.3	-0.3 to -0.2	-0.2 to -0.1	-0.1 to -0.0	> 0.0	Total
Number of Cities	1	9	13	5	3	31

Table 2 supports Hypothesis 1 in nearly all cities since the contemporary correlation coefficient (CCC) nearly always has the expected sign. For the coefficients with an unexpected sign, the estimated coefficient does not differ from 0 significantly (often with a p-value which exceeds 0.5). This table shows that, before enough time has elapsed for the evidence to be published in a regular report and before participants can react to the publication, an increase in excess demand increases prices.

Table 3: Determinants of Contemporaneous Correlation Coefficient

	CCC(S/NL, ΔPI)	CCC(MoI, ΔPI)
Big?	0.022	-0.023
	0.48	-0.64
Isolated?	-0.114	0.05
	-2.50	1.41
Elasticity	0.005	-0.002
	0.78	-0.36
Constant	0.228	-0.177
	5.87	-5.84
N	26	26
R^2	0.252	0.102

Note: The dependent variable is the contemporaneous correlation coefficient between the two equations estimated by the VAR model for each city independently. The first row represents the coefficients estimated using an OLS regression and the second row represents the associated t-statistic.

Table 3 investigates how CCC varies with the characteristics of a city. Most of the coefficients are statistically insignificant, perhaps because the number of cities in our sample is small. The exception are the coefficients associated with Isolated: both have an unexpected sign and a noteworthy t-statistic. The size of the effect of a city being Isolated on the correlation between S/NL and ΔPI is remarkable: the absolute value of the estimated coefficient (-0.114) is more than half of the average CCC for the 26 cities included[18] in this regression (i.e., 0.205, please see Table 5 below). Therefore, our analysis rejects Hypothesis 3A.

Table 4: Granger Causality Relationships

	Only SNL→ ΔPI	Only MoI→ ΔPI	Both→ ΔPI	Both Insignificant	Total
ΔPI→SNL only	5	1	2	0	8
ΔPI→MoI only	0	0	1	0	1
ΔPI→Both	3	0	0	0	3
Both Insignificant	6	0	13	0	19
Total	14	1	16	0	31

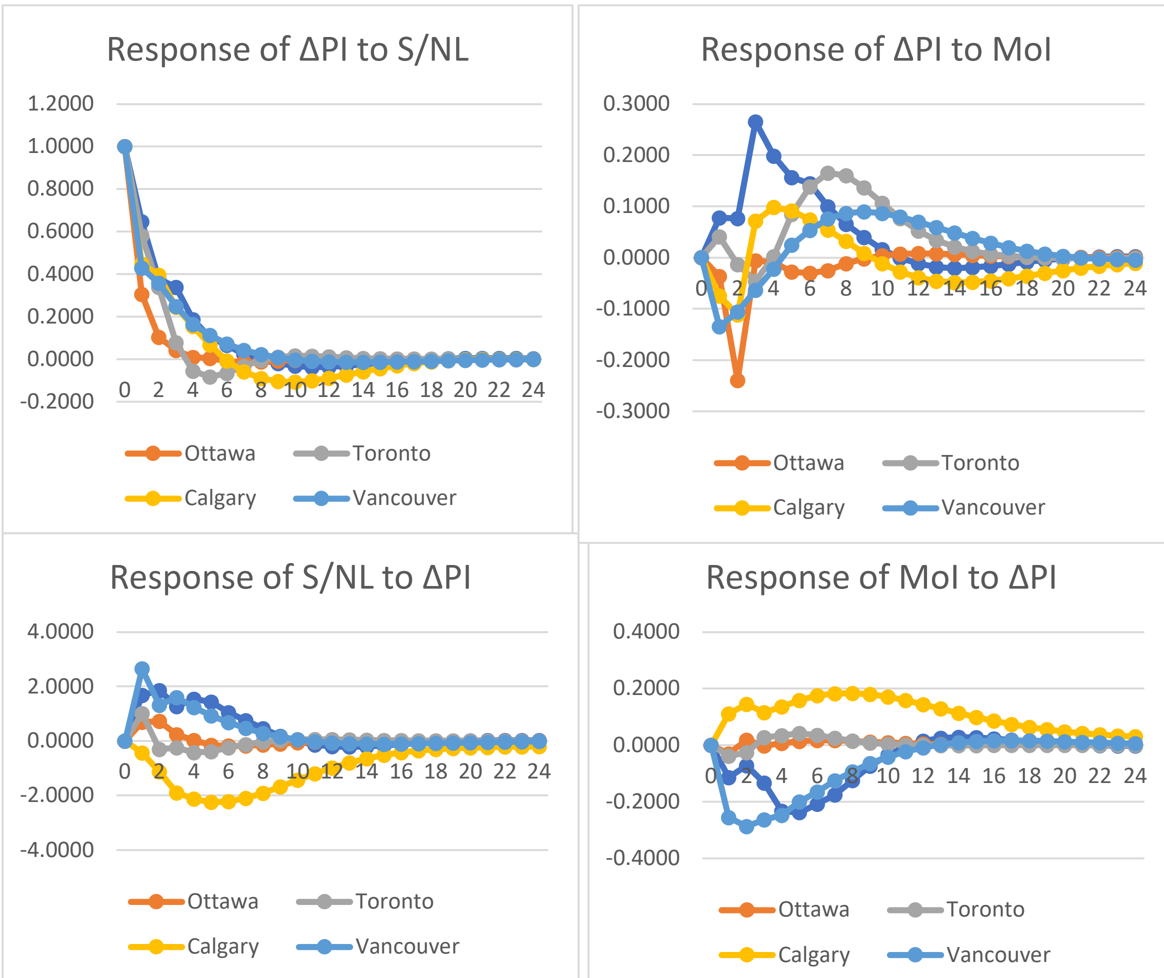
Note: "Statistical significance" is based on a p-value less than 0.05 on the hypothesis that a given dependent variable can be excluded from a given equation. For example, the relationship "Both →ΔPI" implies that the p-value is less than 0.05 when testing the joint hypothesis that S/NL has no effect on ΔPI and that MoI has no effect on ΔPI.

The fact that the sign of the contemporaneous correlation coefficients is usually as expected should be good news for theorists. The fact that so many of them are so small may be sobering. Table 4 shows the results of Granger-causality tests to show whether some of the effects are delayed. There is strong evidence that, in all cities, a change in either S/NL or MoI or (most commonly) both affect prices: measures of excess demand have observable effects on prices. The evidence supporting a statistically significant effect of S/NL on ΔPI is more consistent than the evidence supporting a statistically significant effect of MoI. The evidence on feedback effects, where a change in prices affects either S/NL or MoI, is less consistent: only 12 cities (about 40 percent) display evidence of two-way causality at the 5

[18] The data used in this Table omits five cities for which data on the supply elasticity is missing: they tend to be smaller cities.

percent level of significance. This Table offers strong evidence that including evidence on other indicators of market conditions would improve the quality of forecasts of prices.

Figure 3: Magnitude of Impulse Responses for Four Large Cities



Note: These figures show the response of ΔPI, S/NL or MoI to an impulse of ΔPI, S/NL or MoI. Different lines indicate responses in different cities.

Statistical significance and Granger-causality are useful benchmarks but the economic significance of the relationship depends on the timing of any effects. Figure 3 uses impulse response functions to highlight how a change in S/NL or MoI affects prices (and the reverse) over time. It uses the same cities highlighted in Table 1. The upper left panel shows that the effect of S/NL on ΔPI is nearly the same in all cities: the biggest effect is immediate and the effect size decreases over time. After 12 months, the effect is often near zero or negative. The lower left panel shows that the effect of ΔPI on S/NL is less consistent in terms of direction and timing. The relationship between MoI and ΔPI shown on the right-hand panels is more complicated.

Our formal study of the differences in responses across cities uses the impulse response for the first 24 lags as the dependent variable in an OLS regression. Table 5 summarizes these data. With 26 cities and 24 observations per city, there are 624 observations in total. Table 7 provides the estimated coefficients using the specification outlined in equation (5). Since Table 7 includes many coefficients, we start by discussing some joint hypotheses tests in Table 6.

Table 5: Summary Statistics for the Impulse Responses

Variable	Mean	St.Dev.	25%ile	50%ile	75%ile
IR(S/NL, p)	0.011	0.021	0.000	0.001	0.015
IR(p, S/NL)	0.028	0.412	-0.020	0.001	0.072
IR(p, p)	0.016	0.076	-0.001	0.000	0.010
IR(p, MoI)	0.000	0.051	-0.006	0.000	0.008
IR(MoI, p)	0.014	0.091	-0.008	0.001	0.031
CCC(S/NL, p)	0.205	0.120	0.117	0.215	0.302
CCC(MoI, p)	-0.172	0.085	-0.221	-0.179	-0.123
Big	0.462	0.499	0	0	1
Isolated	0.423	0.494	0	0	1
Elasticity	3.164	3.667	1.008	2.194	4.337

Note: IR(x, y) represents the impulse responses for x on y for 24 lags. CCC(x, y) represents the contemporaneous correlation coefficient between x and y in a city derived from the residuals to the VAR model. This work uses a smaller data set than Table 1, since the data on Supply Elasticity is not available for all cities.

Table 6 shows that, a city being Big, being Isolated or having a high Elasticity usually has a statistically significant effect on responses at the 5 percent level. The exception is that the effect of an impulse in S/NL on ΔPI does not differ significantly in an Isolated city. The differences in the effect of an impulse in ΔPI on S/NL and MoI according to the Elasticity are marginally significant ($p < 0.10$).

Table 6: Tests of Joint Hypotheses

Variable	IR(S/NL, ΔPI)	IR(MoI, ΔPI)	IR(ΔPI, ΔPI)	IR(ΔPI, S/NL)	IR(ΔPI, MoI)
Big	0.005	0.003	0.000	0.000	0.000
Isolated	0.463	0.037	0.000	0.000	0.009
Elasticity	0.000	0.000	0.000	0.098	0.054

Note: This Table reports the p-value for the joint hypothesis that the variable listed on the left-hand side of the table has no interaction effect with the spline variables used to account for any lagged effect in a particular equation (shown in the top row). They are based on a F(4, 607) distribution.

Table 7 displays the individual coefficients associated with equation (5). The first two columns report on the response to an impulse in commonly used measures of excess demand on prices. The third column serves a reference point enabling a comparison with previous studies which consider price trends while excluding measures of excess demand. (Appendix 3 report information concerning feedback effects from price changes to measures of excess demand in a format similar to Table 7.) The first four rows show how the impulse response varies with the lag. The next two rows show how the lagged responses vary with the contemporaneous correlation coefficient (CCC). The following rows show how the effects vary when the lag is interacted with various characteristics of a city. The last two rows of this table report the goodness of fit for two simpler regression specifications which exclude city-specific information: a specification which allows the estimated response to vary by lag independently and a specification which uses the spline. We remind readers that the impulse responses are derived from a VAR model which uses three dependent variables and a simple quartic time trend.

The contemporaneous correlation coefficient has a statistically significant effect on an impulse response from excess demand: an increase in the contemporaneous effect of excess demand reduces the effect on prices later. (Since CCC(MoI, ΔPI) is normally negative, unlike CCC(S/NL, ΔPI), an increase in CCC(MoI, ΔPI) implies *less* correlation contemporaneously.) We note that neither correlation coefficient affects IR(ΔPI, ΔPI) significantly.

Table 7 shows that the size of a city affects the medium term response to a change in S/NL (i.e., IR(S/NL, ΔPI)) and almost no effect for IR(MoI, ΔPI). The patterns are also noteworthy. The effects of S/NL are evident during lags 2, 3 and 4 to 12, where the impulse is larger in a big city until there is a small reversal during months 4 to 12. We conclude that these later results support Hypothesis 2B. In passing, we note that the size of a city has a significant effect in the short term, medium and the longer term on IR(ΔPI, ΔPI).

A city which is Isolated differs little from other cities in terms of the response to an impulse in S/NL: the coefficients are both small and statistically insignificant. The city-specific response to an impulse in MoI is statistically significant, but only in the longer term and with a varying sign of the effect. Therefore, we conclude that there is limited support for Hypothesis 3B. The effect of being Isolated on IR(ΔPI, ΔPI) is significant in the short term and occasionally large. This finding, combined with our earlier finding that the contemporaneous correlation coefficient between S/NL and ΔPI is much lower in Isolated cities, is worth studying.

The statistically significant coefficients concerning interaction with Elasticity show statistically significant effects in the short run response. We conclude that there is support for Hypothesis 4B. Given the average magnitude of Elasticity, the effects seem to be relatively small.

Table 7: Explaining Differences in Impulse Response across Cities

Variable	IR(S/NL, ΔPI)	IR(MoI, ΔPI)	IR(ΔPI , ΔPI)
Lag= 2	0.002	-0.004	0.022
	0.41	-0.11	0.75
Lag≥ 3	-0.006	0.039	-0.131
	-1.22	1.23	-5.57
Lag(4- 12)	-0.004	0.009	-0.002
	-9.91	3.68	-1.36
Lag(13- 24)	0.004	-0.013	0.002
	6.63	-3.40	0.73
CCCSp	-0.011		-0.033
	-2.36		-1.14
CCCMp		0.216	-0.024
		5.40	-0.65
(Lag= 1)× Big	0.004	0.035	0.202
	0.91	1.08	8.45
(Lag= 2)× Big	0.012	0.002	0.084
	2.54	0.08	3.52
(Lag≥ 3)× Big	0.008	0.054	0.025
	3.01	2.96	1.86
Lag(4- 12)× Big	-0.001	-0.003	-0.005
	-2.68	-1.12	-2.20
Lag(13- 24)× Big	0.001	0.001	0.007
	1.95	0.24	2.05
(Lag= 1)× Isolated	-0.009	0.021	-0.154
	-1.9	0.63	-6.38
(Lag= 2)× Isolated	0.002	0.002	-0.087
	0.52	0.05	-3.60
(Lag≥ 3)× Isolated	0.002	0.021	-0.007
	0.67	1.16	-0.53
Lag(4- 12)× Isolated	0.000	-0.007	-0.001
	-0.65	-2.53	-0.55
Lag(13- 24)× Isolated	0.000	0.011	0.003
	0.40	2.53	0.86
(Lag= 1)× Elasticity	0.004	0.016	-0.017
	5.56	3.55	-5.18
(Lag= 2)× Elasticity	0.002	0.026	-0.012
	3.59	5.95	-3.68
(Lag≥ 3)× Elasticity	0.000	0.019	-0.001
	1.4	7.89	-0.43
Lag(4- 12)× Elasticity	0.000	-0.003	0.000
	-1.25	-6.48	0.77
Lag(13- 24)× Elasticity	0.000	0.003	0.000
	1.15	4.96	-0.79
Constant	0.039	-0.051	0.16
	9.54	-1.79	7.53
N	624	624	624
R^2	0.694	0.243	0.407
R^2 (Lags Only)	0.679	0.040	0.271
R^2 (Spline)	0.651	0.028	0.254

Note: The dependent variables are estimated impulse responses implied by a VAR model and Table 7 reports the coefficients and t-statistics estimated using an OLS regression of equation (5). The "Lags Only" specification includes only dummy variables for lags 2 to 24 while the "Spline" specification uses equation (4).

The bottom of Table 7 reinforces the message of economic significance. The third last row reports R^2 for a regression equation using a spline and city-specific interaction variables (i.e., equation (5) whereas the last two rows report R^2 for regressions with no city-specific information but a more precise estimate of time-varying effects. In all cases, using city-specific information produces a better goodness of fit, often much better.

6. Concluding thoughts

Our literature review noted that most of the recent research which study price trends implicitly assumes that other indicators of market conditions are empirically irrelevant. We test that suggestion as well as study how changes in these other indicators persist over time. We find that price and two popular measures of excess demand (the ratio of sales to new listings, S/NL, and Months of Inventory, MoI) are predictable using publicly available information. We find that they are correlated contemporaneously, almost always with the expected sign. We also find that the correlation coefficients vary greatly across cities in Canada. For many cities, we find evidence of two-way Granger causality between price changes and excess demand over a longer period of time (often with a p-value of much less than 0.01). We show that these feedback effects are significant statistically and economically.

The fact that changes in S/NL and MoI are predictable and affect prices has several important implications. The most obvious implication is that predicting prices by extrapolating from past prices, while ignoring other measures of market conditions, overlooks relevant information. Studies of price bubbles, in particular, could benefit by including evidence which reveals how observed excess demand and price co-vary over time. Our analysis also implies that the boundary between a buyers' market and a sellers' market cannot be summarized by a rule as simple as "current S/NL is above (or below) a threshold".

We provide evidence that the relevant threshold tends to shift over time either because of persistence or, especially in the case of MoI, because of a historically significant shift in the normal level.

We find that different cities display similarities and differences. We found partial support for hypotheses concerning the effects of differences between cities concerning size, isolation and supply elasticity. The difference in the contemporaneous correlation coefficient between S/NL and price changes in isolated cities is particularly noteworthy. Future research into the economic significance of any predicted effects will have to refine our understanding of the timing of any effects. In other words, it’s complicated.

Finally, we revisit the idea discussed in the introduction: the challenges with using many indicators of market conditions. Many indicators exist already and technological improvements, such as generative AI and machine learning, imply novel types of indicators will be proposed. Some of these measures will prove to be redundant and some will be hyperlocal or granular in ways which limit their usefulness. We think that the challenge to creating useful indicators is not in the statistical methods but in distinguishing endogenous variables from exogenous variables. Useful data on relevant exogenous variables, such as population growth or zoning policies, may be published too late to be useful to active buyers and sellers. People who want to understand the state of the market currently rely on measures which can be computed quickly and updated frequently by a local real estate board. Identifying useful complementary measures should make home buyers and home sellers more confident about their choices. In the future, data and algorithms may claim to identify “hot neighborhoods” and “overlooked opportunities” in near real time. When challenged by market forces, some of those claims may be revealed as marketing hype with little benefit to decision-makers.

Appendix 1: Classification of City Types

Table A1 indicates how the different cities are classified in terms of size, relative isolation and supply elasticity. The cities in this list are, approximately, ordered from east to west.

Table A1: City Characteristics

	Big City?	Isolated City?	Supply Elasticity
Halifax-Dartmouth	Y	Y	2.556
Moncton		Y	4.501
Fredericton			
Ottawa	Y	Y	1.943
Kingston			1.317
Peterborough			1.179
Greater Toronto	Y		0.887
Mississauga			0.887*
Oakville-Milton			0.887*
Hamilton-Burlington	Y		1.792
Guelph			5.004
Kitchener-Waterloo	Y		5.932
London	Y		19.600
St. Catharines			4.063
Simcoe			
Windsor	Y	Y	2.809
Barrie			3.642
Muskoka			
Sudbury		Y	5.360
Sault Sainte Marie		Y	
Winnipeg	Y	Y	4.337
Regina		Y	0.609
Saskatoon		Y	4.661
Calgary	Y	Y	1.310
Edmonton	Y		1.530
Greater Vancouver	Y		0.637
Chilliwack			2.445
Fraser Valley			2.445*
Okanagan		Y	1.008
Victoria	Y		0.910
Vancouver Island			

*Note: * indicates that this estimate for elasticity is based on the elasticity for a geographically close city.*

A city is considered to be “Big” if its Census Metropolitan Area (CMA, as defined by Statistics Canada) is one of the 15 biggest in Canada. This categorization is crude since, to use Toronto as an example, the cities of Mississauga and Oakville are also included in the Toronto CMA. 11 of the 31 cities considered in our study are identified to be Big.

The categorization of Isolated is based on the authors’ personal opinion of whether a city is near a large city in a geographic sense. This measure is intended to capture the idea that the possibility that a buyer in an isolated city has few outside options when buying a house. As a general guideline, a driving distance of more than two hours implies that a city is Isolated. A buyer in a city which is not isolated could, for example, buy a house in a suburb or in a city within commuting distance and that transaction would not be recorded by the real estate board for the city where they work. 11 of the 31 cities considered in our study are identified to be Isolated.

The evidence on supply elasticity is provided by Paixão (2021). Paixão focuses on annual changes and uses the method proposed in Guren, McKay, Nakamura and Steinsson (2021). Paixão (2021) notes that “The median housing supply elasticity is 2.2 among all [Census Agglomerations] and 1.94 if I restrict the sample to [Census Metropolitan Areas]. These estimates imply that a 1 percent increase in house prices in the median Canadian city is associated with an increase in housing supply of 2.2 percent. Alternatively, we can think that, all else equal, a 1 percent increase in housing demand leads to an increase in house prices in the median city of 0.45 percent (1/2.2).” (Paixão, 2021, p. 5). For three of the cities which are not included in Paixão’s study, we used the estimate from a nearby city.

Appendix 2: Location of Cities included in the Analysis

Source of image: https://en.wikipedia.org/wiki/Provinces_and_territories_of_Canada

Appendix 3: A companion to Table 7

Variable	IR(ΔPI, S/NL)	IR(ΔPI, MoI)
Lag= 2	-0.403	0.004
	-2.35	0.16
Lag≥ 3	-0.717	0.016
	-5.16	0.85
Lag(4- 12)	-0.017	0.002
	-1.56	1.36
Lag(13- 24)	0.010	-0.001
	0.57	-0.32
CCC(S/NL, ΔPI)	0.596	
	4.40	
CCC(MoI, ΔPI)		0.058
		2.42
(Lag= 1)× Big	0.191	-0.003
	1.35	-0.16
(Lag= 2)× Big	-0.121	-0.011
	-0.86	-0.59
(Lag≥ 3)× Big	-0.239	0.036
	-3.00	3.29
Lag(4- 12)× Big	0.010	-0.001
	0.75	-0.51
Lag(13- 24)× Big	0.006	-0.002
	0.31	-0.66
(Lag= 1)× Isolated	-0.44	0.022
	-3.08	1.15
(Lag= 2)× Isolated	-0.245	0.036
	-1.72	1.84
(Lag≥ 3)× Isolated	-0.376	0.022
	-4.62	1.98
Lag(4- 12)× Isolated	0.035	-0.001
	2.74	-0.34
Lag(13- 24)× Isolated	-0.023	-0.001
	-1.15	-0.45
(Lag= 1)× Elasticity	-0.034	0.005
	-1.78	1.72
(Lag= 2)× Elasticity	-0.022	0.006
	-1.14	2.26
(Lag≥ 3)× Elasticity	0.018	0.000
	1.65	-0.14
Lag(4- 12)× Elasticity	-0.001	0.000
	-0.7	-0.69
Lag(13- 24)× Elasticity	0.000	0.000
	0.1	0.88
Constant	0.797	-0.035
	6.37	-2.03
N	624	624
R^2	0.293	0.123
R^2 (Lags Only)	0.144	0.013
R^2 (Spline)	0.137	0.013

Note: The dependent variables are estimated impulse responses implied by a VAR model and this table reports the coefficients and t-statistics estimated using an OLS regression of *equation (5). The "Lags Only" specification includes only dummy variables for lags 2 to 24 while the "Spline" specification uses equation (4).*

This table helps readers who are curious about how city-specific variables affect the timing of feedback effects from an impulse of ΔPI on S/NL and on MoI. Briefly, the overall goodness of fit is lower than is reported in Table 7 and fewer coefficients are statistically significant. The notable exception is that the contemporaneous correlation coefficients (CCC) are significant and large. The final two rows reinforce a finding from Table 7: including city specific variables in the regression has a bigger impact on R^2 than using a more flexible specification for how the response varies over time.

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