Search and Matching in the Housing Market[1]

David Genesove[2] Lu Han[3]

January 13 2011

Abstract

Housing markets clear partly through the time buyers and sellers spend on the market. We show that seller time on the market, homes buyers visit and buyer time on the market decrease with demand, although the last much less so. These measures of market liquidity are much more sensitive to demand growth than its level, consistent with a straightforward matching model with a lag in seller response. Our findings also provide an estimate of the elasticity of the buyer contact hazard of -0.17.

1. Introduction

Housing markets have received increasing attention of late. This is not surprising given that housing represents two-thirds of a typical American household's portfolio and that housing markets across the world have recently undergone dramatic fluctuations. Most housing studies have focused on how demand shocks transmit into changes in prices. Little attention has been paid to how these shocks affect liquidity, such as buyers' purchase and sellers' sale time, the number of homes a buyer visits and the number of enquiries a seller receives. The omission is surprising since economic agents value their time, and liquidity has been shown to be an important covariant with market activity (e.g., Mayer and Somerville, 2000). Since housing markets are highly inefficient in perfect asset market terms (e.g., Case and Shiller, 1989), prices alone are unlikely to fully reflect changes in market fundamentals. Such fluctuations are likely to be reflected partly in market liquidity as well.

---

[1] Thanks to Ed Baryla, Paul Bishop, Glenn Crellin, Harold Elder and Len Zumpano for generally providing us with data, codebooks and questionnaires; Travis Chow for excellent research assistance; and Shouyong Shi, Carlos Garriga and other seminar participants at Toronto, Guelph, Ben-Gurion, Hebrew University, Madison-Wisconsin, UBC and Duke.

[2] Hebrew University of Jerusalem and C.E.P.R. Email: genesove@mscc.huji.ac.il.

[3] University of Toronto. Email: lu.han@rotman.utoronto.ca.

Modelling and estimating the liquidity aspects of housing markets is thus crucial to understanding how these markets work. Matching models are particularly suitable for this purpose given their natural fit for modelling search frictions in housing markets. Yet, despite a rapid increase in the theoretical interest of applying matching models to housing (e.g., Wheaton, 1990; Krainer,1997; Novy-Marx, 2007; Albrecht, Anderson, Smith, and Vroman, 2007), the empirical work in this area is limited. The difficulty stems mostly from the fact that the relevant data on both buyers' and sellers' search experience are generally unavailable together.

In this paper we fill this gap in the literature by providing an empirical analysis of a search and matching model in housing markets. The analysis has three objectives. First, we shed new light on the mechanism governing housing market fluctuations by investigating how market liquidity responds to a demand shock in the context of a matching model. We consider three measures of liquidity: seller time on the market, buyer time on the market, and number of home visits. Second, we provide a market level, integrated analysis of buyers' and sellers' search behaviour. Previous empirical studies on home search have focused almost entirely on one-side of the housing market – sellers or buyers. The advantage of using a two-side matching model is that it allows us to recover the buyer-seller ratio, buyers' and sellers' probability of meeting with each other (contact hazard), and to further examine how these variables respond to the demand shock. Third, we obtain estimates of the elasticity of the contact hazards with respect to the buyer-seller ratio. This study is the first to estimate the matching function for housing.

To this end, we aggregate micro data from the biannual/annual National Association of Realtors' buyers and sellers surveys to the Metropolitan Statistical Area (MSA) level, for available years from 1987-2007, to form market-level measures of buyer and seller time on the market, and number of homes visited. As we are considering how the market responds to overall changes in demand, this is the appropriate level of aggregation. The cross-MSA and over-time variation in both buyers' and sellers' search experience, allows us to provide a panel study of search in housing markets and a simultaneous analysis of buyer and seller behaviour.

We preface the empirical work with a search-matching theoretic analysis that we believe captures the essential elements of a steady state analysis of a demand shock and so allows us to interpret the empirical results later in the paper.[4] We use the standard constant returns to scale random matching model. Given the prevalence of multiple listing services in U.S. residential real estate markets, Coles and Smith's (1996) marketplace model might be thought a better fit. However, with market conditions summarized solely by the stock of buyers and sellers random matching is simpler than the marketplace model, for which buyer and seller inflows matter as well. More crucially, a single statistic of the time on the market distribution suffices for an empirical analysis based on random matching; the marketplace model would require at least two.

Our basic theoretical analysis turns on which of buyer or seller inflow to the market is more sensitive to the value of search. Assuming that buyers are, the model predicts that an increase in market-wide housing demand decreases seller time on the market and the number of homes a buyer visits; its effect on buyer time on the market is ambiguous, since the frequency of a buyer's contact with a seller declines, while each meeting is more likely to end in a transaction. However, the model's predictions for the components of the matching function that underlie time on the market – the contact hazards and the buyer-seller ratio - are unambiguous: the seller contact hazard and the buyer-seller ratio will increase, while the buyer contact hazard will fall. We provide a number of extensions to demonstrate the robustness of these predictions.

We then turn to the empirical analysis, which is the main goal of the paper. We start by estimating the effects of our demand proxies, average income and population, on buyer and seller time

[4] Novy-Marx (2007) presents a similar theoretical model. The main difference between his approach and ours is that he considers shifts in the outside option, rather that in the match quality distribution.

on the market and the number of home visits, controlling for year and market fixed effects. In principle, we would like to use consumption and production amenities as indicators of demand, but given the difficulties of measuring yearly variations in them, we rely on income and population instead.[5] Consistent with the basic matching model, we find that larger population is strongly associated with shorter buyer and seller time on the market and fewer homes visited, with the effect on buyer time much larger than the effect on seller time. Income follows the same pattern, although the relationship is significant only for seller time on the market.

Having found evidence of demand effects on market liquidity, we then investigate their underlying components. To do so, we examine how the demand shock affects the buyer-seller ratio, buyer and seller contact hazards. These variables are not directly observable. We recover them by imposing theoretical relations derived from the matching model on the data. Our estimates show that an increase in average income is associated with an increase in the buyer-seller ratio, an increase in seller contact hazard, and a much smaller decrease in buyer contact hazard. These findings are again consistent with the basic matching model in the presence of MLS institutions.

Because sellers and buyers may not respond to the demand shock at the same speed, we estimate a dynamic specification that allows one to distinguish between the short run and long run effects of demand shock. This is the core of our results. We find that under an increase in average income or in population, seller time on the market, number of home visits, the seller contact hazard and the buyer-seller ratio all decrease substantially in the short run but largely recover in the long run. The short run effects on buyer time on the market and the buyer contact hazard are also negative, but much weaker and insignificant.

Overall, the findings from the dynamic specification are consistent with a matching model for which: (1) sellers react to the demand shock with a lag; (2) the interest rate is negligible; and (3) the

[5] The appropriateness of income and population as demand proxies is discussed in Section 3.

buyer contact hazard is much less elastic than the seller contact hazard. We provide supporting evidence for these conditions, based on the price premium over the list price, earlier research and the actual matching institutions in U.S. real estate markets. Our estimates imply a buyer contact hazard has an elasticity of -0.17 (equivalently, a seller contact hazard of 0.83).

To conclude, we find the effects of demand shock on market liquidity – in terms of home buyers' and sellers' search behaviour -- well captured by the simple matching model that we proposed for housing markets. We assess the robustness of this conclusion by examining a number of alternative explanations, such as changes in matching technology and search effort, the dynamic response from housing supply, and the measurement error for reported time on the market. None of these considerations alter our conclusion. Thus, our work provides strong empirical support for applying random matching models to housing markets. In this sense, this paper compliments the emerging search-based calibration studies on housing markets, such as Caplin and Leahy (2008) and Ngai and Tenreyro (2009).

Besides an obvious link to studies on matching models, this paper is also closely related to a large body of work on time on the market in the housing markets. On the sellers' side, previous studies have explored a variety of determinants of seller time on the market, such as idiosyncrasy of the property (Haurin, 1988), seller motivations (Glower et al., 1998), initial offer price (Anglin, Rutherford and Springer, 2003), owner's equity (Genesove and Mayer, 1997), previous purchase price (Genesove and Mayer, 2001), initial listing price (Anglin, Rutherford and Springer, 2003) and quite a few on the use of real estate brokers (most recently, Levitt and Syverson,2005; Hendel, Nevo and Ortalo-Magne, 2009; and Bernheim and Meer,2008). On the buyers' side, the literature is much more limited, comprising perhaps only Baryla and Zumpano (1995), Anglin (1997), Elder, Zumpano and Baryla (2000), and D'Urso (2002), Elder, Zumpano and Baryla (1999) and Anglin (1994). These studies typically rely on individual housing unit data in a given geographical market and focus on individual level determinants of either buyers' or sellers' time on market.[6] In contrast, our work provides an equilibrium analysis of *market* determinants of *both* buyer and seller behaviour, using data *across* markets and time.

2. The Model

2.1 Baseline Model

We begin by presenting a search and matching model that guides the subsequent empirical analysis and aids in interpreting the results. The baseline model is designed to be simple and to generate transparent predictions. In Section 2.2, we develop a dynamic extension. In Section 2.3, we assess the robustness of the model's predictions by relaxing a number of simplifying assumptions made in the baseline model.

At the center of any matching model is the matching function, which maps the number of buyers (B) and sellers (S) to the number of contacts between them: $m = m(B, S)$. We make the usual constant returns to scale assumption that the probability that an agent makes a contact with the other side is a function only of the ratio of buyers to sellers, which we denote as $\theta = B/S$. Thus a given buyer will make contact with a seller with probability $h(\theta) \equiv m(B,S)/B = m(1,1/\theta)$, while a given seller will make contact with a buyer with probability $q(\theta) \equiv m(B,S)/S = m(\theta,1)$. It then follows that $q \equiv h\theta$. Standard and intuitive assumptions on the matching function make h a downward sloping function and q an upward sloping function of θ.

Let the net present value of a given buyer owning a given home be X, a random variable whose distribution is $1 - G(X - v)$, where v is a location parameter of the distribution, shifts in which represent movements in demand. X is idiosyncratic to the buyer-home match; its value tells us nothing about the value to the same buyer of any other home, or the value to any other buyer of owning the

[6] Merlo and Ortalo-Magne (2004) consider different markets, defined by two areas and two periods. D'Urso (2002) and Baryla, Zumpano and Elder papers examine housing units located in different geographical markets.

given home. X is assumed unknown to both buyer and seller before the contact, but observed by both of them upon contact. If there is no transaction, both buyer and seller continue searching.

Let V^B denote the value of continued searching for the buyer and V^S for the seller. Under efficient bargaining, there will be a transaction if and only if the value of owning the home exceeds the sum of the value of searching for buyer and seller, i.e., if and only if $X \geq V^B + V^S \equiv y$. The probability of a transaction given a meeting is therefore $G(y - v)$. The expected surplus of a transaction, when positive, is $E[X|X \geq y] - y$, where E is the expectation operator for $1 - G(X - v)$.

We assume Nash bargaining, with the seller obtaining β of the surplus, which is $X - y$. Thus the price is $P = V^S + \beta(X - y)$. Sellers face a cost c^S of search; buyers, c^B. For interest rate r, the asset equations for the value of the seller's search and the buyer's search are

(1) $rV^S = -c^S + q(\theta)\beta G(y - v)(E[X|X \geq y] - y)$

(2) $rV^B = -c^B + h(\theta)(1 - \beta)G(y - v)(E[X|X \geq y] - y)$

These are two equations in three unknowns: V^S, V^B and θ. To complete the model, we need an additional restriction. The baseline model assumes an infinite supply of buyers at $\bar{V}^B$. Implicitly, it assumes that buyers have a large number of markets to choose among, while sellers are tied to a specific market. In Section 2.3, we present a variant model that assumes that the inflow of buyers is more sensitive to the value of search than is the seller inflow and show that the variant model yields the same qualitative results.

We assume a greater buyer inflow sensitivity because we think this assumption reasonable for housing markets. Nevertheless, it is easy to show what the model would predict if we assume that seller inflow sensitivity is greater. As it turns out, the first assumption generates predictions that are consistent with the data, whereas the second assumption does not.

With V^B a constant, one can rewrite the above equations as

(3) $ry = -(c^S - r\bar{V}^B) + q(\theta)\beta G(y - v)(E[X|X \geq y] - y)$

(4) $0 = -(c^B + r\bar{V}^B) + h(\theta)(1 - \beta)G(y - v)(E[X|X \geq y] - y)$

Each of these equations can be interpreted as representing the asset equation of a hypothetical searcher, with offer distribution $1 - G$ and optimal reservation value y. In equation (3), the search cost is $c^S - r\bar{V}^B$, the interest rate is r, and the offer arrival rate is $q(\theta)\beta$. In equation (4), the search cost is $c^B + r\bar{V}^B$, the interest rate zero, and the offer arrival rate $h(\theta)(1 - \beta)$. Since $q^{'}(\theta) > 0$, the solution in y of (3) is upward sloping in θ (Mortensen, 1986); call that the S-curve. Since $h^{'}(\theta) < 0$, the solution to (4) in y (the B-curve) is downward sloping in θ. Where these two curves cross defines the unique equilibrium in y and θ (see Figure 1). [7] The corresponding average transaction price is

(5) $EP = \beta(E[V|V \geq y] - y) + V^S = \beta(E[V|V \geq y] - y) + y - \bar{V}^B$

which is obviously increasing in y.

The effect of a positive demand shock, represented by an increase in v, is easy to discern with the help of standard results from search theory. From Mortensen (1986, p. 864), we know that an

[7] For existence it suffices that (a) $q(\theta) \longrightarrow 0$ as $\theta \rightarrow \infty$ and (b) a bounded support of $1 - G$. (b) can be replaced by $1 - G$ a Generalized Pareto distribution, with shape parameter $c > -1$, which permits it to be unbounded.

increase in v will increase the threshold value y, but so long as the interest rate is positive, the increase in y will be less than the increase in v itself. Thus an increase in v will shift up the S- curve, but by less than the increase in v, while it will shift up the B- curve one for one. This will result in a higher buyer-seller ratio, a higher y, but a lower $y - v$, as in Figure 2.

Intuitively, the B-curve shifts up one for one, since, for any given θ, and so contact hazard, the surplus value, i.e. $G(y - v)(E[X|X \geq y] - y)$, must remain the same to ensure a constant value of search for buyers. This can only be ensured by the threshold value y adjusting fully to the new demand, leaving $y - v$, and so the acceptance rate, unchanged. But such full adjustment of the threshold value at the initial θ would, by (1), leave the seller value of search unchanged as well. That would mean, in turn, that some positive surplus transactions, specifically those with match quality values of X that exceed the unchanged sum of buyer and seller search values but fall below the new threshold y, would remain unconsummated, which contradicts efficient bargaining. Thus, the S-curve must shift up less.

Our goal in this section is to investigate the consequences of a demand shock for market liquidity. They are as follows. With the reservation surplus value y increasing less than the location parameter, the acceptance rate $G(y - v)$ must rise. This is the central prediction of a model with an endogenous acceptance rate, or 'stochastic matching', as Pissarides (2000, ch. 5) labels it. In the context of the housing market, this implies that the average number of homes that a buyer visits before purchasing will fall.

On the seller's side, the increase in θ implies that the seller contact hazard q increases. That is, each seller is more likely to meet with a potential buyer. Since $G(y - v)$ also increases, the probability that a seller will sell, $qG(y - v)$, increases, and hence seller time on the market decreases.

For buyer time on the market, matters are more complicated. In general, the contact hazard h is decreasing in θ, so it will fall. The probability that a buyer will buy, $hG(y - v)$, thus may go either up or down. Not surprisingly, which effect dominates depends upon the shape of the match quality distribution. For example, the purchase probability will remain unchanged when $1 - G$ is exponential.[8]

The size of these responses depends crucially upon two factors: the elasticity of the buyer's contact hazard with respect to the buyer-seller ratio, and the interest rate. First, if $|h'(\theta)|$ is small, the buyer contact hazard will obviously not change much, regardless of changes in θ. In addition, the B-curve will then be nearly flat, implying that $y - v$, and so the acceptance rate will stay very nearly remain the same. Thus an increase in demand will not have much effect on buyer time on the market and the number of home visits. However, θ will increase substantially, given the upwards shift in the S-curve and the nearly flat B-curve; consequently, the seller contact hazard and time on the market will decrease substantially as well.

Second, a small interest rate will make all the responses small. Consider the case of a zero interest rate. In this case, a positive demand shock will shift up the seller reservation price one for one as well, so that the reservation surplus value will increase by the amount of the demand increase. θ will remain unchanged, as will the acceptance rate, and so the probability of a transaction by either buyers or sellers will stay the same as well. Obviously, the outcome for a small positive interest rate will be similar.

In the presence of both a small buyer contact hazard elasticity and a low interest rate, we still expect the seller contact hazard and time on the market to react more than the other outcome variables, since the responses of both the buyer's contact hazard and the acceptance rate are

[8] The change in the purchase probability is $h'G\frac{d\theta}{dv} + hG'\left\{\frac{dy}{dv} - 1\right\} = h'G\frac{r/\beta}{\Delta}hG + hG'\left(\frac{h^2AG}{\Delta} - 1\right) = \frac{r/\beta}{\Delta}h'hG^2\left\{1 + \right.$ $G'G(EXX\geq y-y)$, where $\Delta = A(-h'.(r\beta)+h2G)$, $A \equiv Gy-vEX|X\geq y-y$. For the Generalized Pareto Distribution, $G(X; c, k, v) \equiv (1 - c(X - v)/k)^{1/c}$, $X \geq v$, $G'/G = -1/(k - c(y - v))$, and, for $c > -1$, $E[X|X \geq y] - y) = (k - c(y - v))/(1 + c)$. Thus hG is unchanged for $c = 0$ (the exponential distribution), increases if the match quality distribution hazard is decreasing, and decreases if the hazard is increasing.

proportional to the *product* of the interest rate and h'. We will argue below that both are indeed likely to be small.

2.2 Lagged Seller Response

Here we offer a simple dynamic extension to our basic model. As will been seen, some dynamic analysis is necessary to rationalize our empirical results. Say that sellers only react to the shift in the match quality distribution with a lag. This is reasonable: when buyers arrive with large offers, sellers will tend to think at first that these are simply large offers from an unchanged distribution, and will not fully adjust their reservation price, as in Lucas (1972). More frequent buyer visits may also be mistakenly attributed at first to chance. Moreover, sellers list and buyers do not, and so while buyers see the change in sellers' numbers (and, though unmodelled here, their list prices), sellers do not see the change in the number of buyers or in their willingness to pay. This would further justify the assumption that sellers lag in apprehending the changed environment, at least relative to buyers. Stein (1995) and Genesove and Mayer (1997, 2001) have offered additional reasons for slow seller adjustment when prices are falling, such as down-payment constraints and loss aversion. However, as we shall see, the vast majority of our data cover time periods in which prices were rising, not falling.

Consider, then, a two period model, in which, for simplicity, sellers maintain their initial reservation price in the first period and then fully adjust to the new stationary state in the second. If we maintain the assumption that buyers flow in and out of the market so as to keep the value of buyer search constant, the enhanced willingness to pay must be offset by an increase in the buyer seller ratio in the first period. Specifically, θ increases to θ' in Figure 2, which is the value that ensures that equation (3) holds at the new match quality distribution, with $\bar{V}^B$ and V^S (and so y as well) held constant. Consequently, q increases and h decreases. The acceptance rate $G(y-v)$ increases by an amount much greater than in the steady state (where the increase results from the acceptance threshold not quite fully adjusting to the higher offer distribution, and arises only due to a positive interest rate). The number of homes visited and seller time on the market fall substantially, then. With h and $G(y-v)$ moving in opposite directions, the effect on buyer time on the market is ambiguous.

To recall, we assume that in the second period, there is full adjustment to the new stationary equilibrium, at E^*. Thus sellers increase their reservation price, so that y now increases, while θ falls to a level above its initial one. Relative to the first period, q and $G(y-v)$ fall, although to levels above their initial values. h increases, although to a level below its initial value.

Incorporating a lagged seller response thus generates substantial overshooting of buyer and seller time on the market and homes visited, with long run and short run effects in the same direction, but with the latter effect much greater. Both homes visited and seller time on the market should fall substantially at first, then only partially recover, with full recovery for a zero interest rate. The behaviour of buyer time on the market is ambiguous. Clearly, price rises less in the short than in the long run; it can even fall in the short run.[9]

2.3 Static Theoretical extensions.

The baseline model makes a number of simplifying assumptions. In this section, we relax these assumptions and assess the robustness of the key predictions from the model.

The first assumption to relax is that the supply of buyers is infinitely elastic. Dropping this assumption requires one to model the inflow of buyers and sellers. Assume, then, that the flow of buyers into the market is a linear function of the value of buyer search, $a_B + d_B V^B$, and that likewise, the flow of new sellers is $a_S + d_S V^S$. The latter may represent the construction and sales of new homes or entry to the market by more existing homes, whose owners then depart for some other market. Ideally, the inflow of existing homes would be proportional to the stock of homes not currently offered for sale; we view our specification as approximate to the ideal one, when the share of homes on the market is sufficiently small.

[9] From (5) it is clear that where $1-G$, is the exponential distribution, EP is independent of v , for given y.

In the stationary state, these flows must equal each other. Using the definition of y, we obtain

$$V^S = -\frac{a_S - a_B}{d_B + d_S} + \frac{d_B}{d_B + d_S} y$$

$$V^B = \frac{a_S - a_B}{d_B + d_S} + \frac{d_S}{d_B + d_S} y$$

and so buyer and seller surplus reservation value equations

$$r\frac{d_B}{d_B + d_S} y = -\left(c^S - \frac{a_S - a_B}{d_B + d_S} r\right) + q(\theta)\beta G(y - v)(E[X|X \geq y] - y)$$

$$r\frac{d_S}{d_B + d_S} y = -(c^B + \frac{a_S - a_B}{d_B + d_S} r) + h(\theta)(1 - \beta)G(y - v)(E[X|X \geq y] - y)$$

From Mortensen (1986) again, we have that at the equilibrium θ, the S- and B-curves shift up by

(7) $dy/dv = [q(\theta)\beta G(y - v)]/[r\frac{d_B}{d_B + d_S} + q(\theta)\beta G(y - v)]$

(8) $dy/dv = [h(\theta)(1 - \beta)G(y - v)]/[r\frac{d_S}{d_B + d_S} + h(\theta)(1 - \beta)G(y - v)]$,

respectively, so that the B-curve will shift up more if and only if $d_S/d_B < (1 - \beta)h(\theta)/\beta q(\theta) = (1 - \beta)/[\beta\theta]$. This generalizes our baseline model, for which d_B is essentially infinite. It seems a reasonable assumption that even if not infinite, the buyer inflow is more sensitive to the search value than is the seller inflow, both because buyers may have a number of location options and because building new units takes time. Unless sellers have very little bargaining power, or the ratio of buyers to sellers is very large, the baseline model's conclusions will still hold.

Note that we have considered only the inflow of agents who are either buyers or sellers, and not that of owners who decide to offer their homes for sale and search for a new home in the same market. Since the inflow of such 'dual' agents has no effect on the net inflow of buyers less sellers, ignoring them is inconsequential to the steady state analysis and does not affect the linear relationships between y and V^S and V^B shown above, so long as their subsequent actions as buyers or sellers are independent of each other. Our treatment is consistent with a number of papers, such as Williams (1995) and Krainer (2001), although admittedly not in others, notably Wheaton (1991).

Note also that variation in v generates a positive price-volume correlation. The inflow (and so the steady state outflow, i.e., the number of transactions), is increasing in y, which is increased by v; while price is also increased by v. Such a correlation is widely thought to hold,[10] and has generated a number of possible explanations (such as Stein, 1995 and Genesove and Mayer, 2001). This analysis shows that a simple matching model will generate the correlation as well.

We also relax the assumption that buyers do not anticipate being sellers at some point in the future. Appendix A adds that possibility into the model by assuming that an owner has a constant hazard of becoming mismatched with his home. Doing so makes no essential difference to the results.

A third extension is to allow sellers to act as monopolists, offering a take-it-or-leave it price to the buyer regardless of the buyer's quality match to the home. Such a model obviously entails an inefficient number of transactions, but as Appendix B shows, it has the same comparative statics.

A fourth extension, explored in Appendix C, includes induced search effort. Our results continue to hold here, unless search effort is very cheap on the margin. Following Pissarides (2000, chapter 5), we assume that an agent can increase its contact hazard by expending more effort; agents' effort on the other side of the market increases this hazard, while that of other agents on its own side decreases it. Assuming an efficiency unit specification, as in Pissarides (2000), but adding stochastic matching, we show that our comparative static results for y and θ continue to hold so long as the marginal cost of effort rises sufficiently fast, seller effort is sufficiently dissipative, or the buyer hazard is sufficiently decreasing in θ . How much of any observed response to a demand shock can be attributed to the

[10] A positive time series correlation is documented by Stein (1995) and Berkovec and Goodman (1996) for the US, and by Andrew and Meen (2003) and Ortalo-Magné and Rady (2004) for Britain; panel data confirmation is provided by for Hong Kong by Leung, Lau, and Leong (2002). However, Follain and Velz (1995) find zero correlation in a fixed effects panel study of 22 US MSAs, while Hort (1999) finds a negative correlation for 19 Swedish regions.

mechanism captured in our baseline model, i.e., the changing acceptance rate and buyer-seller ratio, rather than to induced effort is explored in our discussion of our empirical results.

Finally, the model can be extended by allowing bargaining power to vary with the buyer-seller ratio. It seems reasonable that if that was so, then β would be increasing with θ.[11] Then $\beta(\theta)q(\theta)$ would be increasing in θ, and $(1-\beta(\theta))q(\theta)$ decreasing, and our results would follow as before.

3. From the Model to the Data

Our empirical analysis focuses on three directly observed measures of market liquidity: buyer time on the market (BTOM), seller time on the market (STOM), and the number of home visits (BVIS). Imposing the theoretical relations implied from the matching model, we can further infer underlying components of those varaibles: q, h, and θ.

Given the model's stationarity, time on the market for buyers and sellers is exponentially distributed. Thus, the expected time to sell is $1/(qG)$, and its logarithm is $-\ln(qG)$. Likewise, the log of the average buyer time on the market equals $-\ln(hG)$. Stationarity likewise implies that the number of homes visited follows a geometric distribution, so that the expected number of homes that a buyer will visit *before* the one he purchases is 1/G.[12] Note that the number of homes visited does not depend at all on the offer arrival rates, as homes visited is a count variable, independent of the time that lapses between each visit.

Moreover, combinations of these three variables yield the log contact hazards and buyer to seller ratio. Given $STOM = 1/(qG)$, it follows that $lnq = lnBVIS - lnSTOM$. Similarly, $BTOM =$

[11] Rubinstein and Wolinsky's (1985) model of sequential bargaining under the threat of interruption by the arrival of an alternative seller or buyer at the same contact hazard rates would generate such a relationship. So do models such as Julien, Kennes and King (2000), in which the probability that more than one buyer will show up at the house of a given seller and that an auction (an un-modelled phenomenon here) will ensue is increasing in θ.
[12] This is also the expected number of enquiries a seller receives before selling, which we do not observe.

$1/(hG)$, implies that $lnh = lnBVIS - lnBTOM$. In addition, as $(1/hG)/(1/qG) = (m/S)/(m/B) = \theta$, we can use the ratio of buyer time on the market to seller time on the market as a proxy for the buyer-seller ratio, that is $ln\theta = lnBTOM - lnSTOM$. Intuitively, if buyers are spending half the time on the market than sellers are, then they must have twice the likelihood of transacting as do sellers (under stationarity). However, as buyers and sellers have to leave the market in pairs, this must imply that there are twice as many sellers as buyers. There is thus no need to use measures of the stock of sellers and buyers in the market.

In principle, we would like to use consumption and production amenities as indicators of demand, but given the difficulties of measuring yearly variations in them, we rely on income and population instead. We justify using income as a proxy for demand in two ways. First, those with higher income have a higher willingness to pay for consumption amenities, so that improvements in these amenities will be accompanied by higher income people moving into the area. Second, complementarity between individual skill and productive opportunities implies that an improvement in the latter, which increases willingness to pay, will also attract higher wage people (Moretti, 2004). Population should also be correlated with consumption amenities: in an open city model, increasing an amenity leads to population inflow until the increased commuter cost at the new urban edge just offsets the greater amenity value. This shifts up the bid-offer curve throughout the city. Note that sellers' willingness to pay also increase under these scenarios, but by less than that of the incoming buyers. For simplicity, our model will consider the effect of shocks to buyers' willingness to pay only.

In theory, other types of shocks can generate the opposite correlations between housing demand and income and population proxies. Population increases can follow from relaxations in zoning laws, although to the extent that the changes in zoning laws are endogenous responses to demand pressure, as strongly suggested by Wallace (1988) and McMillen and McDonald (1991), no bias is introduced. With homogenous labour, pure consumption amenities should increase home prices but decrease wages (Roback, 1982), and hence decrease labour income; this tends to decrease the correlation between house prices and income. But empirically, the sign of the correlations is consistent with our approach: in Gyourko and Tracy (1991), as in Gabriel et al. (2003), any significant effects of amenities on wages and prices are almost always of the same sign,[13] Rauch (1993) shows that cities with higher average education exhibit both higher housing prices and higher labour income, while Capozza, Hendershott and Mack (2004) have shown that prices depend positively on median real income and population in both pooled and fixed effects regression. Gallin (2006) and Mickhed and Zemcik (2009) cast doubt on the consistency of the estimates from Capozza *et al* (2004), given the inability to reject the null of no co-integrating relationship in each city. However, these tests have little power, as Gallin emphasizes. Indeed, Glaeser and Gyourko (2005), who use long differences of thirty years, show the relationships quite robustly: population growth and price growth are positively correlated; they react similarly to the technological shock of weather adaptation; and growing cities have an increasing share of college graduates. These results further justify our use of income and population as demand proxies.[14]

4. Data

We constructed a panel dataset from three different sources. Our source of time on the market and homes visited is the micro data of twelve separate surveys of homebuyers conducted biannually between 1987 to 2003, and annually since 2003, by the Research Division of the National Association of Realtors (NAR). We lack only the 1997 and 1999 surveys. We aggregated the 53,505 micro level survey responses up to the MSA level, by year. The combined sample covers 334 unique metropolitan statistical areas (MSAs) and primary metropolitan statistical areas (PMSAs), which we will refer to

[13] The same is true of Blomquist *et al* (1988), except that the standard errors are grossly underestimated.
[14] Glaeser and Gyourko (2005) emphasize the asymmetries in those relationships due to housing's durability.

collectively as MSAs. We include only MSAs that appear in more than one year. The resulting panel is heavily unbalanced: the number of years that an MSA is observed with seller time on the market has a mean of 6.3, a standard deviation of 3.9 and a maximum of 17. Given that we miss two survey years and that the sample is highly unbalanced, along with the fact that the early surveys were held two years apart, our dynamic analysis is per force rudimentary. Yet the results are so stark that it is difficult to believe they would not be present in a more sophisticated dynamic specification, were the data so permitting.

The questionnaires were sent to recent home buyers to collect information on the homebuying process. Those who had owned and sold a previous home also provided information on their home selling process, although the year of sale is ascertainable only if it was within two or three years of the purchase date. Thus, the survey method, combined with our data requirements, selects only sellers who bought another house within two or three years after selling. In order to have our buyer and seller data cover the same years, we use only the seller data from the 2008 survey, which also avoids the special circumstances of that year. Also, prior to 2007, respondents are not asked for the city of their previous residence, so we only use responses for sales in which the respondent reported moving fifty miles or less. We suspect that looking at sellers who subsequently buy within two years in the same MSA is not restrictive, since the post-2007 data show that such sellers remain on the market a mere 3 percent longer than those who end up buying elsewhere, and from Sinai (1997) we know that extremely few owners ever become renters, and of those who do, one-third buy again within two years.

A more serious concern is the extremely low response rates of the NAR surveys, which never exceed 19 percent and fall as low as 6 percent in one year. Yet, despite the low response rates, several reasons make these data are attractive for our purposes. First, the NAR surveys are the only available data that document both buyers' and sellers' search experience,[15] which is essential to an empirical investigation of matching models in housing markets. Second, these data contain variation both cross-MSA and over-time. Third, although one might suspect, say, that average time on the market among respondents differs from that of the universe of households (respondents might be more patient than non-respondents, for example), one might be less suspect of the responsiveness of the variables to market shocks. Indeed, Appendix D shows that the estimates are robust to inclusion of demographic characteristics for the respondents that are likely to control at least partially for variations in responsiveness. The appendix also shows that the mean responses are similar to those from surveys with much higher response rates.

Using the individual NAR level data, we construct the following time-varying MSA level medians: (1) time on the market for buyers; (2) time on the market for sellers; and (3) number of homes visited by buyers. These are the key measures of market liquidity that form the basis of our empirical analysis. We use the median and not the average, since the variables are top coded in certain years. The responses to these variables are requested in open form in some years and in an unchanging set of brackets in others. Our solution is to construct the bracket for those years in which responses are chosen freely, and then assign the midpoint of the chosen bracket as the value of the variable. Our results are nearly identical when we use the alternative approach of maintaining the value for those years in which brackets are not used and assigning the midpoint value otherwise.

Buyer time on the market is based on responses to the question 'How long did you actively search before you located the home you recently purchased?', while seller time on the market is based on responses to 'How long was this home on the market?'. In both cases, the answers are provided in number of weeks. Number of homes visited is based on responses to the question 'Including the home

[15] Anglin (1994) is the only other study to empirically examine both buyer and seller behaviour, but it covers only a single market over a limited amount of time.

you purchased, how many homes did you walk through and examine before choosing your home?' The wording of the question suggests that we need to subtract one from the responses to form the desired variable – the number of homes visited before the purchase. However, in several years the questionnaire permits an answer of zero, and there are respondents in all years who so answer.[16] We thus interpret the question as referring to the number of homes visited, not including that purchased. Our results are qualitatively the same when we chose the alternative approach.

MSA-level population and income are obtained from the Bureau of Economic Analysis. Yearly repeat sales housing price indices are derived from the Office of Federal Housing Enterprise Oversight (OFHEO), which tracks average single-family house price changes in repeat sales or refinancing. On average, about three thousand repeat transactions underlie a given year and MSA's index value.

Table 1 provides descriptive statistics of the variables in our study. An observation is an MSA X year combination. All statistics are weighted by the number of underlying micro level responses. We will be using three different samples: the Seller sample, the inclusion condition for which is that seller time on the market is available; the Buyer sample, for which buyer time on the market and the number of homes visited are available; and the Joint sample, which is the intersection of the previous two. Note that the number of observations in the Seller sample falls substantially short of that in the Buyer sample. This is because the NAR survey is sent to a sample of purchasers; only to the extent that purchasers were also sellers are there observations on sellers. However the Seller sample is not a subset of the Buyer sample, as an individual may have sold in a different year than he purchased.

The weighted average (across MSA X year observations) of the median time on the market for sellers in the Seller sample is 7.3 weeks. That for buyers in the Buyer sample is 8.2 weeks. Multiplying these numbers by 1.44 (the ratio of the median to mean for the exponential distribution) yields an

[16] In addition to those who misread the question, there may be respondents whose spouse or partner saw the home, and some who may truly have purchased sight-unseen.

estimate of the mean under the model's stationarity assumption. The weighted average median number of homes that buyers see is 9.9. These numbers do not differ much across the samples. Although the statistics for the levels of time on the market for buyers and sellers are quite close, the effect of the log transformation is such that $ln\theta$, the difference between the log of buyer and seller times on the market and the implied percentage difference between the buyer and seller stock, is 0.25. All these variables vary substantially over time and across space, which is a necessary condition for their playing some role in the market's adjustment to changes in demand conditions.

The means for log average income and log population are reported. Average population is two percent greater in the Seller than Buyer sample, and three percent greater again in the Joint sample. Average income is two percent smaller in the Buyer than in the Seller and Joint samples. Finally, average yearly price appreciation is six percent. In only 7 to 9 percent of the observations is price falling, suggesting that the equity and loss aversion effects demonstrated in Genesove and Mayer (1997, 2001) are not relevant for the vast majority of markets in our sample.

6. Reduced-Form Analysis of Demand Effects on Matching Behavior

6.1 Income and Population as Demand Proxies

Table 2 examines how buyer and seller behavior change in response to variations in demand proxies, such as income and population. Standard errors are robust and clustered at the MSA or PMSA level, which of course accounts for any kind of auto correlation in the errors,[17] as well as heteroskedacticity across MSAs. Clustering and robustness appreciably increases the standard errors, by at least a quarter and sometimes much more, but except in one case, which we will point out, there is

[17] This would be a concern only for the homes visited regressions, which occasionally fail Wooldridge's (2002, p. 275) test for the null of no serial correlation based on the difference between the regression of the error on its lagged value (where available) and its predicted value under zero correlation, i.e., $M^{-1}\sum_i 1/(T_i+1)$, where $M$is the number of MSAs and $T_i$is the number of observation for MSA i. The seller and buyer time on the market regressions always pass the test.

no appreciable effect on significance status at conventional levels. All specifications include MSA fixed effects and dummies for both the year of the survey and the year of transaction. MSA fixed effects are included to control, e.g., for differences in the efficacy of the MLS system, or the degree of integration of different market segments, which determines the cost of search. All variables are in logs. To adjust directly for heteroskedacticity resulting from differences in the number of transactions underlying an MSA X year observation, all regressions are weighted thus.

In Columns (1), (3), and (5) of this table, we examine the effect of income and population levels on seller time on the market, buyer time on the market, and the number of visits. As predicted, greater average income is associated with a shorter seller time on the market and fewer homes visited, although the latter is only weakly significant. The coefficient of -1.43 on average income in column (1), for example, implies that an extra ten percent in income is associated with about a thirteen percent shorter seller time on the market, while the coefficient of -0.25 in column (5) predicts three percent fewer home visits. At *mean* values, this is slightly more than nine days fewer on the market, and one third of a home less. Buyer time on the market, for which the model provides no unambiguous predicted response to a demand increase, has a negative but very small and insignificant income coefficient. Population has significant negative effects on all the variables. A ten percent greater population is associated with an eleven percent shorter time on the market for sellers and a four and a half percent shorter time for buyers, and five percent fewer homes visited. These results are consistent with the basic model, although hard to reconcile with a negligible interest rate.

There are further predictions of the model that can be assessed by comparing across the columns. As log time on the market is simply the log number of homes visited minus the hazard rate, the sensitivity to the demand proxies should be greater for seller time on the market than for homes visited (since the seller hazard should increase with demand), but greater for homes visited than for buyer time on the market (since the buyer hazard should decrease with demand). Also, buyer time on the market should increase more than seller time on the market as their log difference is the log buyer-seller ratio. It is easy to see that all those predictions hold, both for income and population.

Those comparisons, however, may be contaminated by the non-coincidence of the Buyer and Seller samples. We thus regress the linear combinations $lnq \equiv lnBVIS - lnSTOM$, $lnh = lnBVIS - lnBTOM$, and $ln\theta \equiv lnBTOM - lnSTOM$ on the demand proxies, using the Joint sample. These regressions are shown in Columns (1), (2) and (3) of Table 3. The estimates are noisier than before, in part because the sample is smaller. We see that the implied seller contact hazard and the buyer-seller ratio increase with average income and population, although only average income is significant. The effects on the implied buyer contact hazard are negative, although never significant. These results are all consistent with the model.

The remaining columns of Tables 2 and 3 distinguish between short run and long run effects by adding income growth and population growth. This is a barebones dynamic specification, but the realities of our panel, in which the dependent variable is missing in most years (either because the survey was conducted biannually before 2003, or because the MSA was not covered in that year), forces that upon it. Furthermore, we are forced to identify the short run with a year, which is somewhat longer than we would prefer, given the rarity of either a buyer or seller being on the market that long, and our suspicion that the information flow is faster than that. We are constrained by the frequency of our data, however. Nonetheless, it should be clear that use of a too long period for the short run should bias our estimate of the true short run effect downwards in magnitude. Also note that any pattern of autocorrelation in the errors will be accounted for in the clustered standard errors.

We stress that, given the inclusion of the MSA and year fixed effects, the short run and long run effects are identified from variations in the level and growth rate around the average for that MSA (relative to the calendar year). To see that, write the regression as

(9) $$y_{it} = Ax_{it} + B\Delta x_{it} + u_t + v_i + e_{it},$$

where i indexes the MSA, t the year of the transaction, u_t the time effect, v_i the MSA effect, and $\Delta x_{it} \equiv x_{it} - x_{it-1}$. Then our regression amounts to $y_{it} - \overline{y_i} - \overline{y_t} + \bar{y} = A(x_{it} - \overline{x_i} - \overline{x_t} + \bar{x}) + B(\Delta x_{it} - \overline{\Delta x_i} - \overline{\Delta x_t} + \overline{\Delta x}) + \{e_{it} - \overline{e_i} - \overline{e_t} + \bar{e}\}$ (Balestra, 1992). Consider, for example, x constant over periods 1 through s, and then constant at a different level from s+1 until the final period T. Then, intuitively, the difference between the mean STOM over 1 through s and the mean from s+2 through T (all zero growth periods) contributes to identification of the level effect, while the difference between the STOM in s+1 (a growth period) and the mean in all other periods contributes to identification of the growth effect (ignoring year effects).

Table 2 exhibits the striking result that both income growth and population growth strongly decrease seller time on the market. The semi-elasticity of seller time on the market with respect to income growth is about seven, while that with respect to population growth about 14.5. In contrast, the effects of the income and population levels are much smaller, with the income coefficient insignificant.

These responses are consistent with our dynamic extension of the model, in which sellers and buyers react to changes in the economic environment at different speeds: in the short run (reflected in the sum of the coefficients on the level and change, and shown in the table's second panel) there is a large fall in seller time on the market upon a demand increase, as buyers offer more, while sellers have not yet adjusted to the new demand reality. In the long run (seen in the level coefficient alone), sellers increase their reservation value, and so the fall in their time on the market is predicted to be much less dramatic. If the interest rate is negligible, there will hardly be any change at all. Our results are consistent with this extension. They indicate that a one percent increase in income decreases seller time on the market by three and a half days in the short run, but by only an (insignificant) quarter of a day in the long run; an equivalent increase in population is associated with a full week's decline in seller time on the market in the short run, but only a (significant) half day in the long run.

The dynamic extension of the model also implies that homes visited should decrease substantially in the short run upon a demand increase. This can be seen from Column (6), which shows significant short run population and average income elasticities of -4.5 and -1.2. Both long run effects are small, and certainly much smaller than the short run effects, although under the robust standard errors one cannot reject the null of equal short and long run effects. One can reject the null under the usual OLS standard errors.[18]

Turning to buyer time on the market, we see in column (4) that although the four regressors all have negative signs, only the population level coefficient is significant. To recall, the model makes no unambiguous prediction here, as the buyer contact hazard is predicted to fall while the acceptance rate is expected to increase. Since, in contrast, the seller contact hazard rate is predicted to increase, the model does predict that time on the market for buyers can not fall more than that of sellers, and indeed the coefficients are all much smaller than those for seller time on the market, as expected.

Columns (2), (4) and (6) of Table 3 add income and population growth to the lnq,lnh , and $ln\theta$ regressions, run on the Joint sample. Not surprisingly given the previous estimates, and in line with the dynamic extension to the model, the short run effects are much larger in magnitude than the long run effects, with long run effects being insignificant in all cases. The short run effects are significant for both lnq and $ln\theta$, and, for average income, for lnh, and have the predicted signs. The effects for the buyer contact hazard are much smaller in magnitude than those for the seller, for which we will offer an explanation based on the real estate listing institutions in Section 6.3.

The assumption that income and population affect the dependent variables only through their correlation with a common effect (the model's v) can easily be tested. Within a regression, this is simply the test of the null hypothesis that the ratio of the coefficient on log population to that on log income

[18] This is the only case in which use of robust standard errors implies an insignificant coefficient, while that of the usual OLS standard errors implies a significant one.

equals to the corresponding ratio for the change in the log variables, that is $\frac{A_{pop}}{A_{inc}} = \frac{B_{pop}}{B_{inc}}$, where A and B are the coefficient vectors in equation (9). This test is shown as "F-stat" in tables 2 and 3, and we can see that it is never rejected. A more comprehensive test is that for the null that the ratio is the same not only within a regression, but across all three regressions. This test is distributed asymptotically as a chi-squared distribution with five degrees of freedom, and takes the value .53 (p-value of .99) for Columns (2), (4) and (6) of Table 2 and 2.99 (p-value of .70) for the corresponding columns of Table 3, indicating very strongly that the null cannot be rejected.

Finally, our model also makes predictions about prices. Given that many others have investigated the relationship between housing prices and income and population before (see the Introduction) without requiring our unique panel, we conduct only a cursory investigation. Column (1) of Table 6 shows the regression of the (log) OFHEO price index on income and population levels and growth rates. MSA and year fixed effects are included, and standard errors are robust and clustered at the MSA level. With no breaks in the data series for the dependent variable, we are able to include its lagged value. We use the Buyer sample. The estimates imply a long-run elasticity of price with respect to average income of .063/(1-.938)=1.02 (s.e. of .41) and a short-run elasticity of .063 +.437 =.50 (s.e. of .07). The long and short run elasticities with respect to population are 2.48 (s.e. of .55) and 1.55 (s.e. of .38). That the long run effect exceeds the short run effect is consistent with the dynamic extension of the model. Consistent with the hypothesis that income and population proxy a single demand shock, one cannot reject that the ratio of the long run to short run effect is equal for both proxies.

6.2 Estimating The Contact Hazard Elasticities

Our estimates of the implied buyer-seller ratio's response to the demand proxies, along with that of one of the contact hazards, provide an estimate of the matching function, or more precisely, the elasticity of the contact hazard with respect to θ. From Table 3, we see that a one percent increase in income growth, for example, increases $ln\theta$ by 7.64 percent, while decreasing lnh by 1.19 percent, implying that the elasticity of the buyer hazard with respect to the buyer-seller ratio is -0.16. By construction of our dependent variables, the elasticity of the seller hazard with respect to θ equals one plus the buyer hazard elasticity, which equals 0.84. The result from using the other significant regressor, population growth, implies a buyer hazard elasticity of -0.20.

These calculations are essentially informal instrumental variables estimates. A two-stage least squares regression of lnh on $ln\theta$, with the usual MSA and year fixed effects, and with income growth and population growth as instruments, yields an estimate of -0.17, with a robust, MSA clustered standard error of 0.10. As the theoretical range of the elasticity is $[-1,0]$, this should be seen as a small estimate. Of course, these results are valid only to the extent that income and population growth are valid instruments for estimating the matching function, that is, that they are uncorrelated with within city changes in the matching technology – of which more later.

6.3 Supporting Evidence

So far, we have shown the following: first, when the market experiences a demand shock, there seller time on the market, number of home visits, and the implied buyer-seller ratio overshoot in the short run. Second, these large effects tend to diminish in the long run. Third, the demand effect on buyer time on the market is much smaller than the corresponding effect for sellers. Overall, these findings are consistent with the dynamic extension of the matching model we proposed in Section 2 under the following conditions: (1) lagged seller response; (2) a negligible interest rate; and (3) a small buyer contact hazard elasticity. We now present supporting evidence for each of these conditions.

(1) Lagged seller response: If sellers' response lags, than we should expect the list prices they set to lag as well, and thus the price premium – the log ratio of the transaction to list price – to increase with demand in the short run.[19] Column (2) of Table 6 shows the regression of the premium on the levels and growth rates of the demand proxies. We see that the premium does increase in the short run with both demand proxies. There is also a positive and significant long run population effect, not explained by our lagged seller adjustment argument. One possible objection is that whereas transaction prices are set at the time that the seller exits from the market, whereas the list price is set at the time of entry, the difference between the two will increase with demand; and so will price growth, even in the absence of lagged seller adjustment, as long as list prices are set according to contemporaneous transaction prices. But, as we have seen in Table 1, the average median seller time on the market is 7.3 weeks, implying an average duration of 10.5 weeks, which is about one fifth of a year.[20] Clearly, the growth in prices from Column (1) is too small to explain Column (2)'s result, suggesting that the time difference alone cannot explain the coefficients on the income and population growth terms. This lends support to the assumption that sellers react to demand shocks with a lag.

(2) A negligible interest rate: To investigate whether the interest rate is indeed small enough to mute the long run demand effects, we refer back to equation (7), which shows that, when $r\frac{d_S}{d_B+d_S}$ is much smaller than $q\beta G$, an increase in demand will shift up the reservation value almost one by one, so that neither y nor θ will change, and the liquidity measures will all remain unchanged. Our discussion of Table 1 shows that the mean seller time on the market is 7.32 X ln2 X 7 days, which is equivalent to 1/qG in the steady state. This implies a daily hazard rate of sale (qG) of 1.36 percent. In contrast, Genesove and Mayer (1997) infer a yearly interest rate of about 20%, which was subsequently used in Levitt and Syverson (2005). This implies a daily rate of only one-twentieth of a percent. Clearly, unless sellers

[19] Our model has no role for list prices, but consider Julien, Kennes and King (2000), in which multiple buyers can show up at a single seller. With many buyers, an auction takes place; where there is only one buyer, the buyer pays the list price. They show that in large markets, the list price is set equal to the seller's reservation price. We ran two separate regressions using the premium reported by respondents as sellers and that as buyers, but there being no significant economic or statistical differences between them, we show the combined regression only.

[20] The relevant duration for buyers' responses would be smaller than this if they report not the 'original' list price (as requested), but that which prevailed when they first saw the home.

receive only a very small share of the surplus, $r\frac{d_S}{d_B+d_S}$ is strongly dominated by $q\beta G$.[21] Thus, small long run effects are precisely what we should have expected.

(3) Small buyer contact hazard: The matching institution of most U.S. real estate markets is the multiple listing service, in which sellers list their property but buyers typically do not advertise themselves. Sellers list, and not buyers, because it is easier to describe the home - and perhaps the sellers' willingness to sell (via the list price) - than to describe the buyer's preferences. That buyers seek out sellers but not the other way around makes it likely that q will be more sensitive than h to θ. Consider a limiting case: for any given buyer, if his opportunity to search (an hour free of work and other duties to go out with a real estate agent) arises independently of other buyers' at a constant rate ρ, and if the buyer (or his agent) chooses listed homes to look at randomly, then the probability of a match for a given buyer at any given moment is $h = \rho$, the matching function $m = \rho B$,[22] and $q = \rho\theta$. The actual situation is not so extreme: buyers' search opportunities do agglomerate somewhat in time and offers last over some interval of time, during which another buyer can show up. To the extent that this is so, a buyer's contact hazard will be decreasing in the number of buyers, with whom he competes. Relatedly, the buyer's contact hazard will be increasing in the number of sellers, as having more sellers increases the chance that any other buyer will end up elsewhere. Nevertheless, it is reasonable, given the asymmetry in the parties' roles in the listing institution, to presume that h will be less responsive than q to θ, and that is what the small buyer contact hazard elasticity estimated in Section 6.2 implies. A small $|h'|$ is also consistent with the increase in the acceptance rate effect dominating the decrease in the buyer contact hazard in the short run, so that the number of homes visited falls with demand in the short run, which we find as well.

[21] Sufficiently high seller bargaining power is an appropriate assumption, given Chen and Rosenthal 's (1996) theoretical result that setting a 'ceiling' list price accords seller full bargaining power in certain circumstances.
[22] See Mortensen and Pissaridies (1996). This is the specification used in Wheaton (1991).

6.4 Price as a Demand Proxy

Given the possibility of bubbles during parts of the period covered by our data, we also consider price itself as a possible demand proxy. Prices are, of course, endogeneous in the model. But it seems reasonable to investigate the relationship, given the number of authors, including Case and Shiller (2003), Glaeser, Gyourko and Saiz (2008), Himmelberg, Mayer and Sinai (2005), Piazzesi and Schneider (2009), Mikhed and Zemčik (2009), and Campbell et al. (2009) who have argued that many markets were characterized by housing bubbles during parts of the period we examine. Indeed if bubbles are pervasive, we should not expect to find other good proxies for demand in those periods, unless the bubbles are simply magnifications of underlying demand shocks (as in Glaeser et. al., 2008).

Table 4 regresses the measures of liquidity on prices. Columns (1), (3) and (5) show the regressions on the price level and price growth rate only. As predicted, seller time on the market falls dramatically in the short run with house price appreciation, with an elasticity of about four, but, contrary to the model, actually rises somewhat in the long run. As in Table 2, buyer time on the market is unaffected by 'demand' growth. Home visits fall in the short run with price, but there is no long run effect, as we would expect with slow-adjusting sellers and a negligible interest rate. The results are robust to including population, income, and their growth rates (the remaining columns). For the most part, the coefficients on these variables are much reduced when price growth is included.

6.5 Alternative Dynamic Supply Explanations

It is tempting to view inelastic short run supply coupled with a more elastic long run supply as an alternative explanation for our dynamic results. A differential elasticity can arise out of the time to build new housing, so that short run supply response includes only that of existing home owners, while that in the long run includes developers as well. Intuitively, a market subject to a demand shock will be characterized initially by an increased buyer-seller ratio, as new buyers flow in. In the long run, an increased price will induce developers to build new homes for sale. This inflow of newly constructed homes will then lower the buyer-seller ratio. Thus even without recourse to a formal matching model, the slow adjustment of housing supply would seem capable of explaining our finding that seller time on the market decreases substantially in the short run but largely recovers in the long run.

However, this alternative explanation fails to explain the behaviour of the remaining variables we examine. Most crucially, an inelastic short run supply and elastic long run supply implies that a demand shock will increase price in the short run more than in the long run, while the regression in column (1) of Table 6 shows price rising more in the long than in the short run. As noted, the matching model with lagged seller response predicts that price will increase more in the long run than in the short run, as sellers' adjustment of their reservation prices pushes up transaction prices even further.

The alternative explanation is also at odds with the behaviour of the number of homes visited. Prices come down in the long run due to the inflow of sellers willing to transact at a lower price that covers only land and construction costs, and not the additional idiosyncratic ties that owners have to their homes. These sellers are willing to accept lower offers than the existing home sellers – that is the meaning of the long run supply curve being more elastic. So in the transition from the short run to the long run, sellers' reservation prices fall, and with demand remaining at its new higher level, the probability of sale must increase. Thus the number of homes visited should be greater in the short run than in the long run, according to the alternative. This is not what we see, however.

Nor can out of steady state transition dynamics explain our results. Pissarides' (2000) analysis has the system immediately jumping to the long run θ and y, which implies that all three measures of liquidity will also immediately adjust. Thus the transition dynamics do not predict any overshooting, in contrast to the empirical results.[23]

[23] Pissarides' (2000) analysis has the level of buyers and sellers adjusting in the transition to the new steady state. We have no measure of those variables in our analysis.

6.6 The Definiteness of Buyer Search Time

One additional concern with our results might be that the relative insensitivity of buyer time on the market, although predicted by the model, is also consistent with time on the market being less well defined for buyers than for sellers. As a rule, sellers begin their search by signing a contract with an agent; whereas a buyer might visit advertised homes intermittently and haphazardly. So respondents might report time on the market as buyers with greater error than as sellers. Since time on the market is only used as a dependent variable, the concern here is with the precision of the estimates only. In fact, the standard errors in the buyer time on the market and buyer contact hazard regressions are typically only about half those in the corresponding seller regression. Hence it is the fact that the estimated coefficients are typically smaller in magnitude in the buyer regressions that explains the insignificant results. The relative indefiniteness of searcher status for buyers might alternatively lead respondents to report focal values that do not vary with the actual experience; but belying that explanation is the fact that buyer time on the market does vary significantly with income level and Internet use, and (although not shown) across MSAs.

6.7 Variations in Technology and Search Costs

Our interpretation of the empirical results obviously requires that the matching function and search costs not vary systematically with demand. These are assumptions generally made for empirical models of labour markets, but the former in particular may be inappropriate for housing over the sample period. This was a time of dramatic advances in communication and digitalization, to which housing attributes are surely much more amenable than is labour.[24] Any national level differences in

[24] Improvements in photographic developing and processing – the spread of one hour photo kiosks - let agents have pictures of the home in hand more quickly; camera digitalization decreased the cost of taking pictures and further increased processing speed. An early use of computerization was to speed the dissemination of MLS updates, with brokers receiving weekly update diskettes, rather than paper changes. Finally, the Internet sped up MLS updating even more, and permitted buyers to visually assess properties from the comfort of their own home.

matching technology over time, or fixed differences across MSAs, will be picked up by the fixed effects, of course, but clearly that will not suffice if technological adoption was non-uniform across markets.

It is important to distinguish between economically exogenous and demand induced technological change or effort. First consider economically exogenous, but statistically endogenous, technological changes. New technology is more likely to be available in high income markets and, due to fixed costs of adoption, in large markets as well. Its adoption would have increased the matching rate, i.e., caused a greater number of effective contracts for a given number of buyers and sellers. Thus the flow of new technologies over time might seem to explain the negative partial correlations of income and/or population with buyer and seller time on the market. Also, to the extent that the new technologies improve the pre-screening that households do before they go out to see a home, with more, and more easily accessible, pictures, and even videos, allowing the buyer to better choose which home to visit, they can be seen as decreasing the spread of the match quality distribution. This could explain the negative correlations between homes visited and the demand proxies.

Yet a closer look shows that our empirical results are not easily explained by income and population proxying for technological changes. Since a contact hazard is simply the matching function divided by the number of agents of that type, technological adoptions that increase the matching rate will have the same direct effect on buyer as on seller time on the market (holding the buyer seller ratio constant). Yet we see that such is not the case at all. As Column (4) of Table 3 shows, the buyer contact hazard does not increase with income and population levels and growth, as one would expect from a correlation with technological improvements; indeed, it falls with average income in the short run.

Also, technological changes that increase the contact rate, and not the acceptance rate directly, will not produce the observed correlation between homes visited and the demand proxies. An increase in the hazard rates will increase each side's search reservation value for a given θ, thus increasing the threshold value, and so decreasing the acceptance rate and increasing homes visited; but this is the opposite of what we observe.

Furthermore, the dynamic regression results are rather difficult to explain based on changing search costs or technology. There is no obvious reason why income and population growth rates should be associated with a more efficient matching technology. While we might see real estate firms *adopting* newer technologies in a high growth period, the *level* of technology, which is the relevant factor for the *level* of time on the market or homes visited, should not necessarily be greater in times of greater growth, and certainly should not evidence such large effects. (Recall that the MSA fixed effect will control for differences in MSAs' average growth rates in the dynamic regressions.) So our large estimates of short run effects are likely to be robust to the presence of economically exogenous technological change.

What about technological change induced by changing demand? Although a full analysis is beyond the scope of this paper, our analysis of endogenous search effort in Appendix C can guide us. There we show that although buyer effort is unchanged (under a constant value of buyer search assumption), seller effort is increasing in y. The latter relationship provides an additional mechanism by which the seller hazard increases with demand, while mitigating the fall in the buyer hazard, or even causing it to rise on net. We are unable to isolate any effects of induced effort or technology in our results, but the negative coefficients in the buyer hazard regressions do suggest that any induced effort or technological change is dominated by the primary mechanism of the dependence of the contact hazards on the buyer-seller ratio.

Our main argument for the changing buyer-seller ratio interpretation is empirical, however. One can assess the effect of unobserved technological change on our estimates by looking at how including technology proxies affects our results. Although we lack measures of adoption of the earlier technologies, we do have a good one for Internet use: the fraction of buyers who report finding the eventually purchased home via the Internet. This variable is a report by buyers about their experience, but it clearly reflects the conflation of their access to the Internet and sellers' (or their agents') postings on websites. Figure 3 shows the evolution of the variable mean over time. Obviously, Internet use is not a possible response in the earlier surveys, but it does appear as far back as 1995, when commercial Internet use was in its infancy (as that year's mean shows). We thus set the variable to zero for all earlier years.

One might be concerned with endogeneity here. We think it unlikely that a household on the verge of moving to a new home will hook up to the Internet in the existing home in order to facilitate search. Of greater concern is the decision of agents or the MLS to post listings on the Internet. Better managed (relative to the city average in a given year) MLSs may choose to put listings on the web, but the main effect of the better management may be reflected in other aspects of the matching. It cannot all be bias, as websites are costly and so can reflect good managerial policy only if effective. But measuring website efficacy is not our objective here; controlling for the matching technology is. In this sense, it does not matter whether the measured Internet use effect originates in better management rather than Internet use.[25]

Table 5 shows regressions with and without Internet use. Indeed, in all three regressions, the Internet use coefficient is large, and significant for buyer time on the market and homes visited. The estimates predict that an area in which all buyers find their homes through the Internet would have a twenty four percent greater buyer time on the market and thirty percent more homes visited than an area in which none do. The effect for buyer time on the market is nearly exactly the same as that of D'Urso (2002), which is based on a single cross-section. The effect on seller time on the market is of a similar magnitude as that on buyers, but is insignificant. Nevertheless, the table makes clear that

[25] Since Internet use equals zero for pre-1995 years, no variable reflects managerial ability during those years. This entails no bias, since the fixed effects ensure that those deviations are uncorrelated across time in any case.

including the Internet variable has no noticeable effect on the coefficients on income and population and their changes. Given that the Internet is surely the dominant technological change over the last decade of our sample period, and that our measure of Internet use is evidently sufficiently good to show a strong correlation with buyer time on the market and homes visited, it is difficult to imagine that other, unmeasured, technological changes are responsible for our earlier results. [26]

We can also rationalize the Internet coefficient estimates. Increases in Internet use shift up the B- and S-curves, causing the equilibrium to move from E0 to E^{*}, as in Figure 2, leading to an increased y and, if we assume efficiency unit technological change,[27] θ. Thus the acceptance rate $G(y-v)$ falls, the seller hazard increases – both directly from the technological change and via the increase in θ -, and for the same reason, the effect on the buyer hazard is ambiguous. These results imply, in turn, that the effect on both buyer and seller time on the market is ambiguous. Our point estimates are consistent with those predictions that the model yields: homes visited, the implied buyer seller ratio ($ln\theta$) and the implied seller hazard, lnq, all increase, although only the first is significant. The effect on the buyer hazard is essentially zero. The effect on the implied buyer seller ratio is particularly interesting, as its construction strips out the matching function, and thus the direct effect of technological change on the matching function, and so isolates the indirect effect.[28]

Of course, as noted, the use of the Internet might be effective by allowing buyers to better assess the homes before visiting them. That would suggest a positive direct effect on the acceptance

[26] The Internet variable clearly suffers from classical measurement error, so that the true effects are likely to be greater than the measured ones. The samples are a tad smaller than in Table 2, as buyer responses in the year and MSA are needed to construct the variable.

[27] Let i indicate Internet use, and let both q and h be functions of it. Since $q \equiv \theta h$, $\partial q(\theta,i)/\partial i = \theta\, \partial h(\theta,i)/\partial i$. Totally differentiating the B- and S-curves with respect to y and i shows that increases in i shift up both curves, but the B-curve more.

[28] That is $ln\theta = \frac{lnB}{lnm} - \frac{lnS}{lnm} = lnB - lnS$. So changes in θ capture only the indirect effects of the technology change on the buyer-seller ratio, and not any direct effects.

rate, and so negative effect on the number of homes visited. Obviously, any such effect is dominated by that operating on the contact hazard, as described above.[29]

Finally, search costs may be higher for both buyers and sellers in high income cities, if higher income individuals value their time more. At a given buyer-seller ratio, this would lead to lower reservation values and so a higher acceptance rate, and so could impart a negative bias to the long run effect of average income on homes visited. However, that should not impart any direct bias to the hazard rate regressions, and there being no dynamic element in this explanation, to differences between the short run and long run effects.

7. Conclusion

This paper is the first to empirically test a matching model of the housing market. As such, it complements a burgeoning theoretical and calibration-based literature, and quantifies our understanding of how the liquidity of housing markets responds to demand shocks. Applying a straightforward random matching model to a unique dataset that documents information on both buyers' and sellers' home search and sale experience, we obtain results consistent with our proffered model. In the short run, both seller and buyer time on the market decline in response to an increase in demand --the effect for sellers being quite large, while that for buyers is much more moderate. These effects are much smaller in the long run.

We also examine the underlying components of time on the market. The short run response to a demand increase is positive and quite large for the seller contact hazard, and negative and small in magnitude for the buyer contact hazard. In addition, the buyer-seller ratio increases dramatically with

[29] We have also experimented with two alternative measures of Internet availability: the number of broadband operators, and a Current Population Survey based variable. Neither is available as far back as the one we use, and so force us to use much reduced samples, which yield much noisier estimates. Yet our basic result that including a proxy for Internet use does not affect the demand proxy coefficients holds when we use these variables as well.

demand in the short run. The number of homes visited (proxying inversely for the acceptance rate) falls in the short run. The long run effects are all in the same direction as the short run effects, but are insignificant and of a smaller order of magnitude.

Given the irregularity in the timing and coverage of the surveys, which leads to a substantially unbalanced sample, we have presented only an incomplete dynamic analysis,[30] and so are unable to provide a full description of the dynamic behaviour of our variables of interest, as, say, an impulse functions. But the basic pattern should be clear: a large short run response, and a muted, if any, long run response for seller time on the market, homes visited, and the implied buyer-seller ratio. We are also able to externally validate a number of our quantitative findings by consideration of the actual listing institution, the relative size of the interest rate and the behaviour of list prices.

A by-product of our work is an estimate of the elasticity of the contact hazard rates with respect to the buyer-seller ratio. In line with our intuition based on the multiple listing institution, we find a relatively small buyer contact hazard of -.17. This, and our other quantitative results, should prove helpful in search-based calibration models of the housing market, a number of which have already appeared[31], and more of which we expect to see in the future in light of the recent boom and bust in US markets. Comparing our estimates to those obtained from data from markets with different matching institutions, such as those that lack multiple listing services (like England), or from the most recent turbulent time period, which we have avoided, should prove fruitful.

[30] We have run the set of regressions with the lagged (by one year or two, as available) dependent variable included, we have obtained similar results to those reported, although much noisier, as we have had to drop not just the sample's first year but 2001 as well, given that we lack surveys from the second half of the 1990s, as well as additional years giving the missing data. A fuller empirical dynamic analysis might be possible in a few years, should the NAR continue to run its surveys yearly.

[31] Examples include Ngai and Tenreyro (2009), and Diaz and Jerez (2009).

Appendix A

The assumption that buyers do not anticipate being sellers at some point in the future makes no essential difference to the analysis. Assume that an owner has a constant hazard λ of becoming mismatched with his home. The return to being an owner is thus $rV(u) = u + \lambda(V^S - V(u))$, where u is the flow value of the particular owner-house match. A transaction will be consummated if $u \geq (r+\lambda)y - \lambda V^S \equiv z$. The expected surplus, conditional on it being positive, is now

$$E\left[\frac{u+\lambda V^S}{r+\lambda}\middle| u \geq z\right] - y = \frac{1}{r+\lambda}\{E[u|u \geq z] - z\}$$

Thus the surplus reservation value equations can be written as

$$0 = -(c^B + r\bar{V}^B)(r+\lambda) + h(\theta)(1-\beta)G(z-v)(E[u|u \geq z] - z)$$

$$rz = -r(c^S - (r+\lambda)\bar{V}^B) + q(\theta)\beta G(z-v)\frac{r}{r+\lambda}(E[u|u \geq z] - z),$$

so that all our results follow as before, except for the condition for price to increase less than v. The corresponding average transaction price is $EP = \beta(E[V|V \geq y] - y) + V^S = \frac{1}{r+\lambda}\beta(E[u|u \geq z] - z) + \frac{z-(r+\lambda)\bar{V}^B}{r}$. Under the GPD assumption, now with respect to u, this reduces to $EP = \frac{1}{r+\lambda}\beta((k - c(z-v)/(1+c)) + \frac{z-(r+\lambda)\bar{V}^B}{r}$, so that average price also increases, and it increases by more than the willingness to pay if and only if $\beta > \left(r - \frac{dz}{dv}\right)(r+\lambda)(1+c)/[rc(1-\frac{dz}{dv})]$.

Appendix B: Seller Monopoly Pricing

Assume that the seller does not observe V, but knows G, and makes a take it or leave it offer P^M to the buyer, who will accept it if and only if $V - P^M \geq V_B$. Thus P^M maximizes $G(P^M + V_B)P^M + (1 - G(P^M + V_B))V_S$, and so $P^M = V_S + j(P^M + V_B)$, where $j \equiv -G/G'$ (the inverse hazard). Let $y^* = P^M + V_B$.

The buyer's expected capital gain, conditional on a transaction, is $[X|X \geq y^*] - (P^M + V_B) = E[X|X \geq y^*] - y^*$. The seller's is $P^M - V_S = y^* - y$. Using the condition of a constant buyer value of search, the seller and buyer asset value equations are

$$ry = -(c^S - r\bar{V}_B) + q(\theta)G(y^* - v)(y^* - y)$$

$$0 = -(c^B + r\bar{V}_B) + h(\theta)G(y^* - v)\{E[X|X \geq y^*] - y^*\}$$

Considering these as curves in (θ, y^*) space, we see that the B-curve slopes down as before. The analysis for the S-curve is less straightforward. Totally differentiation yields

$$rdy = q(\theta)\{G(y^* - v)(dy^* - dy) + G'(y^* - v)(y^* - y)dy^*\} + q'(\theta)G(y^* - v)(y^* - y)d\theta$$

$$= q(\theta)G(y^* - v)(-dy) + q'(\theta)G(y^* - v)(y^* - y)d\theta$$

so that $dy/d\theta = q'(\theta)G(y^* - v)(y^* - y)/[r + qG] > 0$. We need to know $dy^*/d\theta$. The Generalized Pareto distribution provides a convenient parameterization, in which case $j(y^*) = k - c(y^* - v)$, so that $y^* = (k + cv + y)/(1 + c)$. For $c > -1$ (only then does a mean exist for this distribution), the S-curve slopes up in (θ, y^*) space.

It also clear that the B-curve increases one for one with v, and that the same is true for the S-curve if $r = 0$. More generally,

$rdy = q(\theta)\{G(y^* - v)(dy^* - dy) + G'(y^* - v)(y^* - y)(dy^* - dv)\}$, so that

$dy/dv = -G'(y^* - v)(y^* - y)q/(r + qG) = qG/(r + qG)$.

Under the Generalized Pareto distribution, $d\,y^*/dv = (1 + c)^{-1}\{c + dy/dv\}$. Thus for $c > -qG/(r + qG)$, the S-curve shifts up in (θ, y^*) space less than one for one with v. For $-1 < c < -qG/(r + qG)$, a rather narrow range, given the sale hazard (see our discussion in the text), the S-curve actually shifts down; this also leads to an increase in θ, and changes none of our qualitative predictions on the dependent variables.

Appendix C: Induced Search Effort

Let i_s (i_B) indicate the individual seller's effort, and $\bar{\imath}_S$ ($\bar{\imath}_B$) that of all other sellers (buyers). Search cost is an increasing convex function of effort: $c_S = c_S(i_S)$ and $c_B = c_B(i_B)$. The contact hazards are now written as $q(\theta, i_S, \bar{\imath}_S, \bar{\imath}_B)$ and $h(\theta, i_B, \bar{\imath}_B, \bar{\imath}_S)$; subscripts will indicate partial derviatives. Let $A \equiv G(y - v)(E[X|X \geq y] - y)$. Note that $dA/dy = -G$, $dA/dv = G$.

Sellers choose their search effort so that $0 = -c_S^{'}(i_S) + q_2\beta A$. We consider the symmetric equilibrium in which $i_S = \bar{\imath}_S$ and $i_B = \bar{\imath}_B$. Assuming an efficiency unit specification, $q_2 = q/\bar{\imath}_S$ (Pissarides, 2002, p. 128, equation 5.12); then recalling the seller asset equation (and setting $\bar{V}^B = 0$ for simplicity), we obtain $ry = -c_S(\bar{\imath}_S) + q\beta A = -c_S(\bar{\imath}_S) + \bar{\imath}_S c_S{}'(\bar{\imath}_S)$, so that $\bar{\imath}_S$ is an increasing function of y: $i_S^{'}(y) = r/ic_S{}'' > 0$. A similar analysis yields $0 = \bar{\imath}_B c_B{}'(\bar{\imath}_B) - c_B(\bar{\imath}_B)$, so that $\bar{\imath}_B$ is constant.

The S-curve is upward sloping: totally differentiating the seller asset value equation yields $rdy = \{\left[-c_S^{'}(\bar{\imath}_S) + (q_2 + q_3)\beta A\right]\bar{\imath}_S^{'}(y) - q\beta G\}dy + q_1\beta A d\theta$. Thus $dy/d\theta = q_1\beta A/\left\{r + q\beta G - q_3\beta A\bar{\imath}_S^{'}(y)\right\} > 0$, since $q_3 < 0$ (more effort by other sellers reduces the chance that some buyer will contact the given seller) and $c_S^{'}(i_S) = q_2\beta A$. As before, an increase in v shifts the curve up, but by less than one for one: $dy/dv = q\beta G/\left\{r + q\beta G - q_3\beta A\bar{\imath}_S^{'}(y)\right\}$.

The B-curve's slope is $dy/d\theta = h_1 A/\left\{hG - h_4 A\bar{\imath}_S^{'}(y)\right\}$, which is non-positive as long as $h_4 A\bar{\imath}_S^{'}(y) < hG$. Since $q = h\theta$ and $h_4 = \theta^{-1}[q_2 + q_3]$, this condition can be written as $\left(1 + (q_3/q_2)\right)(r/\beta)/qG < \epsilon$, where $\epsilon \equiv ic_S^{''}/c_S^{'}$, is the elasticity of the marginal cost of effort. Our baseline model has ϵ infinite. The condition will also hold if $q_3 = -q_2$, which corresponds to seller effort being fully dissipative in the sense that increases in it only steal buyers away from other sellers and leave the overall matching rate unchanged. Also, we have already argued in the text that $(r/\beta)/qG$ is likely to be small. We will assume the condition holds.

An increase in v shifts up the B-curve by $dy/dv = hG/\{hG - h_4 A\bar{\iota}_S'(y)\}$. Thus, increases in v shift the B-curve up by more than one for one (for a positive interest rate), so that θ will increase. y will also increase, and thus seller effort as well. Thus q will increase, but the direction of change of h is ambiguous. To know whether y increases more or less than v, and so whether the acceptance rate falls or increases (as in our baseline case), requires solving the system. Doing so, we find find that $dy/dv = h^2G/\Delta$, where $\Delta = h^2G - h_1(r/\beta) + (h_1q_3 - q_1h_4)Ai'$. Some straightforward calculation shows that $dy/dv \leq (\geq) 1$ as $1 + \epsilon \geq (\leq) \left(1 + (q_3/q_2)\right)/|dlnh/dln\theta|$. Thus if effort is completely dissipative, $dy/dv < 1$; on the other hand, if the buyer contact hazard is constant in θ (i.e., $h_1 = 0$), then, so long as effort is not completely dissipative, $dy/dv > 1$.

Appendix D: Sample Issues

We show here that our estimates are robust to inclusion of demographic characteristics for the respondents that are likely to control at least partially for variations in responsiveness. We use the following controls: log mean respondent income, average age of respondents, average number of children in a household, and percentage of couples among respondents, all measured at the MSA/year level. These variables have all been viewed as individual level determinants of duration of home search before, through their effect on the cost of search (e.g., Anglin (1988, 1997) and Baryla and Zumpano (1994)). If our results are due to variation in the mix of buyer or seller types (conditional on year and MSA fixed effects), whether that be through variations in either the response rate or the universe of transactions, than controlling for these demographics ought to affect our results in a substantial way.

Table A1 repeats the estimation in Table 2 for those observations for which respondent demographics are available. This reduces our sample by nearly 40 percent. The impact of controlling for the demographics on the estimates of demand effects is quite limited. Columns (1)-(4) present seller time on the market regressions. The first two columns show that, whether we control for average respondent characteristics (column (1)) or not (column (2)), population and average income level terms have the same negative signs as before. They are no longer significant, but given the much reduced sample size, this is not surprising. When we add the growth terms, the pattern is similar to that in the main text: seller time on the market decreases substantially with demand in the short run but almost fully recovers in the long run (column (3)). When we then add the new controls, neither the estimates nor the significance of the coefficients of interest change much. No demographic control is statistically significant, although they are jointly so at the 10% level.

Columns (5)-(8) show buyer time on the market regressions. Here, too, the controls have little effect on the coefficients of interest, and the results are qualitatively the same as in the main text, with long run effects greater than short run, and those for population greater than for income. However, none of the added control variables are statistically significant, either individually or jointly.

Columns (9)-(12) show the home visits regressions. Again, the results are mostly qualitatively consistent with those in the main text. The one notable change is for income, where the short run effect is now greater in magnitude than the long run, although both remain statistically insignificant. Here the controls are highly jointly significant, with income and couple status positively predicting homes visited. Nevertheless, the impact on the population and income effects of adding the controls is negligible.

We obtain similar results when we repeat the estimation in Table 3 but include average respondent demographics. The results are reported in Table A2. Given that sample size is reduced from 1636 to 1173, it is not surprising that some estimates are less significant than before. In general, however, including the controls does not change the estimated effects on $\ln h$, $\ln q$, and $\ln\theta$.

In other regressions for buyer time on the market and homes visited (not shown), we have added two additional variables: the percentage of first-time home buyer respondents, and the percentage of new homes buyers. The former controls for different information level among buyers, since first-time home buyers have less home purchase experience (Baryla and Zumpano, 1994). The latter proxies for different effort required in home inspections, if new homes involve less hidden information. The only significant estimate for these two variables is that of the percentage of new homes in positively predicted homes visited, but, again, its inclusion has no consequence for the variables of interest.

Of course, even conditional on these controls (and the fixed effects), the mix of respondents may be changing across observations. However, these controls are likely to capture the major dimension of heterogeneity among respondents. As including them has little effect on the estimates of interest, we conclude that it is unlikely that unobservable types introduce any significant bias into the main empirical analysis.

We can gauge the representativeness of our sample in part by comparing it to those of other questionnaire-based studies. For the 1979-80 Federal Trade Commission sponsored study, the median number of homes visited is 11, with a mean of 17. Seller time on the market is not directly reported and must be inferred from the months of listing and accepting the offer. Twenty nine percent of the respondents report that the property was listed and the offer accepted in the same calendar month. The median difference is one month apart; the mean, two. These statistics are similar to those of Table 1. There is no information on buyer time on the market from this survey. This study was administered on recent movers in a standing, nationwide consumer panel used for marketing purposes. 83% of recent address changers that were contact in a first stage responded (Federal Trade Commission, 1983).[32]

Since 1999, the American Housing Survey, has asked respondents who have moved in the past two years the number of homes "looked at before choosing [the] one they bought". The weighted (by number of recent movers) average median across SMSAs and years is 9.7, which is extremely close to

[32] The nature of the sampling in the second stage was such that response rates can not be calculated.

the number in Table 1, while the weighted average is 14.1.[33] This survey has an extremely high response rate, exceeding ninety percent.[34]

The only academic studies of buyer search behaviour not based on the NAR data is Anglin (1994, 1997), where the response rate is about 60 percent. The median buyer time on the market is between 9 to 10 weeks; the median homes visited lies between 10 and 11. These figures are also similar to the numbers in Table 1. Information on seller time on the market was not gathered. The Washington Center for Real Estate Research reports an average buyer time on the market of 12 weeks, and median homes visited of 10, for buyers in that state (November 2003).

[33] The un-weighted average median is 10.3, while the un-weighted mean is 12.5.

[34] See www.aspe.hhs.gov/hsp/06/catalog-ai-an-na/AHS-MS.htm and www.aspe.hhs.gov/hsp/06/catalog-ai-an-na/AHS.htm .

References

Abraham, Jesse and Patric Hendershott, "Bubbles in Metropolitan Housing Markets", *Journal of Housing Research*, 1996, Vol. 7, p. 191-207.

Albrecht, James, Anderson Axel, Eric Smith, and Susan Vroman, "Opportunistic Matching in the Housing Market," *International Economic Review,* 2007, Vol. 42, p. 641-664.

Andrew, Mark and Geoff Meen, "House Price Appreciation, Transactions and Structural Change in the British Housing Market: A Macroeconomic Perspective", *Real Estate Economics*, Vol. 31 (1):99-116, 2003.

Anglin, Paul M., "A Summary of Some Data on Buying and Selling Houses", Working paper, University of Windsor, 1994.

Anglin, Paul M., "Determinants of Buyer Search in a Housing Market", *Real Estate Economics*, 1997, Vol. 25 (4):567-589.

Anglin, Paul, Ronald Rutherford and Thomas Springer, "The Trade-off Between the Selling Price of Residential Properties and Time-on-the-Market: The Impact of Price Setting", *Journal of Real Estate Finance and Economics* , 2003, Vol. 26 (1), p.95-111.

Balestra, "Fixed Effect Models and Fixed Coefficient Models", chapter 3 in László Mátyás and Patrick Sevestre, eds., *The Econometrics of Panel Data: Handbook of Theory and Applications*, Kluwer Academic Publishers, 1992.

Baryla, Jr., Edward A., and Leonard V. Zumpano, "Buyer Search Duration in the Residential Real Estate Market: The Role of the Real Estate Agent", *Journal of Real Estate Research,* 1995, Vol. 10(1), p. 1-14.

Baryla, Jr., Edward , Leonard Zumpano and Harold W. Elder, "An Investigation of Buyer Search in the Residential Real estate Market Under Different Market conditions", *Journal of Real Estate Research*, 2000, Vol. 20(1), p.75-91.

Bernheim, Douglas and Jonathan Meer, "How Much Value Do Real Estate Brokers Add? A Case Study", NBER Working Paper No.13796, 2008.

Blomquist, Glenn C., Mark C. Berger and John P. Hoehn, "New Estimates of Quality of Life in Urban Areas", *American Economic Review*, 1988, Vol. 78(1), p. 89-107.

Campbell, Sean, Morris Davis, Joshua Gallin, and Robert F. Martin, "What Moves Housing Markets: A Variance Decomposition of the Rent-Price Ratio", *Journal of Urban Economics*, 2009, Vol. 66 (2), p. 90-102.

Caplin, Andrew and John Leahy, "Trading Frictions and House Price Dynamics," *NBER Working Paper, 2008* No. w14605

Capozza, Dennis, Patric Hendershott and Charlotte Mack, "An Anatomy of Price Dynamics in Illiquid Markets: Analysis and Evidence from Local Housing Markets", *Real Estate Economics*, 2004, Vol. 32(1), p. 1-32.

Chen, Yongmin and Robert Rosenthal, "On the use of ceiling-price commitments by monopolists", *RAND Journal of Economics*, Vol. 27(2) Summer 1996, p. 207-220.

Coles, Melvin and Eric Smith, "Cross-Section Estimation of the Matching Function, Evidence from England and Wales", *Economica*, 1996, Vol. 63(252), p.589-597.

Díaz, Antonia and Belén Jerez, "House Prices, Sales and Time on the Market: A Search-Theoretic Framework", mimeo, March 2009.

D'Urso, Victoria, "Home Buyer Search Duration and the Internet", MIT Working Paper, 2002.

Elder, Harold W., Zumpano, Leonard V. and Edward A. Baryla, "Buyer Search Intensity and the Role of the Residential Real Estate Broker", *Journal of Real Estate Finance and Economics*, 1999, Vol. 18(3), p.351-368.

Federal Trade Commission, *The Residential Real Estate Brokerage Industry*, U.S. Government Printing Office, Washington, 1983.

Gallin, Joseph, "The Long-Run Relationship between House Prices and Income: Evidence from Local Housing Markets", *Real Estate Economics*, 2006, Vol. 34(3), p. 417-438.

Gabriel, Stuart A., Joe P. Mattey and William L. Wascher, "Compensating differentials and evolution in the quality-of-life among U.S. states", *Regional Science and Urban Economics*, 2003, Vol. 33, p. 619-49.

Genesove, David and Christopher Mayer, "Equity and Time to Sale in the Real Estate Market", *The American Economic Review*, 1997, Vol. 87(3), p.255-269.

Genesove, David and Christopher Mayer, "Loss Aversion and Seller Behavior: Evidence from the Housing Market", *Quarterly Journal of Economics*, 2001, Vol. 116(4), p.1233-1260.

Glaeser, Edward L., Joseph Gyourko, "Urban Decline and Durable Housing", *Journal of Political Economy*, 2005, Vol. 113 (2), p.345-375.

Glaeser, Edward L, Joseph Gyourko, and Albert Saiz. "Symposium: Mortgages and the Housing Crash: Housing Supply and Housing Bubbles", *Journal of Urban Economics*, 2008 Vol. 64(2), p. 198-217.

Glower, M., D. R. Haurin, and P. H. Hendershott, "Selling Time and Selling Price: The Influence of Seller Motivation", *Real Estate Economics,* 1998, Vol. 26(4), p.719-40.

Gyourko, Joseph and Joseph Tracy, "The Structure of Local Public Finance and the Quality of Life", Journal of Political Economy, 1991, vol. 99(4),p. 774-806.

Haurin, Donald, "The Duration of Marketing Time of Residential Housing", *American Real Estate and Urban Economics Association Journal*, 1988, Vol. 16(4), p.396-410.

Hendel, Igal , Aviv Nevo and Francois Ortalo-Magne , “The Relative Performance of Real Estate Marketing Platforms: MLS versus FSBOMadison.com,” *American Economic Review*, forthcoming.

Himmelberg, Charles, Christopher Mayer and Todd Sinai, “Assessing High House Prices: Bubbles, Fundamentals and Misperceptions”, *Journal of Economic Perspectives*, 2005, Vol. 19(4), p. 67-92.

Hort, Katinka, “Prices and turnover in the market for owner-occupied homes”, *Regional Science and Urban Economics*, Vol. 30, p.99–119, 2000.

Krainer, John, “A Theory of Liquidity in Residential Real Estate Markets”, *Journal of Urban Economics*, 2001, Vol. 49, p.32-53.

Johnson, Norman, Samuel Kotz and N. Balakrishnan, *Continuous Univariate Distributions*, Volume 1, second edition, 1994.

Julien, Benoit, John Kennes and Ian Paul King, “Bidding for Labor”, *Review of Economic Dynamics*, 2000, Volume 3, p. 619-649.

Leung, C. K. Y., G. C. K. Lau, and Y. C. F. Leong, “Testing Alternative Theories of the Property Price-Trading Volume Correlation”, *Journal of Real Estate Research*, 2002, Vol. 23, p. 253-264.

Levitt, Steven and Chad Syverson, “Market Distortions When Agents Are Better Informed: The Value of Information in Real Estate”, *Review of Economics and Statistics*, 2005, Vol. 90(4), p.599-611.

Lucas, Robert E., Jr., “Expectations and Neutrality of Money”, *Journal of Economic Theory*, 1972, Vol. 4, p.101-24.

McMillen, D., and J. McDonald, “Urban land value functions with endogenous zoning”, *Journal of Urban Economics*, 1991, Vol. 9, p. 14-27.

Mortensen, Dale, “Labor Search and Market Analysis”, chapter 15 in O. C. Ashenfelter, R. C. Layard, *Handbook of Labor Economics*, North Holland, 1986.

Margaret Stevens, "New Microfoundations for the Aggregate Matching Function", *International Economic Review, 2007,* Vol. 48, p. 847-868.

Merlo, Antonio and Francois Ortalo-Magne, "Bargaining over Residential Properties: Evidence from England", *Journal of Urban Economics*, 2004, Vol. 56, p. 192-216.

Mikhed, Vyacheslav and Petr Zemčik, “Do House Prices Reflect Fundamentals? Aggregate and Panel Data Evidence”, *Journal of Housing Economics*, 2009, Vol. 18(2), 140-149.

Moretti, Enrico. “Human Capital Externalities in Cities” in *Handbook of regional and urban economics*. *Volume 4. Cities and geography*, 2004, pp. 2243-91, Elsevier.

Mortensen, Dale and Christopher Pissaridies, “Job Reallocation, Employment Fluctuations, and Unemployment”, *Handbook of Macroeconomics*, 1996.

Ngai, Rachael and Silvana Tenreyro (2009), “Hot and Cold Seasons in the Housing Market”, LSE wp, 2009.

Novy-Marx, Robert, “Hot and Cold Markets,” *Real Estate Economics*, 2009, Vol. 37, p. 1-22.

Otalo-Magné, F. and Rady, S., “Housing Transactions and Macroeconomic Fluctuations: A Case Study of England and Wales”, *Journal of Housing Economics*, 2004, Vol. 13, p. 288–304.

Piazzesi, Monika and Martin Schneider “Momentum traders in the housing market: survey evidence and a search model”, American Economic Review, Papers and Proceedings, 2009, Vol. 99 (2), p.406-411.

Pissardies, Christopher, *Equilibrium Unemployment Theory*, Second edition, 2002.

Quigley, John M. and Steven Raphael, “Is Housing Unaffordable? Why Isn't It More Affordable? “ *Journal of Economic Perspectives,* 2004, Vol. 18(1), p. 191-214.

Roback, Jennifer, “Wages, Rents and the Quality of Life”, *Journal of Political Economy*, 1982, Vol. 90 (December), p. 1257-1278.

Rubinstein, Ariel and Asher Wolinsky, “Equilibrium in a Market with Sequential Bargaining”, *Econometrica*, 1985, Vol. 53(5), p. 1133-1150.

Sinai, Todd, “Taxation, User-Cost, and Household Mobility Decisions”, University of Pennsylvania mimeo, 1997.

Stein, Jeremy, “Prices and trading volume in the housing market: A model with down-payment effects”, *Quarterly Journal of Economics*, 1995, Vol. 110(2), p. 379-406.

Wallace, Nancy, “The market effects of zoning undeveloped land: Does zoning follow the market?” *Journal of Urban Economics*, 1988, Vol. 23, p.307-326.

Washington Center for Real Estate Research, *Buying or Selling a Home in Washington: 2002 Survey of Recent Home Buyers*, November 2003.

Wheaton, William C., “Vacancy, Search and Prices in a Housing Market Matching Model”, *Journal of Political Economy*, Vol. 2(6), p. 1270-92.

Williams, Joseph, “Pricing Real Assets with Costly Search”, *Review of Financial Studies*, 1995, Vol. 8(1), p. 55-90.

Zorn, Thomas and William Sackley, “Buyers’ and Sellers’ Markets: A Simple Rational Expectations Search Model of the Housing Market*”, Journal of Real Estate Finance and Economics*, 1991, Vol. 4(3), p.315-32.

Figure 1

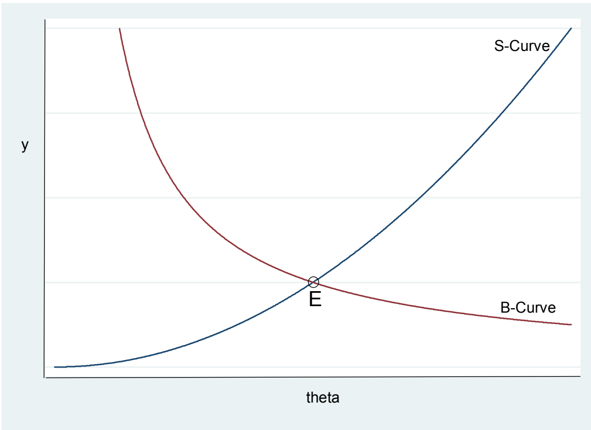

Figure 2

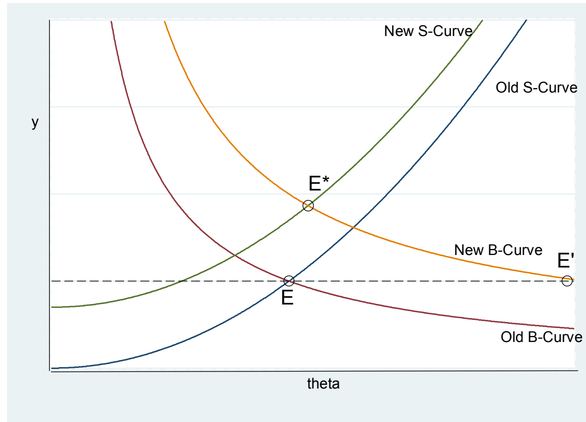

Figure 3

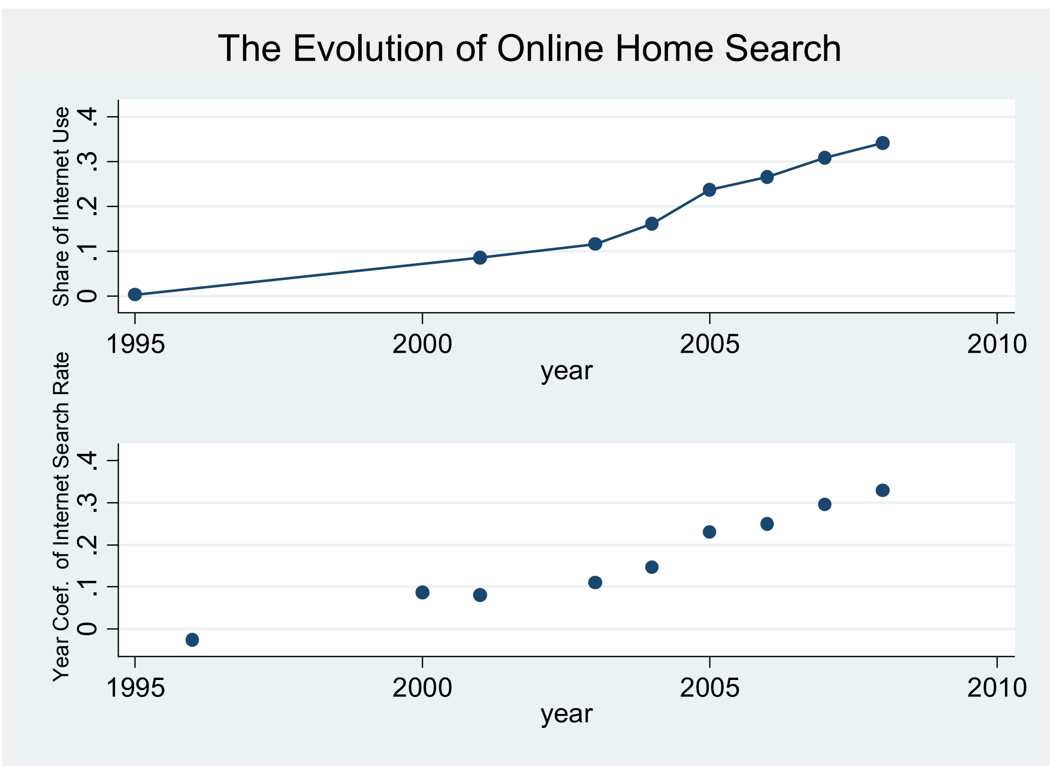

Table 1

	Seller Sample		Buyer Sample		Joint Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Seller Time on Market	7.32	5.60			7.60	5.73
Ln Seller TOM	1.73	0.77			1.77	0.77
Buyer Time on Market			8.18	4.42	8.14	4.25
Ln Buyer TOM			2.02	0.38	2.02	0.37
Homes Visited			9.96	4.34	9.94	4.27
Ln Homes Visited			2.17	0.57	2.17	0.57
Ln Average Income	3.45	0.32	3.43	0.33	3.45	0.33
Ln Population	14.24	0.94	14.22	0.94	14.27	0.91
Annual Δ in Avg. Income	.041	.025	.043	.024	.043	.024
Annual Δin Pop.	.012	.012	.013	.013	.012	.013
Ln THETA					0.25	0.82
Number of Observations	1894		2372		1636	
No. of respondents per (MSAX year) obs.	7.5	15.3	21.6	55.8	38.2	79.5
	Samples with Price Information					
Annual Δ in Price Index	0.065	.053	0.061	.057	0.063	0.060
% with Price Depreciation	0.051	.22	0.074	.26	0.068	.25
Number of Observations	1721		2183		1464	

Table 2						
	Seller Time on the Market		Buyer Time on the Market		Homes Visited	
	(1)	(2)	(3)	(4)	(5)	(6)
Population	-1.19 (0.49)	-1.14 (0.46)	-0.44 (0.15)	-0.43 (0.15)	-0.50 (0.18)	-0.47 (0.18)
Avg. Income	-1.43 (0.77)	-0.42 (0.78)	-0.09 (0.26)	-0.001 (0.29)	-0.44 (0.34)	-0.25 (0.38)
Δ Population		-14.44 (3.53)		-1.88 (1.17)		-4.01 (1.79)
Δ Avg. Income		-6.98 (1.27)		-0.46 (0.42)		-0.98 (0.81)
Short Run Effects						
Population		-15.58 (3.55)		-2.31 (1.14)		-4.48 (1.83)
Avg. Income		-7.40 (1.20)		-0.46 (0.40)		-1.23 (0.74)
F-stat* (p-val)		0.03 (0.87)		0.10 (0.75)		0.09 (0.77)
# of obs.	1894	1894	2372	2372	2372	2372

Note 1: This table shows ordinary least squares regressions at the MSA X year level, weighted by the number of individual responses for each observation. Robust standard errors are reported in brackets and are adjusted for the intra-MSA correlation. All specifications include MSA fixed effects and year dummies (year of survey and year of transaction). All variables are in logs, with Δx indicating $lnx_t - lnx_{t-1}$. All estimates are adjusted for sample weights.

Note 2: F-stat reports the F-statistic for the test of the null hypothesis that the ratio of the coefficient on average income growth to that on the average income equals the corresponding ratio for population.

Table 3						
	lnq: Seller contact hazard		Lnh: Buyer contact hazard		lnTHETA: Buyer-Seller ratio	
	ln(# Homes Visited) – ln(Seller TOM)		ln(# Homes Visited) – ln(Buyer TOM)		ln(Buyer TOM) – ln(Seller TOM)	
	(1)	(2)	(3)	(4)	(5)	(6)
Population	0.67 (0.50)	0.60 (0.48)	-0.04 (0.21)	-0.02 (0.20)	0.69 (0.48)	0.60 (0.44)
Average Income	1.36 (0.82)	0.45 (0.86)	-0.47 (0.45)	-0.30 (0.47)	1.82 (0.80)	0.73 (0.79)
Δ Population		11.57 (3.96)		-2.96 (2.03)		14.61 (3.61)
Δ Avg. Income		6.45 (1.50)		-1.19 (0.92)		7.64 (1.35)
Short Run Effects						
Population		12.17 (4.02)		-2.98 (2.05)		15.21 (3.61)
Average Income		6.90 (1.45)		-1.49 (0.85)		8.37 (1.31)
F-stat* (p-val)		0.02 (0.90)		.01 (0.91)		0.66 (0.20)
# of observations	1636	1636	1636	1636	1636	1636

See Notes 1 and 2 for Table 2.

Table 4						
	Seller Time on the Market		Buyer Time on the Market		Homes Visited	
	(1)	(2)	(3)	(4)	(5)	(6)
OFHEO Price Index	.58 (.28)	.79 (.30)	-.07 (.09)	-.02 (.09)	-.06 (.12)	.04 (.14)
Δ OFHEO Price Index	-5.57 (.69)	-5.06 (.71)	-.16 (.20)	.08 (.24)	-1.60 (.32)	-1.65 (.36)
Population		-.64 (.55)		-.44 (.18)		-.20 (.19)
Avg. Income		-1.84 (.91)		-.22 (.34)		-.60 (.44)
Δ Population		-2.13 (3.61)		-1.77 (1.32)		.41 (1.66)
Δ Avg. Income		-2.18 (1.34)		-.09 (.50)		.69 (.70)
# of obs.	1721	1721	2183	2183	2183	2183

See Note 1 of table 2.

Table 5						
	Seller Time on the Market		Buyer Time on the Market		Homes Visited	
	(1)	(2)	(3)	(4)	(5)	(6)
Internet Use		-.27 (.25)		.24 (.11)		.30 (.12)
Population	-1.29 (.48)	-1.32 (.48)	-.43 (.15)	-.40 (.16)	-.47 (.18)	-.43 (.18)
Avg. Income	-.45 (.81)	-.42 (.80)	.002 (.29)	-.01 (.29)	-.24 (.38)	-.26 (.38)
Δ Population	-14.15 (3.75)	-14.18 (3.74)	-1.88 (1.17)	-1.89 (1.18)	-4.02 (1.80)	-4.03 (1.76)
Δ Avg. Income	-7.27 (1.35)	-7.30 (1.35)	-.46 (.42)	-.43 (.42)	-.98 (.81)	-.95 (.80)
# of obs.	1639	1639	2364	2364	2364	2364

See Note 1 of Table 2.

Table 6		
	OFHEO Price Index	Transaction / List Price:
	(1)	(2)
Population	.154 (.021)	.039 (.020)
Avg. Income	.063 (.028)	.005 (.026)
Δ Population	1.391 (.375)	0.408 (.129)
Δ Avg. Income	.437 (.067)	.120 (.050)
Lagged OFHEO Price Index	.938 (.011)	
# of obs.	2535	2705

See Note 1 of Table 2. However, there is no weighting in column (1).

Table A1												
	Seller Time on the Market				Buyer Time on the Market				Homes Visited			
Pop.	-0.84 (1.21)	-0.70 (1.22)	-0.52 (1.26)	-0.37 (1.26)	-0.77 (0.33)	-0.77 (0.33)	-0.75 (0.33)	-0.75 (0.33)	-0.88 (0.44)	-0.92 (0.41)	-0.72 (0.43)	-0.78 (0.41)
Income	-1.68 (1.20)	-1.60 (1.21)	-0.93 (1.38)	-0.82 (1.39)	-0.02 (0.37)	-0.02 (0.37)	0.21 (0.44)	0.20 (0.44)	-0.55 (0.49)	-0.76 (0.47)	-0.57 (0.63)	-0.75 (0.61)
Δ Pop.			- 12.21 (5.50)	-12.77 (5.48)			-2.44 (1.46)	-2.44 (1.46)			-4.12 (2.50)	-3.82 (2.37)
Δ Income			-3.64 (1.87)	-3.74 (1.87)			-0.71 (0.55)	-0.71 (0.55)			-0.11 (0.87)	-0.14 (0.85)
Respondent income		-0.19 (0.14)		-0.21 (0.14)		0.03 (0.06)		0.03 (0.06)		0.34 (0.08)		0.34 (0.08)
Age*100		0.02 (0.5)		0.05 (0.5)		-0.06 (0.23)		-0.05 (0.23)		0.1 (0.2)		0.1 (0.2)
Couple		-0.18 (0.12)		-0.17 (0.12)		-0.0007 (0.08)		0.0025 (0.08)		0.13 (0.07)		0.13 (0.07)
Children		-0.07 (0.56)		-0.09 (0.08)		-0.02 (0.04)		-0.023 (0.040)		0.02 (0.04)		0.02 (0.04)
F-stat (p-value)		1.92 (0.10)		2.03 (0.09)		0.15 (0.96)		0.14 (0.97)		6.42 (0.00)	2.09 (0.08)	6.39 (0.00)
# of obs.	1368	1368	1368	1368	1622	1622	1622	1622		1622	1622	1622

Table A2												
	lnq: Seller contact hazard				lnh: Buyer contact hazard				$ln\theta$: Buyer-Seller ratio			
Population	0.21 (1.40)	0.11 (1.37)	0.29 (1.40)	0.16 (1.39)	0.02 (0.55)	-0.01 (0.52)	0.19 (0.55)	0.14 (0.53)	0.20 (1.28)	0.12 (1.28)	0.10 (1.28)	0.01 (1.29)
Avg. Income	0.91 (1.47)	0.75 (1.45)	0.037 (1.64)	-0.14 (1.62)	-0.77 (0.76)	-0.87 (0.74)	-0.95 (0.83)	-1.05 (0.81)	1.68 (1.45)	1.61 (1.46)	1.02 (1.59)	0.93 (1.61)
ΔPop.			9.32 (6.53)	10.36 (6.32)			-2.14 (3.12)	-1.51 (3.00)			11.29 (6.04)	11.74 (6.00)
Δ Avg. Income			4.33 (2.26)	4.46 (2.19)			-0.52 (1.18)	0.60 (1.14)			3.71 (2.06)	3.77 (2.05)
Respondent income		0.50 (0.21)		0.52 (0.21)		0.31 (0.12)		0.31 (0.12)		0.20 (0.19)		0.22 (0.19)
Age*100		-0.03 (0.8)		-0.1 (0.8)		-0.3 (0.4)		-0.3 (0.4)		0.2 (0.7)		0.2 (0.7)
Whether Couple		0.29 (0.15)		0.28 (0.15)		0.09 (0.14)		0.08 (0.14)		0.18 (0.19)		0.18 (0.19)
Children		0.10 (0.10)		0.11 (0.10)		0.02 (0.07)		0.02 (0.07)		0.09 (0.10)		0.17 (0.19)
F-stat* (p-value)		3.85 (0.004)		3.92 (0.004)		2.06 (0.09)		2.01 (0.09)		0.91 (0.46)		0.09 (0.10)
# of obs.	1181	1181	1181	1181	1181	1181	1181	1181	1181	1181	1181	1181