DISCUSSION PAPER SERIES

No. 7777

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ISSN 0265-8003

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Discussion Paper No. 7777
April 2010

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CEPR Discussion Paper No. 7777

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ABSTRACT

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JEL Classification: R21
Keywords: housing, matching, search and time on the market

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Submitted 28 March 2010

Thanks to Ed Baryla, 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 and other seminar participants at Toronto, Guelph, Ben-Gurion, Hebrew University, Madison-Wisconsin, UBC and Duke.

Search and Matching in the Housing Market[1]

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Abstract

Housing markets clear, in part, through the time that buyers and sellers spend on the market. We show that demand generally leads to shorter seller time on the market and fewer homes that buyers visit, while buyer time on the market is much less sensitive to demand. Furthermore, seller time on the market and homes visited are much more sensitive to demand growth than its level, consistent with sellers responding to demand with a lag. Those same findings also provide an estimate of the elasticity of the matching function.

1. Introduction

The idiosyncratic nature of homes, and the consequent need for buyers to examine one before making an offer on it, makes trading in this market time consuming. Since economic agents value their time, housing markets might clear not only through price but also through time on the market. In particular, increased demand need not translate solely into a higher price but may also affect buyers' purchase and sellers' sale time, the number of homes a buyer visits and enquiries a seller receives. The focus on price increases and subsequent declines over the past few years, without a simultaneous consideration of the search and matching aspects of the market, might understate the extent of the shock to this market, especially over the short run. Modelling and estimating the search aspect of real estate market is thus crucial to understanding how these markets work. This paper lays out a

[1] Thanks to Ed Baryla, 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 and other seminar participants at Toronto, Guelph, Ben-Gurion, Hebrew University, Madison-Wisconsin, UBC and Duke.
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theoretical framework for the co-determination of the search variables, which it then uses in interpreting an MSA level, empirical analysis of the variables. The empirical analysis is the first to simultaneously analyze the search experience of agents on both sides of the markets. Our findings shed new light on the mechanisms governing housing market fluctuations, and in particular, show a substantial short-run overshooting of these variables in their adjustment to a new demand level.

There is a relatively large number of studies that have explored the *individual* level determinants of seller time on the market, such as the property's idiosyncrasy (Haurin, 1988), seller motivation (Glower et al., 1998), the initial offer price (Anglin, Rutherford and Springer, 2003), the owner's equity (Genesove and Mayer, 1997), the previous purchase price (Genesove and Mayer, 2001), the 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)). All of these papers use individual housing unit data in a given geographical market. Any time variation is used, if at all, to analyse the effect of the changing environment for the individual seller.[4]

There is a more limited literature on the individual determinants of buyer time on the market, comprising perhaps only Baryla and Zumpano (1995), Anglin (1997), Elder, Zumpano and Baryla (2000), and D'Urso (2002). Elder, Zumpano and Baryla (1999) are alone with Anglin in examining the number of homes visited, the former only via 'buyer search intensity', the ratio of the number of homes visited to buyer time on the market. The five papers focus on the mechanisms of search, such as real estate brokers and Internet use. Although the D'Urso and Baryla, Zumpano and Elder papers examine housing units located in different geographical markets, the analysis is once again at the individual level.[5]

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[4] Merlo and Ortalo-Magne (2004) consider different markets, defined by two areas and two periods only.

[5] Anglin's data come from a survey of Windsor, Ontario. The other papers use data from N.A.R. surveys. D'Urso (2002) uses US state level data only in constructing an instrument for an individual's Internet use, to control for endogeneity. This is not a market level analysis, which would be based on the fraction of Internet users in the area. Elder, Zumpano and Baryla (2000) uses three years of N.A.R. data and is the only paper to use a market level variable – year dummies for interest rate effects – but lacks any market level equilibrium analysis or interpretation.

Missing from the literature to date is any study of the *market* determinants of buyer and seller behaviour. This paper is meant to remedy that. We aggregate the micro data from the biannual/annual National Association of Realtors' buyers and sellers surveys to the 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. We then estimate the effects of demand, proxied by average income and population, on the search variables, interpreting them in the context of the canonical matching model. Given the possibility of bubbles during parts of the period covered by our data, we also consider price itself as a possible demand proxy. To our knowledge, no one has conducted a panel analysis of search in real estate markets, nor in an empirical analysis studied buyer and seller behaviour in an integrated fashion.[6]

We preface our empirical results by a search-matching theoretic analysis that we believe captures the essential elements of a steady state analysis of a shock to demand in this market.[7] A crucial assumption is that the inflow of buyers is more responsive to the value of search that that of sellers, infinitely so in our baseline model. We think greater buyer inflow sensitivity is a reasonable assumption, but it is easy to see what would obtain if the opposite obtains. In any case, it is the former that is necessary to rationalize the empirical results, given the model's remaining structure.

We use the standard random matching model, rather than Coles and Smith's (1996) marketplace model, which given the prevalence of multiple listing services might be thought a better fit to U.S. residential real estate markets. Our motivation is the greater simplicity of the random matching model. In this model, market conditions are summarized solely by the stock of buyers and sellers (under constant returns to scale their ratio only), and not, as in the marketplace model, by the flows of buyers and sellers as well. More crucially, a single statistic of the distribution of time on the market (we use the

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[6] Anglin (1994) is the only other study we know to empirically examine both buyer and seller behaviour.
[7] Novy-Marx (2007), which is a theoretical paper only, presents a similar model. The main difference lies in his considering shifts in the outside option, rather that in the match quality distribution.

median) suffices for an empirical analysis that is to be interpreted on the basis of the random matching model, whereas the marketplace model would require at least two.

The theoretical analysis shows that, in general, an increase in buyer willingness to pay decreases seller time on the market and increases 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 predictions for simple linear combinations of the three observed variables that isolate the contact hazards and the buyer-seller ratio are stronger and unambiguous. We provide a few extensions that demonstrate the robustness of the model.

We then turn to the empirical analysis: the estimation of the effects of our demand proxies, average income and population, on buyer and seller time on the market and homes visited. In principle, consumption and production amenities would be better proxies, but given the difficulties of measuring variation in them at a yearly or so frequency, we rely on income and population instead. Justifying income as a demand proxy is, first, that higher income people have a higher willingness to pay for consumption amenities, so that improvement in local public goods, which will increase all buyers' willingness to pay, will be accompanied by higher income people moving into the area; second, complementarity between individual skill and productive opportunities imply that an improvement in the latter, which increases willingness to pay, will also induce higher wage people to in migrate (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.

Theoretically, other types of shocks can generate the opposite correlations. Population increases can follow from relaxations in zoning laws, although to the extent that the latter 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 so labour income; this tends to decrease the correlation between prices and income. But empirically, the correlations are of the sign consistent with our approach: in Gyourko and Tracy (1991), as in Gabriel et al (2003), amenities' effect on wages and prices are almost always of the same sign, where they are significant,[8] 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) throw doubt on the consistency of the estimates for the last of these studies, given the inability to reject the null of no co-integrating relationship in each city. However, these tests have little power, as emphasized by Gallin. 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, and react similarly to the technological shock of weather adaptation; growing cities have an increasing share of college graduates. These results are all consistent with our using income and population as demand proxies.[9]

We find that greater demand decreases both buyer and seller time on the market and homes visited, although the findings are not always significant. Controlling for MSA fixed effects, higher average income is associated with both a lower seller time on the market and a smaller number of homes visited by buyers, but only for time on the market is the relationship significant. Buyer time on the market is unaffected. The implied seller contact hazard increases, the buyer contact hazard falls (by much less), and the implied buyer-seller ratio with higher average income. Higher population has a

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[8] The same is true of Blomquist et al (1988), except that the standard errors are grossly underestimated.

[9] Glaeser and Gyourko's emphasize the asymmetries in those relationships due to durability of the housing stock.

significant negative effect on all three directly observed outcomes variables, with the effect on seller time on the market much larger than that on the other two outcome variables. The population effect on the implied contact hazards and buyer-seller ratio are as for average income, but much smaller in magnitude, with the effect on the buyer contact hazard essentially zero. These findings are all consistent with theory, and as we will argue, the matching institution in these markets.

Because sellers and buyers may not respond at the same speed, we consider how the outcome variables react not only to the level of the demand proxies, but also to their growth rates. This is the core of our results. We find that income growth and population growth strongly decrease seller time on the market, the seller contact hazard, the buyer-seller ratio and homes visited, as predicted by a simple dynamic extension to our model in which sellers' reaction to demand lags that of buyers. The effect on buyer time on the market and the buyer contact hazard are also negative, but much weaker and insignificant, consistent with the model and the matching institution.

We also consider how the outcome variables respond to the price level and price growth. Prices are, of course, endogeneous in the model, but as a 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) have argued that many markets were characterized by housing bubbles during parts of the period we examine, it seems reasonable to investigate the relationship. Indeed if bubbles are preeminent, we should not expect to find other good proxies for demand, unless they are simply magnifications of demand shocks. As with income and population, we find negative effects, with much larger short run than long run effects, seller time on the market affected most and buyer time on the market least.

Finally, we consider the effects of technology proxies on our variables of interest. We find evidence that the technology proxies affect the outcome variables, but in general their inclusion does not alter our previous conclusions.

2. The Model

2.1 Baseline Model

At the center of any search/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 $h(\theta) \equiv m(B,S)/B = m(1,\theta)$, while a given seller will make contact with some buyer with probability $q(\theta) \equiv m(B,S)/S = m(\theta,1)$. Note $q = h\theta$.

Standard, and intuitive, assumptions on the matching function make h a downward sloping function and q an upward sloping function of θ. 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. Seller 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. To take a limiting case: if the opportunity to search (an hour free of work and other duties to go out with a real estate agent) arises independently of other buyers' (all buyers don't search on Sundays) at a constant rate ρ, and buyers (or their agents) choose 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 $m = \rho B$,[10] and $q = \rho\theta$. The 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. Thus a buyer's contact hazard will be decreasing in the number of buyers, with whom he competes, and

[10] See Mortensen and Pissaridies (1996). This is the specification used in Wheaton (1991).

increasing in the number of sellers (which increases the chance that any other buyer will end up elsewhere than where the given buyer visits). 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.

Let the net present value of a given buyer owning a given home be X, a random variable whose distribution is $1 - G(X - v)$. v is a location parameter, 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 given home. X is assumed unknown to both the buyer and seller before the contact, and observed by both of them upon the 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 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. Thus 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. A variant model, which we explore in the following section, assumes that the inflow of buyers is more sensitive to the value of search than is the seller inflow; that model yields the same qualitative results.

We made this assumption because we thought it reasonable. As it turns out, it fits our empirical results, whereas assuming a seller inflow more sensitive than the buyer inflow would not. In presenting our results, we will use the language of testing the specific model that incorporates our assumption. But we have no objection to viewing the model as incorporating either case, and inferring the greater buyer inflow sensitivity from the empirical results.

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 of course downward sloping in θ. Where these two curves cross defines the unique equilibrium in y and θ (see Figure 1). [11] 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 an increase in buyers' willingness to pay is easy to discern, with the help of standard results from search theory. From Mortensen (1986, p. 864), we know that an increase in ν will increase the reservation value, but so long as the interest rate is positive, that increase will be less than the increase in ν itself. Thus an increase in ν will shift up the S- curve, but by less than the increase in ν, while it will shift up the B- curve one for one. This will result in a higher buyer-seller ratio and a higher (although by less than the increase in the willingness to pay) y 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. $G(y - \nu)(E[X|X \geq y] - y)$, 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 $y - \nu$, 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 match quality values above the unchanged sum of buyer and seller search values but below the new threshold y, would remain unconsummated, which contradicts efficient bargaining. Thus the S-curve must shift up less.

The implication of the demand shift for the variables of interest is as follows. With the reservation surplus value y increasing less than the location parameter, the acceptance rate $G(y - \nu)$ must rise. Thus the average number of homes that a buyer visits before purchasing will fall. This is the central prediction of a model with an endogenous acceptance rate, or 'stochastic matching', as

[11] 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.

Pissarides (2000, ch. 5) labels it. With an increased θ, the seller contact hazard q increases. Thus the probability that a seller will sell, $qG(y-v)$, also increases, and 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, it can be shown that the purchase probability will remain unchanged when $1-G$ is exponential.[12]

The size of these effects depend upon the buyer contact hazard's dependence on θ. If it is small, as we have argued it is likely to be, the buyer contact hazard will obviously not change much. In addition, the B-curve will then be nearly flat, implying that $y-v$, and so the acceptance rate and therefore buyer time on the market, will stay very nearly remain the same. In this case, however, θ will increase substantially, and so the seller contact hazard as well.

A small interest rate will make all the changes in the outcome variables small. Consider the case of a zero interest rate. Then an increase in the willingness to pay 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 willingness to pay. θ will remain unchanged, as will the acceptance rate, and so the probability of a transaction by either agent type as well. Obviously, the outcome for a small positive interest rate will be similar. In the presence of both a small interest rate and a small h', we still expect the seller contact hazard and time on the market to react more than the other outcome variables, since the buyer's contact hazard and the acceptance rate are both proportional to the *product* of the interest rate and h'. We will argue below that the interest rate is indeed likely to be small, although some of our empirical results belie that.

[12] For the Generalized Pareto Distribution, which nests the exponential, the purchase hazard increases if the inverse hazard of the match quality distribution is decreasing, and decreases if it is increasing.

2.2 Static Theoretical extensions.

The model makes a number of simplifying assumptions. The first is that the supply of buyers is infinitely elastic. Dropping it 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 sale of new homes or the putting on the market of 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.

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

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

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

and so buyer and seller surplus reservation value equations

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

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

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

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

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

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 that are either buyers or sellers, and not that of owners who decide to offer their home 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 in particular to 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. Such is the case in a number of papers, such as Williams (1995) and Kraimer (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 in steady state, the 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,[13] and has generated a number of possible explanations (such as Stein, 1995 and Genesove and Mayer, 2001).

A second assumption is 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.

[13] 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.

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

A fourth variation, explored in Appendix C, includes induced search effort. 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 the hazard, while that of agents on its own side decreases it. Assuming an efficiency unit specification, as in Pissarides, 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, the buyer hazard is sufficiently decreasing in θ, or seller effort sufficiently dissipative. A crucial question is how much of any observed response to a demand shock can be attributed to the mechanism we modelled in our baseline model, i.e., the changing acceptance rate and buyer-seller ratio, rather than induced effort. We consider that issue in discussing our empirical results.

A fifth is that bargaining power varies with the buyer-seller ratio. It seems reasonable that if that is the case, then β will be increasing with θ.[14] Then $\beta(\theta)q(\theta)$ would be increasing in θ, and $(1-\beta(\theta))q(\theta)$ decreasing, and our results follow as before.

2.3 A Dynamic Extension

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 with a lag to the shift in the match quality distribution. 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

[14] For example, in an auction based model such as Julien, Kennes and King (2000), an increase in θ increases the probability that more than one buyer will show up at a given seller, and that an auction (an unmodelled phenomenon here) will ensue.

attributed at first to chance. That it is sellers that lag in apprehension of the changed environment, and not buyers, or at least that sellers lag relative to buyers, is easily justified: sellers list and buyers do not, and so while buyers see the change in sellers' numbers (and, unmodelled here, their list prices), sellers do not see the change in the number of buyers or their willingness to pay. 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, but 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 decrease. The acceptance rate $G(y-v)$ increases, and by an amount much greater than in 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. Nonetheless, we expect the acceptance rate effect to dominate, given our earlier observation about real estate market institutions in the United States implying a small $|h'(\theta)|$.

To recall, we assume that in the second period, there is full adjustment to the new stationary equilibrium, at E_1. Thus sellers increase their reservation price, so that y now increases, while θ falls, but 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.

We thus expect 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 the latter 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 run than in the long run; it can even fall in the short run.[15]

3. From the Model to the Data

Given the stationarity of the model, the time on the market for buyers and sellers is an exponential distribution. 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 $-\ln(hG)$. The model's stationarity likewise implies that the number of homes visited (including the one purchased) follows a geometric distribution, so that the expected number of homes that a buyer will visit *before* the one he purchases is 1/G. (This is also the expected number of enquiries a seller receives before selling, which we do not observe.) Note that the number of homes visited does not depend at all on the offer arrival rates, as homes visited is a count variable, and is independent of the time that lapses between each visit.

Finally, note that combinations of these three variables yield the log contact hazards and buyer to seller ratio. The log difference between the expected number of homes visited and buyer time on the market is simply lnh, the log buyer contact hazard; that between the expected number of homes visited and seller time on the market is simply lnq. Since $(1/hG)/(1/qG) = (m/S)/(m/B) = \theta$, 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. Intuitively, if buyers are spending half the time on the market than sellers are, then they must have twice the likelihood of transacting as sellers (under stationarity); but as buyers and sellers have to leave

[15] It is easy to see from (5) that where $1 - G = \int_y^\infty X\, e^{-(X-v)} dX$, EP is independent of v, for given y.

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.

4. Data

We constructed a panel dataset from three different sources. Our source for buyer and seller time on the market and homes visited is the micro data of twelve separate surveys of home buyers and sellers conducted by the Research Division of the National Association of Realtors (NAR). These surveys were conducted biannually between 1987 to 2003, and annually since 2003. 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 MSAs and PMSAs, which we will refer to collectively as MSAs. We include only MSAs that appear in more than one year. The resulting panel is heavily unbalanced: the number of periods 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, the fact that the early surveys were held two years apart and the two missing survey years, 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 home buying process. Among these buyers, those who have owned and sold their previous homes also provided the 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 requirement selects only those sellers who have bought another house within two or three years after selling their home. In order that our buyer and seller data cover the same years, we use only the seller data from the 2008 survey. Doing so also avoids the special circumstances of that year. Also, since prior to 2007 respondents are not asked for the city of the house that they sold, we only use responses for sales where the respondent reported moving fifty miles or less.

We should also state outright that the response rates of these surveys are extremely low, never exceeding 19 percent and falling as low as 6 percent in one year. We nonetheless use these data for lack of any other useful panel data source for buyer and seller behaviour. Also, whereas one might suspect, say, that average buyer time on the market among respondents differs from that of the universe of buyers (respondents might be more patient than non-respondents, for example), one might be less suspect of the responsiveness of the variables to market shocks. We will also see that the mean values of our variables are similar to those of other surveys with much better 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; (3) and number of homes visited by buyers. 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 as the value of the variable the midpoint of the chosen bracket. 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 the number of weeks. Number of homes visited is based on responses to the question 'Including the home 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 tracts 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 the individual may have sold in a different year than he purchased.

The weighted average (across MSAXyear 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 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

[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.

effect of the log transformation is such that lnTHETA , 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. Note the substantial variation in all these variables.

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.

These figures are not far from those of other questionnaire based studies. For the well known 1979-80 Federal Trade Commission sponsored study, which was administered on a very different population (members of the National Family Opinion Panel who had reported buying or selling a home in the previous year), 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.

The number of homes that buyers “looked at before choosing [the] one” they bought has since 1999 been asked of those American Housing Survey respondents who have moved in the past two years. The weighted (by number of recent movers) average median across SMSAs and years is 9.7, extremely close to the number in Table 1, while the weighted average is 14.1.[17]

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

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

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. 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).

Our figures on seller time on the market do tend to differ from of state realtor association websites. We have located 37 of them, but they report days on the market for only 25 MSAs, only 19 of which are in our panel. The mean days of the market is 102 in those data, while the average median in our data is 25. Even inflating the latter by 1.44, leaves the website mean at nearly three times that of our panel. One possible explanation (although clearly not the whole explanation) for the difference is that the websites include new homes, while those in our Seller sample are existing homes only.

Seller time on the market in our data is sufficiently short that the interest rate can be regarded as negligible. The mean median seller time on the market implies a daily hazard rate of sale (qG) of 1.36 percent, [18] while even a yearly interest rate of about 20%, which Levitt and Syverson (2008) infer from Genesove and Mayer (1997), implies a daily rate of only one-twentieth of a percent. Equation (8) then shows that, unless sellers receive only a very small share of the surplus, the comparative statics will be close to those of a zero interest rate.[19]

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

[18] This is the inverse of 7.32 weeks times ln(2) times seven days/week.

[19] This would still be the case were one to triple seller time on the market in line with the web sites' figures. 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.

level, which of course accounts for any kind of auto correlation in the errors,[20] 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 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. All variables are in logs. To adjust directly for heteroskedacticity resulting from differences in the number of transactions underlying an 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, an increase in average income is associated with a decrease in both seller time on the market and in the number of 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 that in column (5) predicts three percent fewer home visits. At *mean* values, this is slightly more than nine days less 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 four and a half percent 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.

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[20] 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.

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 homes visited (since the seller hazard should be increasing in demand shocks), but greater for homes visited than buyer time on the market (since the buyer hazard should be decreasing in homes visited). Also, buyer time on the market should increase more than that of sellers, 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 relevant linear combinations , $lnq \equiv lnBVIS - lnSTOM$, $lnh = lnBVIS - lnBTOM$, and $ln\theta \equiv lnBTOM - lnSTOM$ on the demand proxies, using the Joint sample (to recall, that of MSA X year observations for which both seller and buyer time on the market are available). These regressions are shown in Columns (1), (2) and (3) 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, much smaller in magnitude and never significant. These results are consistent with the theory and real estate institutions. While the point estimates indicate that the buyer contact hazard falls with the demand proxies, we can not reject the hypothesis that it is constant.

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 held only two years, 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 a period for the short run should bias downwards in magnitude our estimate of the true short run effect. Also note that any pattern of autocorrelation in the errors will be accounted for in the clustered standard errors.

Table 2 exhibits the striking result that both income growth and population growth strongly decrease seller time on the market, while the effects of the income and population levels are much smaller, and, for income, insignificant. The semi-elasticity of seller time on the market with respect to income growth is about seven, while that with respect to population growth is about 14.5. We stress that, given the inclusion of the MSA and year fixed effects, the short run and long run effects are identified off variations in the level and growth rate around the average for that MSA (relative to the calendar year).[21]

These large responses are consistent with our dynamic extension to 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 seller time on the market is predicted to be much less dramatic. If the interest rate is negligible, as we have argued it is, there will be hardly any change at all. Our results are consistent with this extension. They indicate that a one percent increase

[21] Let the relationship be $y_{it} = Ax_{it} + B\Delta x_{it} + u_t + v_i + e_{it}$, where i indexes the MSA, y the year of the transaction, the u's are the time effects, the v's are the MSA effects, 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) contribute 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).

in income decreases seller time on the market by three and a half days in the short run, but by only an (insignificant) fifth of day in the long run; an equivalent increase in population is associated with a full week's decline in seller time on the market, but only a (significant) half day in the long run.

The dynamic extension implies that homes visited should also decrease substantially in the short run upon a demand increase. We see that in 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 can not reject the null of equal short and long run effects. One can reject the null under the usual OLS standard errors.[22]

Turning to buyer time on the market, for which, considered alone, there are no unambiguous predictions, we see in column (4) that although the four regressors have the same negative sign, only the population level coefficient is significant. In magnitude 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, which are insignificant. The former are significant for both lnq and $ln\theta$, and, for average income, for lnh, and have the predicted signs. As our discussion of the listing institution suggested, the effects for the buyer contact hazard are much smaller in magnitude than those for the seller.

The assumption that income and population affect the dependent variables only through their correlation with a common effect (the model's v) can be tested by a simple specification test. 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 equals to the corresponding ratio for the change in the log variables. This test is

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

shown as F-test 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. 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 can not be rejected.

We also note here that our estimates of the response to the demand proxies of the implied buyer seller to ratio along with 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 buyer hazard has an elasticity of -0.16. By construction of our dependent variables, and the constant returns to scale assumption inherent in this calculation, which makes the hazards functions of the buyer seller ratio only, the elasticity of the seller hazard with respect to θ is one plus the buyer hazard elasticity, or 0.84. The result from using the other significant regressor, population growth, is similar: a buyer hazard elasticity of -0.20. The estimates accord with our earlier claim that the seller listing institution is likely to make the buyer hazard much less sensitive than the seller hazard to the buyer-seller ratio.

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. This accords with our a priori argument for a small buyer hazard elasticity, especially as its theoretical range is $[-1,0]$. 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.

6.2 Price as a Demand Proxy

Unless bubbles are simply a magnification of underlying demand (as in Glaeser et. al., 2008), fundamentals will not adequately represent demand during years and in markets characterized by bubbles. In such a case, price itself is the best indicator of demand conditions. Prices are, of course, endogenous in the model, so a fair bit of skepticism is certainly in order in using price as a demand proxy. But if bubbles were prevalent during the sample period, income and population may not sufficiently reflect buyer willingness to pay.

Table 4 considers the correlations between prices and the dependent variables. 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.

6.3. 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 the demand proxies. 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.[23] Any national level

[23] 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

differences in 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 partial negative 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.

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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.

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 period of high growth, 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.) 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 theoretical efforts in this paper, our analysis of endogenous search effort in Appendix C can guide us. There we show that although buyer effort is unchanged (for a constant value of buyer search), 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 that the point estimates show the buyer hazard falling with demand does 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 offered interpretation is empirical, however. One can assess the effect of unobserved technological change on our estimates by how including technology proxies affects our results. Although we lack indicators of adoption of the earlier technologies, we do have a good one for Internet use: the fraction of buyers who report finding the home they eventually purchased 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 equal to zero for all earlier years.

One might be concerned with the endogeneity of the variable. We think it unlikely that households on the verge of moving to a new home will hook up to the Internet in their existing home in order to facilitate their search. Of greater concern is the decision of real estate agents or an MLS to post listings on the Internet. Better managed (in that year, relative to the city average) 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 can not all be bias, as maintaining a web site is costly and so can reflect good managerial policy only if it is effectual. But measuring the degree of the efficacy of real estate web sites is not our central objective here; controlling for the matching technology is, so that it matters not if the measured Internet use effect originates in better managerial behavior rather than Internet use.[24]

Table 5 shows regressions with and without the Internet use variable. 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. 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. Seller time on the market would be smaller by a similar

[24] Since the Internet variable 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.

magnitude as buyers, but the effect is insignificant. Nevertheless, the table makes clear that including the Internet variable has no noticeable effect on the estimated 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 it is evidently sufficiently good to show a strong correlation with buyer time on the market and homes visited,[25] it is difficult to imagine that there are other, unmeasured, technological changes responsible for our earlier results.

We can also rationalize Internet coefficient estimates. Increases in Internet use shift up the B- and S-curves, causing the equilibrium to move from E0 to E1, as in Figure 2, leading to an increased y and, if we assume efficiency unit technological change,[26] 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 – which 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.[27]

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

[25] 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.

[26] Let i indicate Internet use, and assume $m(B,S,i) = p(i)m(B,S)$, so that $q(\theta,i) = p(i)q(\theta)$ and $h(\theta,i) = p(i)h(\theta)$. Totally differentiating the B- and S-curves with respect to y and i shows that increases in i shift up the B-curve by $dy/di = p'(i)$, and the S-curve by $dy/di < p'(i)$, for $r > 0$, at the initial θ. So θ will increase.

[27] 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 the contact hazard, as described above.[28]

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.

6.4 Transaction and List Prices

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 that of the short run is consistent with the dynamic extension of the model.

[28] We have also experimented with two alternative measures of Internet availability: the number of broadband operators, and a CPS based variable. Neither are 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 effect the coefficients on the demand proxies holds when we use these variables as well.

Consistent with income and population proxying a single demand shock, one can not reject that the ratio of the long run to short run effect is equal for both proxies.

As a final check on the interpretation of the dynamic effects, we consider the price premium – the log ratio of the selling to list price. Since the list price is set by the seller only, and must surely be closely related to the seller's reservation value, we would expect the premium to increase in the short run with a positive demand shock to which sellers do not immediately adjust.[29] Column (2) 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 price, growth, even in the absence of lagged seller adjustment, so long as list prices are set according to contemporaneous transaction prices. But, as we have seen, the average median seller time on the market is 7.3 weeks, implying an average stay that is but one fifth of a year;[30] so that the growth in prices from Column (1) is too small to explain Column (2)'s results.

7. Conclusion

This paper has shown that both seller and buyer time on the market decline in the short run in response to an increase in demand, the effect on the former being quite large, while that on the latter

[29] 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, 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.

[30] The relevant time 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.

much more moderate. Long run responses are much smaller. Underlying time on the market is a contact hazard and the acceptance rate. The short run response to a demand increase is positive and quite large for the seller contact hazard, and negative and small in magnitude (and for one demand proxy, insignificant) for the buyer contact hazard. Consequently, the implied buyer-seller ratio increases dramatically with 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 of an order of magnitude smaller and insignificant.

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,[31] 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.

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 haphhazardly. 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. It is that the estimated coefficients are typically smaller in magnitude in the buyer regressions that explains the insignificant

[31] 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.

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 that buyer time on the market does vary significantly with income level and Internet use, and (although not shown) across MSAs, belies that explanation.

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 -.15 or -.20. 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[32], 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 which lack multiple listing services (like England), or the most recent turbulent time period, which we have avoided, should prove fruitful.

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

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

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

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

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: $i_S'(y) = r/i{c_S}'' > 0$. 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 $rdy = \{[-c_S'(\bar{\imath}_S) + (q_2 + q_3)\beta A]\bar{\imath}_S'(y) - q\beta G\}dy + q_1\beta A d\theta$. Thus

$dy/d\theta = q_1\beta A/\{r + q\beta G - q_3\beta A\bar{\iota}'_S(y)\} > 0$, since $q_3 < 0$ (more effort by other sellers reduce 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: $dy/dv = q\beta G/\{r + q\beta G - q_3\beta A\bar{\iota}'_S(y)\}$.

The B-curve's slope is $dy/d\theta = h_1 A/\{hG - h_4 A\bar{\iota}'_S(y)\}$, which is non-positive as long as $h_4 A\bar{\iota}'_S(y) < hG$. Since $q = h\theta$ and $h_4 = \theta^{-1}[q_2 + q_3]$, this condition can be written as $\big(1 + (q_3/q_2)\big)(r/\beta)/qG < \epsilon$, 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 leaves 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 $1 + \epsilon \geq (\leq) \big(1 + (q_3/q_2)\big)/|dlnh/dln\theta|$. 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, $dy/dv > 1$.

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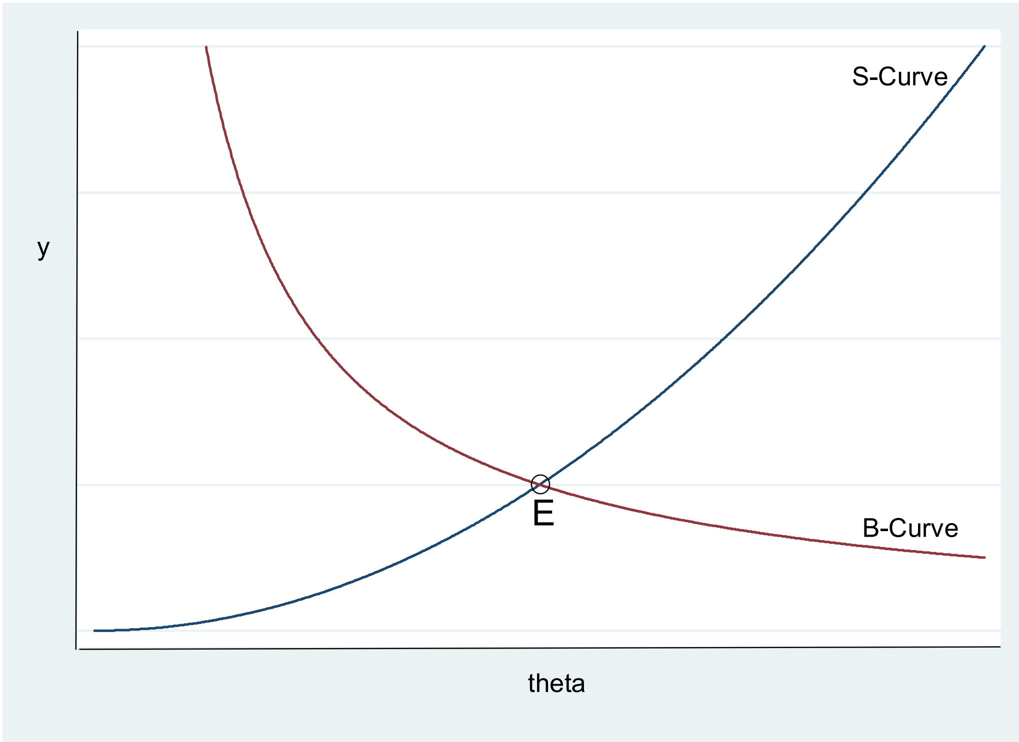
S-Curve
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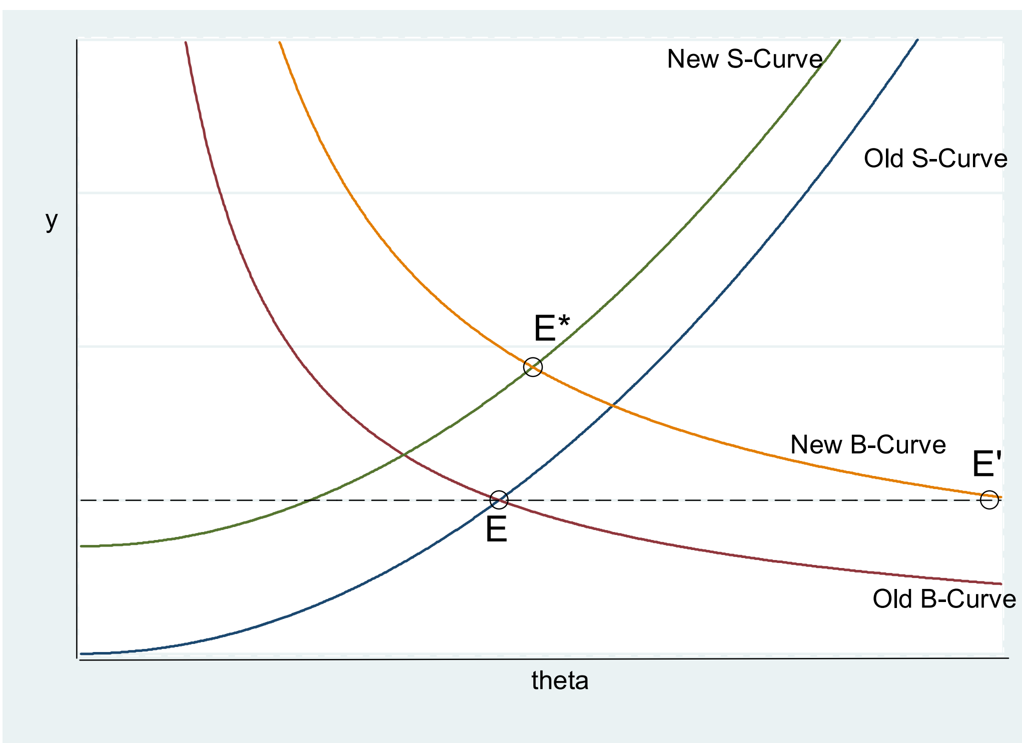
Figure 1


New S-Curve
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Old B-Curve
theta

Figure 2

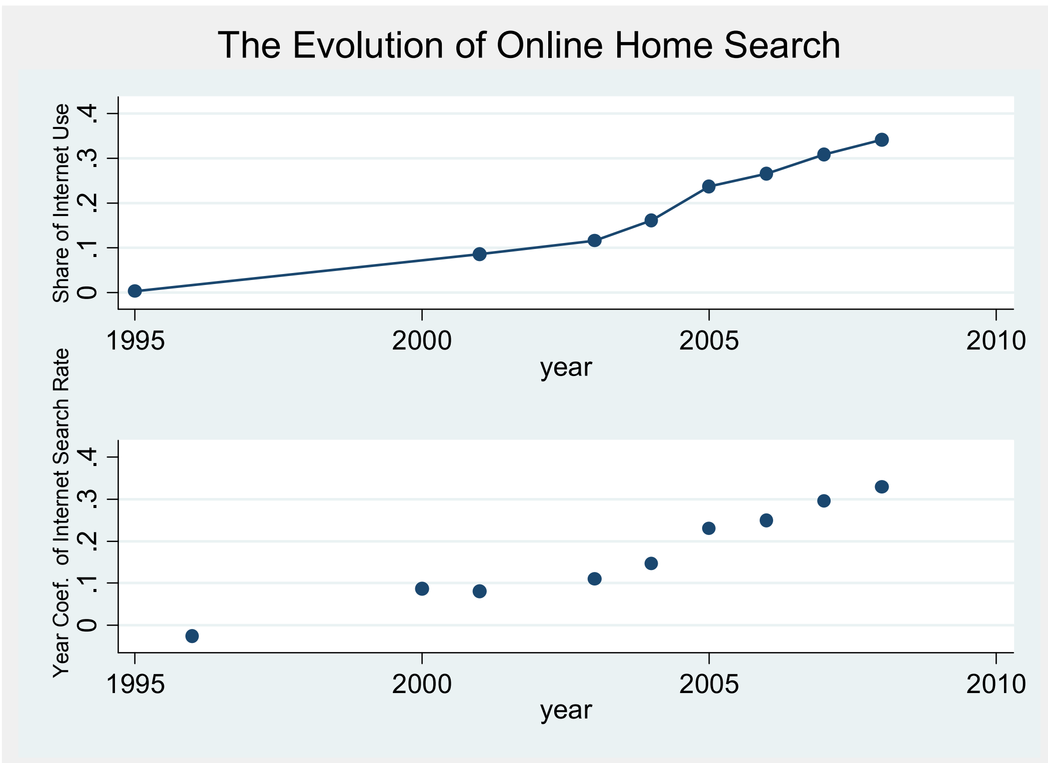

Figure 3

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 Change in 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 MSAXyear 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).