On the Slope of the Beveridge Curve in the Housing Market*

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Abstract

The co-movement of buyers and vacancies, i.e. the Beveridge Curve, is a key determinant of the cyclical properties of the housing market. It determines the sign of the correlation between prices and key measures of liquidity such as vacancies (i.e. houses for sale), sales and time-to-sell. As recent work has shown, to account for the core stylized facts of the housing market, search and matching models must be consistent with a positively correlated co-movement of buyers and vacancies—the Beveridge Curve must be upward-sloping. This paper provides empirical evidence that buyers and vacancies are positively correlated along the housing cycle, i.e. that the Beveridge Curve in the housing market is upward sloping. Using data on vacancies and time-to-sell, we construct a series for buyers and estimate the slope of the Beveridge Curve. This approach requires only one minimal structural assumption: the existence of a matching function. The regression results confirm the positive relationship between buyers and vacancies over the business cycle. In addition, we provide an estimate of the elasticity of vacancies with respect to buyers.

JEL Classification: E2, E32, R21, R31.
Keywords: Housing market; Search and matching; Beveridge Curve; Housing liquidity.

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1 Introduction

A defining feature of the housing market is the presence of search frictions: it takes time for buyers to find a home, and for sellers to find a buyer. Furthermore, the market has pronounced business cycle fluctuations: prices and measures of liquidity such as sales, vacancies (i.e. houses for sale), and time-to-sell exhibit significant volatility. Due to the frictional nature of the market, the cyclical properties of sales and time-to-sell are determined by the behavior of vacancies and buyers: when the market features relatively more buyers, more houses are sold and they sell faster; when there are relatively few buyers, few houses are sold and we observe longer time-to-sell. Thus, the cyclical co-movement of buyers and vacancies, i.e. the Beveridge Curve, is a key determinant of housing market dynamics over the business cycle.

The importance of the Beveridge Curve in the housing market is highlighted by the varied levels of success in the recent literature in explaining housing market dynamics. Most of the existing literature has attempted to explain these dynamics without paying close attention to the joint behavior of buyers and vacancies—for example Caplin and Leahy (2011), Diaz and Jerez (2013), Novy-Marx (2009), Ngai and Sheedy (2020).[1] As a result, such studies fail to account jointly for three key stylized facts in the housing market: prices are (i) positively correlated with sales and (ii) vacancies (i.e. houses for sale), but (iii) negatively correlated with time-to-sell.[2] As Gabrovski and Ortego-Marti (2019) show, these stylized facts uniquely determine the join behavior of the key variables in the housing market and imply that the slope of the Beveridge Curve is positive, i.e. buyers and vacancies are positively correlated.[3] This is in sharp contrast with most search models of the housing market à la Diamond-Mortensen-Pissarides (DMP), which naturally generate a downward-sloping Beveridge Curve. This is why, with the exception of Gabrovski and Ortego-Marti (2019), existing models are unable to match the observed sign of the co-movement between the key variables in the housing market—they lack a mechanism that leads to a larger measure of buyers in the market when more houses are listed for sale.[4]

[1]Since the seminal work in Arnott (1989) and Wheaton (1990), the literature on search and matching models of the housing market also includes, among others, Anenberg (2016), Burnside *et al.* (2016), Gabrovski and Ortego-Marti (2019, 2021a,b, 2022a,b) , Garriga and Hedlund (2020), Genesove and Han (2012), Han *et al.* (2021), Head *et al.* (2014, 2016), Kotova and Zhang (2020), Krainer (2001), Ngai and Tenreyro (2014), Ngai and Sheedy (2020), Novy-Marx (2009), Piazzesi *et al.* (2020) and Smith (2020). Han and Strange (2015) provides an additional review of this large literature.

[2]These facts have been reported by many studies. For example, see Genesove and Mayer (1997, 2001), Glaeser and Gyourko (2006), Krainer (2001), Krainer *et al.* (2008), Ortalo-Magne and Rady (2006), Stein (1995) and Diaz and Jerez (2013). See Gabrovski and Ortego-Marti (2019, 2021b) and the discussion therein for a review of the stylized facts from the literature.

[3]Note that under the assumption of a matching function sales are uniquely determined by buyers and vacancies, so the behavior of buyers is fully determined by the stylized facts.

[4]Some papers in the literature feature both entry of buyers and sellers, but they may be viewed as endogenous participation models. Papers with such an endogenous participation margin include Arefeva (2020), Garriga and Hedlund (2020), Han *et al.* (2021) and Head *et al.* (2014, 2016). However, as Gabrovski and Ortego-

In spite of the importance of the co-movement in buyers and vacancies, surprisingly little is known about its sign and magnitude. To our knowledge Gabrovski and Ortego-Marti (2019) is the only existing work that points out evidence in favor of the positive sign of the Beveridge Curve.[5] The main reason behind the lack of evidence on the slope of the Beveridge Curve is that no data on buyers is available for the housing market. This is in contrast to the labor market literature, which has devoted much effort studying the Beveridge Curve since the seminal work of Beveridge (1944) (see Pissarides (2000)), given the importance of unemployment as a measure for economic activity and the provision of government services such as unemployment insurance. In particular, many data sets measure unemployment and search intensity to get a precise estimate of the number of unemployed, i.e. *searchers* in the market. Unfortunately, there is no such analog when it comes to the housing market. One would need to survey households and ask them whether they are actively searching for houses, similar to how the Current Population Survey (CPS) surveys households on their active search for jobs to construct a measure of the unemployment rate.

In this paper we provide additional evidence on the positive slope of the Beveridge Curve by combining available data on time-to-sell and vacancies. Our paper is related to Gabrovski and Ortego-Marti (2019), who circumvent the issue of the availability of data on buyers by using insights from search and matching theory. In that study the authors show that, when viewed through the lens of a benchmark search and matching model, the stylized facts of the co-movements of prices, sales, vacancies, and time-to-sell imply that buyers and vacancies must be positively correlated. Here we take an alternative, more direct approach to estimate the slope of the Beveridge Curve. We make one minimal structural assumption, namely, we *only* assume the existence of a matching function. Using the relationship between time-to-sell, vacancies and buyers given by the matching function, we combine data on time-to-sell and vacancies to back out the entire series of buyers. A limitation in this empirical strategy is that it assumes a constant matching efficiency, similar to other studies in the literature (Anenberg and Ringo, 2021; Genesove and Han, 2012). However, this is a minor concern given our focus on business cycle fluctuations, since matching efficiency is unlikely to change on a monthly or quarterly

Marti (2021b) show, models with an endogenous participation in general suffer the same issue: they generate a downward-sloping Beveridge Curve once calibrated to U.S. data. For example, Head *et al.* (2014) report the behavior of buyers and also find that they are negatively correlated with vacancies (see their figure 4, page 1195). Intuitively, in these papers as more houses are listed for sale, more households enter the market and become buyers. The issue is that, conditional on becoming a buyer, households find houses faster when more houses are listed for sale, which depletes the stock of buyers. Therefore, whether buyers are positively or negatively correlated with vacancies depends on which effect dominates. Using a standard calibration the second effect (buyers find houses more quickly) clearly dominates and leads to a downward-sloping Beveridge Curve, as Gabrovski and Ortego-Marti (2021b) show.

[5] Piazzesi *et al.* (2020) cannot observe buyers, but they do find some evidence that in cities in the Bay area there is a positive correlation between online searches and houses for sale over the long-run.

basis.[6] We then de-trend the data using an HP-filter and regress the constructed series for buyers on the data for vacancies to estimate the sign of the relationship over the business cycle. This estimation reveals a positive and clearly significant sign of the slope of the Beveridge Curve in the housing market over the business cycle. In addition, the regression results report that a 1% increase in vacancies is associated with about 2% increase in the measure of buyers. We hope that these results will help future researchers in this area, and will contribute to future work in the calibration of search models of the housing market.

In addition to Gabrovski and Ortego-Marti (2019), our paper is most closely related to Genesove and Han (2012), who were the first to exploit key search-theoretic relationships to back out unobservable variables due to the lack of buyer data. Their methodology combines time-to-sell and time-to-buy measures from the National Association of Realtors (NAR) surveys to back out market tightness in the housing market and study its behavior, with a special emphasis on liquidity, as in this paper. Their study focuses on the long-run trend behavior and does not study the joint behavior of buyers and vacancies. Our paper uses instead information on vacancies and sales from US Census data to construct a series for buyers at the business cycle frequency (monthly). In addition, we study the empirical relationship between buyers and vacancies, a key moment to explain housing market dynamics (Gabrovski and Ortego-Marti, 2019). Our paper is also related to findings in Anenberg and Ringo (2021), who use a similar approach to back out housing demand to quantify the contribution of demand and supply factors in explaining the behavior of prices and time-to-sell during the Covid-19 pandemic. This paper focuses on using the constructed series to find evidence on the sign of the correlation between buyers and vacancies, and to quantify the elasticity between the two variables to guide future quantitative work in the area.[7]

2 Backing out buyers

Unfortunately, no data is available on the number of buyers in the housing market. We circumvent this issue by drawing on the relationship between buyers, vacancies, and time-to-sell present in most search-theoretic models. This allows us to construct a series for buyers from the observable series for vacancies and time-to-sell. Specifically, the majority of the literature captures frictions through the means of a matching function à la Pissarides (2000). In the context of the housing market, such models include Burnside *et al.* (2016), Diaz and Jerez

[6]Matching efficiency is affected by events such as the spread of one-hour kiosks that allowed agents to quickly develop pictures, camera digitalization, improvements in MLS dissemination due to computerization, the Internet and more recently online platforms such as Zillow or Redfin. These improvements have a one-time level effect on matching efficiency, but are unlikely to change matching efficiency significantly at a business cycle, monthly frequency.

[7]The findings in Anenberg and Ringo (2021) and in this paper were independently derived and released at the same time.

(2013), Gabrovski and Ortego-Marti (2019), Gabrovski and Ortego-Marti (2021a,b, 2022a,b), Garriga and Hedlund (2020) and Genesove and Han (2012), among others. This function may be viewed as a production function for matches. It gives the number of matches, which we denote by $M(b, v)$, as a function of the measure of buyers b and vacancies/houses for sale v.[8] This "black box" approach captures the fact that it takes time for buyers to find a suitable home and for sellers to find a buyer in a convenient way, and may be viewed as analogous to the standard production function commonly used in economics.

As is standard in the literature, we assume that the matching function is Cobb-Douglas, i.e. $M(b, v) = \mu b^{1-\alpha} v^{\alpha}$. Importantly, we show in section 4 that our estimates are not sensitive to the functional form of the matching function. In particular, the estimates remain unchanged under two alternative and commonly used matching functions: the Den Haan-Ramey-Watson (DRW) matching function (den Haan *et al.*, 2000), and an urn-ball matching function. Under the assumption of random meetings, a seller finds a match for her vacancy at a Poisson rate $M(b, v)/v$ (and similarly, buyers find a house at a rate $M(b, v)/b$). This implies that on average the time-to-sell (TTS) is given by the inverse of the matching rate, i.e. $TTS \equiv v/M(b, v)$. As a result, we can derive the following relationship between buyers, vacancies, and time-to-sell

$$b = v \left[\mu TTS\right]^{-\frac{1}{1-\alpha}}. \tag{1}$$

To back out our series for buyers, we set $\alpha = 0.16$, based on the empirical findings from Genesove and Han (2012), and normalize $\mu = 1$. The results are exactly the same for any alternative normalization of the parameter μ.

The measure of buyers constructed above assumes that matching efficiency is constant. Given our focus on business cycle fluctuations, it is unlikely that matching efficiency changes significantly on a monthly basis. Examples of improvements in matching efficiency include the spread of one-hour kiosks that allowed agents to quickly develop pictures, camera digitalization, improvements in MLS dissemination due to computerization, the Internet and more recently online platforms such as Zillow or Redfin. These improvements are likely to have a level effect or to affect the trend of matching efficiency, but are unlikely to change matching efficiency significantly at a business cycle, monthly frequency.[9] Alternatively, one can interpret our constructed measure as capturing effective search by buyers, i.e. buyers and the efficiency of search combined. Genesove and Han (2012) and Anenberg and Ringo (2021) also assume that

[8] Note that buyers are the analog of unemployed in the labor market. A buyer is an agent who does not own a house but is actively searching to purchase a house, just like an unemployed worker is an agent without employment but actively searching for jobs. Therefore, buyers need not equal houses for sale, just like unemployed workers need not equal vacancies.

[9] To some extent, it resembles how credit cards and similar improvements increased the velocity of money because it reduces the need to hold money balances.

matching efficiency is constant, since one cannot separate matching efficiency from buyers.[10]

There is some empirical evidence that suggests that a constant matching efficiency is not a bad approximation. Genesove and Han (2012) find that the hazard rate does not change with demand proxies when they include internet use, perhaps the latest most important factor affecting matching efficiency, suggesting that changes in matching efficiency are not as important as movements in buyers and sellers to explain housing market dynamics, or at the very least that their effect is gradual and affects trend behavior. Given that our focus is on business cycle fluctuations in the housing market, and that changes in matching efficiency seem to affect mostly trend behavior (if at all), the assumption that matching efficiency is constant over the cycle is a good approximation. Finally, our results are also robust to including a time trend or random variation in μ.

3 Empirical estimates

The data on vacancies (Houses For Sale) and time-to-sell (Median Months for Sale) are taken from the New Residential Sales Release reported by the U.S. Bureau of Census. The main advantage of the data is that it is available monthly starting from January 1975, which provides us with 540 observations (we end the sample at December 2019 to avoid bias related to the COVID-19 pandemic).[11] We combine the data on vacancies and time-to-sell using the relationship in (1) to construct our series for buyers. Figure 1 depicts the constructed series for buyers along with the time series for vacancies. Graphically, one can readily observe that buyers and vacancies co-move closely, with buyers being a bit more volatile. Most notably, the two series exhibit similar dynamics during the 2007 market crash and subsequent recovery.

Since we are interested in the cyclical relationship between buyers and vacancies, we filter the two series to derive their cyclical components using an HP filter of the natural logs of buyers and vacancies with a smoothing parameter of $129,600$. Our results are robust to using alternative smoothing parameter values of 10^5 and $14,400$, which are commonly used in the literature. Figure 2 shows the cyclical relationship in two plots. The left panel depicts the time series for the cyclical components of buyers and vacancies. The figure confirms the close co-movement suggested by the raw series. The right panel depicts the scatter plot of the two variables and shows the strong and significant positive correlation between the two series. The estimate of the correlation coefficient is 0.69 with a standard error of 0.03.

[10] One cannot use sales to identify matching efficiency, since TTS=v/sales. In Genesove and Han (2012), the authors use long-run data on TTS and time-to-buy (TTB) to construct market tightness, and hold matching efficiency constant to estimate the elasticity of the hazard rate to market tightness. Following a similar procedure as in our paper but utilizing data on sales, Anenberg and Ringo (2021) assume that matching efficiency is constant to back out a measure of buyers, what they refer to as *demand* side factors.

[11] Note that these variables are drawn from Census data, which are used to calculate GDP measures, and are not subject to time aggregation bias as in labor studies such as in Shimer (2005).

To confirm the positive slope of the Beveridge curve, we estimate the following regression equation

$$\tilde{b}_t = c + \beta \tilde{v}_t + \varepsilon_t, \tag{2}$$

where tildes denote percent deviations from trend, c is a constant and β is the coefficient of interest. It represents the elasticity of buyers with respect to vacancies and governs the sign of the slope of the Beveridge Curve. We find an estimate of $\beta = 1.95$, with a standard error of 0.087, i.e. significant for any standard confidence level. This estimate implies that a 1% increase in vacancies relative to its trend is associated with about a 2% increase in the measure of buyers over the trend.

4 Robustness check, alternative matching functions

The previous section assumed that the matching function was Cobb-Douglas, a standard assumption in the housing literature. This section shows that the results obtained using a Cobb-Douglas matching function are practically unchanged under two alternative matching functions: (1) the Den Haan-Ramey-Watson (DRW) matching function (den Haan *et al.*, 2000), and (2) an Urn-Ball matching function. Both specifications are increasing in each term, satisfy constant returns to scale and displays diminishing returns to each argument.

4.1 DRW matching function

Following den Haan *et al.* (2000), assume the following specification for the matching function $M(b, v) = bv/(b^l + v^l)^{1/l}$. The main advantage of the DRW matching function over a Cobb-Douglas specification is in discrete time environments, as it guarantees that the matching probability is between zero and one.

We follow the same procedure as with the Cobb-Douglas matching function. Figure 3 depicts the constructed series for buyers along with the series for vacancies. To calibrate the parameter l in the DRW matching function, as with the Cobb-Douglas specification we target an elasticity of the matching function of 0.16 based on Genesove and Han (2012). This yields a value for l equal to 1.191. Figure 4 depicts the time series for the cyclical components of the two series (left-hand side panel) and their scatter plot (right-hand side panel).

With the DWR matching function specification the strong and significant positive correlation between buyers and sellers remains. The estimate of the correlation coefficient is 0.70 with a standard error of 0.031, which is statistically indistinguishable from the value of 0.69 under the Cobb-Douglas specification. Next, we conduct the same regression (2) to find the elasticity of buyers with respect to vacancies over the business cycle. Table 1 reports the regression results. Relative to their trend, a 1% increase in houses for sale is associated with a 1.926% increase in buyers, with a standard error equals 0.085. This value is remarkably close to the value obtained with the Cobb-Douglas specification, and one can easily reject that the two estimates are statistically different.

4.2 Urn-Ball matching function

An urn-ball matching function describes the assignment of buyers to sellers as the random assignment of a large number of balls to a large number of urns. Assuming that buyers can only make one offer and that sellers can only accept one offer, the Poisson distribution properties imply that the matching function in this environment is given by $M(b, v) = v(1 - e^{-b/v})$.

Figure 5 depicts the corresponding series for buyers and vacancies after following the same procedure as in previous sections. With an urn-ball matching function, the correlation between buyers and sellers remains strongly positive, with a correlation coefficient of 0.71 and a standard error of 0.031. The regression in (2) implies that a 1% increase from trend in houses for sale is associated with a 1.889% increase in buyers relative to its trend, with a standard error 0.081.

The overall result from this robustness exercise is that the specification for the matching function barely affects the results. The Cobb-Douglas, DRW and urn-ball matching functions all deliver remarkably close results. Table 1 highligths this result by showing the elasticity of buyers with respect to vacancies over the business cycle for each of the specifications. One can easily reject that the estimates are statistically different.

5 Conclusion

The cyclical properties of the housing market are governed by the co-movement of buyers and vacancies, which determines the sign of the correlation between prices and key liquidity measures such as vacancies, sales, and time-to-sell. The slope of the Beveridge Curve has important implications for the mechanics of housing market dynamics. To account for the core stylized facts of the housing market, search and matching models must be consistent with an upward-sloping Beveridge Curve. In this paper we provide further evidence that buyers and vacancies are positively correlated along the housing cycle, i.e. the Beveridge Curve in the housing market is upward sloping. The positive slope of the Beveridge Curve was highlighted by Gabrovski and Ortego-Marti (2019), who show that the stylized facts of the housing market inevitably lead to a positive correlation between buyers and vacancies when examined through the lens of a benchmark search-theoretic model. The evidence provided in this paper uses an alternative, more direct approach. First, we back out a series for buyers using data on vacancies and time-to-sell. We then use the constructed series to estimate the slope of the Beveridge Curve. Our findings confirm the positive relationship between buyers and vacancies over the business cycle, i.e. an upward sloping Beveridge Curve. In addition, we provide estimates of the elasticity of vacancies with respect to buyers and find that a 1% increase in vacancies is associated with a 2% increase in buyers. We hope that the findings in this paper will help future researchers working in this area.

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Matching Function	Estimated β	Standard Error
Cobb-Douglas	1.95	0.087
Den Haan-Ramey-Watson	1.926	0.085
Urn-Ball	1.889	0.081

Table 1: Regression Results

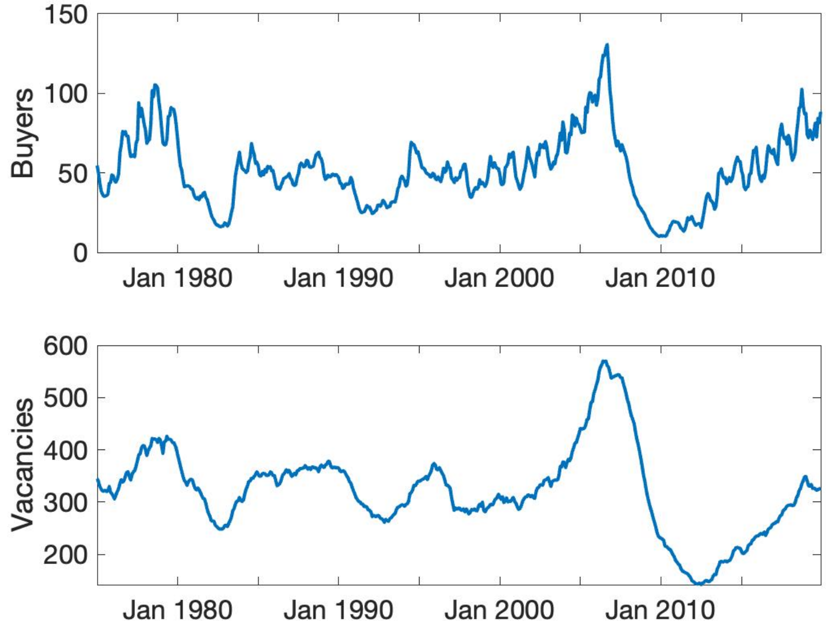
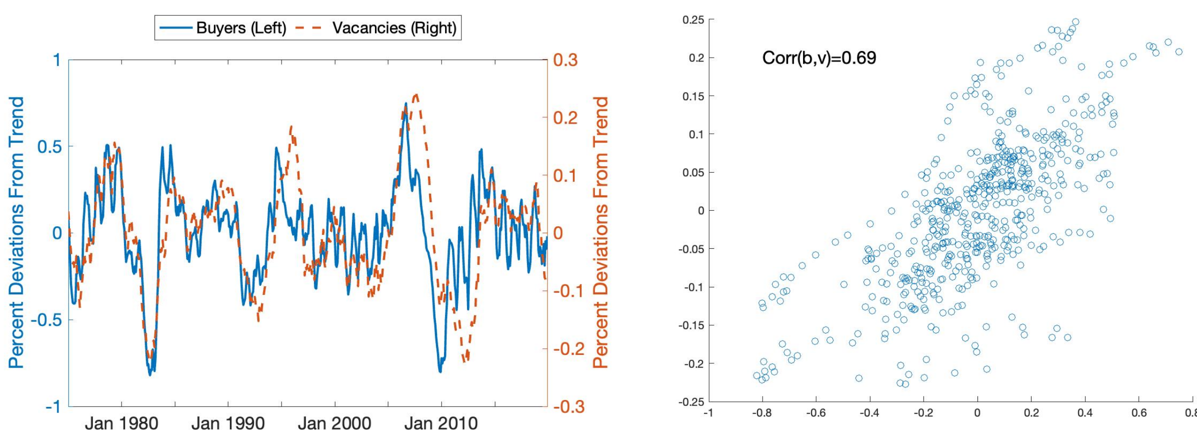


Figure 1: **Time series for buyers and vacancies.**
Note: *The data on vacancies is the Houses for Sale series from the New Residential Release reported by the U.S. Bureau of Census, at monthly frequency for the period of January* 1975 *- December* 2019. *The series for buyers is constructed combining data on vacancies and time-to-sell (Median Months for Sale) and equation (1).*



(a) Cyclical Movements in Buyers & Vacancies (b) Correlation, Buyers & Vacancies (Cyclical).

Figure 2: **Cyclical Movements in Buyers and Vacancies.**
Note: *The left panel depicts the percentage deviation from trend for buyers and vacancies using the Hodrick-Prescott filter with a smoothing parameter* 129, 600. *The right panel shows the scatter plot of the two series. The correlation coefficient is* 0.69 *with a standard error of* 0.03.

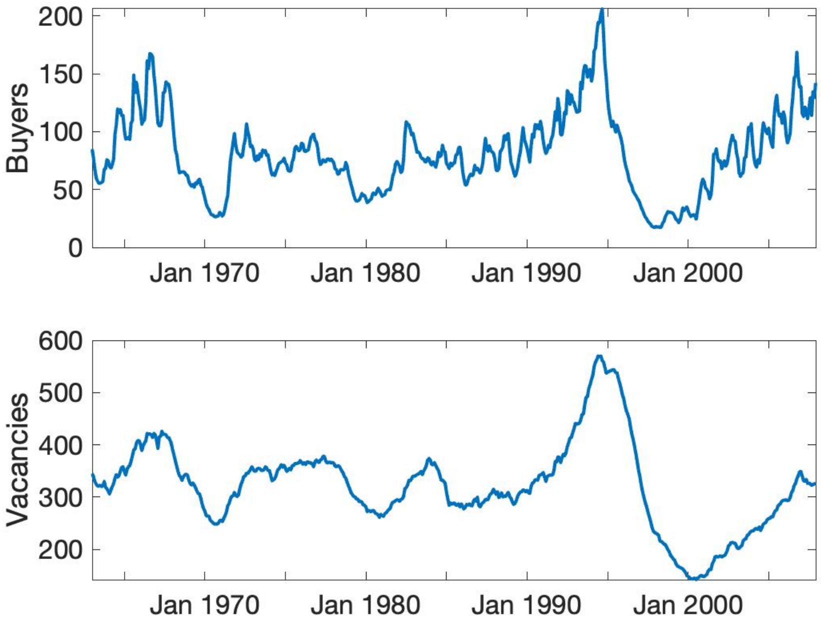
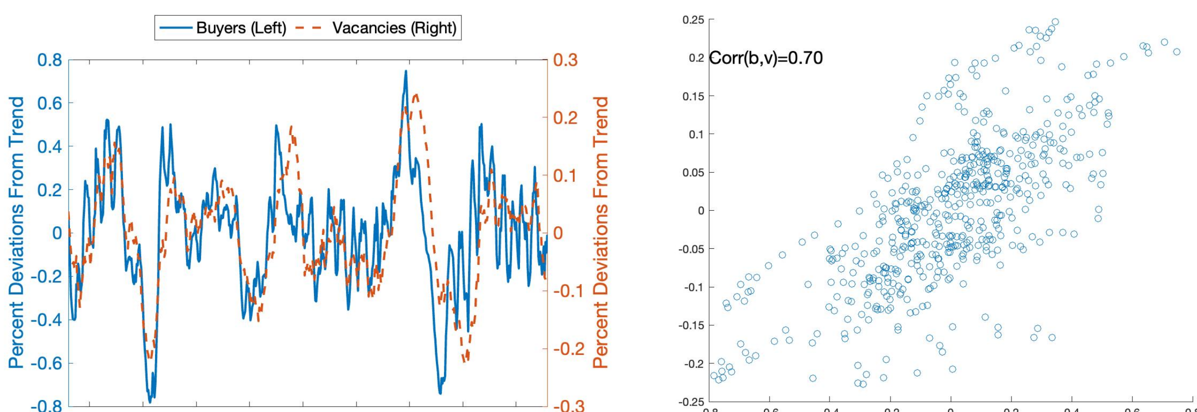


Figure 3: **Time series for buyers and vacancies, DRW matching function.**
Note: *The data on vacancies is the Houses for Sale series from the New Residential Release reported by the U.S. Bureau of Census, at monthly frequency for the period of January* 1975 *- December* 2019*. The series for buyers is constructed combining data on vacancies and time-to-sell (Median Months for Sale) and equation (1).*



(a) Cyclical Movements in Buyers & Vacancies. (b) Correlation, Buyers & Vacancies (Cyclical).

Figure 4: **Cyclical Movements in Buyers and Vacancies, DRW matching function.**
Note: *The left panel depicts the percentage deviation from trend for buyers and vacancies using the Hodrick-Prescott filter with a smoothing parameter* 129, 600*. The right panel shows the scatter plot of the two series. The correlation coefficient is* 0.7 *with a standard error of* 0.031*.*

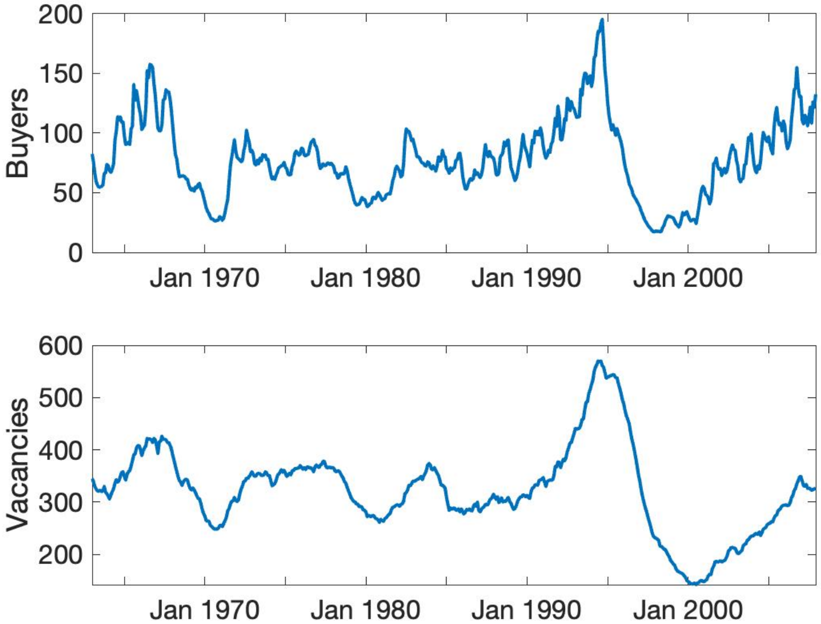
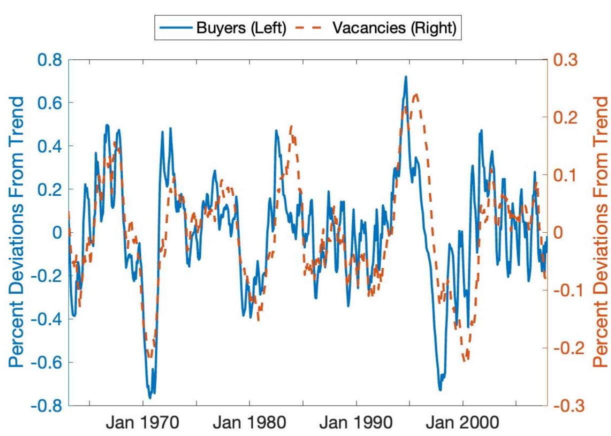
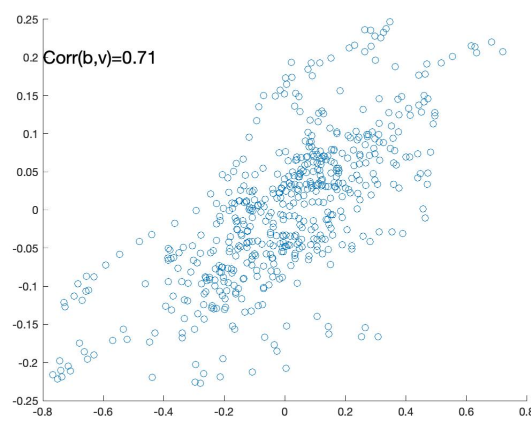


Figure 5: **Time series for buyers and vacancies, Urn-Ball matching function.**
Note: *The data on vacancies is the Houses for Sale series from the New Residential Release reported by the U.S. Bureau of Census, at monthly frequency for the period of January* 1975 *- December* 2019*. The series for buyers is constructed combining data on vacancies and time-to-sell (Median Months for Sale) and equation (1).*



(a) Cyclical Movements in Buyers & Vacancies.



(b) Correlation, Buyers & Vacancies (Cyclical).

Figure 6: **Cyclical Movements in Buyers and Vacancies, Urn-Ball matching function.**
Note: *The left panel depicts the percentage deviation from trend for buyers and vacancies using the Hodrick-Prescott filter with a smoothing parameter* 129, 600*. The right panel shows the scatter plot of the two series. The correlation coefficient is* 0.71 *with a standard error of* 0.031*.*