# New Evidence on the Co-integration of House Prices and Rents

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Using data not previously available on single family rental rates for 50 CBSAs, we examine the relationship between the price (user cost) of owner-occupied housing and rents. We find that during the period 2009-2015, prices and rents are, in general, co-integrated. Moreover, the two market segments respond to each other in ways consistent with economic theory, though with a time lag. An additional contribution of our work is to incorporate measures of cross-sectional variation in credit scores and supply elasticities across metro areas to explain why some CBSA do not reach equilibrium in terms of the cost of buying versus renting.

Key words: house prices, user cost, rents

Economic Literature Codes: R31, G21

## 1. Introduction

As of December 2016 the homeownership rate in the U.S. had fallen to 63.7% ña rate that has not been seen since the early 1960s, and a sizable drop from the 69.2 percent peak recorded at the end of 2004.ò [1] It appears that we are becoming more of a renter society[2]. The ascendency of the rental market is one of the major outcomes of the housing bust and subsequent Great Recession. Many people cannot, or do not want, to become homeowners. Low credit scores, an inability to gather a down payment, or a lack of financial knowledge[3] all can preclude many renters from becoming homeowners. In addition, institutional capital has entered the single family rental business perhaps making renting a more uniform process[4]. But the two markets -- renting and owning -- are not distinct. Theory, and common sense, tells us that prices in the two markets should affect each other. If the cost of buying relative to renting is too high, more households will rent; likewise, if the cost of renting relative to buying is too high, more households will buy.

But empirical tests over the past 20 years have not supported the theory. Earlier studies find at best a weak relationship between owning and renting. Of course, the theory behind most of these papers requires a frictionless world with completely rational economic agents, somewhat possible in some markets, but hardly likely in most housing market. This paper expands the existing body of knowledge in three ways: First, we have more granular data on rents of single family detached properties that were not previously available to earlier researchers. Secondly, we show that the

[1] See a U.S. Census data release on January 31, 2017.
[2] See Acolin, Goodman, Wachter (2016), Haurin (2016) and Nelson (2016) for a similar view.
[3] See, for example, Huang et al (2017) on how little consumers know about minimum required down payments, maximum allowable debt-to-income ratios, and other important dimensions of loan underwriting.
[4] Institutional players Invitation Homes, American Homes 4 Rent, Colony Starwood Homes, Silver Bay Realty Trust and Tricom American Homes owned about 143,000 SFR rentals as of Sep-16.

housing and rental markets responds as theory would suggest, but not in every CBSA. Each CBSA (each market) is idiosyncratic. As importantly, thirdly, our panel data on renter credit distribution by geography allows us to explain why certain geographic markets reach a steady state, even though rents might not equal user costs ï a steady state, but not an equilibrium.

To preview our three main findings: (1) the user cost of housing and rents are, indeed, co-integrated ï they move together over time within the time period of our data sample; (2) the user costs of housing adjusts negatively in a market where the user costs exceed rents. Rents adjust positively, as we would expect. Finally, (3) although most of our CBSAs reach a steady state, not all do. Cross-sectional data on 50 CBSAs allows us to quantify the principal economic drivers when a market is co-integrated, and simultaneously the cost of owning does not equal the cost of renting (a steady state outcome, but not an equilibrium). Where user costs are continuously lower than rents, we note that a high share of the renting populations has weaker credit and the supply elasticity is high. Where user costs are continuously higher than rents, we note that a high share of the renting populations has good credit but the supply elasticity is low and the CBSA has a history of strong price appreciation.

Our finding are intuitive. Weak credit is an impediment to buying. Markets require a high share of their populations to have adequate credit to substitute buying for renting. Without good credit, renters seldom become a homebuyers (the renter might be willing, but he is not able)[5]. Also a shortage of buildable lots, restrictive zoning legislation, and well-documented not in my backyard (ñNIMBYò) attitudes create market frictions impeding response on the supply side. At the other extreme, an abundance of buildable land puts downward pressure on prices. Thus the speed which

[5] The spectrum of credit scores for renters in many CBSAs is often lower than the minimum requirements of the FHA. The FHA minimum requirement for a 3.5% down payment loan is roughly 580. Equifax data show that 15% of people in the U.S. who had a credit card had a credit score < 580. It is not hard to assume that most of this cohort are renters.

prices and rents adjust from disequilibrium towards equilibrium appears to be determined by supply elasticities and access to credit. A third element which produces market friction is that in some CBSAs (those with volatile economies and a history of strong home price appreciation) buying a home is riskier[6] than other CBSAs. In such markets, home-buying may be driven by speculative motivations (ñanimal spiritsò see Akerlof and Shiller (2009)), or foreign capital seeking a safe haven in U.S. real estate assets.

The remainder of the paper is organized as follows: Section 2 reviews existing literature. Section 3 outlines the standard theories on the user cost of housing and sets out the theoretical assumptions required to establish a relationship between the rental and purchase markets. Section 4 describes the data used. Section 5 focuses on the frictionless assumption required by theory and presents evidence that it does not hold true in certain CBSAs. Section 6 presents the empirical methods and model estimation results. Section 7 concludes.

## 2. Literature Review

Early authors on the subject (Gallin, 2008 and Case and Shiller, 1989) have compared the housing and rental markets to stock prices as a function of future dividends. Others have viewed housing as any other durable good whose rent should equal its user cost (Verbrugge, 2008 and Diewert, 2003). But, as previously noted, empirical tests over the past 20 years, however, have not supported theory.

[6] Risk here could be either measured by the standard deviation of home price changes over time or regressing the local market home price against the national home price.

Case and Shiller (1989) perform tests of the weak-form efficiency of the housing market using data from the Society of Real Estate Appraisers tapes for the years 1970 to 1986 for Atlanta, Chicago, Dallas and San Francisco/Oakland. The hypothesis tested is whether housing is inefficient in the financial sense where ñbull marketsò (temporary upwards inertia in housing prices) exist and in which individuals could find profitable opportunities. Thus owning a home is nearly identical to someone owning and trading a stock which they believe is under or overvalued. Researchers essentially build a dividend price ratio similar that of a publicly traded stock and rent is the implicit dividend in the form of housing services. To Gallin (2004, 2006), the analogy to the stock market is straightforward. The buy/rent ratio in the housing market is like the price/dividend ratio. He points out that Campbell and Shiller (2001) find that when stock prices have been high relative to dividends, future price growth has been subdued. Housing could work similarly.

Obviously, however, houses differ from equity shares in significant ways. Transactions cost are high and selling a house involves costly moving. The homeowner would needs to live somewhere if the house were to be sold. Thus, arbitrage (selling oneõs house for a short period of time if one thinks home prices will fall, and then buying it back at a discount after prices have fallen) is not practical[7].

Diewert (2003) approaches the topic differently. Following standard definitions, he notes that a durable good is one that delivers services longer than the period under consideration. He reviews two broad methods for estimating the imputed cost for using a service of a durable good during a period. ñIf a renting or leasing markets for a comparable good exist, then this market rental price could be used as the cost of using the durable good. This method is known as the rental equivalence

[7] A well-functioning sale-leaseback market in residential real estate (as exists in commercial real estate) would address this issue.

approach. If used or second hand markets for the durable good exist, then the imputed cost of purchasing a durable good at the beginning of the period and at the end of the period could be computed and this net cost could be used as an estimate for the cost of using the durable good during this period. This method is known as the user cost approach.ò In many simple models of durable goods, an *ex-ante* user cost consists of the expected financing, maintenance and depreciation costs minus the present value of the expected price.

It is true that a house is like a durable good in that the house provides a flow of services over time and can be resold. However, most durables have a steep markdown when the owner tries to resell which may or may not happen when selling a house and most often the future price of the home is not known. So the price of a durable may not be the best measure of the costs accruing to the owner/buyer of a house. For Verbrugge (2006), a simple frictionless model of durable goods imply that a durable goodôs rental price will equal its user costs, assuming a rental market exists.

Both approaches have their merits along with their drawbacks. Importantly, early tests find a weak, or no relationship between owning and renting. Outlining the fundamental problem tackled by this paper, Verbrugge (2006) writes ñThe divergence between rents and user cost highlights a puzzle: rents do not appear to respond very strongly to their theoretical determinantsò. His findings accord with the earlier works of Follain, Leavens and Velz (1993), DiPasquale and Wheaton (1992) and Blackley and Follain (1996). This is also the same finding of later works by Gallin (2004) and Gallin (2008).

More recently, Pavlidis et al. (2016) correctly shows that rents and prices can diverge for long periods of time due to episodes of exuberance. In part, early researcher expected quick mean reversion. Their paper is insightful, but they do not tackle the core issue of this paper that within the periods when prices and rents are not explosive, homebuyers and rents respond to market disequilibrium ï prices and rents are cointegrated. Finally in a recent paper Verbrugge et al. (2017), using a hedonic function finds that rents are sticky, but also that differential rent changes are not explained by the variables in his hedonic function. In other words, property characteristics do not drive rents.

If we may be permitted to generalize, there are three major problems with the earlier papers: (1) the data used was not sufficiently granular; (2) attempts to explicitly model buyer expected home price growth ($g_t$) relied on backward-looking measures of home price changes which may have included observations from the 2006-2008, or some earlier housing bust; and (3) few, if any, markets can reasonably be characterized as near-frictionless.

The issue of the assumptions that economists make about housing has to be addressed head on: Do the assumptions correspond to what we see happen to prices and rents, every month, month after month, in the U.S. mortgage market? Do they universally fit every geographic market? And if not, why? What is equilibrium? Theory, requires that we assume a frictionless world that arbitrage is possible and that buyers and sellers are rational. First, there is the issue of transactions costs. Second, for most households, there is the issue of qualifying for a mortgage. Third, homebuyers (and their expectations) certainly may vary across markets[8] and buyers in fast appreciating markets might not always be rational. Also given the long-term trend in migration from the Rust Belt to the Sun Belt, buyers in the former may have less incentive to own because they recognize that trend. So a relatively frictionless purchase market assumption may be true, or not be true,

[8] Case and Shiller (2003) show that in fast growth markets buyers perceive little risk in their housing investment, have unrealistic expectations about future price increases, and hold economically implausible beliefs about home price behaviorð findings consistent with a bubble.

depending on geography. One could argue that expectations are endogenous to the buy/rent exchange and should be part of a demand function. We treat it as an exogenous.

The rental market, on the other hand, involve less friction from the renterõs point of view because renting involves only signing a lease and risking a relatively small security deposit. Another reality is that rental markets function slightly differently because not every housing markets has a deep single family rental market[9]. We show evidence that prices indeed do equilibrate to the buy/rent disequilibria. Rents, however, adjust much less easily and may be affected by landlord-tenant law. Finally if housing were like a stock-like, arbitrage conceptually would be possible. This may be relatively easy to do in the stock market, but it is not in the housing market because transactions are high and again vary city by city.

This recognition -- that each CBSA meets long-held assumptions to different degrees -- is important because, once adopted, it contributes to explaining why results differ across markets. Continuous large deviations in the buy/rent ratio, over decades, is our first clue that a market cannot be characterized as meeting the standard economic assumptions. Among the 50 CBSAs that we analyze here, rents and prices do adjust towards each other after a period of time in roughly 25 cases. These markets function as we would expect. They fulfill the requirement of the cost of renting equaling the monthly cost owning or, at least, this ratio trends towards that equilibrium. In these ñwell-functioningò geographies, we do approximate the frictionless world envisioned by economists.[10]

[9] For example, New York City.

[10] There are three important caveats to be made here: 1) this paper does not try to establish whether housing markets are efficient in the financial sense and follow a random walk. Our results show many markets exhibit autocorrelation which would preclude a random walk. 2) Also, some earlier researchers talk about housing prices and user costs

Understanding how ñwell-functioning marketsò operate yields three important implications for forecasters and policy makers: (1) the buy-to-rent ratio tell us something about the direction of future price changes in ñhealthyò markets; (2) we can see why some markets may be more prone to price bubbles than others; finally (3) we begin to understand how difficult it will be for homeownership rates to increase in markets in which the B/R does not revert toward the mean over very long periods of time.

### 3. The User Costs of Housing

We adopt the specification used by Verbrugge (2008) as shown in his Equation 3. This specification ignores the preferential tax treatment given to homeowners.[11] To introduce our notation, we use R for the variable rent and B (buy) for the user cost of housing.

Rent = user cost, or $R_t = B_t$ or $R_t = P_t \text{Ț} k_t + P_t \text{Ț} \tau_t \text{ ï } G_t$. (1)

$R_t$ represents monthly rent in time period t, $P_t$ is the price of the house, $\tau_t$ is the property tax rate, $G_t$ is the expected constant growth in home prices each period = $(E(P_{t+1}) - P_t))$, $k_t$ is some discount rate.

In Equation 1, $P_t \text{Ț} k_t$ is the cost of owning the home which includes the monthly payment on any borrowed money. Alternatively, one can think of $P_t \text{Ț} k_t$ as the opportunity cost of the foregone

displaying reversion to a ñtrueò value. We are concerned with user costs and rent being jointly co-integrated rather than co-integrated to a third true value. 3) We characterize equilibrium as conditions when 0.8 <= B/R <=1.2, not B/R =1.

[11] One could also consider the federal income tax deduction and maintenance costs. In such a case, the user cost (Equation 1) would look like $P * k \text{ ï } T(P * k \text{ ï } P * \tau) + P * \tau \text{ ï } G + m = R$, where T is the federal income tax rate and m is maintenance. However, relatively few taxpayers deduct mortgage interest and one would need to assume that maintenance costs would not vary between CBSAs.

income that the homeowner would have earned by investing in something other than a house.[12] The user cost of owning a home also includes taxes ($P_t \times \tau_t$). These costs are offset by any expected price appreciation. The combined three effects should equal the rent that an investor could earn by renting that house out (or, the rent that someone would need to pay to occupy the house). If the left-hand side were higher than the rent, then being a renter makes more sense.

Equation 1 is the textbook model of house prices and rents which states that in a frictionless market, hovering near equilibrium, the user cost of capital (the one-month, or one-year) cost of owning a home should equal the cost of renting a home over the corresponding time period. Thus in equilibrium,

$$(P_t \times k_t + P_t \times \tau_t - G_t)/R_t = B_t/R_t = 1. \quad (2)$$

Since owning and renting are economic substitutes, theory tells that any significant difference in the pricing of the two should draw more demand to the less expensive option, therefore driving up prices and removing the difference.

Finally, Equation 1 can be re-written also as,

$$R_t/P_t = k_t + \tau_t - g_t \quad (3)$$

Where $g_t = (E(P_{t+1})-P_t)/P_t$ is the expected constant growth rate in the price of the house.

[12] We could also think of k as a required rate of return if an investor used all cash to buy a house.

Equation 3 is a version of a constant growth model of asset prices in which the rent-price ratio is related to the current real interest rate, the tax rate and the expected growth in home prices. Written this way, long-run capital gains on owning an investment property adjusted for taxes and the cost of money should equal the long-run return on renting out an investment property. Any divergence between price and rent is due to expected capital gains or tax changes. There is no room for a divergence between the two in the long term unless expected future changes in home prices (g) are very high or low, k is divorced from g.[13]

The point of this restatement is that, even in a structurally frictionless market, the equilibrium described by Equation 3 may not hold because homebuyers have a stronger positive or negative expectation about the future and those expectations might differ from that of the landlord who is charging rent. One case would be an asset bubble. In this case, expectations drive a large discrepancy between the cost of owning (our buy variable (B)) and our rent variable (R) which tells us something about the strength of expectations. In an asset bubble, markets again are not equilibrating. If we think of Equation 3 as the view of a landlord for a given $P_t$, if expectations of future price growth are high, then landlords will settle for lower rents because they anticipate greater future gains. On the other hand, if expectations of future price growth are weak (or negative), then potential landlords will demand higher rents to offset weak expected future price gains, or not buy and just let prices fall. If, however, renters do not have the ability to buy a home, nor afford the higher rents that landlords would expect to charge, this could drive down the cost of owning relative to renting for long periods of time (thereby precluding the equilibrium we were expecting in Equation 1, and which we currently see in many CBSAs).

[13] This is a valuation of a long-lived assets approach.

One may, or may not consider very strong (or very weak) expectations as exogenous friction. And just how large a difference between the cost of owning and the cost of renting (either B > R, or B/R >1) signals that something is wrong with buyersô expectations? Markets most often deviate from equilibrium and still can be considered as trending around equilibrium. One might say, for example, that if the cost of owning exceeds the cost of renting by 20 percent that homebuyers are paying too much. We adopt this admittedly somewhat arbitrary standard throughout the remainder of the paper.

**4. Data**

*4a Rent Data*

As noted, a major problem with earlier work was the lack of data on single family detached properties by city. Most researchers chose to work with CPI data that is based upon surveys. Single family rental data was simply not available.[14] The following are some representative approaches: Gallin (2004, 2008) uses national data of the tenant rent index from the Consumer Price Index. Larson (2011) uses CBSA data on Rent of Shelter Index. The problem with the CPI survey data is that it is usually gathered every six months and includes data from multifamily structures. Also, the CPI rent data includes rent-controlled apartments. Finally, the CPI adjusts for quality changes

[14] The expenditure weight in the CPI basket for ownersô equivalent rent of primary residence is based on the following question that the Consumer Expenditure Survey ask of consumers who own their primary residence: ñIf someone were to rent your home today, how much do you think it would rent for monthly, unfurnished and without utilities?ò Similarly the following question, asked of consumer who rent their primary residence, are the basis of the weight for tenant rent: ñWhat is the rental charge to your household for this unit including any extra charges for garage and parking facilities?ô

in the dwelling whose rents are being tracked. This quality controlled adjustment smooths out the time series and dictates that any price series should also be quality controlled. National data, also, would hide regional variation in buyer and renters preferences. The property that the individual is thinking about buying should be in the same markets as the property that the individual is thinking about renting. Furthermore these rent data series are not distinguished in terms of property types such as number of bedrooms.

A second approach which gets around the problem of not having rental data at the local level is to use either the BLS ownerôs equivalent rent for 11 CBSAs or tenants rent for 12 CBSAs. Verbrugge (2006) uses individual CBSAs to correct for the problems above. He works with 10 CBSAs of the 12 by constructing his own monthly rent index using post-1987 CPI rent micro data of only single family detached dwellings. Chart 1 below shows both the ownersô equivalent and tenants rent for Los Angles as an index starting in January 2000. Neither series shows much variation and seldom any decline. This stability is due to the way the series were constructed and the likelihood of owners preferring not to report a decline in the propertyôs value.

In 2013, however, data on single family detached rental property became available by CBSA from two sources. Zillow.com (ñZillowò) started releasing the median rent of properties by CBSA and by number of bedrooms. They compile the rent data from rental properties listed on their website, developed a rent index model on the data that they have, and then apply the results of their model to all properties in a given geographical area. Thus their rent estimates are model based, but they are publicly available on their website. Zillow reports median monthly rents on five different bedroom property types.

A second source of rental data is RentRange. RentRange gathers asking and actual rents from a large sample of property managers of single family properties. Rents from units in multifamily properties are not included in the sample. They provide the median rent for five different bedroom counts on a monthly basis.[15] The data is neither seasonally adjusted, nor adjusted for quality. It also does not include the cost of utilities.

Chart 2 show a comparison of three possible choices for rental data for Los Angeles. The RentRange 3-bedroom SFR data track the ownerôs equivalent rent and the tenants rent from Census pretty well. This gives us some comfort about the reliability of the RentRange data. Chart 2 also highlights the problem using the BLS data -- the two BLS series almost never decline and show very little volatility.

Is our data robust? Does it track well other sources such as the BLS ownersô equivalent rent and the Zillow rent series? Does it consistently yield buy/rent ratios that make sense? We contend that the answer is yes to all three of these central questions.

In the estimation process described below, we use the RentRange data for three bedrooms properties. The choice of data on three bedroom properties stems from a desire to restrict the population and because investors tend to choose two and three bedroom properties rather than one, four or five bedroom properties because they are easiest to rent out. The data starts in January 2009 and extends to July 2015 for all CBSAs.[16]

It also must be pointed out that in addition to the research described above there is a large body of similar work using error correction models to estimate inverse demand functions for housing. These inverse demand functions for homes are often used to forecast home prices. The pioneering

[15] RentRange purchases its rental data from investors, property managers and other proprietary data sources. In addition they use MLS data where possible. On a weekly or bi-weekly schedule, their data providers provide them with both asking and actual rents. As a result, they have current asking and actual rents at the CBSA, County, City and Zip level. RentRange estimates that they have around 15% to 30% coverage of the rental properties outstanding in each of the CBSAs.

[16] This gives us 79 observations for our long-run and 67 observations for our short-run model described below which explains year-over-year changes. Tables 1 provides descriptive statistics.

work in this area was done by Abraham and Hendershott (1996) and Capozza, Hendershott and Mack (2004). This basic approach was adopted by Beracha and Hirschey (2009) Shen and Stehn (2011) and by several researchers at the Organization for Economic Co-operation and Development and the IMF including Rae and Van De Noord (2006), Hufner and Lundsgaard (2007), Buitron and Denis (2014) Sanchez and Johansson (2011) looking at non United States data. Larson (2011) also uses this approach when testing which modelling process determine turning points better on United States data.

This approach is similar to ours in that home price appears on the left-hand side of their long-run demand function. Importantly, however, our work differs from theirs in that most authors include income, population, and/or housing stock in addition to the user cost on the right-hand side. Thus, they are estimating an inverse demand function (often along with a supply function). We are only estimating a long-run equilibrium condition -- the cost of owning equilibrates to the cost of renting. The price of the relative good only drives the consumerÕs buying decisions. In essence, we believe that income and population drive the cost of owning and renting equally. We next turn to the price data.

*4b. Home Prices and User Cost Data*

The central driving force in any housing decision is the user cost of capital (and the home price embedded in it). Ideally we want price data on three bedroom properties to match our rental data since we want consistent values for both the numerator and denominator of Equation 2. Since our rent data from RentRange is not seasonally adjusted and not quality controlled, our price data should have the same characteristics. Zillow reports monthly median home prices on three bedroom properties going back to 1996. We only use home price data starting in January 2009 because that is when the RentRange rent series starts. The Zillow home price series includes sales on all types of bedroom properties. Another possible source of data is CoreLogic. In comparing both the CoreLogic and the Zillow house price data to data reported by local realtor websites, we noticed that the CoreLogic data matched more closely than did the Zillow for all bedroom types. Unfortunately CoreLogic does not report median home price by bedroom. Faced with this dilemma, we elected to use the CoreLogic data, but to adjust the reported median price on properties regardless of bedroom counts from CoreLogic by the relative difference between the three bedroom and all bedroom median prices from Zillow. In essence, we created a three bedroom CoreLogic median home price.

The dotted line in Chart 3 below shows how the three bedroom median home price series moves with the RentRange and the BLS rent series for Los Angeles. All of our home price series are based on a CoreLogic CBSA median home price adjusted by the Zillow relative three-to-all bedroom price ratio. In Section 5, we will test for co-integration between the two variables depicted in this chart (user cost, B and rent, R) by CBSA.

An important practical issue is how to construct a user cost measure that makes sense across time and CBSA. We measure the user cost of owning (i.e., our buy variable B) using three easily available variables related to median home purchase decision: monthly principal, interest and taxes. The interest rate is from the Freddie Mac survey rate over time. Property tax rates are derived from rates from the Tax Heritage Foundation. So the numerator of the B/R ratio is the cost of owning a property (using our user cost of capital) based upon the constructed CoreLogic median three bedroom home price data and the denominator is rental data on three bedroom single family homes from RentRange.[17] The viewpoint is from the potential homebuyer think about only his monthly payments going forward. This buy/rent approach is similar to the price/rent index developed by Beracha and Johnson (2012) and formalized as the Beracha Hardin & Johnson index. This index focuses on the buy/rent choice from a wealth creation standpoint. In order to do this, the authors include the rent/price ratio, mortgage rates, expected rates of inflation, real past stock market rates of return, the cost of maintenance and other specific costs to owning a home. Their index is thus more detailed than ours. These authors, however, are taking snapshots at different given points in time using 30 years of history for 23 major cities and asking does buying makes sense. Our paper looks at the buy/rent decision over a long period to see if prices and rents adjust as expected.

A final issue to address is expected house price growth ($g_t$) which we do not attempt to explicitly measure. Several earlier authors attempt to measure $g_t$ with backward looking estimation such as $g_t = (P_t - P_{t-1})/ P_{t-1.}$ There are three major problems with using past home price growth: 1) the most important is that $g_t$ , define as $g_t = (E(P_{t+1}) - P_t)/ P_t$ is already built into $P_t$; 2) it misses turning points and 3) it misleadingly lowers the user cost of CBSAs with low B/Rs and makes their B/Rôs even more unrealistic.

It is well known that the one period expected rate of return from buying a house is $k_t = (R_{t+1} + P_{t+1} - P_t)/P_t$ Smith ( ). An investors wants a rate of return on his money and a buyer who intends to live in it has an opportunity cost of not renting it out or, at least needs to know he would have to pay rent to live elsewhere and that he is consuming a good. Rearranging, we can solve for $P_t$ as $P_t$

[17] The authors recognize that a weakness of using CBSA data is that the property for rent might not be in the same zip code area as the property which the potential buyer want to locate to. Too many properties for rent in a zip code relative to where the home buyers want to live would distort the B/R ratio in a CBSA.

$= (R_{t+1} + P_{t+1})/(1+k_t)$.[18] The buyer pays the price $P_t$ with the hope/expectation that the property will appreciate in value. The value of $g_t$ is already in $P_t$. Trying to calculate $g_t$ using past data would leave a residual between what has happened last year and what the home buyer is expecting. Moreover, since $G_t$ in Equation 2 carries a negative sign, its explicit introduction reduces the calculated numerical user cost value (B) for all CBSAs since HPA has been positive across the nations for several years now. That is good for CBSAs with B/Rs greater than one in that they make our B/Rs closer to theory (near 1). It is bad for CBSAs with B/Rs less than one because it takes their B/R away from a range that is consistent with theory. Our B/R calculations for the 50 MSAs (Chart 4) show that some MSAs have B/R greater than 1 and some do not. The results make intuitive sense. Including an estimate of $g_t$ would lower the user cost for all the CBSAs. It would lower the user cost for the MSAs on the right side of the chart by more than those on the left side of that chart because the fast growth CBSAs are on the right. This would ameliorate, a bit, the current issue that our 50 CBSAs have such a wide distribution of buy/rent ratios. However, it would move more of the B/Rs in Chart 4 away from one.

Taking all of these factors into account, we do not include an explicit value for $g_t$ arguing that it implicitly built into the purchase price $P_t$. If B is significantly lower than R, then expectations of future price growth must be very low or even negative. Table 1 presents descriptive statistics for the 50 CBSAs.

## 5. Frictions

[18] If we assume that rents are fixed ($R_{t+1} = R_t$) we can rearrange terms and get our equilibrium statement (Equation 1)

As previously described, earlier authors on the subject have compared the housing and rental markets to equity prices as a function of future dividends (Gallin, 2008). Others viewed housing as any other durable good whose rent should equal its user cost (Verbrugge, 2006). But tests find a weak, or no, relationship between owning and renting. Theory, requires that we assume a frictionless world, arbitrage is possible (which would allow for more supply when there is a shortage of homes), and that potential homebuyers are rational. These assumptions might hold in the stock market and durable goods market, but hold at best weakly in the housing market, especially since local geographies differ.

Indeed, we have witnessed through time that housing adjusts slowly to exogenous shocks. Some of this slow adjustment can be attributed to market friction. Di Pasquale and Wheaton (1994) argue that product heterogeneity and costly search lead to a slow clearing in the housing market. Specifically, if the housing market is in equilibrium and a shock occurs, this creates a disequilibrium, causing a wedge between the equilibrium price ($P_t^*$) and the actual price level ($P_t$) due to such rigidities. On the supply side, if the demand for housing is greater than the existing supply, a positive wedge would appear between actual price of housing and the equilibrium price. House prices being higher than what they should be, should bring on additional supply. But new housing supply comes on very slowly as it takes time for builders to adjust and try to estimate time lines of supply. In some CBSAs, there may be severe zoning or land restrictions. So supply might not adjust unless there are bid price increases. On the demand side, if $(P_t - P_t^*) > 0$ (prices are higher than the equilibrium price (say higher than what income can support)), then demand should fall off, as potential buyer choose to rent and not buy. Or, inversely if $(P_t - P_t^*) < 0$ (prices are lower than what incomes can support), then demand should rise, as potential buyers leave their rental unit and buy a house. This transactional friction certainly exists, but we do not see it as significant for our analysis here because buyers can surmount this over time.

We see other constraints on renters: difficulty gathering a down payment, unstable income, and impaired credit, among others. It is not just the price of the house but also the ability of the renter to get into the house. We thus focus on our buy variable (B) instead of P. The variable B is at least a reasonable estimate of the user cost of housing incorporating the effect of interest rates on the buying decision.

If $(B_t/R_t) > 1$ (or, $B_t - R_t > 0$) then it is cheaper to rent than to own and the rational would-be buyer should choose to rent rather than buy, and home prices should fall. The decision maker in this paper is the would-be buyer (the renter) right before he decides to own or rent (it could also be any investor right before he decides to purchase a rental property). At that moment in time, the time of the purchase decision, information is essentially costless and the would-be buyer can easily switch between the near-identical goods (owning or renting a three bedroom home). Conversely, if $(B_t/R_t) < 1$ then it is cheaper to own than rent and the rational would-be buyer should choose to own rather than rent, and home prices should rise over time to push $(B_t/R_t)$ closer towards 1. However, if over a reasonably long period of time $B_t/R_t$ does not approach 1 then maybe our assumption of frictionless or near frictionless markets do not hold. And perhaps this friction causes home prices to adjust faster (or slower) than rents in a given CBSA.

This becomes clearer examining Charts 4 through 6. Chart 4 show the buy/rent ratio for 50 CBSAs as of January 2015. The B/Rs differ considerably by CBSA. The CBSAs on the right-hand side of the chart are CBSAs with a strong technology base (e.g., San Jose, CA). In those CBSAs, expectations about future prices (our g variable in Equation 3) suggested to potential-homebuyers, rightly or wrongly (in January 2015) that it made more sense to buy a home than rent the home. In other words, in January 2015, it was cheaper to rent the identical home than to buy it, but homebuyers chose to pay the inflated price though the summer of 2015. Then by December 2015 (Chart 5), the relationship between renting and owning did contract slightly, but remained above 1.2 -- homebuyer expectations in the San Jose metro area were that price growth will continue to outpace income. Could it be that buyers in San Jose, CA were/are irrational?[19]

Geographic markets are, of course, heterogeneous. Some have limited amounts of buildable land or there are severe zoning rules. In these markets, higher prices do not bring about a significant amount of new construction. So a homebuyer might be rational paying too high a price because he recognizes (expects) price gains to exceed income growth. This is then a bet that now is better than later, because later might never come. These individuals might also see the long term potential of such urban cores.[20]

Los Angeles tells a different story. In January 2015, the buy/rent ratio was 1.08. The ratio fluctuates, but by December 2015, it ends pretty close to 1.08. Both prices and rents increased quickly over that time. So rents do move. Seattle is also a market that equilibrates. The buy/rent ratio in the first half of 2014 was greater than 1.2. However, as prices rose, rents rose quicker. This has brought the buy-to-rent ratio closer to one. Both markets trended towards equilibrium (a B/R =1). One might conclude that Los Angeles and Seattle meet our requirement of rational buyers and frictionless markets because they adjust as theory would tell us.

CBSAs on the other end of Chart 4 show a much different story. Chart 6 shows the buy/rent for Tampa, Cincinnati and Nashville. The B/R is near 0.8 for almost the entire period from 2010

[19] If a homebuyer buys into a very hot market and prices go up for another five years then that individual might not be termed irrational, if a homebuyer buys into a very hot market and prices go up for six months and then fall then that individual might be termed observationally equivalent to rational, but unlucky. For this paper, paying 20% percent more to own than to rent is irrational.

[20] See Glaeser and Gyourko (2005).

forward for all three CBSAs. How can B/R < 1.0 and not approach one over time? Chart 7 shows explicitly how user costs and rents move in Cincinnati. In that chart, B/R = 0.76 in July 2010, and then through time the percent change in buy and rent moved roughly together (i.e., they are stationary (corroborated by the results in Table 2). At the end of the time period in the chart, B/R = 0.73. Since the cost of owning and renting are both driven by the incomes and the economics of the CBSAs, it is reasonable that these two variable are co-integrated. However, the would-be buyer should consider buying if it is cheaper to own. For some reason, in Cincinnati, home prices never rise quicker than rents and B/R never moves into a steady state with B/R = 1. When B/R is stationary, but does not equal 1.0 for a long period of time, we term this as a steady state outcome but not a long-run equilibrium as opposed to when B/R is stationary and oscillates around B/R = 1.0. We characterize the latter case as a long-run equilibrium.

If B/R < 1 and does not approach one over time then there could be a number of things wrong. It could be that potential-buyers have expectations of negative home price growth in these CBSAs. Buyers in this case could be considered rational by not buying. If they donǿt buy then they need to rent.[21] If a large number of individuals thinks it is best to rent then there could be/should be a supplier of rental properties who feels comfortable earning $R_t$. This would lead to higher demand for single family houses to rent out and prices of detached single family houses would rise.[22] The price of single family houses should rise until B/R = 1. Charts 4 and 6 shows us that this does not happen in every market area.

[21] The authors are aware that another possibility is that individuals choose to live with their parents i.e., they do not form a household.

[22] This indeed has happened in many CBSAs in which institutional investors and other cash buyers have purchased properties to rent. See the list in Footnote 4.

So why donꞌt prices rise faster than rents in Tampa, Cincinnati and Nashville (or rents fall faster when prices fall)? If potential-home buyers donꞌt have the income or savings for a down payment or if their credit is not good enough, or if they just do not have the desire to buy then they will rent. So here, friction comes in the form of too many barriers to home ownership which potential-buyers cannot surmount. With enough potential-homeowner precluded from buying homes, prices are prevented from rising faster than rents and the rental and purchase markets never equilibrate. We call these CBSAs the ñrental CBSAsò. Essentially, the local economy does not generate enough income to propel renters into homeownership. Or, if credit scores are not high enough, the CBSA does not have enough renters with the ability to buy a house.

Thus there are four sources of friction in addition to high transaction cost: (1) some geographies do not have buildable land; (2) homebuyers in fast growth CBSAs might be rational doing an irrational thing (buying a property overvalued in term of what it would cost to rent the property) because she anticipates that prices will rise faster than incomes; (3) potential homebuyers do not have access to credit[23] and (4), potential homebuyers in Rust Belt CBSAs may have different expectation of future home price growth than in Sunbelt CBSAs, given well-documented long term population migration patterns. There are some CBSAs which fall in the middle of these categories which might be termed ñwell-functioningò because they come the closes to meeting the frictionless world assumption.

This paper thus has three nested hypothesis which we address in three separate stages of the paper: First, for the time period from January 2009 to July 2015, we test if rents are co-integrated with

[23] Interestingly for this paper, the CBSAs which have low supply elasticities are generally those with high incomes and high credit scores.

our user cost of capital variable (our buy variable, B). Economic theory suggests that they should be and thus we would expect that rents and users costs are co-integrated in most CBSAs.

Then, following Gallin (2004, 2006) we go one step further, and hypothesize that user costs adjust negatively to B/R disequilibria and rents adjust positively to B/R disequilibria. This provides a second set of testable hypotheses. We anticipate that speed at which the cost of owning (through prices) and the cost of renting adjust to a disequilibrium are not uniform across CBSAs. [24]

In Stage 3, we take a microeconomic viewpoint of how the housing and rental markets function in our 50 CBSAs. In particular, we attempt to identify the forces which drove B/R differences in the 50 CBSAs at two distinct points in time.

## 6. Empirical Analysis of User Costs as a Function of Rents

### *6.1 Stage 1: Long-run Model Specification*

Let the variable $R_t$ be the actual median rent for a single family detached three bedroom property in each CBSA at a given point in time (t). The variable $B_t$ is our buy variable computed from principal, interest and taxes. Following Gallin (2004, 2006), we test our user cost relationship from Equation 1. There the equilibrium cost of owning $B_t$ is determined at each time period t by the cost of renting a near-identical property in that same CBSAs, or

$$\text{Ln } B_t = \beta_0 + \beta_1 \ln R_t + z_t \qquad (4)$$ [25]

[24] In this paper we only note that the speeds of adjustment vary. We reserve the topic of causes for subsequent research.
[25] It must be pointed out again that Equation 1 is not an inverse demand function which might say that the long-run home prices are a function of income and population and some other variables. Equation 1 is an equilibrium condition. We, however, are arguing that rent is a measure of an equilibrium value of the cost of owning a home ($B_t$). Authors who estimate inverse demand functions often use $P_t$* from the inverse demand curve as the estimated long-run equilibrium value of a home in time t. Hufner and Lundsgaard (2007) use this approach to estimate their long-run or ñequilibriumò price and include the user cost of housing. See literature review above.

for each CBSA.

*6.2 A Co-integration Test*

A straight forward approach to the buy versus rent question is an error correction framework. This approach does not require that each variable be stationary in levels, but does necessitate that the two variables B and R exhibit co-integration. Thus, the conditions that must be satisfied in order for rents and the cost of owning (our buy variable B) to be co-integrated are: each series must each be I(1), and the error term in Equation 4 must be I(0). For CBSAs that have stationary co-integration vectors, the rent and the buy variables share a common random walk component and the short-run regression coefficients are consistent. We test for unit root for $z_t$ for each of our 50 CBSAs using the augmented Dickey-Fuller (ñADFò) test.

*6.3 Regression Results and Tests for Co-integration*

The results for the test are shown in Table 2 of the Appendix[26]. We present the R-squared of the long term model and the significance test on the lagged one period level of the ADF test. Forty-seven of the 50 markets pass the co-integration test at a 10% significance level or better. Our sample data is from January 2009 through July 2015. The three markets which did not show co-integration between buying and renting during this period were Las Vegas, Miami, and Riverside[27]. All three of these CBSAs show large price gains in the tail end of the sample period which likely impacted the ADF result. Digging deeper into this, Chart 8 shows the B and R

[26] Since these results are lengthy and merely the first step in a multipart analysis, we place them in the Appendix.
[27] We note initially the high volatility of house prices in these markets and high level of foreclosures, as well.

movement over the sample period into October 2016 for one of these five CBSAs -- Miami. The chart shows the enormous run-up in home prices in Miami in 2014 even as rent appreciation was barely positive. From January 2009 to about December 2013, the B/R was in steady state near 0.6. From January 2015 to October 2016, B/R reaches a steady state near a B/R value of only 0.8. Data on Riverside and Las Vegas show the same structural break and pattern of B/R not approximating 1.0. Empirical test using data from June 2013 to July 2016 verify that buy and rent are co-integrated in these remaining 3 CBSAs. So for all three which failed the ADF test in our original sample, data show that B and R are, indeed, co-integrated outside of the structural break.

The idea of structural breaks in housing data has been recently explored in detail by Pavlidis et al. (2016), Philips, Wu and Yu (2011), Phillips, Shi and Yu (2015). All three papers show that rents and prices can diverge for long periods of time due to episodes of exuberance. They explicitly test for this exuberance by selectively performing an Augmented Dickey-Fuller test (ADF) taking subsamples of their time series on price/rent and price/income and looking for test statistics to exceed their critical values. Thus they are explicitly looking for structural breaks in which prices and rent are not cointegrated. In these situations, $\Delta$ P (or for this paper, $\Delta$ B) and $\Delta$ R do not respond to B/R disequilibrium. This in a sense is just the opposite of what we do here. Those three papers are looking for bubbles. The sample period over which we estimate our model (chosen based upon using reliable rent data) is relatively free from large structural breaks except for Las Vegas, Miami, and Riverside.

### *6.4 Stage 2: Two Short-run Model Specifications*

Having shown that 50 out of our 50 CBSAs pass the test for co-integration allows us to move forward and estimate two short-run models for each CBSA:[28] 1) Δ ln B as a function of the ln(B/R) and 2) Δ ln R also as a function of ln(B/R). A market is underpriced if (B < R) in the sense that the cost of owning a three bedroom house is cheaper than renting a similar property for one month. If the market is underpriced, then house prices should rise and rents should fall. How fast this happens is an empirical question. However, from Section 4, our priors are that the relationship between ΔB and B/R should be negative and the relationship between ΔR and B/R should be positive. These are the two nested hypotheses of Stage 2 of this paper.

Prices affect rents and rents affect prices. Since the direction of causality is unknowable, an agnostic approach is to apply a Vector Error Correction Model (VECM). This is represented by Equations 5 and 6. Both equations are estimated in a second stage using ordinary least squares in which ln (B/R) is a right-hand side variable.[29]

Market participants respond to information from earlier time periods. Equation 5 implies that changes in the cost of owning in period t are a function of the disequilibrium between B and R from a year ago. Disequilibrium is capture by the ln (B/R) from twelve months ago.[30] A $(B/R)_{t-12}$ > 1.0 is direct indicator that prices paid for houses in the period twelve months earlier were higher than the cost of renting the identical house and it is a rough indicator that that price paid twelve months earlier was higher than a conceptual equilibrium user cost ($B_t$*). It is the same information

[28] If we test for co-integration outside of the structural break, all of our MSAs pass the ADF test. We, therefore, estimate our two short-term models even for the three CBSAs that do not show co-integration.
[29] This essentially two-step procedure was originally suggested by Engle and Granger (1987) and more recently by Lutkepohl (2007).
[30] The 12 month lag was determined empirically by trying different lag and see what lag lengths turned the sign the sign negative on the most CBSAs. We had no priors going into the research.

as the B/R in Chart 4. The sign on $\alpha$ should be negative, but larger than negative one and significant ï buyers overpaying too should lead to a reduction in purchases and a movement toward renting. We find this to be the case; it just does not happen right away but over 12 months.

Equation 6 implies that changes in the cost of renting are a function, again, of the disequilibrium between $B_t$ and $R_t$, twelve months earlier. Since a $(B/R)_{t-12} > 1.0$ is an indicator that buyers may be overpaying. In Equation 6, the sign on $\hat{\alpha}$ should be positive, but less than one and significant ï buyers paying too much for a home 12 months prior should lead to increased demand for rentals and, therefore, for rents to rise.

$$\Delta \ln B_t = \text{const} + \alpha\,[\ln (B/R)_{t-12}] + \phi\,\Delta \ln B_{t-3} + \gamma\,\Delta \ln R_{t-3} + \lambda\ \text{ITS}_{t-12} + e_t \quad (5)$$

$$\Delta \ln R_t = \text{const} + \hat{\alpha}[\ln (B/R)_{t-12}] + \hat{\phi}\ln \Delta B_{t-3} + \hat{\gamma}\Delta \ln R_{t-3} + \hat{\lambda}\,\text{Vac}_{t-9} + e_t \quad (6)$$

The symbol $\Delta$ denotes the year-to-year change of a variable. Ln $(B/R)_{t-12}$ is the natural log of buy/rent disequilibria one year earlier. The variables $\Delta \ln R_{t-3}$ and $\Delta \ln B_{t-3}$ are the same year-over-year change variables, but lagged one quarter to capture momentum. Home price appreciation tends to be persistent. We specified the functional form (of Equations 5 and 6) to not vary from city to city. The coefficient $\phi$ captures the momentum on owning, and $\gamma$ captures the momentum on renting. The impact of supply and demand would likely overwhelm the weaker economic forces of disequilibria and thus distort the disequilibria coefficients so we include a ratio of the inventory of homes (I) on the market divided by sales (S, or ITS = I/S). It is a measure of supply and demand.

Vac is the rental vacancy rate on both multifamily and single family properties. Our I/S data is monthly data starting in January 2009 from RedBell[31]. The vacancy data is from the Department of Census.

### *6.5 Short-run Model Results*

With the results in Table 2 essentially validating co-integration for all 50 CBSAs, we move onto reporting the results of the 50 short-run specifications and to test the economic content of the ln $(B/R)_{t-12}$ using Equations 5 and 6.

The $R^2$ results for each CBSAs of both short-run models are reported in Table 3. The convergence coefficient and their p-value for both are shown in Tables 4.a to 4.c. Tables 4.a to 4.c show that $\alpha$ is significant at the 5% level or better and has the correct sign in 47 of 50 cases.[32] Whereas αô is significant at the 10% level or better and has the correct sign in 30 of 50 cases (Tables 5.a to 5.c). Overall, the estimated VECM ñelasticitiesò seem plausible. The price equation fits better for more CBSAs, probably because the purchase market is better developed than the rental market in many cities.

### *6.6 The Purchase Market*

[31] RedBell uses MLS data to calculate inventories on the market and how many homes were sold in the current period.
[32] Only Cleveland, Cincinnati, and Pittsburgh were insignificant. Indianapolis and Santa Rosa had values < -1. Even though the coefficient values for Indianapolis Raleigh and Santa Rosa exceed our required boundaries, a minor adjustment to the lags reduces the convergence coefficients to greater than -1.

Chart 9 shows the convergence criterion coefficients for 47 CBSAs on the buy equation (blue bars). They range from -0.21 for Atlanta and -1.17 for Indianapolis. The results only make sense if the coefficients are negative, significant and larger than negative one. A coefficient of -0.34 (for Seattle) indicates that when B is greater than R by 10 percent twelve months earlier, home price changes (holding interest rates constant) over that year will be 3 percent lower. The more negative the convergence criterion coefficient, the faster the speeds of adjustment in one year.

If we think of the market rent (R) as being an equilibrium to which the user cost should converge then we can think of the -0.34 as being a measure of how much home prices will self-correct to reach equilibrium in one year. In other words, about one third of the overvaluation or undervaluation will be corrected within one year in the Seattle market.

### *6.7 The Rental Market*

Chart 9 also shows the convergence criterion coefficients for 30 of our 50 CBSAs on the rent convergence coefficients that were positive, less than one and significant. They range from +0.21 for Pittsburgh to +0.45 for Indianapolis. The greater a positive convergence criterion coefficient, the faster the speeds of adjustment within one year. Vacancy rates for four CBSAs were not available from Census (Madison, WI, Oxnard, CA, Salt Lake City, UT and Santa Rosa, CA). Thus these four CBSAs have no values shown for this variable in Table 5. We have made several attempts to understand why the rental market does not function as we expect in the 20 remaining CBSAs, but as yet do not have an explanation.

### 6.8 Stage 3: Explaining Cross Sectional Variation in B/R

Wheaton, Chervachidze, and Nechayev (2014) estimate supply elasticities for 68 CBSAs similar to our sample. They then go one step further and look at the macro-implications of knowing the 68 different MSA supply elasticities. We follow Wheaton et al. (2014) by developing a macroeconomic perspective utilizing microeconomic data on our 50 CBSAs.

In all of our 50 CBSAs, the monthly cost of owning a home is co-integrated with rents. Importantly, home prices and thus the cost of owning do adjust to buy/rent disequilibrium as theory would predict, but our second stage models show us something as important -- that adjustment speeds vary by CBSA. These two insights allow us to address a central problem identified by this paper -- why does B/R vary between CBSAs, often with B/R < 0.8 or B/R > 1.2 for long periods of time. This should not happen.

The genesis of this research was the observation that in some CBSAs, homebuyers seem to be indifferent to the relative cost of a virtually identical good. We have argued that frictions can impede this decision making process. We see friction in four forms: (1) potential homebuyers do not have access to credit; (2) some geographies do not have buildable land or unduly restrict new development; (3) potential homebuyers in Rust Belt CBSAs may have different expectations than Sun Belt residents; and (4) homebuyers in fast appreciating CBSAs might rationalize purchasing ostensibly overvalued property if they believe prices will continue to rise faster than incomes consistent with recent market trends.

The first three are testable hypotheses:

We estimate Equation 7 below:

$$BVR_i = \theta_0 + \theta_1 RCS_i + \theta_2 SE_i + \theta_3 Snow_i + v_i. \quad (7)$$

for i = 1 to 49 CBSAs in July 2015 and October 2016. We cannot include Madison, WI because Saiz (2010) does not calculate a supply elasticity for that city.

Here $RCS_i$ = Renter Credit $Score_i$. This is the average credit score of renters in a CBSA. This is a calculated variable by Fannie Mae using Equifax credit data.[33] We use data from two different period as a check for robustness (July 2015 and October 2016).

$SE_i$ = Supply elasticities by CBSA from Saiz (2010).

$Snow_i$ = Average snow fall in a CBSA. Source: National Oceanic and Atmospheric Administration (NOAA). We use this variable as a proxy for Rust Belt versus Sun Belt locations.

The values for snowfall and supply elasticities do not change in the two different time periods that we estimate Equation 7. The results of Equation 7 are presented in Table 5.

We anticipate the sign on $\theta_1$ should be positive. Credit scores ranged roughly from 540 to 739 for our 50 CBSAs in July 2015. Better scores allow potential home buyers to bid up home prices. We assume renters are not constrained by credit.

For $\theta_2$, the sign should be negative. CBSAs with very low home supply elasticities tend to have high B/Rs because new supply does not come on line quickly and prices rise quicker than rents. Conversely, CBSAs with high supply elasticities would have new housing supply that could increase quickly. This would put downward pressure on home prices and B/R never approaches 1.0.

32 A credit score for renters was obtained using the following information: the score for all card holders in a given market (source: Equifax), score for all owners with a mortgage (source: CoreLogic) and the share of owners and renters in each CBSA (source: ACS 2015).

The sign on $\theta_3$ should be negative. Cold weather (our proxy for Rust Belt location) forms negative long term expectations about peopleôs willingness to own and stay in a seasonally harsh location with declining economic bases.

We ran Equation 7 during two time periods. We have 49 observations. The results in Tables 5 show that the all of the variables are significant at 10% or better except the impact of weather in Jul-15 cross sectional estimation.

The results from Equation 7 for $d_1$ (the coefficient for the average credit score) are 0.001for both time periods. We interpret this result as indicating that credit scores tell us something about effective demand. Better scores increase consumerôs ability to buy home and drive the B/Rs higher. Tighter supply elasticities have the same impact but they are a measure of supply side constraints ï low elasticities, suggest low supply response at the margin and higher B/R. The coefficients are roughly identical in the two time periods. Finally, the values of $d_3$ are identical at -0.002 in both sample periods. Colder weather (our Rust Belt proxy) affects long-term expectations and negatively impact home prices and the cost of owning.

## 7. Conclusions

Using data not available to previous researchers, this paper makes three important contributions to our understanding of the U.S. housing market:

1. In all 50 of the CBSAs during the period of this study, the cost of owning a home for a month is co-integrated with renting ï they move together. However, the cost of owning relative to the cost of renting, over time, can (and often does) reach a steady state that is

not equal to one. So from some market position of B not equal to R at time t, B and R might grow (or decline) at roughly the same rate. Such a situation is steady state with B/R roughly equal to some constant (outside the range of $0.8 < B/R < 1.2$), but it is not an equilibrium.

2. Estimation of short-run models of the percentage changes in both buy and rent for our 50 CBSAs over time show that B and R respond as expected to B/R disequilibria with a one year lag. Markets function as we would expect. However, the magnitude of the percentage change in B may stay very close to the percentage change in R and can preclude B/R from reaching unity over very long periods of time, in some CBSAs if B/R is not near 1.0 to start. Understanding this dynamic remains an issue.
3. Using cross-sectional analysis, we show what forces (friction) work to keep B/R from achieving an equilibrium near unity. This friction comes in the form of supply elasticities, expectations about future home price growth and weather, and consumer credit constraints.

We believe there are two important macroeconomic implications of our analysis. First, the buy-versus-rent ratio can tell us something about future prices price changes, it may provide an early warning sign of a housing bubble. Second, our findings suggest that attempts to stimulate housing demand (turning renters into homebuyers, for example) may be less effective in certain markets, because of cross-sectional variation in credit. On the other hand, investors in single family properties would be reasonably attracted to CBSAs with low credit scores. In such markets, investors can economically purchase and own housing which they can then rent out with limited competition from the home purchase market. Future research might usefully explore externalities (both positive and negative) associated with single-family rental investor entry.

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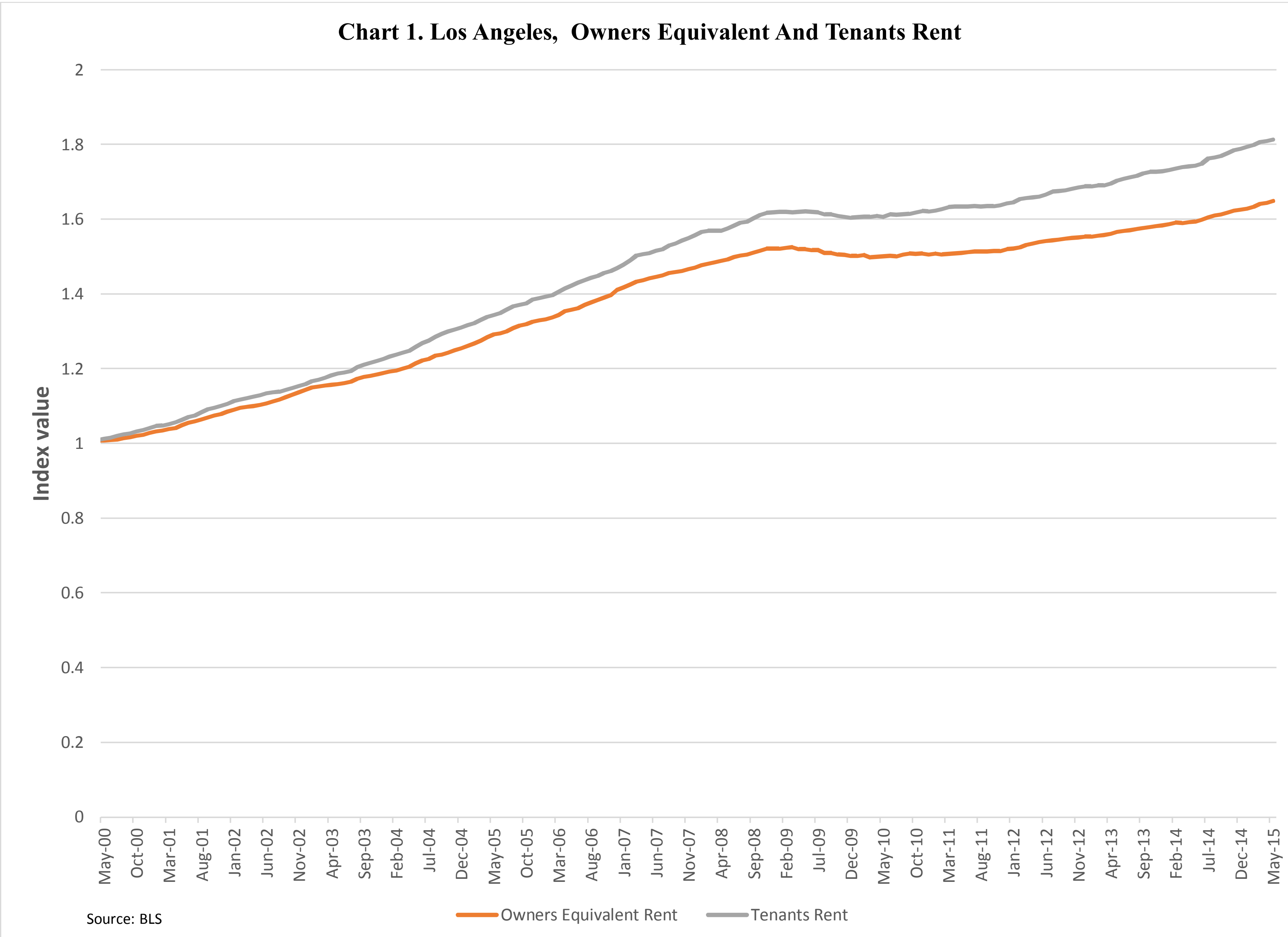
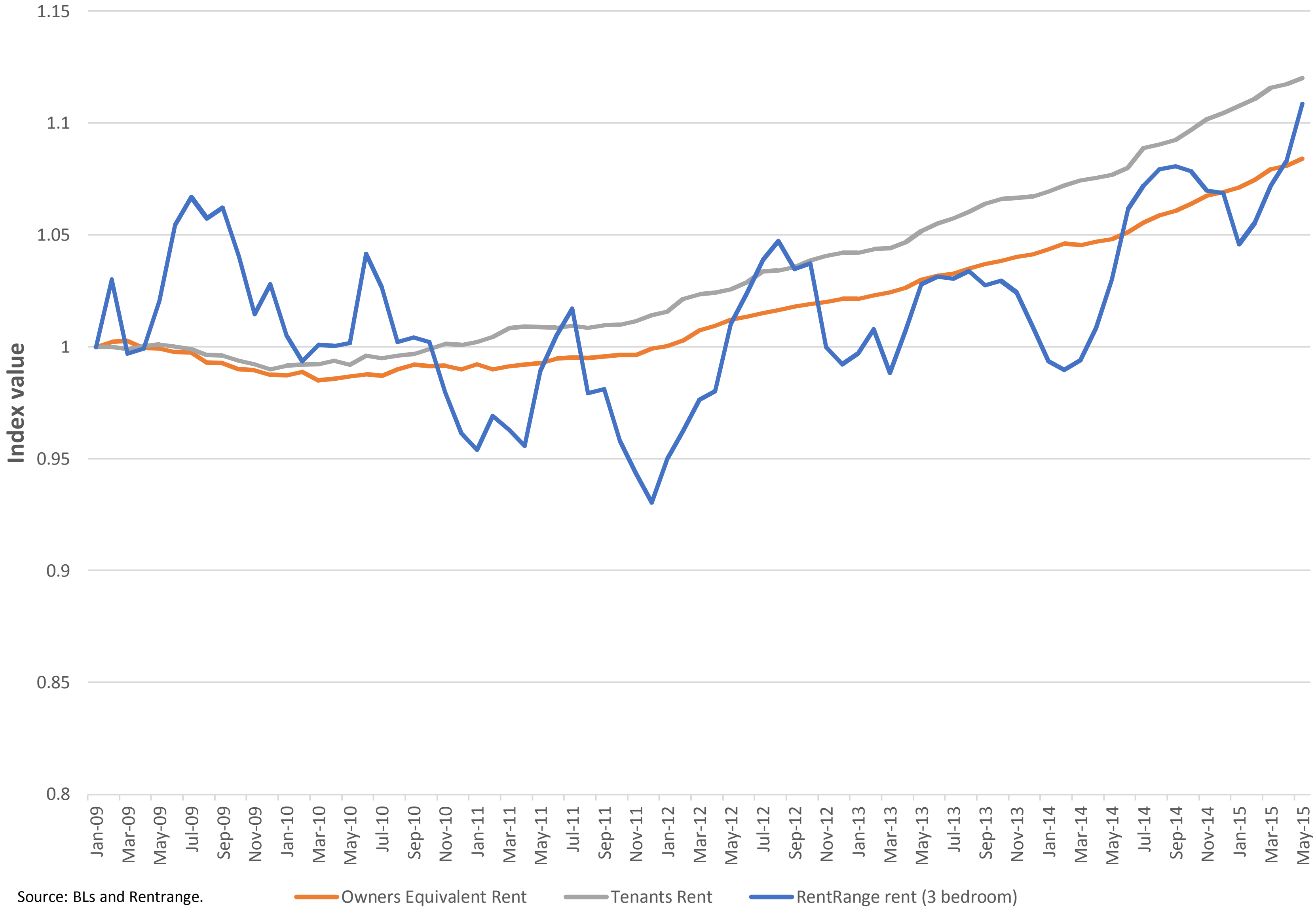


Chart 1. Los Angeles, Owners Equivalent And Tenants Rent
Index value
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
May-00
Oct-00
Mar-01
Aug-01
Jan-02
Jun-02
Nov-02
Apr-03
Sep-03
Feb-04
Jul-04
Dec-04
May-05
Oct-05
Mar-06
Aug-06
Jan-07
Jun-07
Nov-07
Apr-08
Sep-08
Feb-09
Jul-09
Dec-09
May-10
Oct-10
Mar-11
Aug-11
Jan-12
Jun-12
Nov-12
Apr-13
Sep-13
Feb-14
Jul-14
Dec-14
May-15
Source: BLS
Owners Equivalent Rent
Tenants Rent

Chart 2. Los Angeles: Three Sources Of Rent Data




Source: BLs and Rentrange.

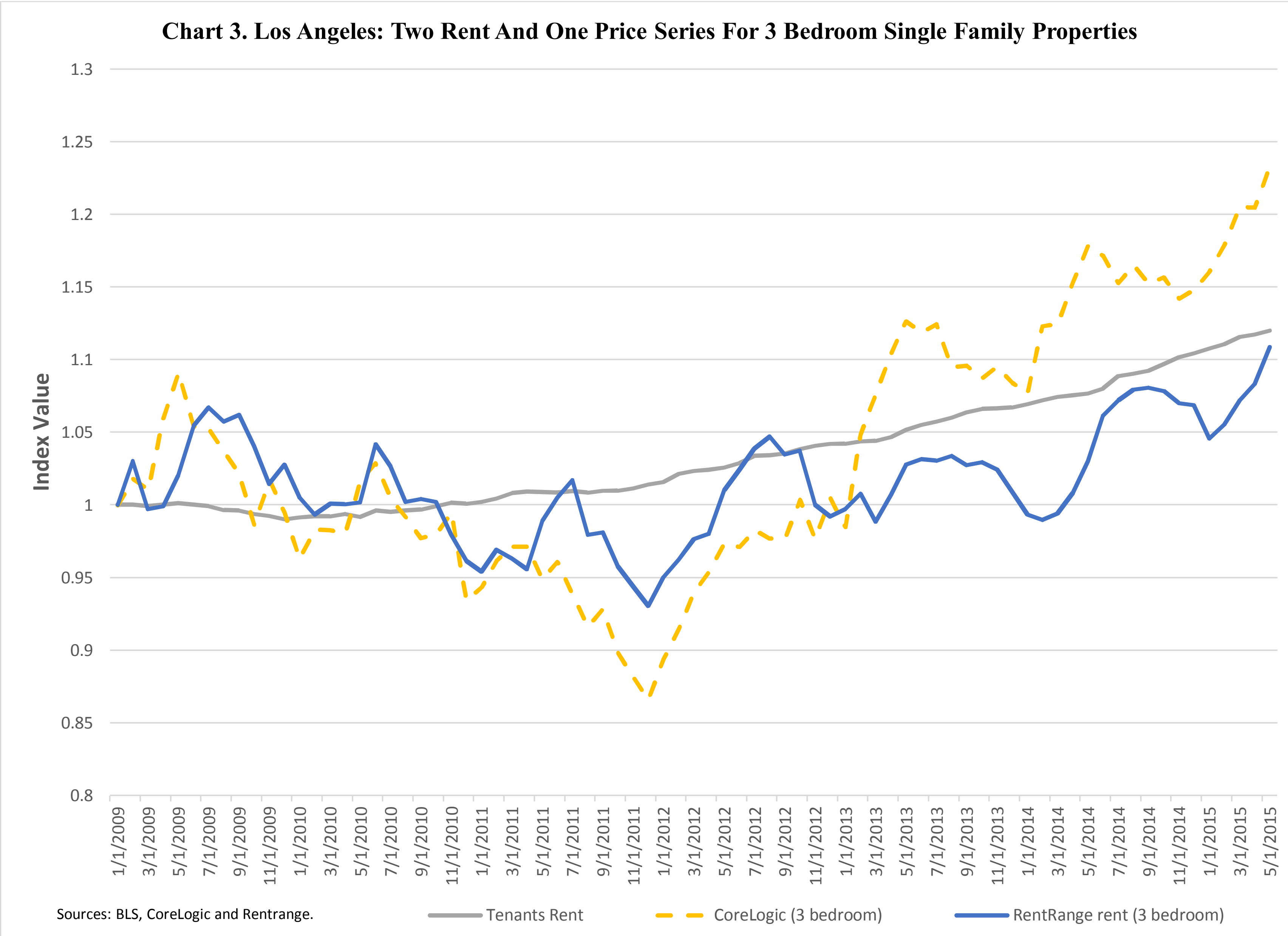
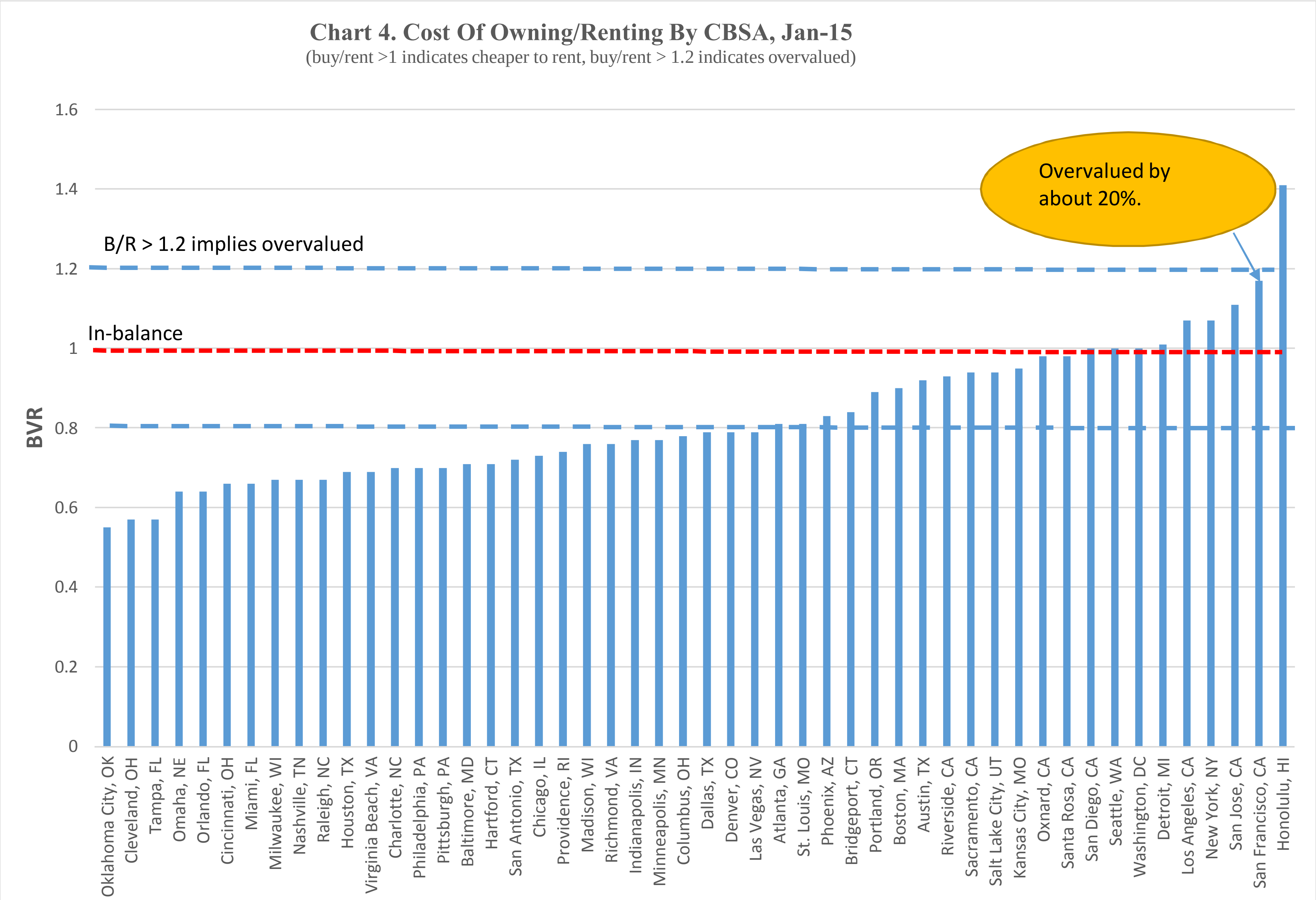


Chart 3. Los Angeles: Two Rent And One Price Series For 3 Bedroom Single Family Properties
Index Value
1.3
1.25
1.2
1.15
1.1
1.05
1
0.95
0.9
0.85
0.8
1/1/2009
3/1/2009
5/1/2009
7/1/2009
9/1/2009
11/1/2009
1/1/2010
3/1/2010
5/1/2010
7/1/2010
9/1/2010
11/1/2010
1/1/2011
3/1/2011
5/1/2011
7/1/2011
9/1/2011
11/1/2011
1/1/2012
3/1/2012
5/1/2012
7/1/2012
9/1/2012
11/1/2012
1/1/2013
3/1/2013
5/1/2013
7/1/2013
9/1/2013
11/1/2013
1/1/2014
3/1/2014
5/1/2014
7/1/2014
9/1/2014
11/1/2014
1/1/2015
3/1/2015
5/1/2015
Sources: BLS, CoreLogic and Rentrange.
Tenants Rent
CoreLogic (3 bedroom)
RentRange rent (3 bedroom)




Sources: Zillow.com and RentRange. Data is for 3 bedroom detached properties.

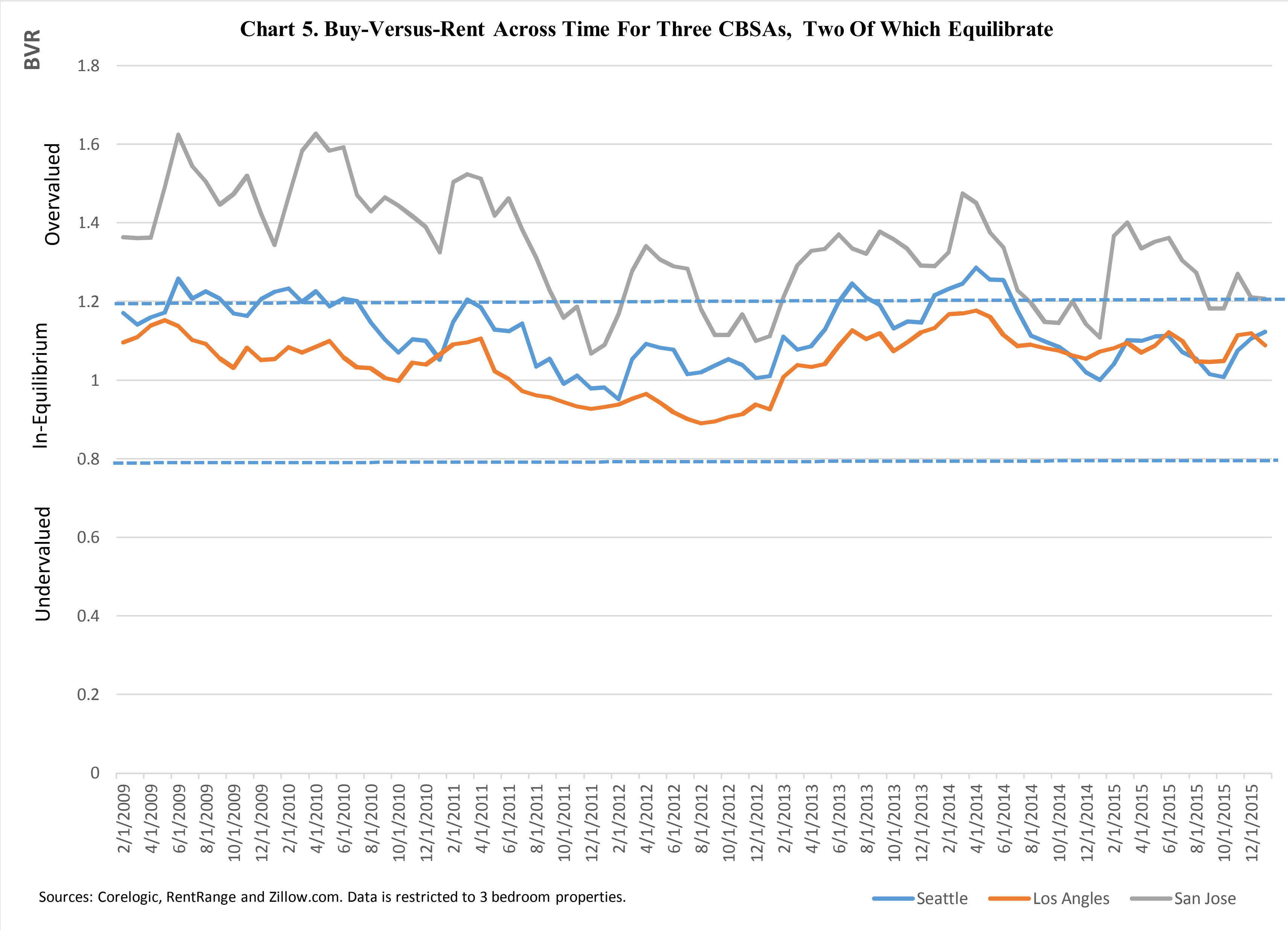


Chart 5. Buy-Versus-Rent Across Time For Three CBSAs, Two Of Which Equilibrate
BVR
Overvalued
In-Equilibrium
Undervalued
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
2/1/2009
4/1/2009
6/1/2009
8/1/2009
10/1/2009
12/1/2009
2/1/2010
4/1/2010
6/1/2010
8/1/2010
10/1/2010
12/1/2010
2/1/2011
4/1/2011
6/1/2011
8/1/2011
10/1/2011
12/1/2011
2/1/2012
4/1/2012
6/1/2012
8/1/2012
10/1/2012
12/1/2012
2/1/2013
4/1/2013
6/1/2013
8/1/2013
10/1/2013
12/1/2013
2/1/2014
4/1/2014
6/1/2014
8/1/2014
10/1/2014
12/1/2014
2/1/2015
4/1/2015
6/1/2015
8/1/2015
10/1/2015
12/1/2015
Sources: Corelogic, RentRange and Zillow.com. Data is restricted to 3 bedroom properties.
Seattle
Los Angles
San Jose

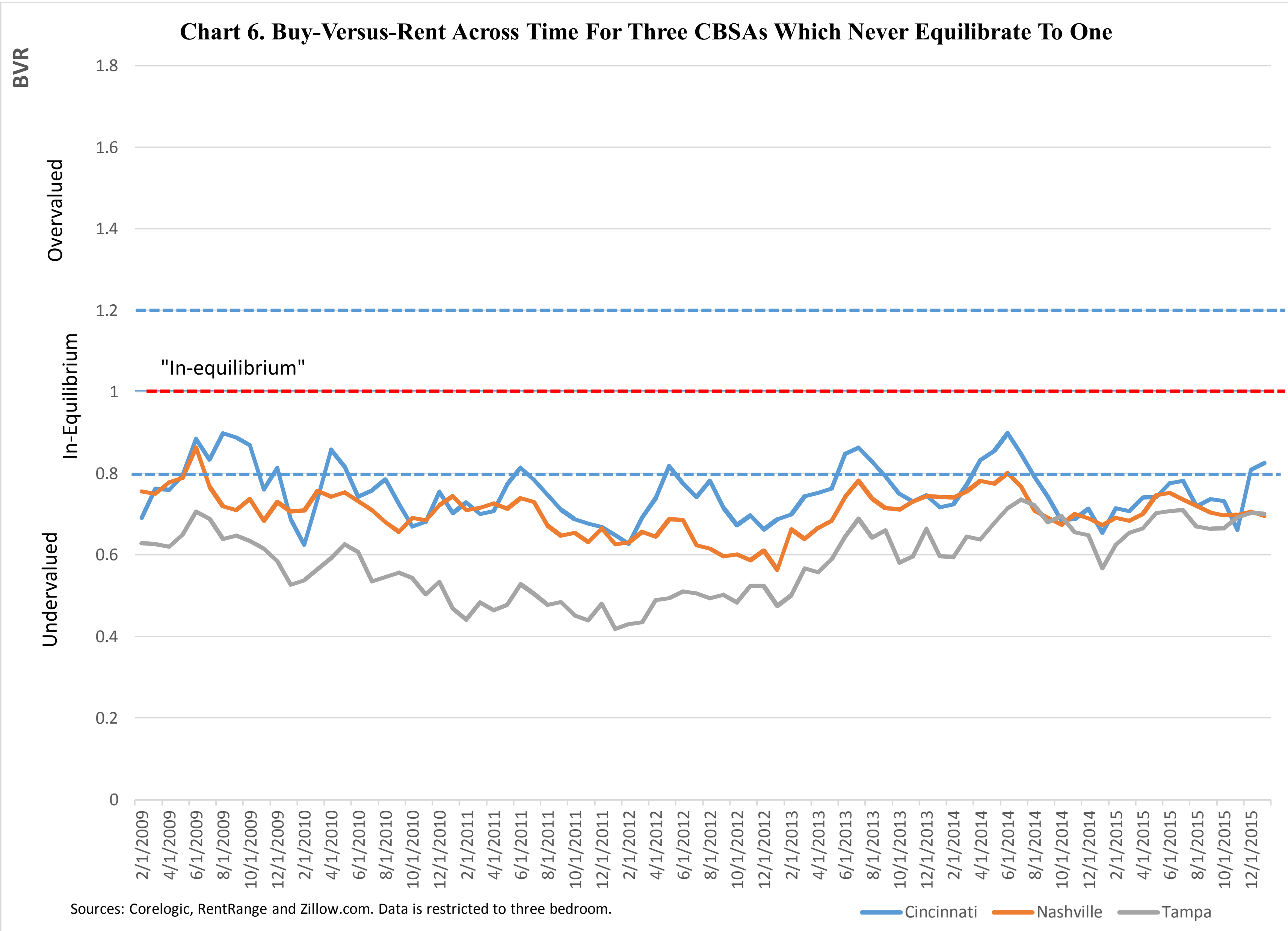
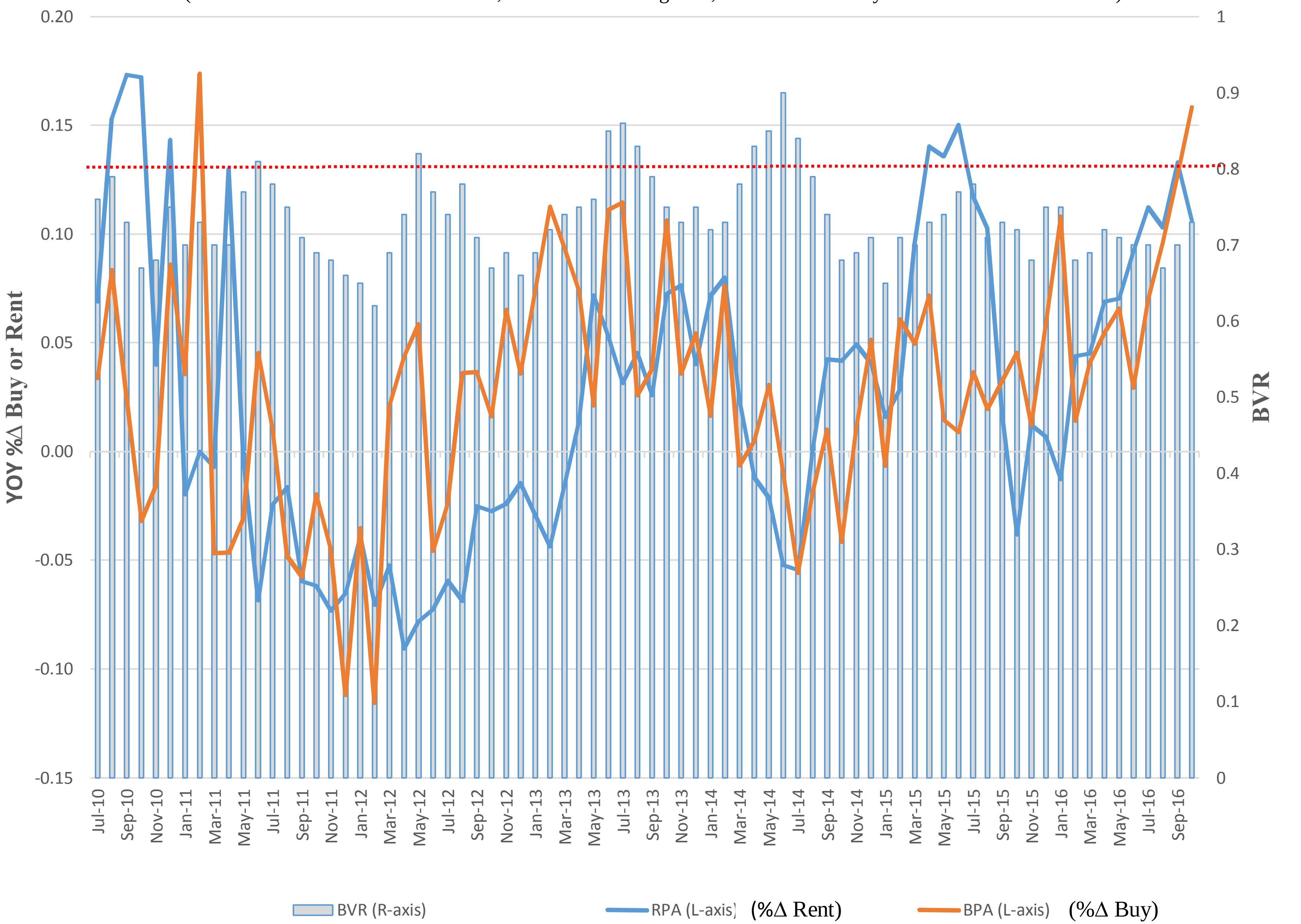


Chart 6. Buy-Versus-Rent Across Time For Three CBSAs Which Never Equilibrate To One
BVR
Overvalued
In-Equilibrium
Undervalued
"In-equilibrium"
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
2/1/2009
4/1/2009
6/1/2009
8/1/2009
10/1/2009
12/1/2009
2/1/2010
4/1/2010
6/1/2010
8/1/2010
10/1/2010
12/1/2010
2/1/2011
4/1/2011
6/1/2011
8/1/2011
10/1/2011
12/1/2011
2/1/2012
4/1/2012
6/1/2012
8/1/2012
10/1/2012
12/1/2012
2/1/2013
4/1/2013
6/1/2013
8/1/2013
10/1/2013
12/1/2013
2/1/2014
4/1/2014
6/1/2014
8/1/2014
10/1/2014
12/1/2014
2/1/2015
4/1/2015
6/1/2015
8/1/2015
10/1/2015
12/1/2015
Sources: Corelogic, RentRange and Zillow.com. Data is restricted to three bedroom.
Cincinnati
Nashville
Tampa

**Chart 7. Cincinnati: %ΔBuy and %ΔRent and B/R**

(L-term model: From Jan-09 to Jul-15, B and R are cointegrated, but there is a steady state with B/R not at B/R=1)




Sources: CoreLogic and RentRange. Data is restricted to 3 bedroom.

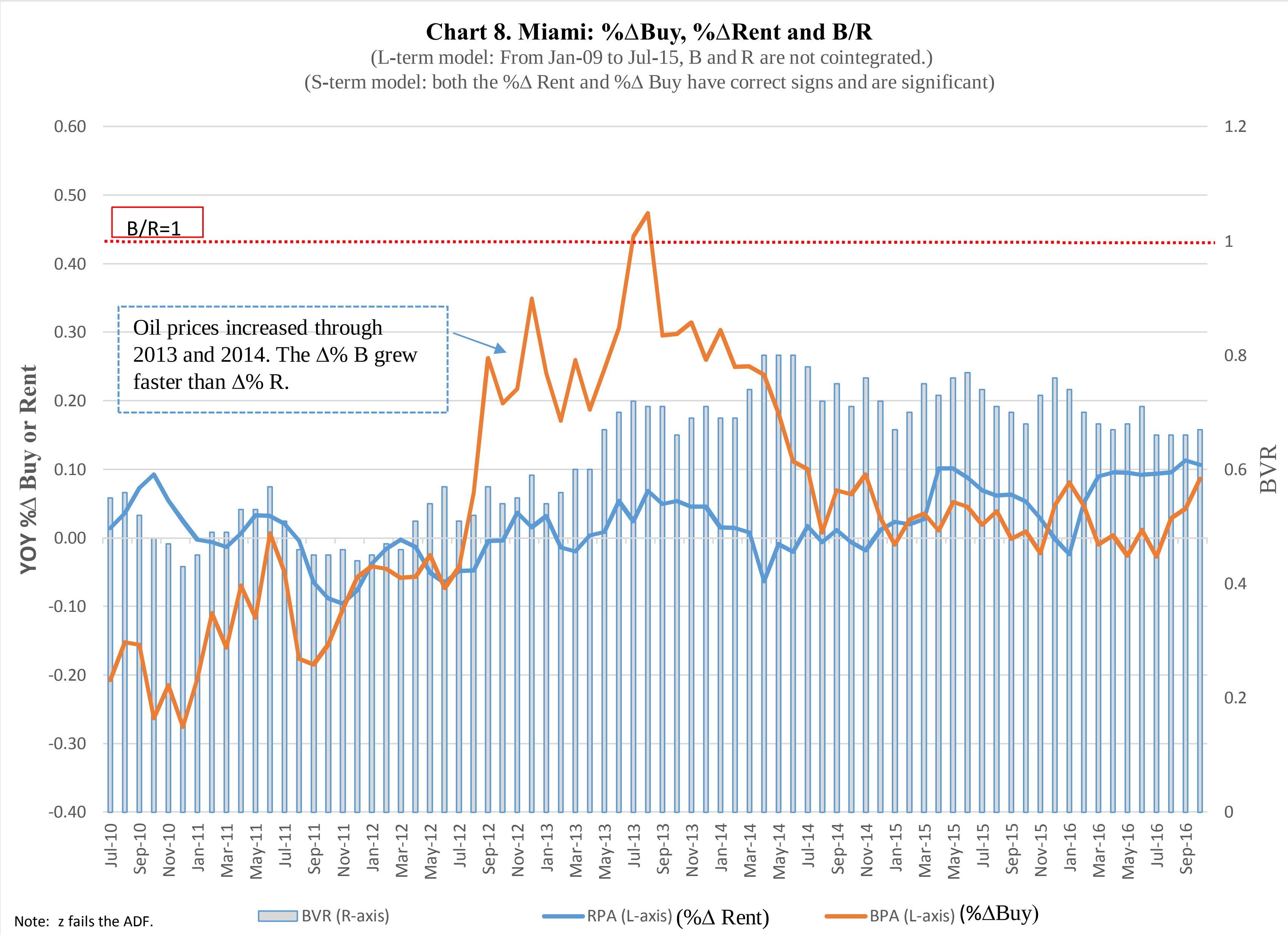


Chart 8. Miami: %ΔBuy, %ΔRent and B/R
(L-term model: From Jan-09 to Jul-15, B and R are not cointegrated.)
(S-term model: both the %Δ Rent and %Δ Buy have correct signs and are significant)
B/R=1
Oil prices increased through 2013 and 2014. The Δ% B grew faster than Δ% R.
YOY %Δ Buy or Rent
BVR
Note: z fails the ADF.
BVR (R-axis)
RPA (L-axis) (%Δ Rent)
BPA (L-axis) (%ΔBuy)

| Table 1.a Selected Descriptive Statistics (means) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Long-Run Specification | | | | | Short-Run Secification | | | Cross Sectional Variaton | | | |
| CBSA | CBSA name | Obs: Jan09-Jul15 | $buy2010[1] | $rent2010[2] | $buy2015[1] | $rent2015[2] | Obs: Apr10-Jul15 | ITS2015[3] | vac2015[4] | Obs: Cross section | Score All Card Holders[5] | Supply Elasticity[6] | Snow (in inches)[7] |
| 1 | Atlanta, GA | 79 | 841 | 1,017 | 895 | 997 | 64 | 3.8 | 8.7 | 49 | 678 | 2.55 | 2.1 |
| 2 | Austin, TX | 79 | 1,270 | 1,233 | 1,500 | 1,557 | 64 | 2.3 | 6.5 | 49 | 701 | 3.00 | 0.9 |
| 3 | Baltimore, MD | 79 | 1,288 | 1,555 | 1,248 | 1,621 | 64 | 4.6 | 8.0 | 49 | 702 | 1.23 | 21.5 |
| 4 | Boston, MA | 79 | 1,972 | 1,882 | 2,100 | 2,251 | 64 | 4.3 | 3.0 | 49 | 719 | 0.86 | 42.8 |
| 5 | Bridgeport/Stamford, CT | 79 | 2,464 | 2,388 | 2,170 | 2,460 | 64 | 7.5 | 8.1 | 49 | 722 | 0.98 | 26.2 |
| 6 | Charlotte, NC | 79 | 833 | 995 | 897 | 1,140 | 64 | 3.7 | 7.2 | 49 | 687 | 3.09 | 5.6 |
| 7 | Chicago, IL | 79 | 1,243 | 1,572 | 1,235 | 1,552 | 64 | 4.5 | 8.0 | 49 | 708 | 0.81 | 38.0 |
| 8 | Cincinnati, OH | 79 | 754 | 1,027 | 765 | 1,052 | 64 | 4.4 | 12.5 | 49 | 704 | 2.46 | 57.6 |
| 9 | Cleveland, OH | 79 | 704 | 1,028 | 664 | 990 | 64 | 5.5 | 6.5 | 49 | 705 | 1.02 | 57.6 |
| 10 | Columbus, OH | 79 | 874 | 1,001 | 905 | 1,107 | 64 | 3.1 | 6.0 | 49 | 700 | 2.71 | 28.2 |
| 11 | Dallas, TX | 79 | 951 | 1,215 | 1,127 | 1,371 | 64 | 2.0 | 7.9 | 49 | 688 | 2.18 | 2.6 |
| 12 | Denver, CO | 79 | 1,311 | 1,373 | 1,524 | 1,780 | 64 | 1.2 | 4.8 | 49 | 721 | 1.53 | 60.3 |
| 13 | Detroit, MI | 79 | 745 | 992 | 1,051 | 896 | 64 | 4.6 | 7.0 | 49 | 678 | 1.24 | 41.3 |
| 14 | Hartford, CT | 79 | 1,438 | 1,508 | 1,296 | 1,635 | 64 | 7.4 | 5.7 | 49 | 720 | 1.50 | 49.6 |
| 15 | Houston, TX | 79 | 923 | 1,314 | 1,071 | 1,482 | 64 | 3.0 | 8.9 | 49 | 682 | 2.30 | 0.4 |
| 16 | Indianapolis, IN | 79 | 771 | 972 | 817 | 1,048 | 64 | 3.9 | 10.2 | 49 | 697 | 4.00 | 23.9 |
| 17 | Kansas City, MO | 79 | 924 | 984 | 974 | 936 | 64 | 3.4 | 7.1 | 49 | 706 | 3.19 | 19.9 |
| 18 | Las Vegas, NV | 79 | 689 | 1,203 | 1,012 | 1,200 | 64 | 3.5 | 7.5 | 49 | 681 | 1.39 | 1.2 |
| 19 | Los Angeles, CA | 79 | 2,466 | 2,334 | 2,751 | 2,527 | 64 | 2.4 | 3.4 | 49 | 705 | 0.63 | 1.0 |
| 20 | Madison, WI | 79 | 1,215 | 1,285 | 1,254 | 1,489 | 64 | 3.8 | n/a | 49 | 738 | n/a | 43.8 |
| 21 | Miami, FL | 79 | 1,024 | 1,901 | 1,424 | 1,946 | 64 | 5.4 | 6.1 | 49 | 675 | 0.60 | 1.0 |
| 22 | Milwaukee, WI | 79 | 949 | 1,145 | 879 | 1,111 | 64 | 5.3 | 4.7 | 49 | 718 | 1.03 | 47.0 |
| 23 | Minneapolis, MN | 79 | 1,104 | 1,401 | 1,165 | 1,435 | 64 | 4.2 | 5.4 | 49 | 727 | 1.45 | 49.9 |
| 24 | Nashville, TN | 79 | 853 | 1,198 | 982 | 1,388 | 64 | 3.5 | 5.5 | 49 | 694 | 2.24 | 10.1 |
| 25 | New York, NY | 79 | 2,441 | 2,069 | 2,366 | 2,223 | 64 | 8.7 | 4.2 | 49 | 707 | 0.76 | 28.6 |
| 26 | Oklahoma City, OK | 79 | 602 | 1,011 | 661 | 1,136 | 64 | 3.6 | 7.2 | 49 | 689 | 3.29 | 9.5 |
| 27 | Omaha, NE | 79 | 818 | 1,019 | 852 | 1,212 | 64 | 2.5 | 8.3 | 49 | 717 | 3.47 | 30.1 |
| 28 | Orlando, FL | 79 | 549 | 1,103 | 893 | 1,286 | 64 | 3.7 | 8.2 | 49 | 682 | 1.12 | 1.0 |
| 29 | Oxnard, CA | 79 | 2,228 | 2,060 | 2,453 | 2,429 | 64 | 2.3 | n/a | 49 | 723 | 0.75 | 1.0 |
| 30 | Philadelphia, PA | 79 | 1,113 | 1,479 | 1,029 | 1,439 | 64 | 6.5 | 8.0 | 49 | 707 | 1.65 | 20.8 |

| Table 1.b Selected Descriptive Statistics (means) | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Long-Run Specification | | | | | Short-Run Secification | | | Cross Sectional Variaton | | | |
| CBSA | CBSA name | Obs: Jan09-Jul15 | \$buy2010[1] | \$rent2010[2] | \$buy2015[1] | \$rent2015[2] | Obs: Apr10-Jul15 | ITS2015[3] | vac2015[4] | Obs: Cross section | Score All Card Holders[5] | Supply Elasticity[6] | Snow (in inches)[7] |
| 31 | Phoenix, AZ | 79 | 727 | 1,075 | 982 | 1,180 | 64 | 3.0 | 7.3 | 49 | 698 | 1.61 | 1.0 |
| 32 | Pittsburgh, PA | 79 | 721 | 872 | 804 | 1,000 | 64 | 5.4 | 6.1 | 49 | 719 | 1.20 | 43.6 |
| 33 | Portland, OR | 79 | 1,382 | 1,251 | 1,494 | 1,592 | 64 | 2.2 | 3.8 | 49 | 720 | 1.07 | 6.5 |
| 34 | Providence, RI | 79 | 1,349 | 1,510 | 1,274 | 1,699 | 64 | 5.5 | 3.1 | 49 | 712 | 1.61 | 36.0 |
| 35 | Raleigh, NC | 79 | 851 | 1,138 | 889 | 1,266 | 64 | 2.8 | 2.9 | 49 | 705 | 2.11 | 7.5 |
| 36 | Richmond, VA | 79 | 1,065 | 1,089 | 1,003 | 1,167 | 64 | 4.1 | 6.6 | 49 | 697 | 2.60 | 13.8 |
| 37 | Riverside, CA | 79 | 1,062 | 1,477 | 1,462 | 1,526 | 64 | 3.6 | 6.3 | 49 | 686 | 0.94 | 1.0 |
| 38 | Sacramento, CA | 79 | 1,213 | 1,314 | 1,476 | 1,493 | 64 | 2.3 | 5.2 | 49 | 714 | 1.02 | 1.0 |
| 39 | Salt Lake City, UT | 79 | 1,171 | 1,197 | 1,248 | 1,298 | 64 | 6.0 | n/a | 49 | 716 | 0.75 | 58.7 |
| 40 | San Antonio, TX | 79 | 846 | 1,088 | 974 | 1,284 | 64 | 3.0 | 9.5 | 49 | 676 | 2.98 | 0.7 |
| 41 | San Diego, CA | 79 | 2,138 | 2,022 | 2,336 | 2,312 | 64 | 2.3 | 2.6 | 49 | 716 | 0.67 | 1.0 |
| 42 | San Francisco, CA | 79 | 3,032 | 2,056 | 3,844 | 2,760 | 64 | 1.2 | 3.6 | 49 | 744 | 0.66 | 1.0 |
| 43 | San Jose, CA | 79 | 3,355 | 2,251 | 4,133 | 3,113 | 64 | 1.0 | 4.0 | 49 | 737 | 0.76 | 1.0 |
| 44 | Santa Rosa, CA | 79 | 2,100 | 1,693 | 2,474 | 2,335 | 64 | 2.1 | n/a | 49 | 733 | 0.76 | 1.0 |
| 45 | Seattle, WA | 79 | 1,766 | 1,506 | 1,842 | 1,706 | 64 | 2.2 | 3.9 | 49 | 731 | 0.88 | 11.4 |
| 46 | St. Louis, MO | 79 | 942 | 1,135 | 953 | 972 | 64 | 4.3 | 10.1 | 49 | 708 | 2.36 | 19.6 |
| 47 | Tampa, FL | 79 | 660 | 1,196 | 841 | 1,273 | 64 | 3.4 | 7.2 | 49 | 695 | 1.00 | 1.0 |
| 48 | Urban Honolulu, HI | 79 | 3,531 | 2,197 | 3,625 | 2,580 | 64 | 3.3 | 5.0 | 49 | 730 | 0.53 | 1.0 |
| 49 | Virginia Beach, VA | 79 | 1,137 | 1,295 | 1,009 | 1,321 | 64 | 6.3 | 6.2 | 49 | 685 | 0.82 | 7.8 |
| 50 | Washington, DC | 79 | 1,889 | 1,800 | 2,029 | 1,908 | 64 | 3.1 | 5.2 | 49 | 708 | 1.61 | 17.1 |

Sources and definitions: 1) The monthy cost of owning a three bedroom single family property. This includes principal, interest and property taxes. The property prices is based upon a price from CoreLogic for all bedrooms and scaled using data from Zillow.com to represent the median price for a three bedroom property; 2) Median rent for a three bedroom property (RentRange); 3) ITS = Inventory-to-sales for all property types (RedBell); 4) Vacancy rates for both single and multifamily properties (Census Bureau); 5) Average credit score for all borrowers (Equifax, Oct-16). The score for renters is a Fannie Mae estimate using the Equifax score and a score for mortgage holders from Corelogic.; 6) Supply elasticities from Saiz (2010). The elasticity for Honolulu and Sacramento are estimates based upon additional data from Wheaton et al., (2014).; 7) Average snowfall in inches (NOAA). A value of one means zero or near zero amounts of snowfall.

| Table 2. Equation 4: Long Run Model & ADF | | | | Table 2. Equation 4: Long Run Model & ADF | | | |
|---|---|---|---|---|---|---|---|
| And ADF Results | Fit | rent | Tau on lag1 | | Fit | rent | Tau on lag1 |
| Atlanta, GA | R-Square | 3.38436 | -2.180 | Oklahoma City, OK | R-Square | 0.83748 | -3.870 |
| | 0.3767 | <.0001 | 0.029 | | 0.2536 | <.0001 | 0.000 |
| Austin, TX | R-Square | 0.73857 | -2.820 | Omaha, NE | R-Square | 0.45301 | -3.340 |
| | 0.6547 | <.0001 | 0.005 | | 0.1396 | 0.0007 | 0.001 |
| Baltimore, MD | R-Square | 0.52705 | -2.880 | Orlando, FL | R-Square | 3.73298 | -2.890 |
| | 0.0758 | 0.014 | 0.006 | | 0.756 | <.0001 | 0.004 |
| Boston, MA | R-Square | 0.39762 | -2.550 | Oxnard, CA | R-Square | 0.92853 | -1.790 |
| | 0.1628 | 0.0002 | 0.014 | | 0.2678 | <.0001 | 0.070 |
| Stamford, CT | R-Square | 0.56882 | -4.020 | Philadelphia, PA | R-Square | 1.42846 | -3.920 |
| | 0.0664 | 0.0219 | 0.000 | | 0.4822 | <.0001 | 0.000 |
| Charlotte, NC | R-Square | 0.62325 | -3.300 | Phoenix, AZ | R-Square | 2.62154 | -2.000 |
| | 0.1164 | 0.0021 | 0.001 | | 0.3483 | <.0001 | 0.044 |
| Chicago, IL | R-Square | 2.08236 | -3.230 | Pittsburgh, PA | R-Square | 0.35875 | -4.360 |
| | 0.4031 | <.0001 | 0.002 | | 0.094 | 0.006 | 0.000 |
| Cincinnati, OH | R-Square | 0.5277 | -4.000 | Portland, OR | R-Square | -0.2332 | -1.880 |
| | 0.0832 | 0.0099 | 0.000 | | 0.1054 | 0.1029 | 0.058 |
| Cleveland, OH | R-Square | 1.38227 | -4.370 | Providence, RI | R-Square | 0.36683 | -1.790 |
| | 0.351 | <.0001 | 0.000 | | 0.0342 | 0.0035 | 0.070 |
| Columbus, OH | R-Square | 0.2217 | -3.740 | Raleigh, NC | R-Square | 0.62088 | -2.840 |
| | 0.018 | 0.2384 | 0.000 | | 0.181 | <.0001 | 0.005 |
| Dallas, TX | R-Square | 1.49796 | -2.460 | Richmond, VA | R-Square | 0.62246 | -2.690 |
| | 0.4751 | <.0001 | 0.014 | | 0.0645 | 0.0239 | 0.008 |
| Denver, CO | R-Square | 0.59377 | -2.600 | Riverside, CA | R-Square | 2.25597 | -1.320 |
| | 0.4962 | <.0001 | 0.010 | | 0.3107 | <.0001 | 0.170 |
| Detroit, MI | R-Square | -0.99407 | -1.660 | Sacramento, CA | R-Square | 2.24213 | -1.810 |
| | 0.1142 | 0.0023 | 0.092 | | 0.3871 | <.0001 | 0.067 |
| Hartford, CT | R-Square | 0.10297 | -2.900 | St Louis, MO | R-Square | -0.14395 | -3.580 |
| | 0.0031 | 0.6262 | 0.004 | | 0.012 | 0.3375 | 0.001 |
| Houston, TX | R-Square | 1.14374 | -3.870 | Salt Lake, City, UT | R-Square | 0.78256 | -2.370 |
| | 0.5119 | <.0001 | 0.000 | | 0.156 | 0.0003 | 0.018 |
| Indianapolis, IN | R-Square | 0.50933 | -3.770 | San Antonio, TX | R-Square | 0.48367 | -2.390 |
| | 0.1779 | 0.0001 | 0.000 | | 0.1504 | 0.0004 | 0.017 |
| Kansas City, MO | R-Square | -0.19535 | -2.280 | San Diego, CA | R-Square | 0.82972 | -1.950 |
| | 0.0153 | 0.2768 | 0.023 | | 0.2011 | <.0001 | 0.049 |
| Las Vegas, NV | R-Square | 2.3328 | -0.430 | San Francisco, CA | R-Square | 0.87745 | -3.880 |
| | 0.1918 | <.0001 | 0.525 | | 0.6054 | <.0001 | 0.000 |
| Los Angeles, CA | R-Square | 1.58714 | -2.140 | San Jose, CA | R-Square | 0.59616 | -3.080 |
| | 0.4476 | <.0001 | 0.032 | | 0.372 | <.0001 | 0.003 |
| Madison, WI | R-Square | 0.16783 | -2.640 | Santa Rosa, CA | R-Square | 0.64011 | -1.950 |
| | 0.0259 | 0.1564 | 0.009 | | 0.3623 | <.0001 | 0.049 |
| Miami, FL | R-Square | 2.18715 | -1.530 | Seattle, WA | R-Square | 0.59388 | -2.420 |
| | 0.1237 | 0.0015 | 0.117 | | 0.1305 | 0.0011 | 0.016 |
| Milwaukee, WI | R-Square | 0.35979 | -2.710 | Tampa, FL | R-Square | 3.67528 | -2.980 |
| | 0.0725 | 0.0164 | 0.007 | | 0.5367 | <.0001 | 0.003 |
| Minneapolis, MN | R-Square | 2.46843 | -2.170 | Honolulu, HI | R-Square | 0.16023 | -4.180 |
| | 0.3481 | <.0001 | 0.030 | | 0.0133 | 0.3117 | 0.000 |
| Nashville, TN | R-Square | 0.80638 | -2.430 | Virginia Beach, VA | R-Square | 0.34044 | -1.930 |
| | 0.2626 | <.0001 | 0.016 | | 0.0089 | 0.4073 | 0.052 |
| New York, NY | R-Square | 0.52041 | -2.370 | Washington, DC | R-Square | 0.48751 | -2.920 |
| | 0.1284 | 0.0012 | 0.018 | | 0.064 | 0.0245 | 0.004 |

| Table 3. Short Run Statisics | Eqn 5 ∆ B | Eqn 6 ∆ R | | Eqn 5 ∆ B | Eqn 6 ∆ R |
|---|---|---|---|---|---|
| Atlanta, GA | R-Square | R-Square | Oklahoma City, OK | R-Square | R-Square |
| | 0.8351 | 0.4296 | | 0.658 | 0.3769 |
| Austin, TX | R-Square | R-Square | Omaha, NE | R-Square | R-Square |
| | 0.5985 | 0.3174 | | 0.6032 | 0.4507 |
| Baltimore, MD | R-Square | R-Square | Orlando, FL | R-Square | R-Square |
| | 0.707 | 0.3445 | | 0.8258 | 0.8383 |
| Boston, MA | R-Square | R-Square | Oxnard, CA | R-Square | R-Square |
| | 0.7851 | 0.2713 | | 0.8784 | 0.2731 |
| Bridgeport/Stamford, CT | R-Square | R-Square | Philadelphia, PA | R-Square | R-Square |
| | 0.2936 | 0.0519 | | 0.6785 | 0.3811 |
| Charlotte, NC | R-Square | R-Square | Phoenix, AZ | R-Square | R-Square |
| | 0.5991 | 0.4856 | | 0.899 | 0.5126 |
| Chicago, IL | R-Square | R-Square | Pittsburgh, PA | R-Square | R-Square |
| | 0.694 | 0.1135 | | 0.2865 | 0.3309 |
| Cincinnati, OH | R-Square | R-Square | Portland, OR | R-Square | R-Square |
| | 0.5922 | 0.4614 | | 0.7643 | 0.5641 |
| Cleveland, OH | R-Square | R-Square | Providence, RI | R-Square | R-Square |
| | 0.2563 | 0.476 | | 0.8105 | 0.6917 |
| Columbus, OH | R-Square | R-Square | Raleigh, NC | R-Square | R-Square |
| | 0.5326 | 0.5907 | | 0.7632 | 0.2154 |
| Dallas, TX | R-Square | R-Square | Richmond, VA | R-Square | R-Square |
| | 0.801 | 0.656 | | 0.6666 | 0.3100 |
| Denver, CO | R-Square | R-Square | Riverside, CA | R-Square | R-Square |
| | 0.7616 | 0.5598 | | 0.8299 | 0.272 |
| Detroit, MI | R-Square | R-Square | Sacramento, CA | R-Square | R-Square |
| | 0.7112 | 0.3159 | | 0.8586 | 0.6142 |
| Hartford, CT | R-Square | R-Square | St Louis, MO | R-Square | R-Square |
| | 0.6213 | 0.1926 | | 0.6623 | 0.5103 |
| Houston, TX | R-Square | R-Square | Salt Lake, City, UT | R-Square | R-Square |
| | 0.6511 | 0.4685 | | 0.7564 | 0.2137 |
| Indianapolis, IN | R-Square | R-Square | San Antonio, TX | R-Square | R-Square |
| | 0.6663 | 0.545 | | 0.6696 | 0.7672 |
| Kansas City, MO | R-Square | R-Square | San Diego, CA | R-Square | R-Square |
| | 0.7651 | 0.4155 | | 0.8828 | 0.4188 |
| Las, Vegas, NV | R-Square | R-Square | San Francisco, CA | R-Square | R-Square |
| | 0.9402 | 0.747 | | 0.8381 | 0.7689 |
| Los Angeles, CA | R-Square | R-Square | San Jose, CA | R-Square | R-Square |
| | 0.9047 | 0.6843 | | 0.7504 | 0.6734 |
| Madison, WI | R-Square | R-Square | Santa Rosa, CA | R-Square | R-Square |
| | 0.6052 | 0.477 | | 0.8966 | 0.6393 |
| Miami, FL | R-Square | R-Square | Seattle, WA | R-Square | R-Square |
| | 0.8115 | 0.444 | | 0.7391 | 0.5989 |
| Milwaukee, WI | R-Square | R-Square | Tampa, FL | R-Square | R-Square |
| | 0.4383 | 0.5645 | | 0.7995 | 0.2148 |
| Minneapolis, MN | R-Square | R-Square | Urban Honolulu, HI | R-Square | R-Square |
| | 0.8954 | 0.2655 | | 0.4336 | 0.4943 |
| Nashville, TN | R-Square | R-Square | Virginia, Beach, VA | R-Square | R-Square |
| | 0.7814 | 0.6005 | | 0.7651 | 0.2436 |
| New York, NY | R-Square | R-Square | Washington, DC | R-Square | R-Square |
| | 0.6813 | 0.3631 | | 0.7415 | 0.5227 |

| Table 4.a | Equation 5 Δ Buy equation coefficients and significance tests | | | | |
|---|---|---|---|---|---|
| VECM Results | Intercept | $LogB/R_{t-12}$ | $\%\Delta B_{t-3}$ | $\%\Delta R_{t-3}$ | $ITS_{t-12}$ |
| Atlanta, GA | 1.515 | -0.217 | 0.602 | 1.510 | -0.007 |
| | 0.001 | 0.002 | 0.000 | 0.003 | 0.050 |
| | Sig* | Sig* | Sig* | Sig* | Sig** |
| Austin, TX | 4.750 | -0.682 | 0.130 | 0.288 | -0.013 |
| | 0.000 | 0.000 | 0.308 | 0.225 | 0.001 |
| | Sig* | Sig* | | | Sig* |
| Baltimore, MD | 4.423 | -0.647 | 0.000 | -0.097 | -0.013 |
| | 0.000 | 0.000 | 0.998 | 0.549 | 0.024 |
| | Sig* | Sig* | | | Sig* |
| Boston, MA | 1.768 | -0.255 | 0.617 | 0.278 | -0.003 |
| | 0.000 | 0.000 | 0.000 | 0.014 | 0.164 |
| | Sig* | Sig* | Sig* | Sig* | |
| Stamford, CT | 2.387 | -0.342 | 0.230 | -0.128 | -0.004 |
| | 0.010 | 0.010 | 0.145 | 0.565 | 0.361 |
| | Sig* | Sig* | | | |
| Charlotte, NC | 2.238 | -0.331 | 0.487 | 0.140 | -0.002 |
| | 0.000 | 0.001 | 0.000 | 0.564 | 0.274 |
| | Sig* | Sig* | Sig* | | |
| Chicago, IL | 2.664 | -0.394 | 0.538 | -0.017 | -0.004 |
| | 0.000 | 0.000 | 0.000 | 0.947 | 0.020 |
| | Sig* | Sig* | Sig* | | Sig* |
| Cincinnati, OH | 2.181 | -0.327 | 0.483 | 0.438 | 0.000 |
| | 0.157 | 0.141 | 0.001 | 0.076 | 0.996 |
| | | | Sig* | Sig** | |
| Cleveland, OH | 1.664 | -0.243 | 0.260 | 0.310 | -0.008 |
| | 0.105 | 0.105 | 0.108 | 0.418 | 0.316 |
| | | | | | |
| Columbus, OH | 1.512 | -0.222 | 0.571 | 0.110 | 0.000 |
| | 0.001 | 0.001 | 0.005 | 0.407 | 0.545 |
| | Sig* | Sig* | Sig* | | |
| Dallas, TX | 4.253 | -0.620 | 0.317 | 0.156 | -0.019 |
| | 0.000 | 0.000 | 0.000 | 0.249 | 0.000 |
| | Sig* | Sig* | Sig* | | Sig* |
| Denver, CO | 2.696 | -0.391 | 0.453 | 0.252 | -0.008 |
| | 0.000 | 0.000 | 0.000 | 0.045 | 0.010 |
| | Sig* | Sig* | Sig* | Sig* | Sig* |
| Detroit, MI | 2.093 | -0.273 | 0.373 | 0.238 | -0.041 |
| | 0.000 | 0.000 | 0.000 | 0.151 | 0.000 |
| | Sig* | Sig* | Sig* | | Sig* |
| Hartford, CT | 3.677 | -0.531 | 0.381 | -0.167 | -0.011 |
| | 0.002 | 0.002 | 0.004 | 0.311 | 0.062 |
| | Sig* | Sig* | Sig* | | Sig** |
| Houston, TX | 3.806 | -0.566 | 0.198 | 0.413 | -0.011 |
| | 0.000 | 0.000 | 0.070 | 0.001 | 0.000 |
| | Sig* | Sig* | Sig** | Sig* | Sig* |
| Indianapolis, IN | 7.924 | -1.165 | 0.169 | -0.026 | -0.012 |
| | 0.000 | 0.000 | 0.148 | 0.885 | 0.002 |
| | Sig* | Sig* | | | Sig* |
| Kansas City, MO | 5.463 | -0.768 | 0.301 | 0.610 | -0.026 |
| | 0.000 | 0.000 | 0.010 | 0.008 | 0.001 |
| | Sig* | Sig* | Sig* | Sig* | Sig* |

| Table 4.b | **Equation 5 Δ Buy equation coefficients and significance tests** | | | | |
|---|---|---|---|---|---|
| VECM Results | Intercept | $LogB/R_{t-12}$ | $\%\Delta B_{t-3}$ | $\%\Delta R_{t-3}$ | $ITS_{t-12}$ |
| Las Vegas, NV | 2.900 | -0.403 | 0.445 | 0.366 | -0.054 |
| | 0.000 | 0.000 | 0.000 | 0.285 | 0.000 |
| | Sig* | Sig* | Sig* | | Sig* |
| Los Angeles, CA | 4.246 | -0.601 | 0.420 | 0.464 | -0.017 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | Sig* | Sig* | Sig* | Sig* | Sig* |
| Madison, WI | 3.668 | -0.521 | 0.122 | -0.130 | -0.010 |
| | 0.000 | 0.000 | 0.408 | 0.232 | 0.001 |
| | Sig* | Sig* | | | Sig* |
| Miami, FL | 1.622 | -0.235 | 0.577 | -0.124 | -0.012 |
| | 0.000 | 0.000 | 0.000 | 0.667 | 0.000 |
| | Sig* | Sig* | Sig* | | Sig* |
| Milwaukee, WI | 3.617 | -0.525 | 0.104 | 0.218 | -0.018 |
| | 0.000 | 0.000 | 0.512 | 0.225 | 0.001 |
| | Sig* | Sig* | | | Sig* |
| Minneapolis, MN | 3.595 | -0.519 | 0.376 | -0.746 | -0.027 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | Sig* | Sig* | Sig* | Sig* | Sig* |
| Nashville, TN | 5.819 | -0.852 | -0.088 | 0.107 | -0.033 |
| | 0.000 | 0.000 | 0.469 | 0.360 | 0.000 |
| | Sig* | Sig* | | | Sig* |
| New York, NY | 6.680 | -0.947 | -0.197 | 0.915 | -0.009 |
| | 0.000 | 0.000 | 0.185 | 0.002 | 0.001 |
| | Sig* | Sig* | | Sig* | Sig* |
| Oklahoma City, OK | 3.771 | -0.559 | 0.116 | -0.443 | -0.029 |
| | 0.001 | 0.001 | 0.433 | 0.032 | 0.011 |
| | Sig* | Sig* | | Sig* | Sig* |
| Omaha, NE | 4.786 | -0.699 | 0.196 | -0.115 | -0.031 |
| | 0.001 | 0.001 | 0.237 | 0.430 | 0.011 |
| | Sig* | Sig* | | | Sig* |
| Orlando, FL | 1.705 | -0.268 | 0.475 | 1.654 | -0.001 |
| | 0.005 | 0.003 | 0.000 | 0.002 | 0.947 |
| | Sig* | Sig* | Sig* | Sig* | |
| Oxnard, CA | 6.043 | -0.860 | 0.270 | -0.758 | -0.016 |
| | 0.000 | 0.000 | 0.003 | 0.116 | 0.036 |
| | Sig* | Sig* | Sig* | | Sig* |
| Philadelphia, PA | 2.763 | -0.410 | 0.413 | 0.140 | -0.008 |
| | 0.000 | 0.000 | 0.000 | 0.347 | 0.003 |
| | Sig* | Sig* | Sig* | | Sig* |
| Phoenix, AZ | 2.401 | -0.353 | 0.640 | 0.756 | -0.020 |
| | 0.000 | 0.000 | 0.000 | 0.001 | 0.021 |
| | Sig* | Sig* | Sig* | Sig* | Sig* |
| Pittsburgh, PA | 1.371 | -0.196 | 0.214 | 0.303 | -0.007 |
| | 0.195 | 0.205 | 0.218 | 0.043 | 0.215 |
| | | | | Sig* | |
| Providence, RI | 3.299 | -0.474 | 0.301 | 0.274 | -0.022 |
| | 0.000 | 0.000 | 0.029 | 0.002 | 0.000 |
| | Sig* | Sig* | Sig* | Sig* | Sig* |
| Portland, OR | 2.745 | -0.394 | 0.559 | 0.029 | -0.002 |
| | 0.000 | 0.000 | 0.000 | 0.872 | 0.482 |
| | Sig* | Sig* | Sig* | | |

| Table 4.c | Equation 5 Δ Buy equation coefficients and significance tests | | | | |
|---|---|---|---|---|---|
| VECM Results | Intercept | $LogB/R_{t-12}$ | $\%\Delta B_{t-3}$ | $\%\Delta R_{t-3}$ | $ITS_{t-12}$ |
| Raleigh, NC | 7.286 | -1.097 | -0.042 | -0.045 | -0.012 |
| | 0.000 | 0.000 | 0.731 | 0.871 | 0.008 |
| | Sig* | Sig* | | | Sig* |
| Richmond, VA | 5.460 | -0.792 | 0.083 | 0.198 | -0.011 |
| | 0.000 | 0.000 | 0.520 | 0.487 | 0.004 |
| | Sig* | Sig* | | | Sig* |
| Riverside, CA | 1.794 | -0.260 | 0.646 | 0.738 | -0.011 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.104 |
| | Sig* | Sig* | Sig* | Sig* | |
| Sacramento, CA | 2.472 | -0.347 | 0.648 | -0.084 | -0.038 |
| | 0.000 | 0.000 | 0.000 | 0.800 | 0.010 |
| | Sig* | Sig* | Sig* | | Sig* |
| St Louis, MO | 4.499 | -0.613 | -0.005 | -0.063 | -0.045 |
| | 0.001 | 0.000 | 0.179 | 0.796 | 0.001 |
| | Sig* | Sig* | | | Sig* |
| Salt Lake City | -0.034 | -0.782 | 0.388 | -0.446 | n/a |
| | 0.001 | 0.000 | 0.000 | 0.375 | n/a |
| | Sig* | Sig* | Sig* | | |
| San Antonio, TX | 4.063 | -0.592 | 0.301 | 0.216 | -0.021 |
| | 0.000 | 0.000 | 0.056 | 0.114 | 0.009 |
| | Sig* | Sig* | Sig** | | Sig* |
| San Diego, CA | 4.464 | -0.629 | 0.214 | -0.105 | -0.027 |
| | 0.000 | 0.000 | 0.082 | 0.603 | 0.007 |
| | Sig* | Sig* | Sig** | | Sig* |
| San Francisco, CA | 3.247 | -0.433 | 0.416 | 0.072 | -0.029 |
| | 0.000 | 0.000 | 0.000 | 0.353 | 0.000 |
| | Sig* | Sig* | Sig* | | Sig* |
| San Jose, CA | 3.208 | -0.430 | 0.270 | -0.291 | -0.023 |
| | 0.000 | 0.000 | 0.011 | 0.020 | 0.001 |
| | Sig* | Sig* | Sig* | Sig* | Sig* |
| Santa Rosa, CA | 7.543 | -1.061 | 0.350 | 0.489 | -0.052 |
| | 0.000 | 0.000 | 0.000 | 0.007 | 0.000 |
| | Sig* | Sig* | Sig* | Sig* | Sig* |
| Seattle, WA | 2.515 | -0.350 | 0.404 | 0.026 | -0.010 |
| | 0.000 | 0.000 | 0.000 | 0.866 | 0.002 |
| | Sig* | Sig* | Sig* | | Sig* |
| Tampa, FL | 2.549 | -0.383 | 0.511 | 0.356 | -0.019 |
| | 0.000 | 0.000 | 0.000 | 0.281 | 0.004 |
| | Sig* | Sig* | Sig* | | Sig* |
| Honolulu, HI | 0.348 | -0.775 | 0.174 | 0.093 | n/a |
| | 0.000 | 0.000 | 0.092 | 0.585 | n/a |
| | Sig* | Sig* | Sig** | | |
| Virginia Beach, VA | 5.982 | -0.872 | -0.047 | -0.010 | -0.027 |
| | 0.000 | 0.000 | 0.713 | 0.961 | 0.000 |
| | Sig* | Sig* | | | Sig* |
| Washington, DC | 3.294 | -0.464 | 0.489 | 0.279 | -0.020 |
| | 0.000 | 0.000 | 0.000 | 0.200 | 0.002 |
| | Sig* | Sig* | Sig* | | Sig* |

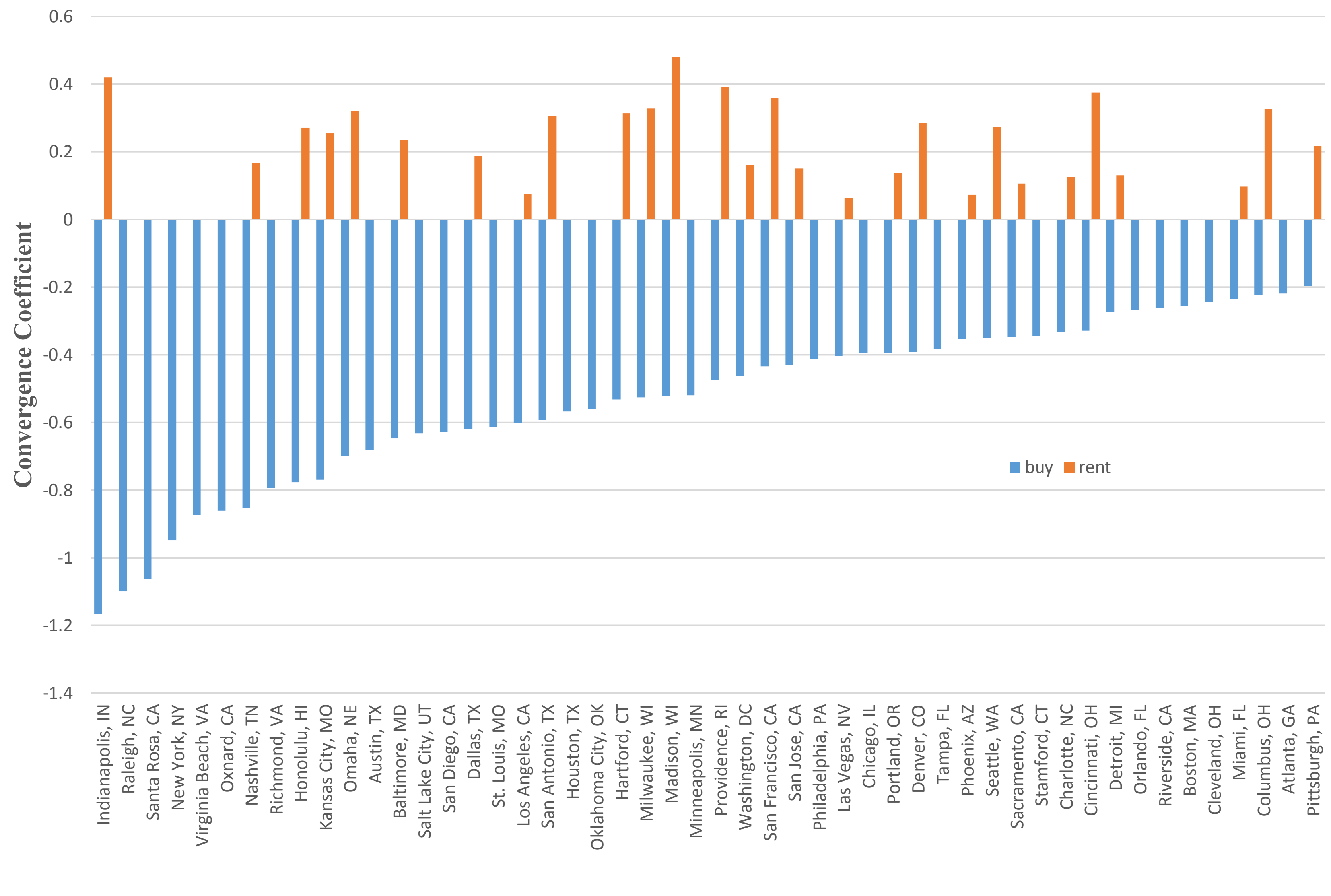
| Table 5.a | Equation 6 ∆ Rent equation coefficients and significance tests | | | | |
|---|---|---|---|---|---|
| VECM Results | Intercept | $LogB/R_{t-12}$ | $\%\Delta B_{t-3}$ | $\%\Delta R_{t-3}$ | $Vac_{t-9}$ |
| Atlanta, GA | 0.034 | -0.012 | -0.002 | 0.351 | -0.004 |
| | 0.018 | 0.562 | 0.895 | 0.018 | 0.003 |
| | | | | Sig* | Sig* |
| Austin, TX | 0.023 | -0.103 | -0.022 | 0.416 | 0.000 |
| | 0.132 | 0.195 | 0.779 | 0.000 | 0.874 |
| | | | | Sig* | |
| Baltimore, MD | 0.092 | 0.234 | -0.068 | 0.593 | -0.003 |
| | 0.069 | 0.017 | 0.471 | 0.000 | 0.392 |
| | | Sig* | | Sig* | |
| Boston, MA | -0.013 | 0.044 | -0.230 | 0.356 | 0.007 |
| | 0.560 | 0.506 | 0.004 | 0.002 | 0.078 |
| | | | Sig* | Sig* | Sig** |
| Stamford, CT | 0.031 | 0.040 | -0.029 | 0.354 | -0.003 |
| | 0.212 | 0.600 | 0.717 | 0.016 | 0.410 |
| | | | | Sig* | |
| Charlotte, NC | 0.059 | 0.126 | -0.066 | 0.613 | -0.002 |
| | 0.007 | 0.021 | 0.207 | 0.000 | 0.170 |
| | | Sig* | | Sig* | |
| Chicago, IL | 0.010 | 0.052 | 0.025 | 0.311 | 0.000 |
| | 0.719 | 0.255 | 0.567 | 0.027 | 0.902 |
| | | | | Sig* | |
| Cincinnati, OH | 0.215 | 0.376 | 0.036 | 0.410 | -0.010 |
| | 0.000 | 0.000 | 0.641 | 0.000 | 0.001 |
| | | Sig* | | Sig* | Sig* |
| Cleveland, OH | 0.052 | 0.060 | 0.007 | 0.640 | -0.003 |
| | 0.169 | 0.261 | 0.921 | 0.000 | 0.322 |
| | | | | Sig* | |
| Columbus, OH | 0.068 | 0.327 | -0.079 | 0.493 | -0.001 |
| | 0.023 | 0.000 | 0.473 | 0.000 | 0.896 |
| | | Sig* | | Sig* | |
| Dallas, TX | 0.075 | 0.188 | -0.119 | 0.631 | -0.002 |
| | 0.001 | 0.001 | 0.028 | 0.000 | 0.362 |
| | | Sig* | Sig* | Sig* | |
| Denver, CO | 0.151 | 0.286 | 0.033 | 0.290 | -0.014 |
| | 0.000 | 0.001 | 0.613 | 0.023 | 0.000 |
| | | Sig* | | Sig* | Sig* |
| Detroit, MI | -0.018 | 0.130 | 0.021 | 0.359 | 0.002 |
| | 0.722 | 0.020 | 0.697 | 0.001 | 0.686 |
| | | Sig* | | Sig* | |
| Hartford, CT | 0.116 | 0.314 | 0.193 | 0.196 | -0.007 |
| | 0.001 | 0.001 | 0.036 | 0.074 | 0.016 |
| | | Sig* | Sig* | Sig** | Sig* |
| Houston, TX | 0.152 | 0.136 | -0.232 | 0.263 | -0.006 |
| | 0.000 | 0.188 | 0.017 | 0.036 | 0.005 |
| | | | Sig* | Sig* | Sig* |
| Indianapolis, IN | 0.178 | 0.421 | 0.033 | 0.421 | -0.007 |
| | 0.000 | 0.000 | 0.701 | 0.000 | 0.014 |
| | | Sig* | | Sig* | Sig* |
| Kansas City, MO | -0.002 | 0.255 | -0.054 | 0.337 | 0.001 |
| | 0.951 | 0.000 | 0.443 | 0.003 | 0.701 |
| | | Sig* | | Sig* | |

| Table 5.b | Equation 6 Δ Rent equation coefficients and significance tests | | | | |
|---|---|---|---|---|---|
| VECM Results | Intercept | $LogB/R_{t-12}$ | $\%\Delta B_{t-3}$ | $\%\Delta R_{t-3}$ | $Vac_{t-9}$ |
| Las Vegas, NV | 0.016 | 0.063 | 0.067 | 0.378 | 0.001 |
| | 0.334 | 0.000 | 0.000 | 0.000 | 0.492 |
| | | Sig* | Sig* | Sig* | |
| Los Angeles, CA | 0.063 | 0.077 | -0.051 | 0.669 | -0.011 |
| | 0.001 | 0.057 | 0.131 | 0.000 | 0.001 |
| | | Sig** | | Sig* | Sig* |
| Madison, WI | 0.058 | 0.481 | 0.109 | 0.452 | n/a |
| | 0.000 | 0.000 | 0.286 | 0.000 | n/a |
| | | Sig* | | Sig* | |
| Miami, FL | 0.102 | 0.097 | -0.003 | 0.146 | -0.005 |
| | 0.000 | 0.003 | 0.945 | 0.255 | 0.113 |
| | | Sig* | | | |
| Milwaukee, WI | 0.089 | 0.329 | -0.099 | 0.535 | -0.001 |
| | 0.001 | 0.000 | 0.375 | 0.000 | 0.830 |
| | | Sig* | | Sig* | |
| Minneapolis, MN | 0.063 | 0.048 | 0.015 | 0.099 | -0.008 |
| | 0.001 | 0.166 | 0.608 | 0.413 | 0.001 |
| | | | | | Sig* |
| Nashville, TN | 0.075 | 0.169 | -0.055 | 0.681 | 0.000 |
| | 0.005 | 0.031 | 0.493 | 0.000 | 0.973 |
| | | Sig* | | Sig* | |
| New York, NY | -0.003 | -0.200 | -0.134 | 0.529 | 0.005 |
| | 0.924 | 0.012 | 0.049 | 0.000 | 0.375 |
| | | Sig* | Sig* | Sig* | |
| Oklahoma City, OK | 0.201 | 0.333 | -0.024 | 0.429 | -0.002 |
| | 0.001 | 0.001 | 0.807 | 0.001 | 0.616 |
| | | Sig* | | Sig* | |
| Omaha, NE | 0.185 | 0.320 | 0.007 | 0.413 | -0.010 |
| | 0.000 | 0.001 | 0.948 | 0.000 | 0.001 |
| | | Sig* | | Sig* | Sig* |
| Orlando, FL | 0.035 | -0.006 | -0.023 | 0.796 | -0.002 |
| | 0.006 | 0.700 | 0.141 | 0.000 | 0.011 |
| | | | | Sig* | Sig* |
| Oxnard, CA | 0.013 | 0.001 | 0.013 | 0.522 | n/a |
| | 0.003 | 0.986 | 0.726 | 0.000 | n/a |
| | | | | Sig* | |
| Philadelphia, PA | 0.018 | 0.067 | 0.146 | 0.381 | 0.000 |
| | 0.653 | 0.377 | 0.085 | 0.003 | 0.936 |
| | | | Sig** | Sig* | |
| Phoenix, AZ | 0.065 | 0.074 | -0.010 | 0.548 | -0.002 |
| | 0.005 | 0.001 | 0.711 | 0.000 | 0.132 |
| | | Sig* | | Sig* | |
| Pittsburgh, PA | 0.055 | 0.218 | -0.105 | 0.197 | 0.004 |
| | 0.131 | 0.003 | 0.341 | 0.074 | 0.389 |
| | | Sig* | | Sig** | |
| Portland, OR | -0.009 | 0.138 | 0.097 | 0.700 | 0.007 |
| | 0.545 | 0.001 | 0.018 | 0.000 | 0.065 |
| | | Sig* | Sig* | Sig* | Sig** |
| Providence, RI | 0.188 | 0.390 | -0.181 | 0.415 | -0.012 |
| | 0.000 | 0.000 | 0.091 | 0.000 | 0.042 |
| | | Sig* | Sig** | Sig* | Sig* |

| Table 5.c | Equation 6 Δ Rent equation coefficients and significance tests | | | | |
|---|---|---|---|---|---|
| VECM Results | Intercept | $LogB/R_{t-12}$ | $\%\Delta B_{t-3}$ | $\%\Delta R_{t-3}$ | $Vac_{t-9}$ |
| Raleigh, NC | 0.054 | 0.041 | -0.143 | 0.387 | -0.003 |
| | 0.080 | 0.618 | 0.025 | 0.002 | 0.022 |
| | | | Sig* | Sig* | Sig* |
| Richmond, VA | 0.044 | 0.005 | -0.004 | 0.299 | -0.002 |
| | 0.011 | 0.922 | 0.942 | 0.020 | 0.076 |
| | | | | Sig* | Sig** |
| Riverside, CA | 0.022 | 0.053 | -0.043 | 0.803 | 0.000 |
| | 0.258 | 0.175 | 0.222 | 0.000 | 0.890 |
| | | | | Sig* | |
| Sacramento, CA | 0.045 | 0.106 | 0.052 | 0.367 | -0.003 |
| | 0.005 | 0.000 | 0.002 | 0.002 | 0.108 |
| | | Sig* | Sig* | Sig* | |
| St Louis, MO | -0.008 | 0.286 | -0.029 | 0.381 | 0.003 |
| | 0.816 | 0.000 | 0.674 | 0.000 | 0.306 |
| | | Sig* | | Sig* | |
| Salt Lake City, UT | 0.013 | 0.092 | -0.005 | 0.398 | n/a |
| | 0.016 | 0.120 | 0.921 | 0.001 | n/a |
| | | | | Sig* | |
| San Antonio, TX | 0.190 | 0.307 | -0.227 | 0.326 | -0.008 |
| | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 |
| | | Sig* | Sig* | Sig* | Sig* |
| San Diego, CA | 0.084 | -0.033 | -0.125 | 0.502 | -0.011 |
| | 0.001 | 0.570 | 0.023 | 0.000 | 0.003 |
| | | | Sig* | Sig* | Sig* |
| San Francisco, CA | 0.048 | 0.360 | 0.056 | 0.375 | -0.030 |
| | 0.224 | 0.000 | 0.462 | 0.000 | 0.000 |
| | | Sig* | | Sig* | Sig* |
| San Jose, CA | 0.062 | 0.152 | 0.016 | 0.417 | -0.014 |
| | 0.006 | 0.015 | 0.772 | 0.000 | 0.000 |
| | | Sig* | | Sig* | Sig* |
| Santa Rosa, CA | 0.026 | 0.034 | 0.169 | 0.498 | n/a |
| | 0.000 | 0.378 | 0.000 | 0.000 | n/a |
| | | | Sig* | Sig* | |
| Seattle, WA | 0.016 | 0.273 | 0.059 | 0.590 | -0.006 |
| | 0.393 | 0.000 | 0.294 | 0.000 | 0.063 |
| | | Sig* | | Sig* | Sig** |
| Tampa, FL | -0.018 | -0.014 | 0.063 | 0.336 | 0.001 |
| | 0.447 | 0.699 | 0.094 | 0.031 | 0.488 |
| | | | Sig** | Sig* | |
| Honolulu, HI | -0.065 | 0.271 | 0.011 | 0.487 | -0.005 |
| | 0.190 | 0.002 | 0.875 | 0.000 | 0.379 |
| | | Sig* | | Sig* | |
| Virginia Beach, VA | 0.010 | 0.020 | -0.117 | 0.354 | -0.001 |
| | 0.526 | 0.682 | 0.067 | 0.005 | 0.626 |
| | | | Sig** | Sig* | |
| Washington, DC | 0.014 | 0.163 | -0.055 | 0.315 | -0.001 |
| | 0.315 | 0.000 | 0.127 | 0.004 | 0.684 |
| | | Sig* | | Sig* | |

**Chart 9. Convergence Coefficients For Buy And Rent Equations**

(coefficients must be the right sign, absolute value < 1 and significant, 47 buy and 30 rent meet these requirements)



| Table 6.a B/R Results From Equation 7 | | |
|---|---|---|
| | R-Square | 0.29 |
| | estimate | Pr > \|t\| |
| Intercept | 0.246 | 0.558 |
| renter credit score | 0.001 | 0.081 |
| supply elasticity | -0.124 | 0.007 |
| snow | -0.002 | 0.156 |
| Date: Jul-15, 49 observations. | | |

| Table 6.b B/R Results From Equation 7 | | |
|---|---|---|
| | R-Square | 0.29 |
| | estimate | Pr > \|t\| |
| Intercept | -0.025 | 0.398 |
| renter credit score | 0.001 | 0.001 |
| supply elasticity | -0.089 | 0.041 |
| snow | -0.002 | 0.001 |
| Date: Oct-16, 49 observations. | | |