NOISE TRADERS, DISTANT SPECULATORS AND ASSET BUBBLES IN THE HOUSING MARKET

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Abstract. Starting with the seminal work of Black (1985 [8]) and De Long et. al (1990 [36]), financial economists have studied the impact of less informed or irrational investors (so-called "noise traders") on mis-pricing. Empirical evidence on noise traders, however, suffers from the twin difficulties of identifying noise traders and demonstrating their impact on asset prices. In this paper we study the price impact of adding noise traders in the form of distant speculators to a financial market using unique transactions level data on US residential housing. Distant purchasers may be less informed about local housing market conditions and prone to excessive reliance on capital appreciation in earning a financial return. Our evidence shows that out of town, but not local, speculators, purchase houses at times and in markets when prices are rising rapidly. Next we show that adding out of town speculators to a market causes excess house price appreciation using a novel experimental design. We also demonstrate that out of town speculators likely earn lower returns than local purchasers. We conjecture that large inflows of distant speculators might help signal newly forming bubbles and outline how our identification strategy can be used to identify potential bubbles in other settings with segmented asset markets.

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1. Introduction

How do bubbles form? Beginning with the work of Black (1985 [8]) and De Long et al. (1990 [36]), many authors have conjectured that uninformed or overconfident speculators have the potential to destablize financial markets and create bubbles. So-called rational investors cannot necessarily restore equilibrium because of binding capital constraints (Schleifer and Vishny (1997 [54])) or because of short sale constraints or a limited supply of tradeable shares (Scheinkman and Xiong (2003 [50], Ofek and Richardson (2003 [45]), and Hong et al. (2006 [30]), for example).

Empirical tests of models that rely on the existence of a well-defined group of noise traders face the problem of not only identifying who the noise traders are but also showing that the existence of noise traders *causes* prices to diverge from fundamental values. This is a tall order using standard financial datasets and econometric tools. So far, the evidence has been mixed. Many studies such as Baker and Wurgler (2006 [4]) suggest that psychological biases such as overconfidence are widespread within the population. But some authors have suggested that individual investors might suffer from overconfidence more than institutional investors and also that individual investors might earn lower returns. However, recent results from Kelley and Tetlock (2011 [34]) show that, if anything, some retail investors appear to earn positive excess returns without evidence of subsequent reversal. Thus retail investors may not exhibit the tendencies often attributed to noise traders. Further complicating the challenge of identifying noise traders, studies of hedge fund trading during the dot com boom do not appear to support the simple hypothesis that these institutional investors are serving as arbitrageurs fighting mispricing by irrational individual investors. For example, Brunnermeier and Nagel (2004 [11]) show that many large funds attempted to time the market to earn excess returns during the run-up rather than just selling when prices appeared to be above fundamental values.

We take a different approach to examining the impact of noise traders on mispricing in examining evidence from the housing boom of the 2000s. The US residential housing market is an excellent laboratory to study bubble formation given the recent boom/bust cycle. We identify out of town buyers as a group of speculators who resemble the definition of noise traders in theoretical papers. These distant purchasers are likely less informed than local investors and also rely to a greater extent on capital gains to earn financial returns relative to local investors.[1] After all, distant investors face higher costs of investment, including travel to examine properties for sale and surrounding neighborhoods and the tendency to rely more heavily on the advice of possibly conflicted real estate agents. Out of town investors also face a tax disadvantage relative to owner-occupants. Of course, out of town investors may also benefit from portfolio diversification relative to investing in their local community. Nonetheless, distant speculators are a well defined group of traders who are likely more susceptible to overconfidence or irrational exuberance when house prices start to rise. Our approach is similar to that in Greenwood and Nagel(2008), who identify inexperienced (younger) fund managers as contributors to the internet bubble by purchasing more internet stocks relative to their style focus during the price run-up and decrease them during the decline. We extend this approach to examine the causality of such trading by distant investors on home prices.[2]

We examine mispricing in the housing market using a unique dataset on individual single family housing transactions in ten metropolitan areas from 2000 to 2008. These data report the date, price, mortgage amount, and address of all property sales along with the mailing address to send the property tax bill. The property tax address serves as a proxy for the location of the new owner, allowing us to identify owner occupants, local investors, and distant speculators, defined as buyers who live in another metropolitan area.

In addition to our ability to identify a well-defined group of investors who might behave as noise traders, we see a number of other advantages in examining bubbles in the housing market relative to the stock market. By studying the US residential housing market, we are able to employ a proxy for mispricing via the user cost model as in Himmelberg et al. (2005 [28]) rather than just using past price appreciation to measure mispricing. Housing markets

[1]Distant speculators have recently been linked to boom bust cycles in other asset markets as well. For instance, see Bruno and Shin (2011 [53]) who look at capital flows between international banks in conjunction with the credit crisis.

[2]Our approach is also related to research showing that asset prices can reflect heterogenous opinions of investors. See recent work by Xiong and Yan (2011), for example, who examine the impact of heterogenous beliefs on bond prices and also summarize previous literature in this area.

have exhibited appreciable cross-sectional differences in mispricing, helping us to isolate factors that vary across markets while holding constant macro economic and credit market factors such as interest rates and subprime lending. Evidence from the 2000s shows very large mispricing in some markets such as Las Vegas and Phoenix, while other midwestern and southern markets exhibited much lower rates of housing appreciation and less mispricing during the boom. Coastal markets also exhibited very high price appreciation during the boom, but many of these markets have exhibited above-average rates of house appreciation for decades (Gyourko, Mayer and Sinai 2006 [25]), which might account for some portion of the high rates of appreciation in the recent boom.

Our evidence comes from several different specifications. In Section 3 we estimate a three variable VAR with change in log house prices, the share of local investors, and the share of distant speculators. The results show that house price appreciation is strongly correlated with the lagged share of distant speculators (our proxy for noise traders), but not with the lagged share of local investors (the share of owner-occupants is the excluded variable). A 1% increase in the share of distant speculators is correlated with a 0.92% increase in house prices in the following year. The share of distant speculators is uncorrelated with lagged house price appreciation or the lagged share of the local investors. Similarly, the share of local investors is uncorrelated with lagged house price appreciation or the lagged share of distant speculators. We get a similar strong correlation with mispricing and distant speculators when we use the ratio of implied rent to actual rent, a variable derived from the user cost model, as our measure of mispricing. While the results from the VAR do not demonstrate causality, these findings suggest a strong correlation between out of town investors and subsequent house price appreciation and overpricing.

In Section 4,we take advantage of the segmentation in the US residential housing market to help determine the causal effect of increasing distant speculator investment intensity on local house price appreciation rates using the Front Door Criterion ntroduced in Pearl (2000 [46]).[3] We face the problem that our noise traders endogenously select which markets to

[3]Cohen and Malloy (2010 [15]) have used this approach to identify the impact of personal connections on Congressional voting decisions.

enter. The standard econometric solution to this causal inference problem is to instrument for subject group assignment–that is, to find instruments for distant investor participation that are uncorrelated with mispricing.

We follow an alternative instrumental variables approach. We want to test the hypothesis increasing the fraction of distant speculators that decide to enter a housing market causes mispricing to rise. An alternative hypothesis is that there exists some other factor that causes the investment choices of distant speculators and mispricing to co-move.[4] To discriminate between these two hypotheses, we instrument for the responsiveness of house price appreciation rates to an increase in trading interest from distant speculators. Our instrumental variable is variation in the size of the investor city j relative to the purchase city i. i.e., we show that after controlling for observable variation, a given percentage flow of investors from a large housing market to a small market will lead to a bigger impact on house prices than the equivalent percentage flow from a small market to a large market.[5] Under the alternative hypothesis where an omitted variable causes distant speculator investment intensity and local house price appreciation rates to rise and fall at the same time, the volume of distant speculators should have no effect.

Our evidence is consistent with a causal relationship between an increased fraction of out of town investors and greater mispricing. We show that 1% increase in the fraction of investors from city j is correlated with a 0.41% increase in the implied rent-to-actual rent ratio (e.g., mispricing of house prices relative to rents). This point estimate captures the overall correlation between distant investor purchases and mispricing. We also include an interaction term between the relative size of cities i and j when investors come from city i to invest in city j. The coefficient on this interaction term is also large and statistically significant. The impact of a high fraction of investors in city i purchasing in city j has more than twice the impact on mispricing in city j when city i is much larger than city i. We

[4]For instance, Friedman (1953 [18]) argues that speculative trading might be more profitable in over-priced markets, so the investment decisions of speculators and the level of mis-pricing might positively covary even if speculative trading in fact helps stabilize prices.

[5]Our key identifying assumption is that noise traders living in larger cities do not differentially invest in mis-priced markets relative to noise traders living in smaller cities.

interpret these findings as showing the out of town investors cause house prices to rise in distant cities when they invest in appreciable scale.

In section 5, we consider how our analysis relates to several alternative theories of bubble formation and mispricing. During the recent housing crisis, the most severe mispricing occurred in markets with the fewest constraints on building new homes, suggesting supply constraints did not play a critical role in exacerbating housing bubbles in this most recent episode. As well, we demonstrate that the investments by distant speculators performed quite poorly relative to local speculators and owner-occupants. In particular, distant speculators purchased at times when mispricing in the housing market was especially severe and house prices were rising rapidly. Our results do not directly speak to the question of whether lower credit standards for subprime loans contributed to mispricing and speculation. The fact that housing bubbles were quite pronounced in some markets and absent in others suggests that subprime lending was not sufficient to have caused the bubble on its own. On the other hand, subprime lending might have facilitated distant speculators purchasing at times when it was otherwise uneconomical.

We conclude by conjecturing that inflows of "distant" speculators might serve as a mechanism to signal newly forming bubbles in asset markets. These findings are consistent with the results by other authors that home biased stock market investors appear to get higher returns than investors who purchase stocks in foreign markets. As well, we suggest that our identification strategy can be used in many other asset pricing settings in which there exists panel data due to market segmentation. This includes studies of local versus foreign buyers in commercial real estate and stock markets.

2. Identifying Housing Bubbles, Distant Speculators and Noise Traders

We identify distant speculators who do not live in the same city in which they purchase their home as noise traders in the US residential housing market. We proceed as follows. First, in Section 2.1 we define mispricing of single-family homes and the previous literature on housing bubbles. Next, in Section 2.2, we describe the basic inference problem analysts face when trying to spot any group of noise traders. Finally, in Section 2.3, we give an overview of the data we use in our analysis.

2.1. **Mispricing in the Housing Market.** Figure 1 shows that cities throughout the US experienced rapid house price growth during the mid 2000s. A number of the markets, including Las Vegas, Los Angeles, Phoenix, San Diego, and Washington saw annual appreciation rates above 20%, with annual house prices rising more than 30% in Las Vegas and Phoenix. Was this rapid house price appreciation due to speculative bubble or a result of a fundamental changes?

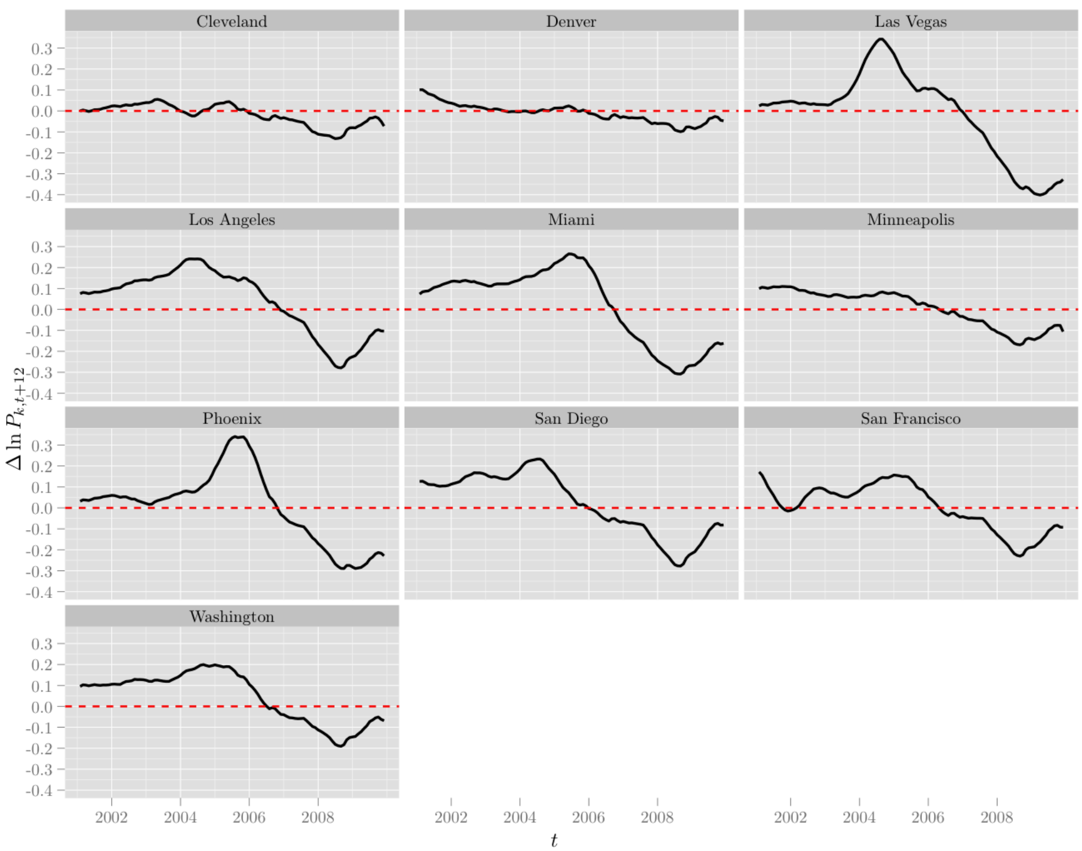

Figure 1. *This figure shows the log 12 month change in house prices from time $t-12$ to time t at the city level. We obtain monthly estimates of the median house price at a ZIP code level from* `www.zillow.com` *a consumer website that provides house prices and other real estate information. Zillow computes their house price estimates using hedonic data from deeds records as well as information from realtor and consumer surveys. Their methodology is proprietary. This figure reads: At the the peak of the housing boom, house prices in Phoenix, AZ were growing at a rate of more than 30% per year.*

A second key challenge in our analysis is to determine how to define a housing bubble. In summarizing the Journal of Economic Perspectives bubble symposium, Joseph Stiglitz wrote that a bubble occurs "...if the reason that the price is high today is only because investors believe that the selling price is high tomorrow- when fundamental factors do not seem to justify such a price-then a bubble exists. At least in the short run, the high price of the asset is merited, because it yields a return (capital gain plus dividend) equal to that on alternative assets." (Sitglitz, 1990 [56]) Operationalizing such a definition is difficult.

Many authors empirically examine bubbles by considering episodes that they posit to be so extreme that a bubble is the only explanation, such as the behavior of internet stocks in the late 1990s or Chinese share prices as in Mei et al. (2005 [40]). Tellingly, in their seminal paper on the inefficiency of housing markets, Case and Shiller (1989 [13]) never use the word bubble. Instead, the authors examine predictability, arguing that serially correlated house prices are inconsistent with efficient markets. Later work by Case and Shiller (2004 [14]) examined the question of housing bubbles with the title, "Is There a Bubble in the Housing Market?," but the authors do not provide an explicit definition of a housing bubble or what would separate a bubble from a less severe mispricing.

Mayer (2011 [37]) summarizes the literature on mispricing and housing bubbles. He notes that previous articles have considered three alternative approaches to examining mispricing in the housing market: the user-cost model based on the relationship between house prices and the present discounted value of rent, a comparison of house prices to economic fundamentals like income and employment, and a comparison the price of housing relative to construction costs.

In this paper we focus on the first approach–the user cost model. Beginning with Poterba (1984 [47]), authors have tried to compare the price of housing relative to the present value of its rental value, taking into account the favorable tax treatment given to owner-occupants and mortgage rates. This is similar to the dividend discount model for the stock market. Unlike the stock market, where analysts have actual dividends and share prices, in housing it is quite unusual to have matched data on house prices and equivalent rents. Himmelberg et al. (2005 [28]) suggest a methodology that allows us to create an index of mispricing by comparing the ratio of imputed rent-to-rent, where the imputed rent equals the user cost multiplied by the price. Himmelberg et al. (2005 [28]) use indexes for house prices and rents at the metropolitan area level, as well as computing the user cost from data on local property taxes and long-term interest and mortgage rates. The authors then compute the owner imputed rent by multiplying the user cost times the price index. When the index in a given metropolitan area exceeds unity, owning a home is more expensive than renting relative to the average index value over the sample period.

Researchers have critiqued the user cost approach in a number of ways.[6] For example, Glaeser and Gyourko (2007 [20]) point out that very few single-family homes are rented, so any rental index is not assured to match up with the price index. Also, the user cost model as estimated above is inherently static, so it cannot easily incorporate time varying factors like risk premia and expected growth rates of house prices.

Nonetheless, a simple analysis of the user cost suggests it performs well for the purposes of our paper. Hubbard and Mayer (2009 [38]) show that a regression of a log-linearized version of the user cost model (e.g., a regression of log price on log rent and log user cost) generates a coefficient on log rents near 1.0 and a coefficient on log user cost of -0.75, both very close to what is predicted by the static user cost model. As well, the user cost model has advantages over the other two approaches in that it allows us to estimate a single index value that proxies for overpricing. Comparing house prices to variables like employment and income has no firm theoretical prediction; for example, failing to adjust to changes in economic fundamentals like interest rates. Comparing house prices to construction cost only works in markets where land has very low value and thus is in abundant supply relative to demand. Even in locations with low land prices, home prices should still equal the present value of rents.

Two recent papers examine the role of investors in housing market booms. Haughwout, et. al. (2011 [27]) explore the relationship between investor purchases and excessive house

[6] See Mayer (2011 [37]) for a more complete discussion of the pros and cons of the user cost model.

price appreciation by examining credit report data that list the number of homes purchased and leverage used. The authors document several important facts, including that investor mortgages represented nearly one-half of all mortgages originated in the four states with most excessive price appreciation (Arizona, California, Florida, and Nevada) at the peak of the market. As well, many investors misreported their motives and subsequently defaulted when house prices begin falling.

Bayer et al. (2011 [7]) examine the role of speculators and middlemen in Los Angeles, defining such participants based on the number of times buyers purchase and resell homes. The authors find that "middlemen" who buy and sell many houses operate equally during booms and busts, but that "speculators" who buy and sell a smaller number of houses appear to try (unsucessfully) to time the market and are strongly associated with neighborhood price instability. This paper has some similarities to our work, including the observation that certain groups of investors do a poor job of timing the market, but the authors' analysis takes place within a single metropolitan area. The results in both papers are complimentary to ours in that both papers document a large growth of investors in the highest appreciation rate locations, but neither is able to attribute causality to these correlations. Our work, below, also extends this analysis to differentiate between local investors, whose purchases appear to be unrelated to house price appreciation or mispricing, and outside speculators whose purchases appear to cause some degree of mispricing.[7]

Also related is recent work by Ferreira and Gyourko (2011 [16]), who examine the timing, magnitudes and potential determinants of the last housing boom by examining price behavior in 94 US markets. The authors find that booms across markets started at different times, but that booms corresponded to a discrete jump in house price appreciation rates. As well, the paper finds "Income growth is large and jumps at the same time as house price appreciation in areas that boomed early and have inelastic supplies of housing, but not in late booming areas and those with elastic supply sides." In our analysis, the largest bubble markets of Las Vegas and Phoenix have elastic supply and also an influx of outside speculators just as

[7]See also Genesove and Mayer (2001 [19]), who show the investors exhibit a lesser degree of loss aversion than owner-occupants when selling condominiums.

the boom was getting started in these markets. Our paper can be seen as testing a specific explanation for some of the facts summarized in Ferreira and Gyourko.

2.2. **Defining Distant Speculators as Noise Traders.** The finance literature has come up with a number of definitions of noise traders. De Long et al. (1990 [36]) suggest that "noise traders falsely believe that they have special information about the future price of the risky asset...in formulating their investment strategies, they may exhibit the fallacy of excessive subjective certainty..." Furthermore, in both De Long et al. (1990 [36]) as well as in Shleifer and Vishny (1997 [54]), the presence of such noise traders creates risk that deters trading by rational arbitrageurs. Thus market prices can deviate significantly from fundamental values for appreciable periods of time. By contrast, as noted in Bloomfield et al. (2009 [10]):

> “In the market microstructure literature, researchers use the terms ’noise trader’ and ’liquidity trader’ interchangeably to describe traders who do not possess fundamental information (e.g., Glosten and Milgrom (1985 [21]); Kyle (1985 [35])). While the motives of these traders are often left unspecified, the justification for their trading is generally assumed to be some hedging or liquidity needs that induce changes in traders’ optimal portfolio holdings.”

While the term speculator is often tossed around in everyday conversation, the motives of speculators can be hard to identify. The US residential real estate market is an excellent market in which to study bubble formation because it contains information on buyers and sellers via deeds records. Namely, for each property transaction in our database, we observe not only an address for the property itself but also a billing address where the county sends the tax bill for the property.

Definition (Speculator)**.** *When the property address and billing address differ, we classify the owner as a speculator.*

Definition (Distant Speculator)**.** *When the billing address lies in another metropolitan area, we classify the buyer as a distant speculator.*

Distant (but not local) speculators closely resemble the attributes of noise traders described above within the context of the residential housing market. These distant speculators are likely less informed than local speculators and home buyers and also likely rely more on house price appreciation to make their investment pay off.

Speculators in the residential housing market could purchase homes for a number of reasons. Speculators might be purchasing a second home with the intention of living in it part-time and possibly renting it out. Other speculators might purchase a house with the intention of renting the home out and selling it for a profit sometime in the distant future. A third group of speculators might intend to purchase a property, possibly fix it up, and flip the property for a profit. In all 3 contexts, these speculators or noise traders are still sensitive to both house price appreciation as well as to the annual flow of dividends (i.e. implied rents) from owning the home. For some potential purchasers, rising prices might stimulate demand to purchase a home earlier than they might otherwise do so out of fear that they will be unable to afford a home in the future. Such motivation, while possibly prevalent for some speculators, is likely to be most pronounced for owner- occupants.

Relative to speculators, owner-occupants face lower costs of owning a home. Owner-occupants pay much lower federal taxes due to non-taxation of imputed rent and sometimes lower property taxes if their community has lower property tax rates on owner-occupied properties. On the other hand, owner-occupants tend to exert more effort maintaining their home, whereas rental tenants will treat their home relatively poorly as it is owned by someone else.

In our analysis, local speculators can serve either as more traditional liquidity providers or arbitrageurs who enter the market when buying opportunities are very attractive. It is of course possible that local investors might exhibit some signs of being noise traders, such as overconfidence in their ability to time markets. Portfolio considerations are less likely to be important for local speculators, as owning multiple homes in a metropolitan area is unlikely to provide much diversification. If anything, portfolio considerations would work against investing in housing in the local market.

Thus we consider distant speculators to most closely resemble noise traders in the finance literature. Due to distance, out-of-town speculators are likely to have less information about a given neighborhood than local investors. Even if distant investors hire an agent to provide local information, the agent may have incentives to provide a rosy picture if the distant investor is more likely to invest more in the neighborhood in the future and thus pay the agent higher fees in the future. In addition, the returns to distant speculators may depend more heavily on capital gains relative to owner-occupants and local investors. Out of town second home buyers can only live in their second house for a short period of time during the course of the year. If it is an investment home, property management is more expensive to monitor from a distance, as are neighborhood changes, so the net rental flow is likely to be lower than for local investors. If capital gains play a more critical role on the financial returns to distant speculators, these types of investment may attract investors who are susceptible to overly exuberant expectations of future price appreciation.

2.3. **Data Description.** As shown in Table 1, we use Deeds records for 11 metropolitan areas (sometimes referred to as cities in our discussion) during the period from January 2000 to August 2008: Cleveland, OH; Denver, CO; Las Vegas, NV; Los Angeles, CA; Miami, FL; Minneapolis, MN; New York, NY; Phoenix, AZ; San Diego, CA; San Francisco, CA; and Washington, DC. These data contain a complete sales history of any parcel of land in each of these markets. In our analysis we focus on property sales; nevertheless, the data also contain an entry each time the owner of a property takes out or extinguishes a new mortgages or line of credit collateralized by the property value.

These deeds records are public due to state information disclosure acts; however, the raw data are housed in `PDF` images on county websites making them inaccessible to computational analysis on a large scale. We post examples of the raw `PDF` records in the appendix. Our data provider compiled information from the county registrar websites that house the public raw data and combined the resulting data into a single dataset.[8]

[8]The data source for this analysis agreed to provide data only if we provided anonymity. Such data are available from multiple sources for researchers interested in replicating or expanding our analysis.

City	Properties
Cleveland, OH	657,768
Denver, CO	739,877
Las Vegas, NV	515,736
Los Angeles, CA	2,593,102
Miami, FL	1,103,367
Minneapolis, MN	970,329
Phoenix, AZ	1,182,178
San Diego, CA	626,847
San Francisco, CA	1,060,709
Washington, DC	1,247,604

Table 1. *This table shows the metropolitan areas (cities) we use in our analysis along with the baseline number of properties in each city as reported in the 2000 tax records.*

To verify the quality of the deeds reporting in each location, we cross-checked the sales counts reported in the deeds records against county and city level sales estimates reported by local realtor associations as well as spot checked individual records against values reported by LexisNexis. We restrict our sample to sales of single family homes with valid sale or mortgage amounts and that contain valid addresses located within the metropolitan areas listed above.

In the mid 2000s, out of town buyer purchases grew appreciably relative to their level at the beginning (and end) of our sample period. Figure 2 plots the percentage of outside speculator purchases relative to total housing units in 2008.[9] Each of the city specific panels in Figure 2 displays a similar hump-shaped pattern. The key insight for our analysis is that the scale of the patterns differ by orders of magnitude. For example, while both Phoenix and Minneapolis show similar percent change rises in the fraction of all homes bought by out of town buyers from 2002 to 2006, but at the peak of the housing boom, Phoenix had around 10 times as large a fraction of homes bought by out of town investors as Minneapolis.

[9]Another metric that some papers use is the percentage of home purchases made by local and distant speculators. At peak, distant speculators still represent a minority of home purchases. In the largest market for distant speculators, Las Vegas, these purchases represented a little more than 13% of all home purchases in 2004, up from 5.1% percent in 2002. We use the percentage of the stock of total units as the denominator in our analysis as total transactions are simultaneously determined with the process of entry and exit by local and distant speculators.

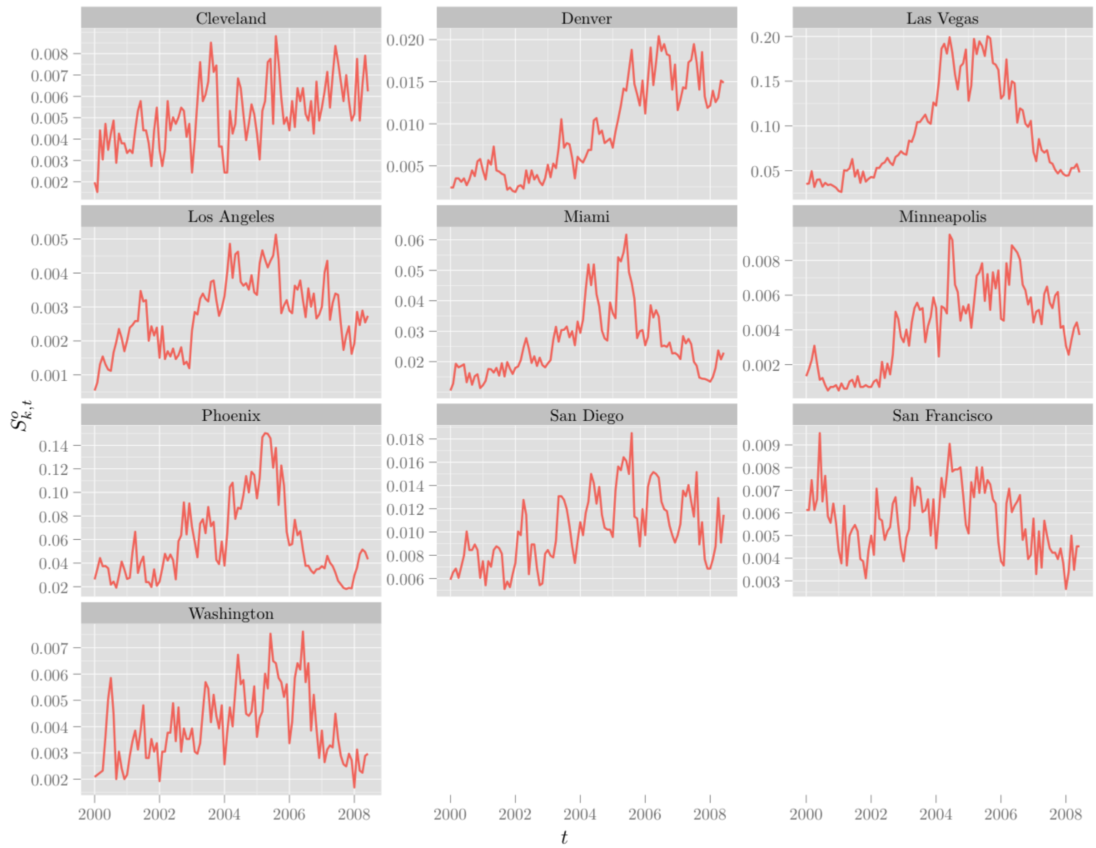

Figure 2. *This figure shows the number of out of town buyer purchases as a percent of all properties in hundredths of a percent. We identify out of town buyer purchases as sales where the property and billing addresses differ and the billing address lies in a different city. This figure reads: At the start of 2005 roughly 0.09% of all properties in Phoenix, AZ were sold each month to buyers living in a different city.*

The introduction of additional out of town buyers does not mean that local buyers must leave the market. There are many ways in which second home buyers from outside the city can purchase homes given that existing residents need a place to live: new homes can be built for investors to purchase, existing homes can sell more quickly with less transitional vacancy, or some local residents can choose to rent instead of purchase. All three factors were likely prevalent during the boom. While regional data for average the time on the market is not available, news stories suggest that the average sale took as little as 1 or 2 weeks in cities like Phoenix, AZ and Miami, FL during the height of the boom. New construction grew rapidly in these markets at the same time investor purchases were high. Homeownership rates in

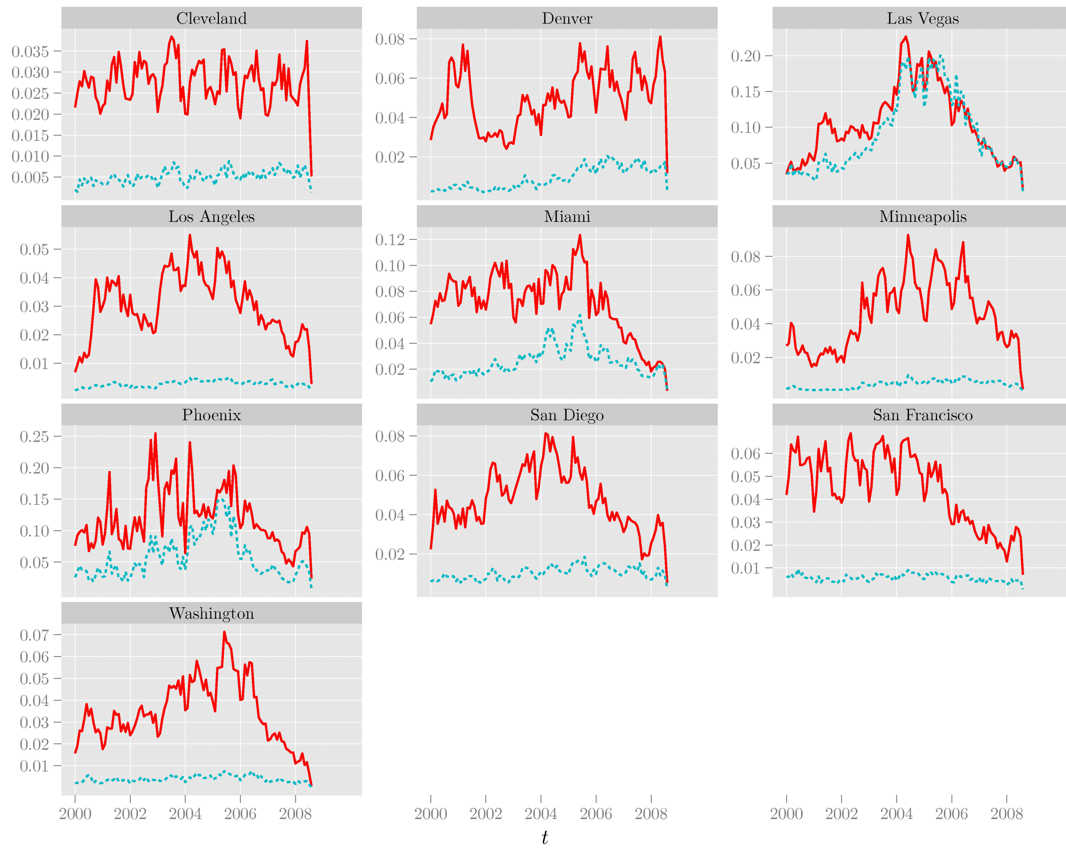

Figure 3. *This figure shows the number of both out of town (blue/dashed) and local (red/solid) speculator purchases as a percent of all properties quoted in hundredths of percentage points. This figure reads: At the start of 2005 roughly 0.06% of all properties in Miami, FL were sold each month to second home buyers living in a different city while 0.12% of all properties were sold to local second home buyers. Note that the scale of the vertical axis for each city in the panel is different depending on the share of investor purchases, with Las Vegas and Phoenix exhibiting the largest peaks and Cleveland and Los Angeles the smallest.*

the US hit their peak during 2004, and were declining two years before home prices stopped rising.

We obtain monthly estimates of the median house price at a ZIP code level from `www.zillow.com` a consumer website that provides house prices and other real estate information. Zillow computes their house price estimates using hedonic data from deeds records as well as information from realtor and consumer surveys. Their methodology is proprietary. We take the average of these ZIP code level estimates in each city k at each month t as the price level in each city.

3. Speculative Mispricing: A VAR Approach

We begin the statistical analysis by quantifying the correlation between local and distant speculators in a city k and the rate price appreciation and extent of mispricing in that city. We estimate the panel regression models specified in Equations (2) and (3). The resulting estimates show that adding out of town second home buyers to a housing market predicts excess price appreciation over the next year as well as mis-pricing at the 1 year horizon. An increase in local speculators, however, is uncorrelated with future appreciation or mispricing.

3.1. **Variable Definitions.** We estimate a model that is indexed by purchase city $k \in \mathcal{K}$ and month of purchase t. We examine two alternative measures of price impact: 1) the log 12 month ahead change in prices and 2) the log 12 month ahead implied rent to rent ratio:

Definition (Log Change in Prices)**.** $\Delta \ln P_{k,t+1}$ *represents the log change in house prices from time* t *to time* $t+1$ *in city* k*.*

Definition (Log Implied Rent to Rent Ratio)**.** *We use the implied rent to actual rent ratio series from Himmelberg, Mayer and Sinai (2005* [28]*) updated through August 2008:*

$$\begin{aligned} U_{k,t} &\approx Z_t\,(1-\tau) + \delta - \mathbb{E}_t\,[\,\Delta \ln P_{k,t+1}\,] \\ I_{k,t} &= (P_{k,t} * U_{k,t})/(R_{k,t}) \end{aligned} \tag{1}$$

In the standard user cost model, the price of a home multiplied by the user cost equals the annual rent, or $P_{k,t} \cdot U_{k,t} = R_{k,t}$*. The user cost is the percentage of the home price that an owner pays in order to live in that home for a year. According to our definition, the owner would borrow money at rate* Z_t *to buy a home, paying a constant proportion of the home value in depreciation costs* δ *while earning the tax shield* τ *on his debt and getting capital gains at the expected price appreciation rate of* $\mathbb{E}_t\,[\Delta \ln P_{k,t+1}]$*. The index,* $I_{k,t}$*, is the ratio of the log price times log user cost divided by rent and is scaled to equal unity for the average value of the index from 1980 to 2008. If the index equals 1.2, for example, it means that* *purchasing a home is about 20 percent more expensive than renting relative to the average of the ratio between 1980 and 2008.*

Intuitively, house prices are "too high" if a potential owner can borrow money, purchase a home and then sell it at a future period for a lower cost than he can rent a comparable property for the same amount of time. The computation in Himmelberg et. al. takes into account additional real-world issues like maintenance expenditures, property taxes, leverage, and a constant housing risk premium.[10] As home prices become more expensive relative to renting, and without a comparable decline in the user cost, the imputed rent becomes proportionately larger relative to the rental value, giving a proxy for mispricing.

Figures 4 and 5 in give an idea of how this measure of mis-pricing varies across a bubble market such as Phoenix, AZ and a stable market such as Denver, CO, respectively. At the peak in Phoenix, a tenant renting an apartment for 1000 dollars a month would have to pay 1600 dollars in mortgage payments and other costs in order to buy an equivalent home and live in it for a year. By comparison, in Denver, this ratio peaked in 1988 and was around 1.1 between 2004 and 2006, so a tenant would have paid about 1,100 dollars to purchase a home that rented for 1,000. While homes in Denver were still priced at a small premium relative to renting at the peak of the national boom, they appeared much less overpriced than homes in Phoenix at the same time.

We predict log 12 month changes in prices and log 12 month ahead implied rent to rent ratios using the out of town second home buyer fraction:

Definition (Distant Speculator Fraction)**.** $S^o_{k,t}$ *represents the percent of all properties in city* k *bought by purchasers in a given month* t *whose property tax bills were sent to an address in a different metropolitan area.*

We normalize the volume of out of town speculators by the total number of properties in the purchase city to control for variation in city size. As a control group, we also include

[10]Himmelberg, et. al., do not allow the risk premium or leverage to change over time. Thus the computation can be thought of as a long-run measure of the relative price of owning versus renting, abstracting from important short-run considerations like easy and cheap leverage in the mid-2000s and time varying risk premia.

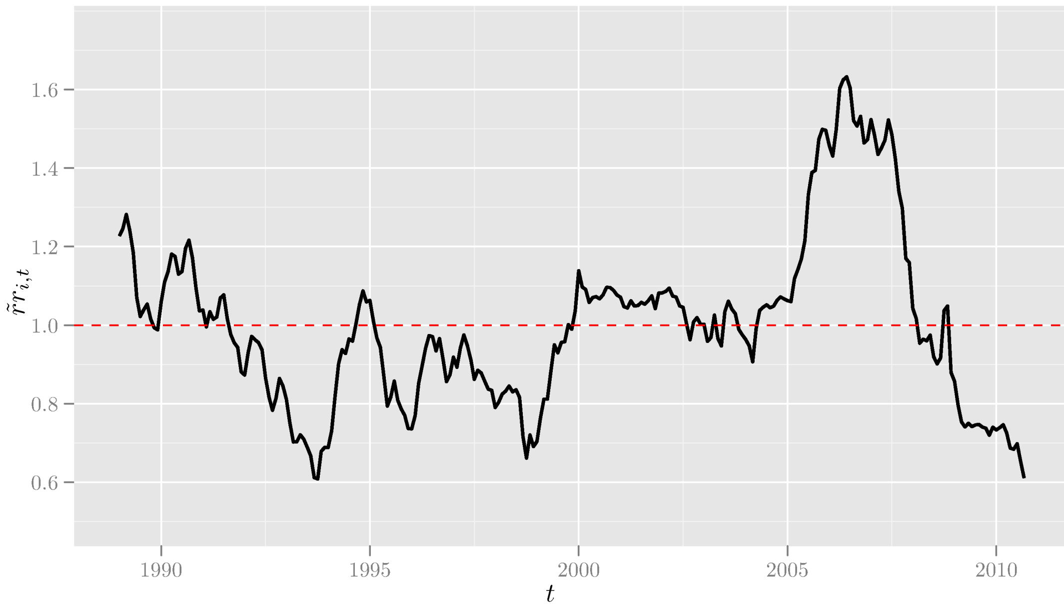

Figure 4. *This figure shows the implied rent to rent ratio for Phoenix, AZ reported by Himmelberg, Mayer and Sinai (2005* [28]*):* $I_t = P_t \cdot U_t / R_t$*. This figure reads: In 2006 the average annual cost of owning a home relative to renting was about* 1.6 *times higher than its average value between 1980 and 2008*

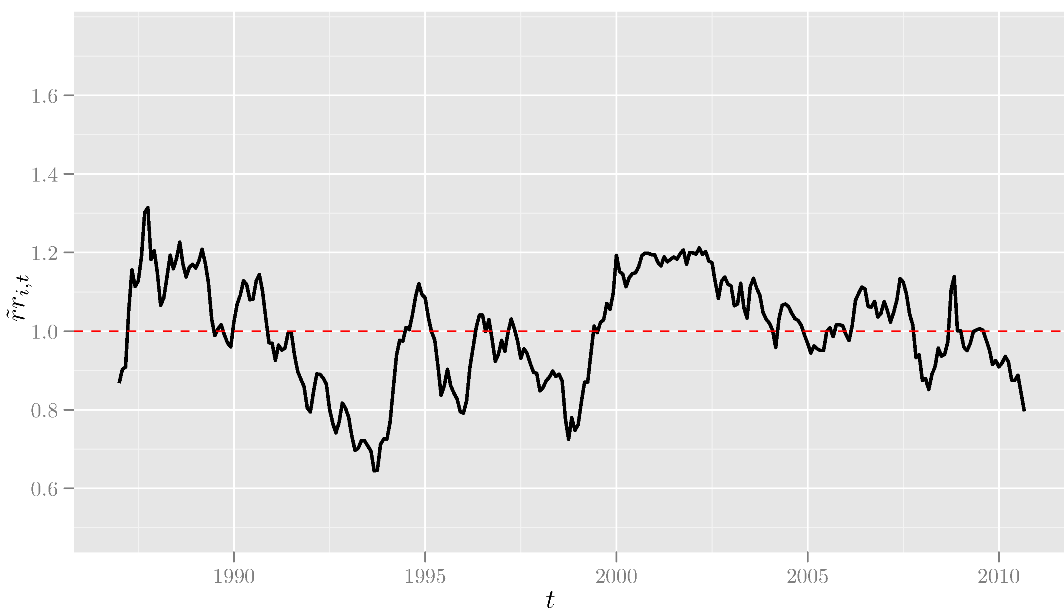

Figure 5. *This figure shows the implied rent to rent ratio for Denver, CO reported by Himmelberg, et. al. (2005* [28]*):* $I_t = P_t \cdot U_t / R_t$*. This figure reads: In 2006 the average annual cost of owning a home relative to renting was about* 1.1 *times higher than its average value between 1980 and 2008.*

a variable for the local speculator fraction. These are speculators purchasing homes within the same city:

Definition (Local Speculator Fraction). $S^l_{k,t}$ *represents the percent of all properties in city* k *bought by purchasers in a given month* t *whose property tax bills were sent to an address within the same metropolitan area that was different than the home that was purchased.*

3.2. **Speculation and Price Appreciation.** We estimate the panel vector autoregression specified in Equation (2) below:

$$\begin{aligned}\begin{pmatrix}\Delta \ln P_{k,t+12} \\ S^o_{k,t+12} \\ S^l_{k,t+12}\end{pmatrix} &= \underbrace{\begin{bmatrix}\hat{\phi}^{(p,p)} & \hat{\phi}^{(p,o)} & \hat{\phi}^{(p,l)} \\ \hat{\phi}^{(o,p)} & \hat{\phi}^{(o,o)} & \hat{\phi}^{(o,l)} \\ \hat{\phi}^{(l,p)} & \hat{\phi}^{(l,o)} & \hat{\phi}^{(l,l)}\end{bmatrix}}_{\hat{\mathbf{\Phi}}} \begin{pmatrix}\Delta \ln P_{k,t} \\ S^o_{k,t} \\ S^l_{k,t}\end{pmatrix} \\ &\quad + \begin{bmatrix}\hat{\delta}^{(p)}_k \\ \hat{\delta}^{(o)}_k \\ \hat{\delta}^{(l)}_k\end{bmatrix} d_k + \begin{bmatrix}\hat{\delta}^{(p)}_t \\ \hat{\delta}^{(o)}_t \\ \hat{\delta}^{(l)}_t\end{bmatrix} d_t + \begin{bmatrix}\varepsilon^{(p)}_{k,t+12} \\ \varepsilon^{(o)}_{k,t+12} \\ \varepsilon^{(l)}_{k,t+12}\end{bmatrix}\end{aligned} \tag{2}$$

The coefficient estimates in the transition matrix $\hat{\mathbf{\Phi}}$ in Equation (2) presented in Table 2 characterize the predictive power of the level of speculation in each city k over the price appreciation in that city over the next year. In the transition matrix $\hat{\mathbf{\Phi}}$, each of the elements' first superscript denotes the dependent variable while the second superscript denotes the independent variable. So, for example, the coefficient $\hat{\phi^{(p,o)}}$ represents the effect of the number of home sales to distant speculators as a percent of total properties in city k at time t on the log change in house prices in city k from time t to time $t+12$.

The regressions include city fixed effects to capture within city trends in the appreciation rate or local or out of town investor purchases.[11] Similarly, there are month-year fixed effects

[11]For example, Gyourko, Mayer and Sinai (2006 [25]) show that there are long run differences in the mean price appreciation rate across cities.

to capture macroeconomic differences such as falling interest rates or easier subprime credit, as well as seasonality in when people decide to buy a home in another city.

We measure changes using 12 month lags to further correct for seasonal factors in our data. Price changes and mispricing exhibit less seasonal variation than sales volumes due, in part, to smoothing by data providers and strong household preferences in when they move during the year. Thus, month fixed effects would not appropriately capture the two different seasonal effects at different frequency. An alternative approach would be to run a filter on the sales data, remove the cyclical component and then run the regressions with a wider variety of lag structures. Following this approach yields estimates that are qualitatively the same as the ones we derive using the panel VAR specification defined in Equation (2) with 12 month lags.

The estimate of the coefficient $\hat{\phi}^{(p,o)}$ in Panel A of Table 2 shows that after controlling for city and month-year fixed effects, the share of homes purchased by out of town buyers in city k predicts house price growth in that city over the next 12 months. The coefficients show that a one standard deviation shock is correlated with a 1.4 standard deviation increase in the house price growth rate in the following year.

If we consider levels rather than elasticities, in Los Angeles, CA where the mean price growth is 4.4% per year as reported in Figure 7, the effect of a normalized unit shock to the out of town buyer purchase rate would be a jump in the price growth rate up to 6.2%. Figures 6 and 7 shows the month $\hat{\delta}_t^{(p)}$ and city $\hat{\delta}_k^{(p)}$ fixed effects from the first equation in the panel VAR specified in Equation (2).

3.3. **Speculation and Mis-Pricing.** Next, we alter the specification in Equation (2) slightly in order to examine the impact of additional out of town buyer purchases on mis-pricing. Specifically, we replace the log change in prices $\Delta \ln P_{k,t+12}$ state variable with the log imputed rent to actual rent ratio $\ln I_{k,t+12}^{(12)}$. We use a linear interpolation to convert the quarterly data reported in Himmelberg, Mayer and Sinai (2005 [28]) to a monthly frequency:

	Estimate	s.e.	s.e.
$\phi^{(p,p)}$	0.15	0.04	0.07
$\phi^{(p,o)}$	**0.92**	0.17	0.20
$\phi^{(p,l)}$	**−0.14**	0.15	0.22
R^2	0.10		
$\phi^{(o,p)}$	−0.03	0.01	0.01
$\phi^{(o,o)}$	0.41	0.05	0.08
$\phi^{(o,l)}$	0.07	0.04	0.08
R^2	0.19		
$\phi^{(l,p)}$	−0.01	0.02	0.01
$\phi^{(l,o)}$	0.07	0.06	0.06
$\phi^{(l,l)}$	0.19	0.05	0.08
R^2	0.05		
	Clustering:	None	month-year

Table 2. *This table shows the results of three panel regressions that estimate the transition coefficient matrix $\hat{\mathbf{\Phi}}$ in Equation (2). The first 3 rows represent the coefficients from a regression of the log of the 12 month change in house price level on the lagged log 12 month change in house price level, the lagged share of homes purchased by out of town speculators, and the lagged share of homes purchased by local investors. Note that the shares of home purchases are calculated based on the number of a given type of investor purchase divided by the number all single-family homes in a given city, similar to how the data in Figures 2 and 3 are computed. All regressions use 800 observations and have 708 residual degrees of freedom and include month-year and city of purchase fixed effects The second three rows represent the coefficients from a regression of the share of homes purchased by out of town buyers as a percent of total properties on the lagged log 12 month change in house price level and the lagged share of out of town and local investor purchases as a percent of all residential properties. The final 3 rows represent the coefficients from the same regression with the share of local second home purchases as a percent of total properties as the dependent variable.*

$$
\begin{aligned}
\begin{pmatrix} \ln I^{(12)}_{k,t+12} \\ S^o_{k,t+12} \\ S^l_{k,t+12} \end{pmatrix} &= \underbrace{\begin{bmatrix} \hat{\phi}^{(i,i)} & \hat{\phi}^{(i,o)} & \hat{\phi}^{(i,l)} \\ \hat{\phi}^{(o,i)} & \hat{\phi}^{(o,o)} & \hat{\phi}^{(o,l)} \\ \hat{\phi}^{(l,i)} & \hat{\phi}^{(l,o)} & \hat{\phi}^{(l,l)} \end{bmatrix}}_{\hat{\mathbf{\Phi}}} \begin{pmatrix} \ln I^{(12)}_{k,t} \\ S^o_{k,t} \\ S^l_{k,t} \end{pmatrix} \\
&\quad + \begin{bmatrix} \hat{\delta}^{(i)}_k \\ \hat{\delta}^{(o)}_k \\ \hat{\delta}^{(l)}_k \end{bmatrix} d_k + \begin{bmatrix} \hat{\delta}^{(i)}_t \\ \hat{\delta}^{(o)}_t \\ \hat{\delta}^{(l)}_t \end{bmatrix} d_t + \begin{bmatrix} \varepsilon^{(i)}_{k,t+12} \\ \varepsilon^{(o)}_{k,t+12} \\ \varepsilon^{(l)}_{k,t+12} \end{bmatrix}
\end{aligned} \tag{3}
$$

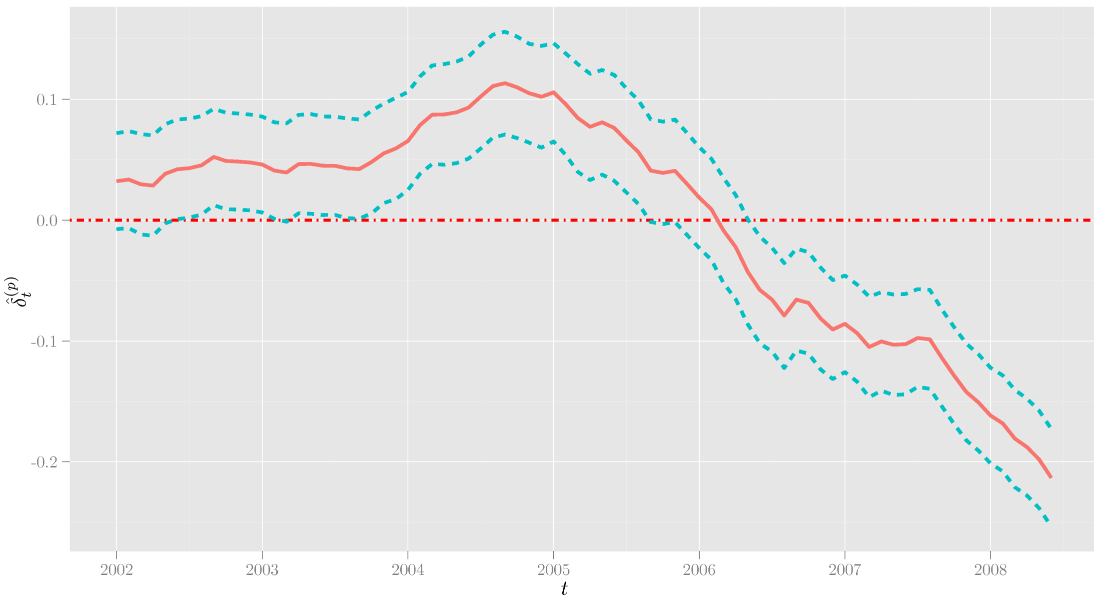

Figure 6. *This figure shows the monthly fixed effect estimates from the panel regression specified using the first row of Equation* (2)*. The solid red line is the estimated value while the dashed blue lines represent the* 95% *confidence bounds. So, for example, in mid 2004 yearly price growth was* 10% *higher than its average level.*

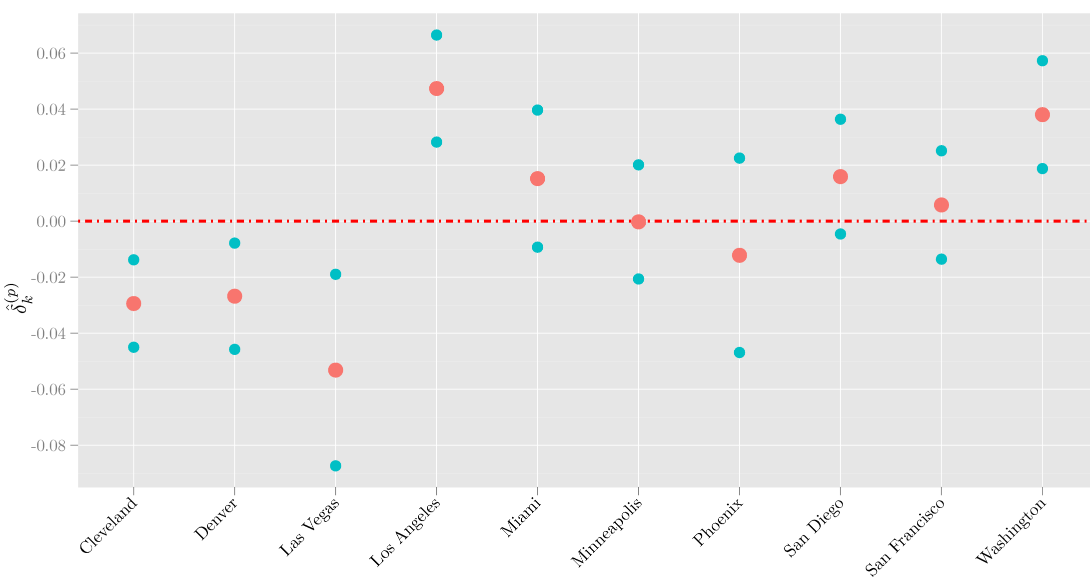

Figure 7. *This figure shows the demeaned city fixed effects from the same panel regression. The large red dots represent the estimated value while the smaller blue dots represent the* 95% *confidence bounds. So, for example, Los Angeles had yearly price growth that was* 4% *higher than the average city.*

Table 3 houses the coefficient estimates for the new transition matrix $\hat{\mathbf{\Phi}}$. The estimate of the coefficient $\phi^{(i,s)}$ in Panel A of Table 3 shows that the number of second home purchases made by out of town buyers as a percent of all properties in the city is a measurable predictor of the imputed rent to actual rent ratio 12 months into the future. A 1 standard deviation positive shock orthogonalized with respect to the percent of existing properties purchased by out of town buyers predicts a 4 standard deviation increase in the mispricing a year into the future.

Table 3. *The first* 3 *rows represent the coefficients from a regression of the log of the implied rent-to-rent ratio on the lagged log of the implied rent-to-rent ratio, the lagged share of homes purchased by out of town speculators, and the lagged share of homes purchased by local investors. Note that the shares of home purchases are calculated based on the number of a given type of investor purchase divided by the number all single-family homes in a given city, similar to how the data in Figures* 2 *and* 3 *are computed. All regressions use* 720 *observations and have* 620 *residual degrees of freedom and include month-year and city of purchase fixed effects The second three rows represent the coefficients from a regression of the share of homes purchased by out of town buyers as a percent of total properties on the lagged log implied rent-to-rent ratio and the lagged share of out of town and local investor purchases as a percent of all residential properties. The final* 3 *rows represent the coefficients from the same regression with the share of local second home purchases as a percent of total properties as the dependent variable.*

	Estimate	s.e.	s.e.
$\phi^{(i,i)}$	0.75	0.02	0.02
$\phi^{(i,o)}$	**2.72**	0.20	0.26
$\phi^{(i,l)}$	**−0.30**	0.14	0.19
R^2	0.70		
$\phi^{(o,i)}$	−0.05	0.01	0.01
$\phi^{(o,o)}$	0.34	0.04	0.10
$\phi^{(o,l)}$	−0.08	0.03	0.06
R^2	0.23		
$\phi^{(l,i)}$	−0.10	0.01	0.01
$\phi^{(l,o)}$	0.04	0.07	0.10
$\phi^{(l,l)}$	0.07	0.05	0.07
R^2	0.22		
	Clustering:	None	month-year

Coefficients $\hat{\phi}^{(p,o)}$ and $\hat{\phi}^{(i,o)}$ in Tables 2 and 3 show that out of town second home buyer share predicts house price appreciation and future mis-pricing; however, coefficients $\hat{\phi}^{(p,l)}$ and $\hat{\phi}^{(i,l)}$ in the same tables show that the share of local purchases does not. If anything, the share of local investors is negatively related with subsequent house price appreciation or mispricing, although the coefficient is marginally statistically different from zero when we cluster by month-year. Local speculators are likely better informed about market conditions and face fewer search costs. What's more, they also have lower costs in renting out an investment property. These results suggest that some speculators are more equal than others.

4. Experimental Design and Results

In the previous section, we documented a correlation showing that out of town speculators invested at a greater rate in housing markets where home prices subsequently appreciated the most and where prices deviated the most from their implied rent to rent benchmark. In this section, we demonstrate that this link is in fact causal and try quantify the magnitude of this effect.

The main challenge we face is that noise traders endogenously select which markets to invest in. For instance, if speculation is most profitable in over-heated markets, then we should expect to see an increase in speculative trading intensity in over-priced markets regardless of the effect of speculative trades on prices. We solve this identification problem using the front door criterion.

4.1. **The Front Door Criterion.** Below, we define the causal estimator implied by the front door criterion in the context of a simple binomial model of mispricing. We then link this inference methodology with an instrumental variable approach and provide a quick numerical example. Our goal is to capture the central intuition underlying the front door criterion in the simplest possible setting.

More specifically, we consider the possibility that the correlation between mispricing in the housing market and the growth of outside investors can be due to two (possibly related) factors: 1) out of town speculators enter overpriced markets for some reason that is correlated with mispricing but does not cause mispricing (for example, maybe investors believe that baby boomers want to live in sand states at a time when sand states are already overpriced); or 2) when a large number of out of town speculators enter a market, mispricing increases.

The first explanation suggests a correlation but not causality, while the second explanation is a causal hypothesis.

In order to establish a causal effect, we posit that an increase in outside speculator demand that is large relative to the size of a local market should increase mispricing more than an increase in speculator demand that is a relatively small portion of market demand. That is, a positive shock in demand by a relatively large group of town speculators entering a small market is less likely to be offset by by other factors, such as a reduction in demand from other possible home buyers, an increase in sales by existing homeowners, or an increase in the supply of new homes by builders. Our measure of the size of a demand shock comes from data that allows us to measure the size of cities where investors are purchasing homes relative to the size of the market they currently live in. A large shock would occur when a given share of investors from a relatively big market (say Los Angeles) decide to invest in a smaller market like Las Vegas. By contrast, a demand shock would be small when the same share of investors living in a small market (Las Vegas) choose to invest in a larger market like Los Angeles. If an unrelated variable is associated with an increase in outside investor purchases at times that markets are subsequently overpriced, we would expect the same correlation between outside speculator purchases and mispricing in both examples–that is, the size of investor flows would not be correlated with the extent of overpricing. If the impact of outside speculators is causal, we would predict that outside speculators going from Los Angeles to Las Vegas (or from any large market into a small market) would have a larger effect on mispricing than the reverse.

To clarify our identification, we develop a very simple binomial model where markets are either overpriced or not, outside investors enter a market or not, and markets are either large or small. Our mechanism suggests that small markets have a higher sensitivity to demand shocks by outside investors than large markets.

In this example, we present a stylized economy with M markets. In each of these markets, house prices can either reflect fundamentals, $P_m = 0$, or be overpriced, $P_m = 1$. What's more, distant speculators either decide to enter a market $S_m = 1$ or they do not $S_m = 0$. For simplicity we hold the number of outside investors fixed in both cities. Next, let Z_m denote whether market m is a small city, $Z_m = 1$, or a large city, $Z_m = 0$.

With this setting in mind, we now define our FDC estimator $\beta_{\texttt{FDC}}$.

Proposition 1 (Binomial FDC Estimator)**.** *The causal effect estimator using the front door criterion in a 2-state system with outcome variable P_m, mechanism Z_m and explanatory variable S_m can be written as:*

$$\begin{aligned}\beta_{\texttt{FDC}} = \{&\mathbb{P}[P_m = 1 \mid S_m = 1, Z_m = 1] - \mathbb{P}[P_m = 1 \mid S_m = 0, Z_m = 1]\} \\ &- \{\mathbb{P}[P_m = 1 \mid S_m = 1, Z_m = 0] - \mathbb{P}[P_m = 1 \mid S_m = 0, Z_m = 0]\}\end{aligned} \tag{4}$$

The first line of the proposition computes the probability of overpricing based on observing that a fixed number of outside investors enter a relatively small city (e.g., the probability of overpricing when the market transitions from $S_m = 0$ to $S_m = 1$). This corresponds to the OLS estimate of the correlation between an increase in out of town investors and mispricing in small cities, an estimate that might be biased if out of town investors are more likely to purchase homes at times when mispricing is higher. The second line corresponds to precisely the same estimate, but for large cities instead of small cities. If all cities are pooled together in the same regression, the OLS equation would give the average correlation between large and small cities.

Combining these two lines gives an estimate, $\beta_{\texttt{FDC}}$, which captures the differential effect of increasing distant speculators in markets where this treatment is more impactful (small markets) relative to where the treatment is less impactful (large markets). I.e., we are allowing for endogenous subject group assignment and instead exploiting an instrument for each market's receptiveness to the treatment effect.

What does this difference in difference estimator tell us about causality? We want test the hypothesis h_A) that the decision of out of town second home buyers to invest in city m causes mispricing in city m against the null hypothesis h_0) that some omitted variable causes both distant speculators to invest and homes to become overpriced. Suppose that the correlation between the likelihood of entry by outside speculative investors in market m

and the overpricing in market m were purely spurious and due to some confounding variable that both drives up prices and stimulates speculator demand. In this case, the differences in both lines would be the same. On the other hand, suppose that the effect is in fact causal. Then entry by distant speculators in smaller cities will cause homes in smaller cities to be more overpriced than homes are in larger cities.

Note that this approach does not rule out the possibility that outside speculators are still endogenously choosing to invest in overpriced markets. For instance, consider the following possibility:

$$0 \neq \mathbb{P}[P_m = 1 \mid S_m = 1, Z_m = 0] - \mathbb{P}[P_m = 1 \mid S_m = 0, Z_m = 0]$$

In this circumstance, even though distant speculators have little causal impact on overpricing, they are still good predictors of over-pricing.

We call Z_m a "mechanism" because the effect the explanatory variable S_m on the outcome variable P_m travels through Z_m. While speculators can still choose which markets to enter, they may or may not arrive in sufficient numbers to affect market house prices. Z_m acts like an instrument for the susceptibility of market m to the treatment effect. Below we give a formal definition of a valid mechanism.

Definition (Mechanism)**.** *A variable Z_m is a mechanism relative to the ordered pair of variables (P_m, S_m) if* 1) *S_m only affects P_m through Z_m, and* 2) *Z_m is independent of any confounding variables affecting both S_m and P_m.*

Our core identifying assumption is that Z_m is uncorrelated with any confounding variables which might jointly determine the likelihood of outside investment and overpricing of homes.[12] For instance, we assume that potential distant speculators living in Los Angeles are not better informed about home prices in Las Vegas than their counterparts living in San Francisco that has 2/5 the population. This seems plausible, for example, as both the SF Chronicle and the LA Times are similar quality newspapers as is access to other information on the internet.

[12]For a more detailed treatment of this idea, read through Ch. 3 of Pearl (2000).

Example 1 (FDC Estimator)**.** *To make these ideas more concrete, consider the table below containing simulated data. This table lays out the four different states of the world that we can possibly observe with respect to the pair of variables* (S_m, Z_m) *as well as their relative frequency and the probability of observing over-pricing in each of these states.*

S_m	Z_m	$\mathbb{E}[S_m = s, Z_m = z]$	$\mathbb{E}[P_m = 1 \mid S_m = s, Z_m = z]$
0	0	0.45	0.10
0	1	0.05	0.50
1	0	0.05	0.20
1	1	0.45	0.70

Using these values, we would compute a causal effect:

$$\beta_{\texttt{FDC}} \;=\; (0.70 - 0.20) - (0.50 - 0.10) \;=\; 0.10 \tag{5}$$

4.2. **Panel Regression Implementation.** The simple econometric model in the previous subsection shows how using the front door criterion is tantamount to instrumenting for treatment effect receptiveness. What's more, we also saw that the causal estimator $\beta_{\texttt{FDC}}$ takes the form of a difference in difference estimator. This fact suggests that we can use a regression specification with an interaction term to estimate this value. In this subsection, we formalize this insight.

We examine a panel dataset in which each observation represents an ordered city pair, with the city the investor lives in and the city of the purchased home representing the two markets in the pair. The dependent variable in our regression specification is the implied rent-to-actual rent ratio in a given local city i. This variable is higher when the cost of owning a home in the user cost model is relatively high compared to renting. Independent variables in the regression are the fraction of out of town investors from each city j investing in city i and an interaction of the fraction of out of town investors multiplied by an indicator of whether the local market i was smaller or larger than the out of town metro area j.

Let $\ln I_{i,t}^{(12)}$ denote the log implied rent to rent ratio in city i over the time interval $[t, t{+}12)$. Let $S_{i,j,t}$ be the fraction of second home buyers living in city j that decide to invest in city i at time t. We omit the reference category of $S_{i,i,t}$ for all cities. Finally, let H_i be the population of city i. This value is roughly constant over our data sample.

The proposition below shows how we use a interaction term to estimate $\beta_{\texttt{FDC}}$:

Proposition 2 (Panel Regression Implementation of $\beta_{\texttt{FDC}}$)**.** *Equation* (6) *estimates the causal effect of an increase in the fraction of distant speculators from city j buying second homes in city i on the level of mis-pricing in city i using the front door criterion:*

$$\begin{aligned} \ln I_{i,t}^{(12)} \;&=\; \delta_{i,j} \;+\; \gamma_t \;+\; \theta \cdot \ln I_{i,t-12}^{(12)} \\ &\qquad\qquad +\; \lambda \cdot S_{i,j,t} \;+\; \beta_{\texttt{FDC}} \cdot \left\{ \; S_{i,j,t} \cdot \left(\frac{H_j - H_i}{H_i} \right) \right\} \;+\; \varepsilon_{i,j,t} \end{aligned} \tag{6}$$

The main coefficients of interest are λ and $\beta_{\texttt{FDC}}$. λ is the coefficient on the variable representing the share of out of town investors from market i purchasing in market j at time t, where the share is computed based on the number of investors divided by the total number of homes in market j. It is equivalent to the correlation between share of out of town investors and subsequent mispricing from the VAR regression presented in the previous section. $\beta_{\texttt{FDC}}$ is the coefficient on the variable representing the interaction between the share of outside speculators and a dummy variable that equals 1 if the city that investors are entering is in the bottom one-third of city size while the city that investors are coming from is in the top one-third of city size. In other words, the interaction variable represents 1 for city pairs where the city that investors are coming from is relatively large compared to the city where the investment is taking place.

We include other variables to control for location and time fixed effects. The $\delta_{i,j}$ parameter represents an ordered city pair fixed effect. This parameter value controls for factors like the distance between any 2 cities and differences in weather. For instance, people are more likely to by second homes in nearby cities and residents of cold weather cities are likely to buy second homes in cities with mild climates. The γ_t parameter represents a month-year specific fixed effect which allows for time series variation in the level of mis-pricing due to factors such as aggregate credit availability or other macroeconomic variables. We include a single 12 month lag of the log implied rent to rent ratio to allow for persistent mis-pricing.

4.3. **Estimation Results.** Finally, in this subsection we present our main regression results, which demonstrate that increasing the intensity of out of town speculators increases the level of mispricing. Table 4 gives our estimated values for the θ, λ and $\beta_{\mathtt{FDC}}$ parameters from Equation (6) using data from January 2000 to August 2008 on second home buyer purchases between the 10 cities listed in Table 1. There are $6,624$ observations for a balanced panel of 72 ordered city pairs and 92 monthly observations per panel.

We find evidence that speculation by out of town second home buyers caused mispricing in the housing market as $\beta_{\mathtt{FDC}} > 0$. This parameter estimate is statistically different from zero even after adjusting our standard errors for clustering by time t or ordered city pairs (i, j). The coefficient on λ shows that a 1% increase in the fraction of investors from city j is correlated with a 0.41% increase in the implied rent-to-actual rent ratio (e.g., mispricing of house prices relative to rents). This point estimate captures the effect of endogenous subject group selection. Nevertheless, the interaction term, $\beta_{\mathtt{FDC}}$, is also large and statistically significant. The impact of a high fraction of investors in city j purchasing in city i has more than twice the impact on mispricing in city i when city j is much larger than city i. In a relatively small market like Las Vegas, a one percent increase in the share of investors coming from a large market like Los Angeles leads to a 0.46 increase in mispricing.

	Estimate	s.e.	s.e.	s.e.
θ	0.73	0.01	0.03	0.02
λ	0.41	0.06	0.12	0.24
$\beta_{\mathtt{FDC}}$	**0.46**	0.12	0.07	0.25
R^2	0.57			
	Clustering:	None	t	(k, j)

Table 4. *This table shows the θ, λ and $\beta_{\mathtt{FDC}}$ parameters from Equation (6) using data from January 2000 to August 2008 on second home buyer purchases between the 10 cities listed in Table 1. There are 6624 observations for a balanced panel of 72 ordered city pairs and 92 month observations per panel.*

To better understand the order of magnitude of these effects, we examine how much of the explained variation in mispricing is due to macroeconomic factors and how much is due to speculative demand shocks, we re-estimate the regression specified in Equation (6) using random rather than fixed effects. This technique assumes that the fixed effects and the estimation error are each drawn from homoskedastic, normal distributions and then estimates the relative size of the variance of each of these distributions. We find that time effects account for 77% of the explained variation while speculative demand shocks account for 20% of the explained variation. Given that most of the impact of investors occurred in a small portion of the sample period in a few markets, these results are consistent with a shock by distant speculators explaining a large portion of the bubble in markets like Las Vegas and Phoenix.

Variable	Share of variation
Time fixed effects: t	77%
City pair fixed effects: (k, j)	3%
Included regressors for investor purchases	20%

Table 5. *This table shows the share of the total variation in the log implied rent to rent ratio* $\ln I^{(12)}_{k,t}$ *explained by the regressors given in Equation* (6) *that is due to the individual* (k, j) *and the time* t *dimensions using a random effects model.*

5. Alternative Explanations

How do the results and estimation strategy studied in Sections 3 and 4 relate to existing theories of bubble formation and efficient pricing? We consider three alternative lines of thought: In Subsection 5.1, we discuss other popular bubble formation models, suggesting that our findings are complementary to models where portfolio constraints contribute to bubble formation, but are inconsistent with models where coordination problems between rational investors exacerbate bubbles. In Subsection 5.2, we discuss recent studies finding that the extension of cheap credit drove up aggregate house price levels during the mid 2000s, concluding that the extension of credit might have helped amplify the mechanism we develop in this paper, but that the extension of credit alone is unlikely to fully explain our findings.

5.1. **Bubble Theories.** We compare our results to the predictions and assumptions of two broad classes of bubble theories: bubbles created by 1) portfolio constraints and those created by 2) coordination problems. Santos and Woodford (1997 [49]) give an excellent taxonomy of potential bubble models.

5.1.1. *Portfolio Constraints.* In order to have equilibrium mispricing, models typically present two offsetting constraints. In this subsection, we consider models in which the core constraint is on portfolio allocations. For example, we have in mind papers like Hong, Scheinkman and Xiong (2006 [30]) and Ofek and Richardson (2003 [45]), in which short-sales constraints allow for excess price appreciation. Case and Shiller (1989 [13]) argue that the lack of short selling allows house prices to deviate from their efficient levels.

In the above papers, a second offsetting constraint is limited asset supply. Bubbles form yielding $\mathbb{E}P^S > \mathbb{E}P$ as prices reflect the beliefs of the most optimistic traders. This mechanism yields 2 predictions: 1) the most supply constrained markets are the most prone to over-pricing and 2) the collapse of the bubble is driven by a positive supply shock.

The prediction that bubbles are most likely to form in supply constrained markets is consistent with historical observations in the US residential housing market. Himmelberg, Mayer and Sinai (2005 [28]) and Glaeser, Gyourko and Saiz (2008) show that the most supply constrained cities also have the most volatile house price levels relative to fundamentals. However, these models make the sudden explosion of prices in cities like Phoenix, AZ and Las Vegas, NV even more puzzling, as these markets have historically been among the least supply constrained in the country. However, some observers have argued that recent developments in these markets such as newly announced limits on the future availability of land from the Bureau of Land Management in Las Vegas or the State of Arizona in Phoenix may have made such supply constraints more likely in the future.

Yet, we can also reject the hypothesis that a sudden positive supply shock burst the price bubbles in cities like Phoenix, Las Vegas and Miami. Figure 8 shows that the number of properties reported in the Deeds records did not balloon in these cities immediately prior to the collapse of their housing markets. While the number of properties in each city grew over time throughout our sample, there was no sudden supply shock as in Ofek and Richardson (2003 [45]).

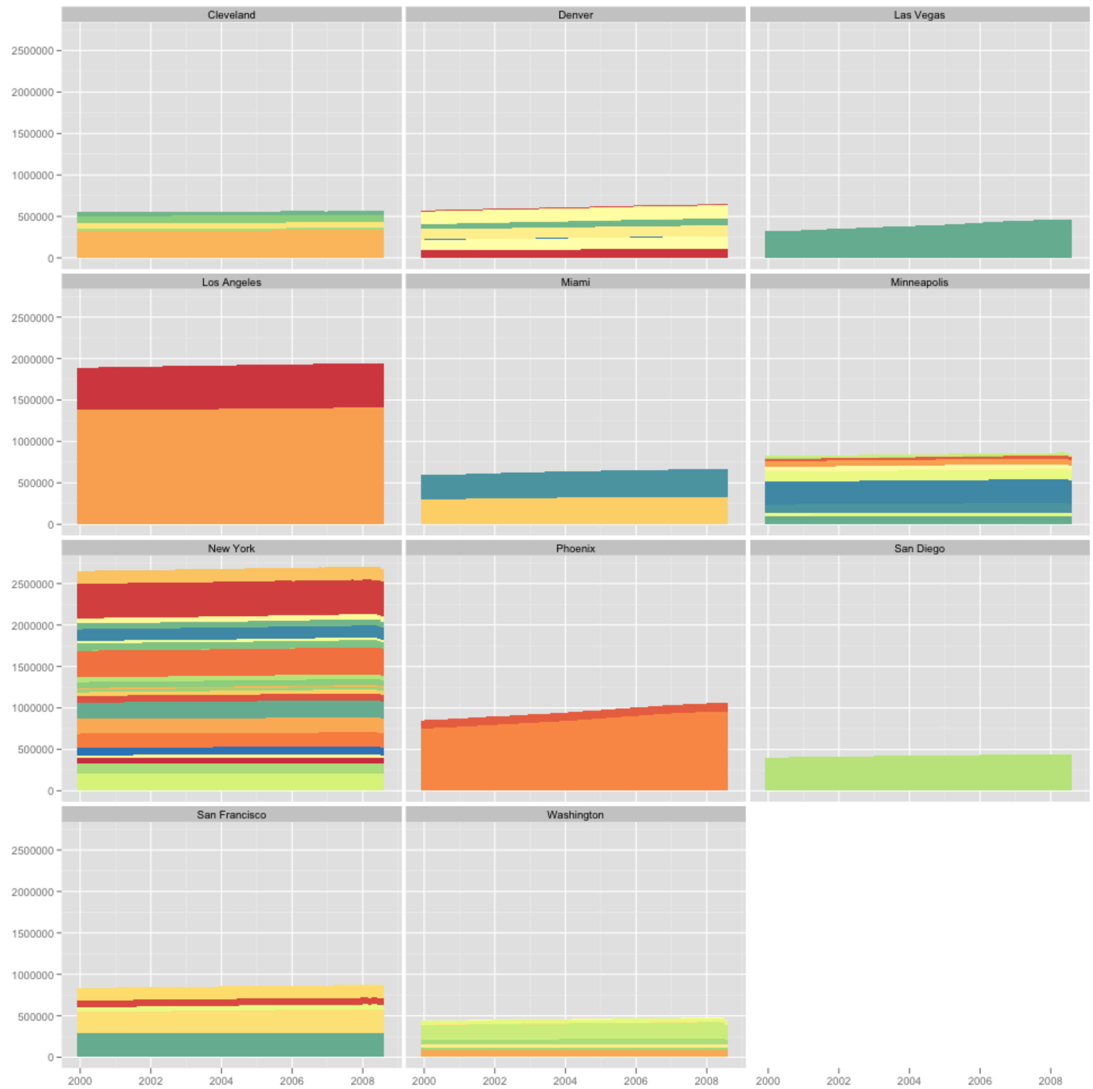

Figure 8. *This figure shows the numer of residential properties reported in the county tax and Deeds records for each of the cities we use in our analysis. The different colors represent individual counties within each city. To create this figure, we start with the number of properties reported in the tax records in 2008. Then, for each month starting in August of 2008 we subtract the number of new home sales reported in the county Deeds records.*

5.1.2. *Coordination Constraints.* We also consider models in which the core constraint is in the information available to agents rather than on their possible portfolios. For instance, we have in mind models like Abreu and Brunnermeier (2003 [1]) in which bubbles form exogenously and rational arbitrageurs suffer from a coordination problem. In this model, speculators optimally ride the bubble on the way up and strategically exit the market at the peak. In a follow up paper, Brunnermeier and Nagel (2004 [11]) show that hedge funds appear to have behaved this way during the Dot-Com bubble.

Our evidence is inconsistent with this type of model. Out of town speculators do not appear to successfully time the bubble's burst in each market. For instance, Figure 9 shows that the return earned by a speculator who bought during the bubble and sold at the end of our sample dropped below 0 during 2005 in each of the cities. However, this figure also shows that this was the peak buying time of the out of town speculators, who represented their largest share of home purchases for these dates.

Thus, our results appear to be more consistent with the intuition behind models like Hong and Stein (1999 [31]), Tirole (1982 [58]), or Scheinkman and Xiong (2003 [50]) in which outside speculators incorrectly value the underlying asset.

5.2. **Low Interest Rates and Subprime Lending.** During the recent boom in housing prices, many analysts argued that easy access to credit propped up house prices to levels well above their fundamental values. For instance, see Mian and Sufi (2009 [41] and [42]) for well cited empirical investigations that come to this conclusion. From a theoretical perspective, Stein (1995 [55]) shows how the credit supply channel can amplify price shocks leading to sudden jumps in prices. Many observers point to low interest rates and easier credit from the subprime crisis as an aggregate shock that likely increased home prices across the country, and thus would be adequately controlled for by the inclusion of time fixed effects in our earlier specification. However, as noted below, in some models, easier credit might have also amplified the the demand shock by impact distant speculators.

For example, Himmelberg, Mayer, and Sinai argue that low interest rates have a disproportionate impact on home prices in faster price-growth markets like those on the coasts. In their user cost model, low interest rates raise home prices further in fast growing markets due to a simple compounding effect; higher future growth in rents or prices is worth more today if the future is discounted at a lower rate, as when long-term interest rates fall. The authors point out that home prices grew especially quickly in markets like San Francisco,

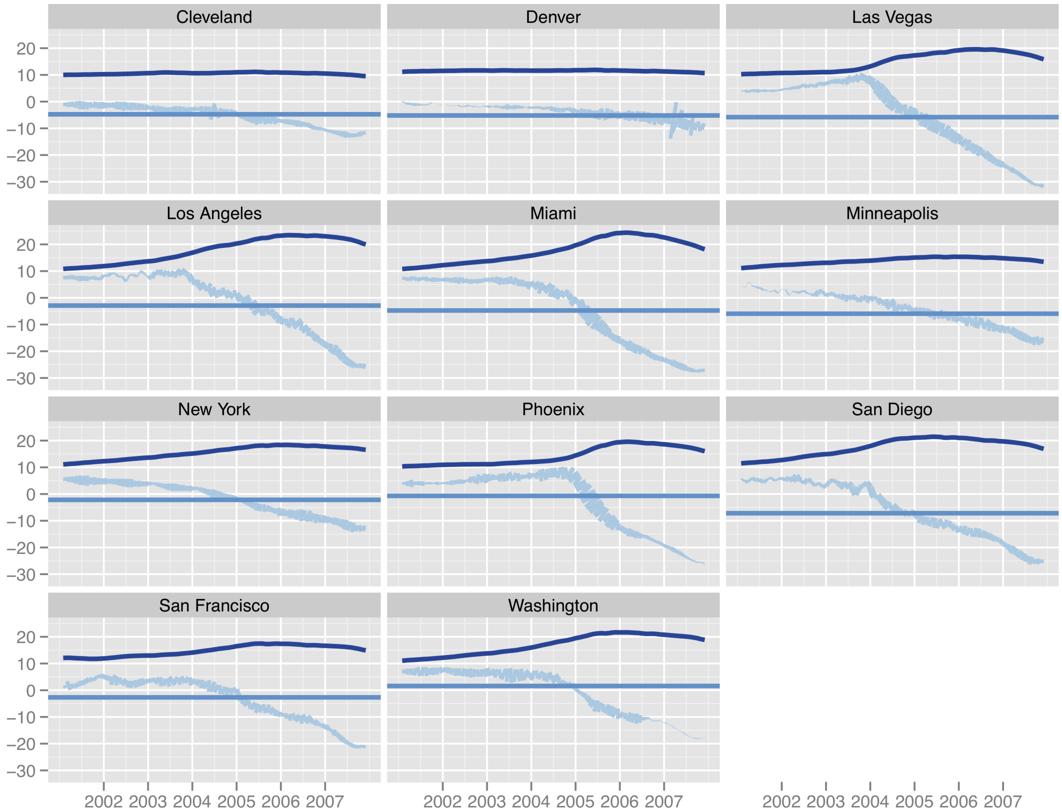

Figure 9. *This figure the realized mean annual return to buying a home conditional on the purchase date split by distant speculators (light blue) and local investors (dark blue). The straight line in each plot marks a* 0% *return. The width of the line represents the relative number of buyers of each type normalized with respect mean for each city. To create this figure, we take all of the homes sold in each month and compute the number of months until the home is resold. We then compute the price appreciation during this time interval for each sale. For homes that do not resell before August 2008, we compute the price appreciation through August 2008. Finally, we average over each buyer type for each city at each purchase date. This figure says that, on average, a foreign second home buyer in Phoenix, AZ in 2004 earned roughly a* 10% *return on his investment; whereas, a foreign second home buyer in Phoenix, AZ in 2005–just a year later–lost around* 10% *of his home value. Nevertheless, due to the thickness of the lines, we know that distant speculators invested most heavily in Miami, Phoenix, and Las Vegas in 2004, 2005, and parts of 2006, exactly the times that resulted in the most negative returns over our sample period.*

Los Angeles, New York, and Boston, as would be predicted by the user cost model. Of course, our measure of mispricing explicitly accounts for the idsproportionate impact of low interest rates on home prices in coastal markets. However, low interest rates might have also facilitated the formation of a bubble in markets like Las Vegas. Phoenix, and Miami if low rates helped amplify the impact of excessive expectations of home price appreciation among some outside investors.

Similarly, Mian and Sufi argue that increased access to credit disproportionately increased demand for homes in previously credit-constrained locations. While their evidence appears to apply mostly to owner-occupants, it might also apply to investors if credit shocks allowed distant speculators to become more aggressive in purchasing homes outside their local market. These findings would also be consistent with the findings in Haughwout, et. al. (2011 [27]) in which states like Arizona and Nevada had a large increase in the use of often unreported use of subprime loans by investors to purchase homes.

6. Conclusion

Can noise traders destabilize markets and generate asset pricing bubbles? While this has been an important topic of discussion in light of the recent financial crisis, empirical analysis of the effects of noise traders has remained difficult as an empirical researcher must not only identify a well defined group of noise traders but also demonstrate that this group of traders is causally affecting prices.

In this paper we address these difficulties by studying the impact of noise traders in the form of out of town investors using transactions level data on US residential housing. These "distant speculators" are likely less informed about local housing market conditions and more reliant on house price appreciation to earn a positive return. We find that out of town, but not local, speculators purchase houses at times and in markets when prices are rising rapidly. We then show that adding out of town speculators to a market *causes* excess house price appreciation using the front door criterion and data based on the relative size of cities facing a shock by distant speculators.

It is quite possible that noise traders or distant speculators have contributed to bubbles in markets beyond US housing in same ways we show for the the recent crisis. For instance, consider the residential housing market in Spain, where many observers suggested that home purchases from buyers in other countries fueled the boom. `www.economywatch.com` reported in Aug. 2008 that "...an estimated quarter-million Spanish homes are owned by Britons. With significant increases in the UK property market, due to lack of new construction, and low interest rates in Spain, these Iberian properties have long been attractive investments for Brits. This has fueled a property bubble in Spain that burst around the end of 2008's Q1." Notice as well that low downpayment mortgages were not available in Spain during the boom, so subprime lending cannot have been an appreciable contributor to the bubble that hit Spain in the last decade.

The United States commercial real estate market also appeared to suffer through a similar phenomenon during its boom in the late 1980's. After the tax code changed in 1986, making purchases of commercial real estate less attractive, foreign investors, particularly those from Japan, began large scale purchases of commercial office buildings, apparently driving prices to new heights. Aloian et al. (1996 [48]) discuss the purchase of Rockefeller Center by Mitsubishi Trust, Co. for more than $1 billion in the late 1980s, only to file for bankruptcy within 5 years, losing their entire investment.

This phenomenon may not be restricted to real estate markets. During the Dot-Com bubble, many analysts suspected that the influx of day traders who had the technical ability to trade but little knowledge or experience in internet stocks fueled the price appreciation realized by NYSE technology stocks. Recently, Griffin et al. (2010 [23]) give evidence supporting precisely this story. As well, consider the VC funding during the BioTech boom in the 1980's. Many new venture capital firms entered the market without previous experience in this space. Terry McDermott, writing in 101 Theory Drive (2010 [39]) states: The mere fact "...that an article published in a nonscientific journal had cachet in biotech venture-capital conference rooms gives some indication of why so many start-up biotech companies failed: no one understood what they were doing, least of all the capital underwriters."

Further research is needed to understand the extent to which the entry of distant or uninformed speculators in these markets had a causal impact on excess price appreciation or mispricing. We believe that the methodology developed in this paper might help explore potential bubbles in these other settings with appropriate data. Our analysis of the impact of noise traders on financial markets relies on two features: First, we use transaction level microdata with which we identify a group of noise traders. Second, the US residential housing market is segmented into local markets enabling us to identify a causal effect using exogenous variation in the responsiveness of home prices in individual markets to flows of noise traders.

The ability to identify noise traders and their impact on asset prices may have practical value if it provides a new tool for investors and policy makers to identify bubbles in real time. While the asset pricing literature contains numerous econometric techniques designed to test for the existence of bubbles[13], each of these tests crucially relies on a variance or second moment based estimator to look for mispricing, effectively asking: "Did prices move around too much given their initial levels and minimal economic restrictions?" A major drawback to using these sorts of second moment based estimators is that the estimators cannot identify bubbles in real time. In order for a price path to look like a bubble path, these estimators require high volatility. This means that both the up and the downside of the bubble price path is needed to pick out bubbles. Our approach suggests that bubbles can diagnosed, in part, by the appearance of uninformed buyers paying higher prices than local buyers at at time that prices already appear high.

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