The Mean Streets of Sydney

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ABSTRACT

Bubbles are episodes where observed prices differ from what they should be. Exploiting the concept of spatial autocorrelation, we use data for 1,006,036 individual transactions yielding 80,113 postcode-month records on Sydney property prices from February 1996–December 2015 to create a proxy for bubbles for both apartments and houses. Bubbles exhibit positive and robust relationships to proxies for investors seeking lottery-like outcomes. Given the definition of bubbles, the presence of a bubble need not be related to changes in prices. We establish, however, that there are positive relationships of returns of Sydney apartments and houses.

JEL Classifications: G02, R31, G12.

Keywords: behavioral finance, bubbles, residential real estate.

Highlights:

- Bubbles metrics are from derived variations in spatially autocorrelated prices.
- Bubbles are present in the Sydney real estate market.
- Bubbles have a positive association with lottery-seeking behavior.
- Bubbles have a positive association with the returns of Sydney property.

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ABSTRACT

Bubbles are episodes where observed prices differ from what they should be. Exploiting the concept of spatial autocorrelation, we use data for 1,006,036 individual transactions yielding 80,113 postcode-month records on Sydney property prices from February 1996 to December 2015 to create a proxy for bubbles for both apartments and houses. Bubbles exhibit positive and robust relationships to proxies for investors seeking lottery-like outcomes. Given the definition of bubbles, the presence of a bubble need not be related to changes in prices. We establish, however, that there are positive relationships of returns of Sydney apartments and houses.

1. Introduction

Bubbles are episodes where observed prices differ from what they should be (Stiglitz, 1990). This notion is challenging: bubbles represent violations of market efficiency. Mispricing implies that prices have not adjusted to reflect all available information. As such, any examination of a *prima facie* bubble must confront the challenge of the joint hypothesis (Fama, 1970, 1991). When we observe a *prima facie* bubble, it is impossible to determine whether we are observing mispricing or if our model of expected returns in wrong. In other words, are we observing mispricing or do we simply not understand the market we are observing?

We exploit transactional data on Sydney property prices to create proxies for bubbles. In doing so, we need to make an assumption about expected prices—but we only need to make a *simple* assumption (although, as Fama highlights, we must have some assumption or expectation about the market). Property prices are believed to exhibit spatial autocorrelation: "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p. 236). Therefore, we should observe two adjacent identical houses, selling at the same time, to sell at the same price; any violation of this expectation would be a violation of the law of one price. Our bubble metrics are based on the law of one price applying to spatially autocorrelated properties. We operationalize bubbles, where observed prices do not equal theoretical prices, by considering if the law of one price is violated: two adjacent identical houses selling at the same time may not sell at the same price. In practice, we cannot observe "pure" spatial autocorrelation because the size and history of our dataset make close inspection of the complete characteristics set impossible, and therefore we create a bubble proxy. This bubble proxy, discussed and presented in Section 2 of this paper, finds periods where *prima facie* mispricing is lower, and others where it is higher.[1] Bubbles are therefore a persistent feature of the market we study. The variations in size of the bubbles we look at, however, suggest that when the metric is lower, barriers to arbitrage (Shleifer and Vishny, 1997) militate against values of zero.

The Australian residential real estate market is dominated by individuals. While many may be gifted amateurs, individual investors are commonly considered to be less capable than institutional investors and more prone to behavioral biases (Feng and Seasholes, 2005; List, 2003). As such, real estate may be a domain of investor behavior in which behavioral biases are more readily observed than, say, the stock market, which is likely to be dominated by more sophisticated investors (such as institutions).

Our data is, in some ways, similar to transaction stock market data, which Behavioral Finance has exploited to create proxies for investor biases and affect. We take the opportunity to create analogous proxies for the real estate model and use these to model the behavioral determinants of the bubble. The clear message from the tests we present in this paper is that the proxy for lottery-seeking investor behavior has a positive association with bubbles. We discuss lottery-like investments, highlighting

[1] "…in testimony on February 23, 1999, Mr Greenspan [then Chairman of the Federal Reserve] as asked whether he thought there was still irrational exuberance. His reply was "That is something you can only know after the fact" Garber (2000, p. 6). The metrics we create belie Greenspan's belief. McQueen and Thorley (1994) measure bubbles as a run of high returns followed by a crash and this precludes considering bubbles until they appear to have ended.

images people form, associated with lottery-like outcomes, and the results linking bubbles and lottery-seeking behavior, in Section 3 of this paper.

Secondly, bubble metrics allow us to consider the role of bubbles and prices. Higher returns may be associated with prices deviating from fundamentals, but this need not be the case, given Stiglitz's notion of bubbles: mispricing, which refers to a value at a specific time, need not be associated with *changes* in prices. We examine whether bubbles are associated with real estate returns in Section 5 of this paper, and find that bubbles have positive and statistically significant with the returns of both units and houses. For units (but not houses), we also find evidence that returns have a positive association with bubbles.

Operationalizing bubbles as a violation of spatial-autocorrelation (and, therefore, a *prima facie* violation of the law of one price) provides an insight into *why* bubbles might have a positive association with returns. The absence of a bubble indicates *no* mispricing; market participants receive the expected value of the property they buy or sell. The presence of a bubble is indicative of mispricing: market participants do not necessarily receive, or pay, what they expect. As bubbles increase, the risk of not receiving, or paying, the expected price becomes greater, and *vice versa*. Therefore, a positive relationship of returns to a bubble may be viewed as rational compensation for risk (Merton, 1980). Therefore, we model bubbles as a quasi-rational phenomenon; we can, however, utilize a notion based on rational expectations to link bubbles to returns.

The analysis in this paper, and the resulting findings, may be contrasted with the analysis in papers that concentrate on price or return time series. For example, Shi et al. (2016) test time series real estate prices in Australian capital for "mildly explosive" episodes of growth.[2] Although Shi et al. recognize Stiglitz' notion of mispricing, their methodology inherently excludes consideration of fundamentals. As

[2] Shi et al. (2016) utilize the time series methodology of Philips et al. (2015a,b) which, in turn, develops Philips, Wu and Yu (2011). Baur and Heaney (2017) follow a similar approach and confirm Shi et al.'s findings.

such, the question of whether the structural breaks (in what, for this analysis, are a dependent variable) are associated with a bubble cannot be addressed.

We write at an interesting, and potentially critical, time for the Australian economy. Politicians and the press appear obsessed with Australia's supposed house price bubble and its consequences for housing affordability. Australia's financial sector, which represents a little under 40% of the benchmark ASX 200 index[3], has considerable exposure to the mortgage market, which regulators are monitoring.[4] The behavioral analysis of bubbles presented in this paper suggests that mispricing and its ramifications are persistent features of Australian real estate markets. The Australian discussion on Australian property prices has, thus far, ignored this aspect of the market. More generally, the world has been chastened by the American-led Global Financial Crisis which, in part, had its roots in a house price bubble from 2000–2009 and its subsequent "bust" (Blinder, 2013).[5] The lessons we present from Sydney have important ramifications for all economies.

2. Data and Method

2.1 Sample construction

Transaction and attribute data for all residential properties in the metropolitan area of Sydney, Australia are sourced from CoreLogic via Sirca for the period 1 January 1995 to 31 December 2015. The data includes the transaction price and date, the property type (house or unit[6]), the postcode, and several structural features of the property. Each property is marked with a unique numerical ID, which allows identification of repeat sales of the same property through time.

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[3] See https://www.blackrock.com/au/individual/literature/fact-sheet/ioz-ishares-core-s-p-asx-200-etf-fund-fact-sheet-en-au.pdf (accessed on June 6th, 2017).

[4] See http://www.rba.gov.au/publications/fsr/2017/apr/ (accessed on June 6th, 2017).

[5] Pages 31 to 40 of Blinder (2013) are particularly relevant.

[6] Units are the common terminology in Australia for strata title properties including apartments and flats.

There are 984,083 individual sales records, after removing incomplete and duplicate entries. Summary statistics for our data set are presented in Table 1. Houses make up 604,919 (61.47 per cent) of sales records in the sample, with units making up the remaining 379,164 (38.53 per cent). There are more unique houses than units in the sample. Analysis of repeat sales shows that on average units are held for a shorter period (5.21 years) than houses (5.59 years) and turn over more frequently than houses. The average price for houses ($554,849) is greater than for units ($472,458) across the sample, and average prices exceed median prices by around 35 to 40 per cent, indicating significant positive skew in the price distribution.

[Table 1 about here]

Sydney unit and house prices have varied substantially through time. Figure 1 charts the monthly median sales price in Sydney for both. The median house price increased approximately 500 per cent in nominal terms between 1995 and 2015, while the median unit price approximately trebled in this time. Figure 2 creates an index of the median house prices presented in Figure 1 and compares the growth in this series with that of the ASX 200 index (the benchmark index for the Australian market), and shows that investment in Sydney real estate compares favorably with investing in Australian stocks on an average return basis.[7]

[Figure 1 about here]

[Figure 2 about here]

We treat houses and units as separate samples in our analysis. There are important but potentially separate influences on these markets. These influences include demographics (household size and incomes are positively biased towards houses), geography (units are more concentrated near the CBD), owner type (owner-occupiers are more likely to purchase houses while investors are more concentrated in

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[7] The depiction of the ASX 200 in Figure 2 does not adjust for dividends. This facilitates comparison with the house and apartment data which do not include rental income. Not including rental income is appropriate for both Figures 1 and 2 as housing is predominately purchased for direct consumption and not for leasing.

units), and regulatory policies (various government-driven housing market incentives have affected distinctly targeted house and unit markets during the sample period).

2.2 Bubble metrics

We operationalize our bubble metric using two methods. In our first approach, we measure the relative "price distance" of each sale from the median sale price in the postcode. We refer to this as the *Median-to-Observed* (henceforth MTO)[8], calculated for the i^{th} property in postcode k in month t as given by Equation 1:

$$MTO_{i,t} = (Price_i - Median_{k,t}) / Median_{k,t} \quad (1)$$

where $Median_{k,t}$ is the median sales price in postcode k in month t

Our second approach uses the repeat transactions subsample, and measures the difference between the expected price at the second sale date based on growth in the median price index during the holding period and the observed sale price. In other words, this approach measures the price performance distance between individual properties and the market index. We refer to this bubble metric as the *Indexed-to-Observed* (henceforth, "ITO") and calculate it as given by Equation 2:

$$ITO_{i,t} = (Price_i - EPrice_{i,t}) / EPrice_{i,t} \quad (2)$$

where $EPrice_{i,t} = Price_{i,s} \text{ x } (Median_{k,t} / Median_{k,s})$;

s is the date of the first sale of the repeat transaction pair; and

t is the date of the second sale of the repeat transaction pair.

We calculate MTO_t and ITO_t as the monthly city-wide average for each property type. In aggregating transaction-level observations, we require a minimum of ten transactions within a postcode for a given property type in the month for inclusion. This is done to limit outlier effects in thinly-traded postcodes.

$SKEW_{MTO,t}$ and $SKEW_{ITO,t}$ are subsequently measured as the sample skewness of the distribution of the bubble metrics. The respective equations for the skewness of MTO_t and ITO_t are given by Equations 3a and 3b:

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8 A table containing definitions of the key variables used in this paper is included in Appendix A.

$$SKEW_{MTO,t} = \frac{n_t}{(n_t-1)(n_t-2)} \sum_{k=1}^{K} \left(\frac{MTO_{i,t} - \overline{MTO_t}}{\sigma_{MTO,t}} \right)^3 \quad (3a)$$

$$SKEW_{ITO,t} = \frac{n_t}{(n_t-1)(n_t-2)} \sum_{k=1}^{K} \left(\frac{ITO_{i,t} - \overline{ITO_t}}{\sigma_{ITO,t}} \right)^3 \quad (3b)$$

where n_t is the number of transactions in month *t*;

$\overline{MTO_t}$ is the average *MTO* for all properties in month *t*;

$\overline{ITO_t}$ is the average *ITO* for all properties in month *t*;

$\sigma_{MTO,t}$ is the sample standard deviation of the *MTO* bubble metric in month *t*;

$\sigma_{ITO,t}$ is the sample standard deviation of the *ITO* bubble metric in month *t*.

2.3 Summary statistics

Tables 2 and 3 present summary statistics for the dependent and independent variables used in the analysis. Statistics for the sample of units may be found in Table 2; those for houses in Table 3. We find that the average values of *bubble(MTO)* and *bubble(ITO)* are positive for both units and houses: bubbles, reflecting violations of spatial autocorrelation, are the expected state of the Sydney market. The standard deviations observed for these mean values indicate that the extent of bubbles varies and the maxima and minima we observe indicate that we find instances of no bubble (a minimum of zero are reported for *bubble(ITO)* for houses in Table 3) and negative bubbles (a minimum of -0.03 is reported for *bubble(ITO)* for units in Table 2); although these instances would appear less likely than positive bubbles and are also perhaps a function of the way bubbles are calculated (the ITO methodology).

The relative price performance of property and the Australian stock market is presented in Figure 3, where panel A contains the unadjusted index values and panel B contains the indices rebased to 100 at the start of the sample period.

[Table 2 about here]

[Table 3 about here]

Tables 2 and 3 also show that average (median) monthly returns for units are 0.62% (0.45%), and 0.90% (0.94%) for houses. For the same period, monthly returns of the ASX 200, the benchmark stock index in Australia, recorded average (median) figures of 0.50% (1.06%). Australians often say that things, even investments, are "as safe as houses”; the standard deviation of unit and house returns, and the associated maxima and minima, suggest that this expression is somewhat delusionary. The standard deviation of unit returns is 0.04 and that for houses is 0.06, compared with 0.0375 for the ASX200 index. The maxima (minima) for units are 15% (-13%) and 19% (-18%) for houses. These results are more extreme than the maxima (7.47%) and minima (-12.66%) of the ASX200 for the comparable period.

Tables 2 and 3 also present *Q*-statistics testing the null of autocorrelation at one lag (Ljung and Box, 1979), and in a number of instances we find evidence of autocorrelation. We discuss autocorrelation and how we accommodate it when we discuss the regressions we will estimate. We also report Phillips–Perron tests of the null that the variables have a unit root (Phillips and Perron, 1988). Where we reject the null, we calculate first differences and also report summary statistics for these transformed variables (denoted by “Δ” before the variable name), which we will use as independent variables in the regressions we estimate in the tables.

Estimated correlation coefficients for the sample of units may be found in Table 4; those for houses in Table 5. In both tables, parametric measures are presented above the diagonal and non-parametric measures appear below the diagonal. Given our working assumption that bubbles are associated with returns, it is noteworthy that we do not find significant correlations between unit returns and either bubble metric (*bubble(MTO)* and *bubble(ITO)*) for units in Table 4. We also fail to find significant correlations between house returns and bubble metrics in Table 5. Chan et al. (2017) prove that different proxies for the same underlying phenomena should be correlated. *Bubble(MTO)* and *bubble(ITO)* have significant positive correlations for units (Table 4). For houses (Table 5), *bubble(MTO)* and *bubble(ITO)* also have significant positive correlations, but for the Pearson coefficient we find that the significance is at the 10% level.

[Table 4 about here]

[Table 5 about here]

2.4 Regression analyses and endogeneity

We analyze the data using regression analyses. We begin by analyzing the determinants of bubbles—$bubble_t$—for units and houses. We conduct our analysis using measures derived using the MTO and ITO methods. For the period beginning in February 1995 and ending in December 2015, we estimate:

$$Bubble_t = \widehat{\beta_1} + \widehat{\beta_2} Bubble_{t-1} + \widehat{\beta_3} Volume_t + \widehat{\beta_4} Volume_{t-1} + \widehat{\beta_5} Skewness_t + \widehat{\beta_6} Skewness_{t-1} \quad (4)$$

The subscripts *t* and *t-1* refer to the current and past months' observations of the variable (variable definitions are summarized in Appendix A).[9] The summary statistics presented and discussed above indicate that autocorrelation is present in the data. Therefore we include lagged observations, as we observe autocorrelation in the variables and adjust standard errors of the estimates for auto-correlation and heteroscedasticity to facilitate valid interpretations of the significance of the estimated coefficients.

Volume is an important proxy in behavioral finance: it is a standard proxy for overconfidence and so we might expect its coefficient (that is, the estimate of β_3 and perhaps also that of its lagged value, β_4) to be positive. It is also one that allows us to distinguish between quasi-rational explanations and those based on economically rational expectations. Mispricing might be a function of restricted supply; and if this proves to be the case, we might expect the coefficient of *volume* to be negative.

Skewness proxies for the lottery-seeking propensity of participants in the unit and house markets. An increasing value of *skewness* may be associated with great lottery-seeking behavior. As we have noted previously, studies on lottery-like investment suggest that its coefficient should be positive.

The data available to us becomes richer from 2004 and we are able to augment equation (4) with *Δrent*, *Δdiscount* and *time-on-market* (see Appendix A) and estimate:

$$Bubble_t = \widehat{\beta_1} + \widehat{\beta_2} Bubble_{t-1} + \widehat{\beta_3} Volume_t + \widehat{\beta_4} Volume_{t-1} + \widehat{\beta_5} Skewness_t \quad (5)$$
$$+ \widehat{\beta_6} Skewness_{t-1} + \widehat{\beta_7} \Delta rent_t + \widehat{\beta_8} \Delta discount_t + \widehat{\beta_9} time-on-market_t$$

Δrent, *Δdiscount* and *time-on-market* are indicative of the state of the market. It is worth noting that *time-on-market*, and perhaps also *Δdiscount*, may also be behavioral

9 We do not include apartment or house price returns when estimating this equation or equation (4). We discuss this below when we discuss equation (5) and also when we elaborate on issues of endogeneity in footnote 12.

proxies. Impulsivity has been associated with pathological gambling (Petry, 2001).[10] Any variation in patience we observe through selling earlier or decreasing the price might be associated with the gambling behavior we seek to capture with *skewness*, our proxy for lottery-seeking behavior.

We also estimate equations (4) and (5) allowing for the possibility of sequentially determined structural breaks (Bai and Perron, 1998), allowing for either homogenous or heterogeneous error distributions across breaks. This has two advantages: firstly, it allows us to acknowledge literature where structural changes are indicative of bubbles (Philips et al., 2015a,b); secondly, it allows us to examine the robustness of our inferences in sub-periods without having to arbitrarily define what those periods might be. Where we find structural breaks assuming either homogenous or heterogeneous errors distributions, we choose to present only the results of the estimation with the lowest value of Akaike's Information Criterion (AIC).[11]

Given our emphasis on operationalizing bubbles as violations of spatial autocorrelation, the question of whether bubbles are associated with returns remains to be addressed. We do so by estimating equation (6), where $bubbleIV_t$ is an instrumental variable obtained from predicated values of $bubble_t$ obtained after estimating equations (1) and (2) [for both MTO and ITO]. The theoretical framework of our analysis proposes that returns are a function of bubbles, and it is also reasonable to believe that bubbles might be a function of returns. Using $bubbleIV_t$ in equation (6) follows standard two-stage least squares methodology when endogeneity is present in the data.[12] Equation (6) is:

$$Return_t = \widehat{\gamma_1} + \widehat{\gamma_2} Return_{t-1} + \widehat{\gamma_3} BubbleIV_t \qquad (6)$$

10 Patience has also been found to have a positive relationship with individuals' long-term prosperity (Moffitt et al., 2011).

11 There is no instance where this choice materially effects the inferences we can make.

12 Therefore, we quarantine $return_t$ from equations (4) and (5). Given the autocorrelation of the variables we have noted when discussing the summary statistics in Tables 2 and 3, might be endogenous to the lagged variables we use. Therefore, we also quarantine $return_{t-1}$ but include it when estimating equation (6).

In estimating equation (6) we follow Staiger and Stock (1997) and only include instruments where the F-statistics of the equation from which they are derived are sufficiently high (the rule of thumb is that it is greater than ten).

The F-statistics generated in the analyses of units indicate that there are instruments for returns which would not be weak (Staiger and Stock, 1997); we are able to extend our analysis to consider the role of returns on bubbles and estimate an equation where $bubble_t$ is a dependent variable and an instrumental variable for return is included as an independent variable in equation (7):

$$Bubble_t = \widehat{\gamma_1} + \widehat{\gamma_2} ReturnIV_t \qquad (7)$$

Given that all of the information available to us is fully utilized in the estimation of bubbles (equations 4 and 5), equation (7) is relatively spare.

We now present the analyses based on equations (4) and (5), analyzing units and then houses.

3. Bubbles

Our first analysis in Table 6 indicates that $skew_t$, the proxy for lottery seeking behavior, has a positive statistically significant relationship with the dependent variable, $bubble_t$. $Skew_t$, the proxy for lottery-seeking investor behavior, will be have to have a positive association with bubbles in each of the subsequent analyses we present. This result introduces the “take-home” message of the paper: lottery-seeking behavior drives bubbles.

Barberis and Huang (2009) demonstrate that if investors behave as Prospect Theory (Kahneman and Tversky, 1979) predicts, investors should prefer positive skewness in returns. Cronqvist and Siegel (2014) present evidence that, in part, investors’ preference for positive skewness and their propensity to exhibit behavior consistent with Prospect Theory has a genetic basis. Kumar (2009) notes a preference for positive skewness (that is, the attractiveness of lottery-like investments) in the portfolio choices of less educated, younger, urban American men. In Australia, the market of interest in this study, Boisen et al. (2015) extend Kumar by studying investments in wildcat oil and gas wells, which closely approximate lotteries. Boisen et al. note literature highlighting the common personality traits driving gambling and investment (Jadlow and Mowen, 2010) and also the euphoria associated with mental images of the hoped-for successful outcomes (Lowenstein et al., 2001; Rottenstreich and Hsee, 2001). Australian gambling advertisements play on the fantasies of how punters will enjoy wealth from big but unlikely wins; we suspect this is also the case outside Australia. Gao and Lin (2015) and Dorn et al. (2015) present similar analyses (based on different datasets) showing that individuals connect lottery outcomes with investing in equity markets. The evidence in this paper is that we see this lottery-seeking behavior, which presumably is associated with fantasies associated with enjoying lottery-like success, driving bubbles in Sydney units and houses.

Table 6 presents results for the full sample period from February 1995 to December 2015. We present estimates derived using equation 4, applying the metrics obtained using the MTO method in Panel A and from the ITO method in Panel B. In both panels, model (1) includes all variables. In Panel B we present model (2), which has fewer variables, a lower AIC, and a higher adjusted R^2. In both models in Panel B we find that $skew_{t-1}$ has a small, but statistically significant, negative relationship with $bubble_t$, consistent with the autocorrelation in this variable that we reported in Table 2.

[Table 6 about here]

We find positive and statistically significant associations with $Skew_t$ in Table 7, which estimates equation (5), where equation (4) is augmented with a richer set of variables, for the period beginning in March 2004 and ending in December 2015. Again we see positive and statistically significant coefficients for $skew_t$, the proxy for lottery-seeking investor behavior. In addition, in Panel A we find a negative association of $bubble_t$ and $\Delta rent_t$. In Panel B, *Δdiscount* and *time-on-market* are found to have positive and statistically significant associations with $bubble_t$.

[Table 7 about here]

We re-estimate both equations (4) (reported in Table 6) and (5) (reported in Table 7), allowing for the possibility of sequentially determined structural breaks (Bai and Perron, 1998). We find structural breaks only for equation 4 using the MTO methodology, and report those results in Table 8. No breaks are found for the data obtained using ITO methodology. We find that the only exception to the positive and significant relationship of $bubble_t$ and $skew_t$ is found in the period beginning in

February 1997 and ending in February 1998. Our inference that bubbles are related to lottery-seeking behavior would therefore appear robust to specific time periods.

[Table 8 about here]

For the first time in these analyses, we find a negative relationship of $bubble_t$ with its lagged value, $bubble_{t-1}$. It is common to talk about "corrections" when discussing bubbles (especially in "popular" finance), but this has no meaning within a theoretical framework built around the EMH. Given the definition of bubble in this paper, the negative coefficient may be interpreted as a correction. *Bubble* is measured as a level (not as a first difference) and, therefore, a negative coefficient suggests that the level of mispricing captured in this metric will fall in the next period.[13] That is to say, prices will be more spatially autocorrelated, and hence more correct, *ceteris paribus*.

The analyses for house prices reinforce the inferences we made about $skew_t$, the proxy for lottery-seeking investor behavior that we made for units. In all the analyses we present for houses, $skew_t$ has a positive association with $bubble_t$. $Skew_t$, is positive and statistically significant in all models presented in Table 9, which presents analyses using data from February 1995 to December 2015. Again, in Table 10, for the sample for the period beginning in March 2004 and ending in December 2015 (where we have a richer dataset), we find positive and statistically significant associations of $skew_t$ and $bubble_t$. We find evidence of structural breaks for data obtained using both MTO and ITP methodology, and we present the sub-period analyses in Panels A and B of Table 11. $Skew_t$, is positive and statistically significant in all sub-periods in both panels (and, as we found in Table 8, $skew_{t-1}$ is found to have a small, but statistically significant, negative relationship with $bubble_t$).

[Table 9 about here]

[Table 10 about here]

[Table 11 about here]

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[13] The summary statistics for *bubble(MTO)* never fall below zero. While it is possible, in theory, that we might observe values less than zero, and hence the negative coefficient might suggest that the subsequent observation would be further away, in absolute terms, from zero, that possibility cannot be reflected in the statistical analysis presented here.

5. Bubbles and Returns

The analyses presented in the previous section demonstrate that bubbles are a behavioral, or quasi-rational, phenomenon, associated with investors' lottery-seeking behavior. As investors' imaginations fuel the euphoria exacerbating bubbles, market participants face increasing risk of *not* receiving or paying what they expect. Bubbles, in other words, may represent risk and, as such, it is plausible to consider if returns are a function of the risk reflected in bubbles. We find that the returns of units do have such a relationship. The evidence we present for houses, however, does not find any significant relationship between returns and bubbles.

As we discussed in Section 2, we estimate equation (6) using $bubbleIV_t$ as an instrumental variable obtained from predicated values of $bubble_t$. Our proposed analysis, however, is hindered by weak instruments for both units and houses (Staiger and Stock, 1997).

Table 12 presents regressions analyzing the determinants of $return_t$ for Sydney units for the period February 1995 to December 2015 (the only period where we found instruments that were not weak (Staiger and Stock, 1997). Panel A reports results where variables have been derived using the MTO methodology; the instrumental variable for bubbles, $bubbleIV(MTO)_t$, is the predicted value obtained using Model(1) in Panel A of Table 6.[14] Panel B presents results where the variables have been derived using the ITO methodology; the instrumental variable for bubbles, $bubbleIV(ITO)_t$, is the predicted value obtained using Model(2) in Panel B of Table 6. Both $bubbleIV(MTO)_t$ and $bubbleIV(ITO)_t$ are found to have positive and statistically significant associations with returns.

[Table 12 about here]

The *F*-statistics reported in Table 12 indicate that instrumental variables for returns would not be weak (Staiger and Stock, 1997) and we take advantage of the availability of these instruments to address the questions of whether returns are associated with bubbles. Given that all available information was exhausted in the

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14 Model (1) was chosen to derive the instrumental variable as its adjusted R^2 is higher than that of model (2).

analyses of bubbles presented in the previous section, we can estimate only the relatively spare equation (7) where bubbles are a function of contemporaneous returns. Table 13 shows that bubbles have a positive relationship to returns using both the MTO and the ITO methodologies. As we have done previously, we re-estimate equation (1) in Table 13 allowing for the possibility of sequentially determined structural breaks (Bai and Perron, 1998). We find two structural breaks only for equation 4 using the MTO methodology in Table 14; in both periods we find that bubbles have a contemporaneous positive an statistically significant relationship to returns.[15] No breaks are found for the data obtained using ITO methodology.

[Table 13 about here]

[Table 14 about here]

Table 14 presents regressions analyzing the determinants of $return_t$ for Sydney houses and follows the same format as Table 12. We present results only where instruments have been derived using MTO methodology; the estimates obtained using ITO methodology produce weak instruments and we do not pursue these further. In Model A, for the period March 1995 to December 2015, the instrumental variable for bubbles, $bubbleIV(MTO)_t$, is the predicted value obtained using Model(1) in Panel A of Table 9. This instrumental variable for a bubble in the market for houses is found to have a positive and statistically significant relationship with returns. In Model B, where we examine the period from March 2004 to December 2015, $bubbleIV(MTO)_t$, the predicted value obtained using Model(2) in Panel A of Table 10, is not statistically significant.

[Table 15 about here]

6. Conclusion

This paper has used transactional data on Sydney property prices to create proxies for bubbles for units and houses in Sydney from February 1995 to December 2015. We operationalize Stiglitz's (1990) definition of a bubble—the difference between observed and theoretical prices—by proxying bubbles using variation in the

[15] The estimates in Table 14 are obtained constraining error distributions to be homogenous across structural breaks. Relaxing that constraint does not change the results. using the constraint that

spatial autocorrelation of prices. In doing so, the only assumption that we believe we make is that the law of one price should hold within reasonable bounds.

Skewness is found to have positive and statistically significant relationships with bubbles in the tests conducted in this paper. A preference for positive skewness is consistent with Prospect Theory (Barberis and Huang (2009). Our findings, however, are consistent with the notion that the desire for skewed, or lottery-like, outcomes is a function of personality traits linked to gambling and lottery-like investors (Boisen et al., 2015; Jadlow and Mowen, 2010; Kumar, 2009; Lowenstein et al., 2001; Rottenstreich and Hsee, 2001). We believe that the bubbles we observe are associated with powerful mental images associated with fantasies of wealth obtained from lottery-like outcomes.

Bubbles, therefore, are functions of prices. The definition does not imply any relationship to returns (that is, the definition of bubbles relates to the level of prices whereas returns refer to the change in prices). As bubbles become bigger, however, participants in the market face increasing risk (that is, the risk of not receiving, or paying, the expected price). Therefore, a positive relationship of returns to a bubble may be viewed as a rational compensation for risk (Merton, 1980). We find evidence that this is the case.

Our study highlights the usefulness, and necessity, of using definitions strictly and consistently when studying bubbles. Returns that are unusual are not bubbles, although they may be signs of bubbles. In examining bubbles and returns as separate phenomena, we are able to uncover both a behavioral basis for bubbles—lottery-seeking behavior—and an economically rational link between the risk this lottery-seeking behavior causes and returns.

Can policy makers benefit from appreciating the behavioral basis of the unit and house price bubbles? Bubbles are always with us; they simply vary in magnitude. The time frame over which they are observed suggests that bubbles have little association with factors that might be tweaked by policy-makers (such as supply and access to transport). We leave it to future research to consider if public pronouncements on real estate exacerbate or reduce the lottery-seeking behavior we believe drives bubbles. We also leave open the question as to how regulators take banks’ exposure to quasi-rational pressures into account when considering the stability of financial systems.

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Appendix A: Variables and their definitions

Variable	Definition
MTO	Difference between observed sales price and postcode median sale price, averaged across all transactions
ITO	Difference between observed sales price and the expected price based on postcode-level median price growth since previous sale, averaged across all transactions
Volume	Total number of sales across all postcodes
Skew	Skewness of bubble measures, MTO and ITO respectively, across all individual transactions
Rent	Median asking rental price, quoted in monthly amounts
Discount	Difference between asking sale price and achieved sale price, scaled by achieved sale price, averaged across all transactions
Time-on-Market	Number of days from the first listing of a property for sale to its sale date, averaged across all transactions

Table 1. Sample Selection

	Houses	Units
Sales	604,919	379,164
Sample distribution	61.47%	38.53%
Unique properties	331,085	189,184
Sample distribution	63.64%	36.36%
Repeat sales	273,834	189,980
Average holding period (years)	5.59	5.21
Average price (nominal)	554,849	472,458
Median price (nominal)	400,000	350,000
Median price (December 2015)	880,000	660,000

Table 2. Summary Statistics: Units.

This table presents summary statistics for Sydney units. Panel A presents statistics for variables for which we have data from 1995 to December 2015. Panel B presents statistics for variables for which we have data from 2004 to December 2015. Autocorrelation reports the Ljung–Box test of the null of no autocorrelation at one-lag (Ljung and Box, 1979). The Phillips–Perron tests the null hypothesis that the data has a unit root (Phillips and Perron, 1988). Variable definitions may be found in Appendix A.

Panel A: Series beginning in January 1995

Variable	Return	Bubble (MTO)	Bubble (ITO)	Skew (MTO)	Skew (ITO)	Volume
Series start date	January 1995	January 1995	January 1995	January 1995	January 1995	January 1995
Mean	0.01	0.20	0.27	10.73	14.39	37,345
Median	0.00	0.18	0.20	9.23	14.26	31,490
Std. Dev.	0.04	0.08	0.27	5.78	7.11	23,709
Maximum	0.15	0.51	1.95	34.96	31.93	144,738
Minimum	-0.13	0.03	-0.03	0.93	-0.93	1,227
Skewness	-0.11	1.10	2.88	1.51	0.07	1.37
Kurtosis	4.43	4.65	14.18	5.55	2.19	5.23
Autocorrelation	119.17***	1.03	0.02	0.29	39.41***	134.05***
Phillips–Perron Test	-25.12***	-15.68***	-15.34***	-16.37***	-11.8***	-6.14***

Panel B: Series beginning in 2004

Variable	ΔRent	Median rental	ΔDiscount	Discount	Δtime-on-market	Time on market
Series start date	March 2004	February 2004	February 2004	January 2004	February 2004	January 2004
Mean	0.40	394.02	-0.00004	-0.06	0.21	67.60
Median	0	400.00	0.0001	-0.05	-0.14	66.96
Std. Dev.	1	72	0.00133	0.01	1.99	18.03
Maximum	5.45	500.00	0.0018	-0.03	9.43	96.33
Minimum	-2	275	-0.0081	-0.08	-2.43	11.38
Skewness	2.17	-0.14	-2.67	-0.27	2.13	-0.22
Kurtosis	9.57	1.74	14.45	2.06	8.74	2.63
Autocorrelation	0.16	141.1***	89.61***	141.13***	108.33***	133.39***
Phillips–Perron Test	-11.54***	-0.40	-6.98***	-1.73	-5.19***	-2.86**[(a)]

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.

Table 3. Summary Statistics: Houses.

This table presents summary statistics for Sydney houses. Panel A presents statistics for variables for which we have data from 1995 to December 2015. Panel B presents statistics for variables for which we have data from 2004 to December 2015. Autocorrelation reports the Ljung–Box test of the null of no autocorrelation at one-lag (Ljung and Box, 1979) . The Phillips–Perron tests the null hypothesis that the data has a unit root (Phillips and Perron, 1988). Variable definitions may be found in Appendix A.

Panel A: Series beginning in January 1995

Variable	Return	Bubble (MTO)	Bubble (ITO)	Skew (MTO)	Skew (ITO)	Volume
Series start date:	January 1995	January 1995	January 1995	January 1995	January 1995	January 1995
Mean	0.01	0.10	0.44	12.19	18.48	71,264
Median	0.01	0.09	0.36	8.73	18.73	56,079
Std. Dev.	0.06	0.03	0.33	9.85	8.09	41,347
Maximum	0.19	0.24	2.86	48.74	43.20	224,469
Minimum	-0.18	0.03	0.00	1.64	0.65	9,672
Skewness	-0.19	1.62	3.27	1.91	0.04	0.95
Kurtosis	3.72	7.50	18.81	6.14	2.80	3.30
Autocorrelation	17.49***	13.19***	0.66	13.86***	56.156***	159.88***
Phillips-Perron Test	-28.91***	-12.94***	-15.25***	-13.3***	-11.1***	-5.4***

Panel B: Series beginning in 2004

Variable	ΔRent	Median rental	ΔDiscount	Discount	Time on market
Series start date:	March 2004	February 2004	February 2004	January 2004	January 2004
Mean	1.20	431.22	0	-0.07	78.60
Median	0	450.00	0	-0.06	83.50
Std. Dev.	4	63	0.00	0.01	20.05
Maximum	20.00	520.00	0	-0.03	107.50
Minimum	-20	330	0	-0.09	9.98
Skewness	0.40	-0.15	-1.77	-0.15	-0.78
Kurtosis	13.12	1.52	7.77	2.11	3.22
Autocorrelation	0.36	141.7***	110.06***	138.57***	130.77***
Phillips-Perron Test	-12.519***	-0.23	-4.92***	-2.32	-3.1**

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.

Table 4. Correlations: Units.

Pearson correlation coefficients are above the diagonal; Spearman rank coefficients are below the diagonal. Variable definitions may be found in Appendix A.

	Return	Bubble (MTO)	Bubble (ITO)	Skew (MTO)	Skew (ITO)	Volume	ΔRent	ΔDiscount	Δtime-on-market	Time on market
Return		0.02	0.08	0.02	0.21***	0.25***	0.05	0.10	-0.09	-0.06
Bubble (MTO)	0.06		0.28***	0.27***	-0.10	0.37***	-0.06	-0.12	0.17**	00.19**
Bubble (ITO)	0.14*	0.18**		-0.05	0.35***	0.11	0.02	00.14*	-0.05	0.21***
Skew (MTO)	0.06	0.35***	-0.03		0.09	0.25***	0.07	-0.07	0.12**	0.07
Skew (ITO)	0.15*	-0.16**	0.48***	0.11		0.24***	0.18**	0.14*	-0.2**	-0.11
Volume	0.23***	0.31	0.04	0.30****	0.18**		0.14*	0.02	0.02	0.2**
ΔRent	0.03	-0.10	0.07	0.01	0.21***	0.09		0.04	-0.03	0.22***
ΔDiscount	0.13	-0.13	0.00	-0.03	0.11	0.21***	-0.01		-0.87***	0.34***
Δtime-on-market	-0.15**	0.15*	0.08	0.03	-0.21***	-0.18**	0.00	-0.77***		-0.12
Time on market	-0.06	0.16**	0.06	0.06	-0.12	0.22***	0.17**	0.31***	0.01	

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.

Table 5. Correlations: Houses

Pearson correlation coefficients are above the diagonal; Spearman rank coefficients are below the diagonal. Variable definitions may be found in Appendix A.

	Return	Bubble (MTO)	Bubble (ITO)	Skew (MTO)	Skew (ITO)	Volume	ΔRent	ΔDiscount	Time on market
Return		-0.01	0.04	-0.10	0.13	0.27***	-0.07	0.07	-0.02
Bubble (MTO)	0.00		0.14*	0.51***	0.03	0.03	0.08	-0.08	-0.03
Bubble (ITO)	0.06	0.22***		-0.02	0.36***	0.00	0.03	0.01	0.08
Skew (MTO)	-0.13	0.55***	-0.04		-0.06	0.00	0.05	-0.12	-0.07
Skew (ITO)	0.12	0.03	0.25***	-0.04		0.49***	-0.01	0.18**	-0.20
Volume	0.28***	0.07	0.06	-0.02	0.46***		0.00	0.12	-0.44***
ΔRent	-0.07	0.09	0.05	0.09	-0.04	-0.01		0.01	0.12
ΔDiscount	0.08	-0.01	0.11	-0.13	0.17	0.31***	-0.05		0.39***
Time on market	-0.02	-0.02	0.18**	-0.08	-0.2**	-0.26***	0.21***	0.31***	

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.

Table 6. Unit Bubbles, February 1995–December 2015

This table presents regressions analyzing the determinants of $bubble_t$ for Sydney units for the period February 1995–December 2015. Panel A reports results where variables have been derived using the MTO methodology; Panel B presents results where the variables have been derived using the ITO methodology Variable definitions may be found in Appendix A.

Panel A: MTO

	Model (1)		Model (2)	
Intercept	0.108	***	0.138	***
t-statistic	(5.79)		(12.23)	
Bubble(MTO)$_{t-1}$	0.024			
t-statistic	(0.46)			
Volume$_t$	0.00000046			
t-statistic	(1.53)			
Volume$_{t-1}$	0.00000046			
t-statistic	(1.49)			
Skew(MTO)$_t$	0.00506790	***	0.005566	***
t-statistic	(5.23)		(6.15)	
Skew(MTO)$_{t-1}$	-0.00039			
t-statistic	(-0.55)			
Adjusted R^2	0.186		0.143	
AIC	-2.293		-2.258	
F-statistic	12.393	***	42.723	***

Panel B: ITO

	Model (1)		Model (2)	
Intercept	0.145	**	0.152	***
t-statistic	(2.33)		(2.65)	
Bubble(ITO)$_{t-1}$	0.073			
t-statistic	(1.33)			
Volume$_t$	-0.000001			
t-statistic	(-0.92)			
Volume$_{t-1}$	0.000001			
t-statistic	(0.63)			
Skew(ITO)$_t$	0.014	***	0.014	***
t-statistic	(4.68)		(4.82)	
Skew(ITO)$_{t-1}$	-0.006	*	-0.005	**
t-statistic	(-2.68)		(-2.25)	
Adjusted R^2	0.092		0.096	
AIC	0.170		0.153	
F-statistic	8.609	***	14.330	***

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.
t-statistics (in brackets under the estimated coefficients) have been adjusted for autocorrelation and heteroscedasticity (Newey and West, 1987).

Table 7. Unit Bubbles: Robustness, March 2004–December 2015

This table presents regressions analyzing the determinants of $bubble_t$ for Sydney units for the period March 2004–December 2015. Panel A reports results where variables have been derived using the MTO methodology; Panel B presents results where the variables have been derived using the ITO methodology. Variable definitions may be found in Appendix A.

Panel A: MTOA

	Model (1)		Model (2)	
Period:	*March 2004 to December 2015*		*March 2004 to December 2015*	
Intercept	0.084	***	0.098	***
t-statistic	(3.54)		(4.97)	
Bubble(MTOA)$_{t-1}$	0.031			
t-statistic	(0.51)			
Volume$_t$	0.0000016	***	0.000002	***
t-statistic	(3.55)		(4.12)	
Volume$_{t-1}$	0.0000009			
t-statistic	(1.38)			
Skew(MTOA)$_t$	0.00296	***	0.00299	***
t-statistic	(2.74)		(2.76)	
Skew(MTOA)$_{t-1}$	-0.00050			
t-statistic	(-0.53)			
Δrent$_t$	-0.009	**	-0.011	**
t-statistic	(-2.07)		(-2.44)	
Δdiscount$_t$	-0.009		0.603	
t-statistic	(0.017)		(0.06)	
Δtime-on-market$_t$	0.006		0.006	
t-statistic	(1.02)		(0.99)	
Adjusted R^2	0.180		0.177	
AIC	-2.343		-2.359	
F-statistic	4.862	***	7.063	***

Panel B: ITO

	Model (1)		Model (2)	
Period:	*March 2004 to December 2015*		*March 2004 to December 2015*	
Intercept	-0.059		-0.016	
t-statistic	(-0.36)		(-0.19)	
Bubble(ITO)$_{t-1}$	0.057			
t-statistic	(0.7)			
Volume$_t$	0.0000002			
t-statistic	(0.13)			
Volume$_{t-1}$	0.000001			
t-statistic	(0.25)			
Skew(ITO)$_t$	0.017	***	0.017	***
t-statistic	(2.84)		(3.0)	
Skew(ITO)$_{t-1}$	0.0001			
t-statistic	(0.04)			
Δrent$_t$	-0.018		-0.017	
t-statistic	(-0.73)		(-0.66)	
Δdiscount$_t$	101.389	***	105.038	***
t-statistic	(2.85)		(2.9)	
Δtime-on-market$_t$	0.059	***	0.061	***
t-statistic	(2.57)		(2.74)	
Adjusted R^2	0.125		0.145	
AIC	0.260		0.209	
F-statistic	3.510	***	6.982	***

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.
t-statistics (in brackets under the estimated coefficients) have been adjusted for autocorrelation and heteroscedasticity (Newey and West, 1987)

Table 8. Unit Bubbles: Robustness—Accounting for Structural Breaks

This table presents regressions analyzing the determinants of *bubble*$_t$ for Sydney units where unknown structural breaks have been estimated following Bai and Perron (1998), allowing for heterogeneous error distributions across the breaks. The analysis spans Sydney units for the period February 1995–December 2015. Variables have been derived using MTO. Variable definitions are found in Appendix A.

Period:	*February 1995 to January 1997*		*February 1997 to February 1998*		*March 1998 to June 2002*		*July 2002 to February 2008*		*March 2008 to December 2014*		*January 2015 to December 2015*	
Intercept	0.267	***	0.421	***	0.070	*	0.174	***	0.129	***	-0.009	
t-statistic	(7.49)		(6.18)		(1.92)		(3.99)		(3.96)		(-0.12)	
Bubble(MTO)$_{t-1}$	-0.455	***	-0.584	***	0.042		-0.280	***	0.003		-0.687	**
t-statistic	(-2.61)		(-4.81)		(0.36)		(-3.82)		(0.04)		(-1.97)	
Volume$_t$	-0.0000078	***	0.0000015		0.0000005		0.0000003		-0.0000002		0.0000011	
t-statistic	(-5.76)		(0.99)		(1.27)		(0.37)		(-0.32)		(1.41)	
Volume$_{t-1}$	0.00000276		-0.00000321	***	0.00000015		0.00000145	**	0.00000015		0.00000726	***
t-statistic	(1.42)		(-2.52)		(0.44)		(2.35)		(0.26)		(3.22)	
Skew(MTO)$_t$	0.013	***	-0.0014		0.0060	***	0.0033		0.0031	*	0.0132	***
t-statistic	(6.244)		(-0.55)		(3.27)		(2.37)**		(1.74)		(4.19)	
Skew(MTO)$_{t-1}$	0.00369		-0.00052		0.00109		0.00129		-0.00049		0.00023	
t-statistic	(1.26)		(-0.29)		(0.79)		(0.78)		(-0.39)		(0.05)	
Adjusted R^2	0.337											
AIC	-2.390											
F-statistic	4.636	***									-	-

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.

t-statistics (in brackets under the estimated coefficients) have been adjusted for autocorrelation and heteroscedasticity (Newey-West).

Table 9. House Bubbles, February 1995–December 2015

This table presents regressions analyzing the determinants of *bubble*$_t$ for Sydney houses for the period February 1995 to December 2015. Panel A reports results where variables have been derived using MTO; Panel B presents results where the variables have been derived using ITO. Variable definitions are found in Appendix A.

Panel A: MTO	Model (1)		Model (2)		Panel B: ITO	Model (1)	
Intercept	0.057		0.056	***	Intercept	0.390	***
t-statistic	(10.17)	***	(12.22)		*t*-statistic	(5.55)	
Bubble(MTO)$_{t-1}$	0.147		0.180	***	Bubble(ITO)$_{t-1}$	0.146	**
t-statistic	(2.32)	**	(3.93)		*t*-statistic	(2.25)	
Volume$_t$	0.00000004		0.00000007	**	Volume$_t$	-0.000001	*
t-statistic	(0.69)		(2.07)		*t*-statistic	(-1.66)	
Volume$_{t-1}$	0.00000003				Volume$_{t-1}$	0.000002	**
t-statistic	(.56)				*t*-statistic	(2.59)	
Skew(MTO)$_t$	0.001		0.001	***	Skew(ITO)$_t$	0.014	***
t-statistic	(9.22)	***	(7.88)		*t*-statistic	(4.68)	
Skew(MTO)$_{t-1}$	0.000140				Skew(ITO)$_{t-1}$	-0.017	***
t-statistic	(0.76)				*t*-statistic	(-4.49)	
Adjusted R^2	0.355		0.358		Adjusted R^2	0.132	
AIC	-4.709		-4.722		AIC	0.484	
F-statistic	28.510	***	47.448	***	F-statistic	8.609	***

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.
t-statistics (in brackets under the estimated coefficients) have been adjusted for autocorrelation and heteroscedasticity (Newey and West, 1987).

Table 10. House Bubbles: Robustness, March 2004–December 2015

This table presents regressions analyzing the determinants of $bubble_t$ for Sydney houses for the period March 2004–December 2015. Panel A reports results where variables have been derived using MTO; Panel B presents results where the variables have been derived using ITO. Variable definitions may be found in Appendix A.

Panel A: MTO

	Model (1)		Model (2)	
Intercept	0.051	***	0.059	***
t-statistic	(4.15)		(13.08)	
$Bubble(MTO)_{t-1}$	0.130	*	0.136	***
t-statistic	(1.8)		(2.79)	
$Volume_t$	0.00000007			
t-statistic	(0.63)			
$Volume_{t-1}$	0.00000001			
t-statistic	(0.09)			
$Skew(MTO)_t$	0.00182	***	0.00183	***
t-statistic	(5.59)		(5.84)	
$Skew(MTO)_{t-1}$	0.00008			
t-statistic	(0.27)			
$\Delta rent_t$	0.0001944			
t-statistic	(0.6)			
$\Delta discount_t$	-0.575			
t-statistic	(-0.43)			
$time\text{-}on\text{-}market_t$	0.00006285			
t-statistic	(0.69)			
Adjusted R^2	0.239		0.266	
AIC	-5.099		-5.174	
F-statistic	6.546	***	26.491	***

Panel B: ITO

	Model (1)		Model (2)	
Intercept	-0.208		-0.177	
t-statistic	(-1.28)		(-1.25)	
$Bubble(ITO)_{t-1}$	-0.060			
t-statistic	(-0.99)			
$Volume_t$	-0.0000027	*	-0.000002	*
t-statistic	(-1.82)		(-1.81)	
$Volume_{t-1}$	0.00000106			
t-statistic	(0.67)			
$Skew(ITO)_t$	0.02243	***	0.022	***
t-statistic	(4.59)		(4.63)	
$Skew(ITO)_{t-1}$	-0.00018			
t-statistic	(-0.04)			
$\Delta rent_t$	0.0013892			
t-statistic	(0.26)			
$\Delta discount_t$	-27.193	*	-24.299	*
t-statistic	(-1.65)		(-1.68)	
$time\text{-}on\text{-}market_t$	0.00288155	***	0.002	**
t-statistic	(2.29)		(2.26)	
Adjusted R^2	0.152		0.170	
AIC	0.304		0.256	
F-statistic	4.154	***	8.211	***

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.
t-statistics (in brackets under the estimated coefficients) have been adjusted for autocorrelation and heteroscedasticity (Newey and West, 1987).

Table 11. House Bubbles: Robustness—Accounting for Structural Breaks

This table presents regressions analyzing the determinants of $bubble_t$ for Sydney houses where unknown structural breaks have been estimated following Bai and Perron (1998). Panel A reports results where variables have been derived using MTO; the estimates in Panel A allow for heterogeneous error distributions. Panel B presents results where the variables have been derived using ITO; the estimates in Panel B constrain error distributions to be homogenous across structural breaks. Variable definitions may be found in Appendix A.

	Panel A: MTO				Panel B: ITO							
Period:	*February 1995–June 2006*		*July 2000–December 2015*		*February 1995–July 1996*		*July 1996–December 1997*		*January 1998–December 1998*		*January 1999–December 2015*	
Intercept	0.063	***	0.058	***	-0.172		0.469	***	0.894	***	0.230	***
t-statistic	(6.18)		(6.49)		(-1)		(4.28)		(2.81)		(3.39)	
$Bubble(MTO)_{t-1}$	-0.126		0.200	*	0.752	***	0.171	**	-1.021	***	0.041	
t-statistic	(-1.52)		(1.89)		(3.62)		(2.55)		(-2.67)		(0.86)	
$Volume_t$	0.00000005		0.00000006		-0.000005	*	-0.000001		-0.000013	***	-0.000001	*
t-statistic	(0.5)		(0.766)		(-1.69)		(-1.21)		(-3.32)		(-1.66)	
$Volume_{t-1}$	0.00000030	***	-0.00000006		0.000009	***	0.000002	**	0.000014	*	0.000001	*
t-statistic	(2.78)		(-0.6)		(5.04)		(1.84)		(1.76)		(1.72)	
$Skew(MTO)_t$	0.001	***	0.001	***	0.094	***	0.023	***	0.080	***	0.015	***
t-statistic	(6.17)		(4.38)		(2.87)		(6.38)		(4.9)		(4.61)	
$Skew(MTO)_{t-1}$	0.000468	**	-0.000099	**	-0.075	***	-0.040	***	-0.055	**	-0.007	**
t-statistic	(2.21)		(2.21)		(-4.64)		(-2.66)		(-2.06)		(-2.47)	
Adjusted R^2	0.386				0.361							
AIC	-4.736				0.244							
F-statistic	15.296	***			7.000	***						

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.
t-statistics (in brackets under the estimated coefficients) have been adjusted for autocorrelation and heteroscedasticity (Newey and West, 1987).

Table 12. Unit Returns

This table presents regressions analyzing the determinants of *return*$_t$ for Sydney units for the period February 1995–December 2015. Panel A reports results where variables have been derived using MTO; the instrumental variable for bubbles, *bubbleIV(MTO)*$_t$, is the predicted value obtained using Model(1) in Panel A of Table 6. Panel B presents results where the variables have been derived using ITO; the instrumental variable for bubbles, *bubbleIV(ITO)*$_t$, is the predicted value obtained using Model(2) in Panel B of Table 6. Variable definitions may be found in Appendix A.

	Model (1)		Eq. (2)	
Intercept	-0.030	***	-0.015	**
t-statistic	(-2.94)		(-1.96)	
Return$_{t-1}$	-0.295	***	-0.273	***
t-statistic	(-6.8)		(-6.73)	
BubbleIV(MTO)$_t$	0.189	***		
t-statistic	(3.91)			
BubbleIV(ITO)$_t$			0.082	***
t-statistic			(3.03)	
Adjusted R^2	0.106		0.107	
AIC	-3.777		-3.778	
F-statistic	15.804	***	15.901	***

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.
t-statistics (in brackets under the estimated coefficients) have been adjusted for autocorrelation and heteroscedasticity (Newey and West, 1987).

Table 13. The Relationship of Unit Bubbles to Unit Returns

This table presents regressions analyzing the determinants of $bubble_t$ for Sydney units for the period February 1995–December 2015. $ReturnIV(MTO)_t$, is the instrumental variable for returns in Model 1 (where the dependent variable is $Bubble(MTO)_t$). $ReturnIV(MTO)_t$ is the predicted value obtained using Model(1) in Table 12. $ReturnIV(ITO)_t$, is the instrumental variable for returns in Model 2 (where the dependent variable is $Bubble(ITO)_t$. $ReturnIV(ITO)_t$ is the predicted value obtained using Model (2) in Table 12. Variable definitions may be found in Appendix A.

	Model (1): $Bubble(MTO)_t$		Model (2) $Bubble(ITO)_t$	
Intercept	0.168	***	0.218	***
t-statistic	(23.138)		(14.08)	
$ReturnIV(MTO)_t$	4.788	***		
t-statistic	(5.866)			
$ReturnIV(ITO)_t$			9.314	***
t-statistic			(4.85)	
Adjusted R^2	0.163		0.068	
AIC	-2.282		0.180	
F-statistic	49.848	***	19.230	***

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.
t-statistics (in brackets under the estimated coefficients) have been adjusted for autocorrelation and heteroscedasticity (Newey and West, 1987).

Table 14. The Relationship of Unit Bubbles to Unit Returns Robustness—Accounting for Structural Breaks

This table presents regressions analyzing the determinants of *Bubble(MTO)*$_t$ for Sydney units where *ReturnIV(MTO)*$_t$, is the instrumental variable for returns. *ReturnIV(MTO)*$_t$ is the predicted value obtained using Model(1) in Table 12. Unknown structural breaks have been estimated following Bai and Perron (1998). The estimates constrain error distributions to be homogenous across structural breaks. Variable definitions may be found in Appendix A.

	February 1995 to January 2008		*February 2008 to December 2015*	
Intercept	0.193	***	0.145	***
t-statistic	(24.822)		(14.26)	
ReturnIV(MTO)$_t$	4.176	***	3.702	***
t-statistic	(4.176)		(4.176)	
Adjusted R^2	0.225			
AIC	-2.351			
F-statistic	25.249	***		

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.
t-statistics (in brackets under the estimated coefficients) have been adjusted for autocorrelation and heteroscedasticity (Newey and West, 1987).

Table 15. House Returns

This table presents regressions analyzing the determinants of *return*$_t$ for Sydney houses. Panel A reports results where variables have been derived using MTO. In Model (1), for the period 1995–December 2015, the instrumental variable for bubbles, *bubbleIV(MTO)*$_t$, is the predicted value obtained using Model(2) in Panel A of Table 9. In Model (2), *bubbleIV(MTO)*$_t$, is the predicted value obtained using Model(2) in Panel A of Table 10. Variable definitions may be found in Appendix A.

	Model (1)		Model (2)	
Period:	*March 1995–December 2015*		*March 2004–December 2015*	
Intercept	0.006		0.075	
t-statistic	(0.28)		(1.59)	
$Return_{t-1}$	-0.261	***	-0.244	***
t-statistic	(-4.37)		(-4.45)	
$BubbleIV(MTO)_t$	0.053		-0.754	
t-statistic	(0.24)		(-1.43)	
Adjusted R^2	0.064		0.070	
AIC	-2.766		-2.579	
F-statistic	9.538	***	6.238	***

***,**,* indicates significance at the 1%, 5% and 10% levels respectively.
t-statistics (in brackets under the estimated coefficients) have been adjusted for autocorrelation and heteroscedasticity (Newey and West, 1987).

Figure 1: Median sales price, Sydney houses and units, January 1995–December 2015

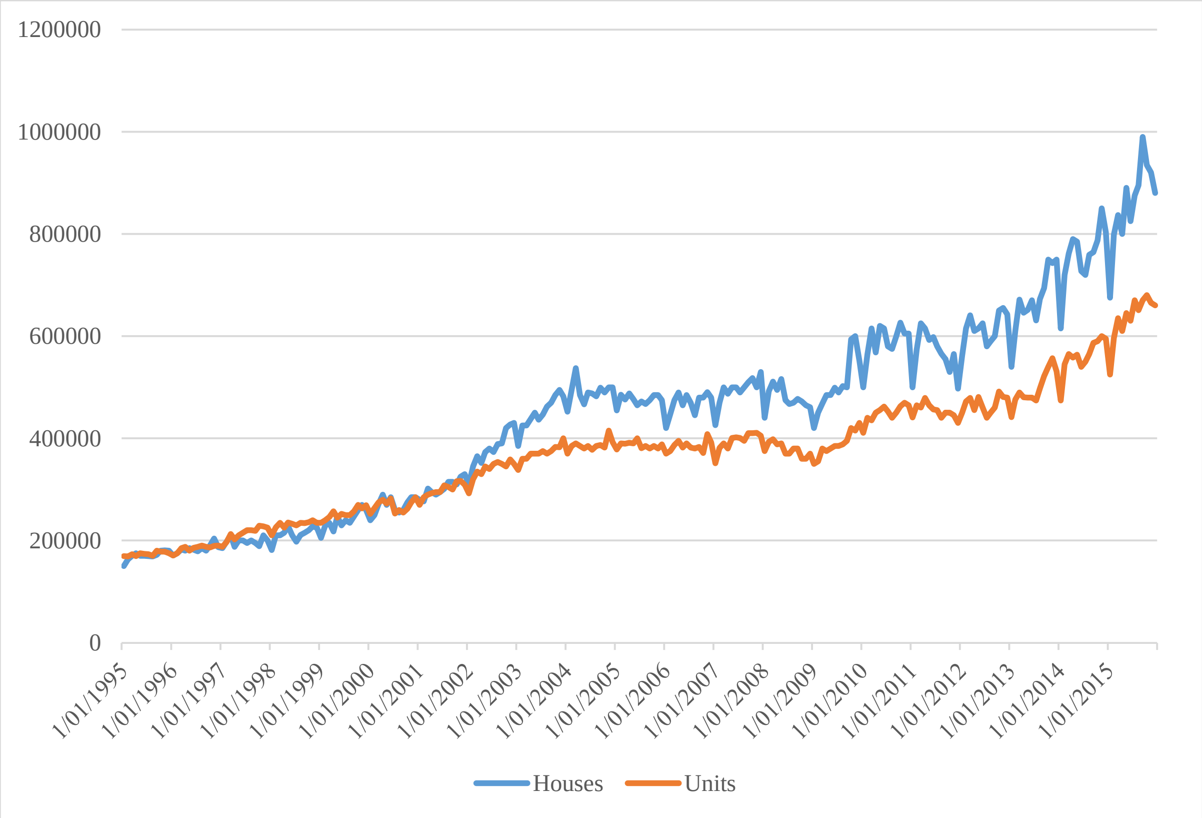

Figure 1 charts the monthly median price (vertical axis) for property sales. Houses and units are analyzed separately. Median prices are determined by measuring the median observed sale price in a given calendar month.

Figure 2: Median sales price, Sydney houses and units, and the S&P/ASX 200 Index, January 1995–December 2015 (January 1995 = 100)

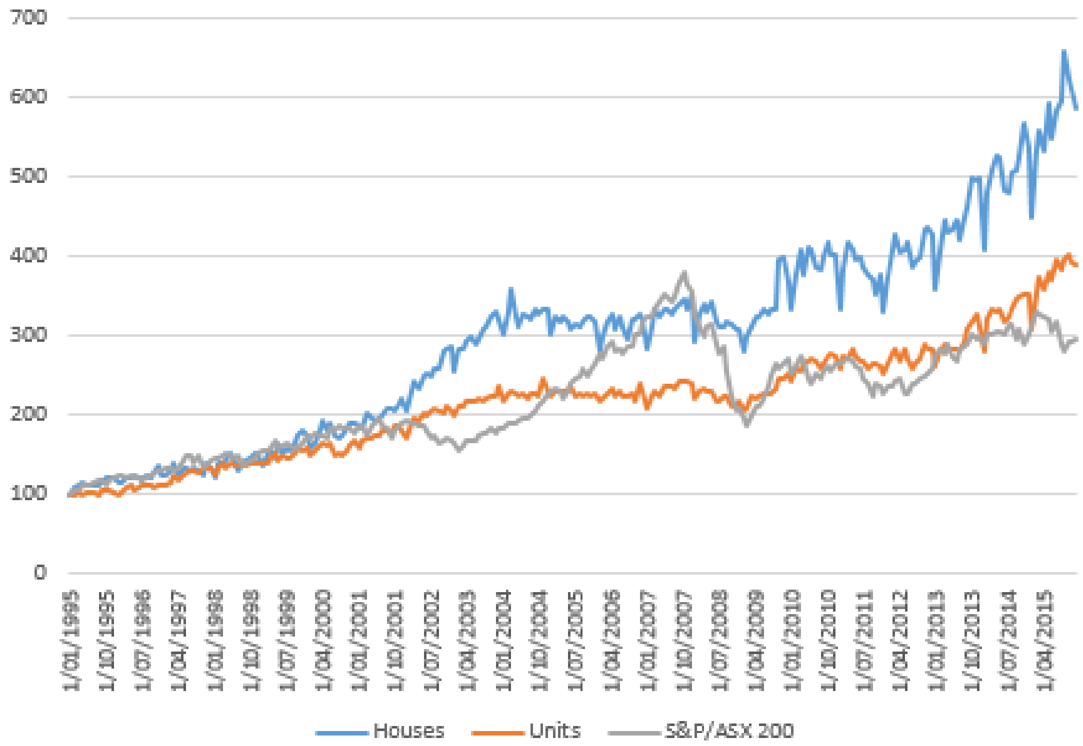

Figure 2 charts standardized median house and unit price indices and stock market indices. House and unit subsamples are analyzed separately. The median house and unit price indices are estimated by calculating the change in median price (the median of observed property prices in a given calendar month) each month. Indices are standardized by rebasing to 100 in January 1995.