Dream Chasers: House Price Booms and the Misallocation of Human Capital*

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Abstract

We examine the effect of the house price boom of the early 2000s on the allocation of human capital. Using detailed data on the career paths of 10 million individuals in the U.S., we document a strong relationship between house price growth and entry into real estate-related professions. We find individuals from across the skill and education spectrum entered realty at a significantly higher rate in areas most likely to have experienced non-fundamental house price increases. The average marginal entrant in these areas was as well off as similar non-entrants during the boom. During the bust, however, the average marginal entrant experienced significant relative wage declines with negative relative wages persisting for over ten years. Overall, our results highlight important long-term effects of asset price cycles on the (mis)allocation of human capital.

Keywords: career choice, house prices, job switching, human capital, real estate industry.

JEL Classification: E32, J24, J31, R21, R31.

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1 Introduction

House prices in the United States experienced a dramatic boom and subsequent bust in the first decade of the 2000s. In some areas, house prices doubled in the span of a few years before contracting severely. It is hard to believe that such house price run-ups and reversals were driven solely by variation in the fundamental values of these assets, particularly for those areas that experienced the widest swings of the boom and bust. Prior literature has examined the impact of the boom and bust on issues such as household balance sheets, consumption, foreclosures, and labor mobility, among others.[1] We add to this literature by examining the impact of the sharp rise and fall in house prices on labor market decisions. Specifically, we examine whether and what types of workers were drawn away from their current job and into real estate during the boom, and then we estimate the long-term wage consequences of that decision.

While changes in house prices are likely to influence the relative attractiveness of a variety of occupations, we focus on the real estate agent (REA) occupation. With relatively low barriers to entry and compensation that is typically driven by a commission that is a fixed percentage of each housing transaction, the lure of the REA profession is likely more sensitive to house price fluctuations than most other occupations.[2] During the boom period, employment in real estate-related professions increased by 14.5% (nearly 200,000 individuals), presumably due to individuals chasing higher wages associated with the skyrocketing house prices.[3] In this paper, we lever detailed data on the education and career path history of

[1]For example, see Pischke (2018), Gilbukh and Goldsmith-Pinkham (2018), Chinco and Mayer (2015), Charles, Hurst, and Notowidigdo (2018), Gao, Sockin, and Xiong (2016), Mian, Rao, and Sufi (2013), Stroebel and Vavra (forthcoming), and Adelino, Schoar, and Severino (2015)

[2]Previous work has documented the supply of realtors to house prices is relatively elastic (see Hsieh and Moretti (2003), Pischke (2018), Han and Hong (2011), Barwick and Pathak (2015)). The number of REAs increases significantly with a rise in house prices, but prior work has shown that average wage is either uncorrelated (Hsieh and Moretti, 2003) or weakly positively correlated with house prices (Pischke, 2018). In other words, individuals switch into real estate in response to an increase in house prices even though the average wage is relatively unchanged. We are interested in the outcomes of these marginal entrants. It is possible the marginal entrants are better off from switching into REA depending on their circumstance (e.g., previous occupation, level of education, etc.).

[3]`https://www.bls.gov/iag/tgs/iag531.htm` NAICS 531.

over 45 million individuals (800,000 of which are in REA at some point in their career) from 2000-2017 in the United States to characterize what types of workers leave their job to switch into REA in response to the jump in house prices and assess the long-run costs and benefits.

Building on prior work that documents that some of geographical variation in house price paths was speculative or non-fundamental (e.g., see Chinco and Mayer, 2015), we are especially interested in the effect of non-fundamental house price increases on an individual's occupational choice and the subsequent consequences for their future wage path. Our ideal experiment would take two identical workers, expose one of them to a non-fundamental shock to house prices (and thus, the perceived benefit of entering REA), and compare their future outcomes. We decompose the analysis into examining the effect of non-fundamental house price shocks on (1) the probability of entering realty, and (2) future wages conditional on entering realty in response to a non-fundamental house price shock. Our empirical tests are constructed to estimate these two effects and provide novel facts and insights on labor allocation responses to the housing bubble. Moreover, our results contribute to the growing literature studying the real effects of assets prices by highlighting an important relationship between asset price signals (here, house price changes) and labor market decisions.

To first understand the relationship between house prices and the real estate occupation, Figure 1 plots the growth in the Case-Shiller national house price index versus the growth in REA employment between 2000 and 2015. This figure suggests a strong link between the housing boom and the propensity of individuals to shift careers and enter realty. We formally examine the relationship between recent house price growth and an individual's propensity to switch occupations into REA using regression analysis and we find that entry is positively correlated with house price growth. The coefficient estimate suggests a 10% increase in house prices in the past year leads to a 6% increase in entry rates over the mean rate of entry. In other words, individuals responded to house price signals when making their labor allocation decisions. These results support previous work documenting the effect of house price changes on REA employment (Hsieh and Moretti (2003), Pischke (2018), Gilbukh and Goldsmith-Pinkham (2018), Han and Hong (2011), Barwick and Pathak (2015)).

We do *not* find significant differences of this entry sensitivity to house prices during the boom. While the stronger price signal (house price increase) during the boom led to higher entry overall, the *sensitivity* of entry to a given unit change in house prices was stable throughout our sample. The stability of this elasticity provides a helpful link for us to quantify potential misallocations of labor that come from distortions to the house price signal.

While prior work has documented REA entry in response to house price increases, those papers are silent about the characteristics of the marginal entrants. The costs and benefits of switching into REA are likely quite different for potential entrants such as leaving a high-skill job versus low-skill job because of factors including foregone wages, human and occupational capital accumulation, etc. Our data, provided by Emsi, Inc., details individual-level, anonymized employment histories with identifiers for firms, occupations, education, and location. This allows us to document the relative sensitivity of entry to house prices across the skill, wage, and educational distribution.

We examine the sensitivity of REA entry to house prices across current occupation job zone (i.e., skill-level), level of education, and current occupation wage. We find positive coefficients across *all* job zone levels (1-5),[4] with the sensitivity to house prices and baseline entry rates highest in the lower-skilled professions. We also find the entry sensitivity to house prices across all levels of education with the exception of Associate's degree. Lastly, we find a positive sensitivity across the entire wage distribution (quintiles 1-5), although the coefficient is statistically significant only for individuals experiencing a 40% or greater wage increase, individuals experiencing a -10% to 10% wage increase and individuals experiencing a 10% to 40% wage decrease. Only individuals that would experience a significant wage decrease (>40%) and those that would experience a modest wage increase are statistically insensitive to house prices. In sum, we find that higher house prices draw entrants from across nearly

[4]REA are in job zone 3.

the entire spectrum of the skill, education, and prior-wage distributions.

Why do people enter the real estate agent profession during the boom? Most likely, individuals are responding to the perceived wage increases from an increase in house prices. Unlike actual REA wage growth, local house price growth is relatively easy to observe, and Case, Shiller, and Thompson (2012) provide survey evidence that individuals do quite well in observing short-term local house price movements. Since the REA commissions are directly a function of house prices, workers seem to use the price signal from local house price changes as a proxy for wages. This assumption would be accurate (holding housing transactions fixed) if the supply of REAs were relatively inelastic. However, as shown by Hsieh and Moretti (2003), the higher per-transaction commissions does not necessarily translate to higher total wage for a given REA because of higher-rates of entry that come from house price increases.

We next examine the wage-path consequences of switching into REA in response to house price increases. While there may be great appeal of the seemingly large potential payoffs from switching to REA during booming house prices, this switch comes with costs. Upon leaving their prior job, the individual is forfeiting their firm-specific human capital and opportunity for advancement (either merit-based on tenure-based) in that job. Any occupation-specific human capital will immediately begin to depreciate and licenses and certifications may lapse. Moreover, the worker is joining an industry that is subject to large swings. Even if an REA is improving in her job skills and building a large client base, a significant decline in house prices and transaction volume will almost certainly lead to wage declines. If prospects then become sufficiently dim, the worker may need to switch occupations yet again, only this second switch is likely to be at a time when the general job market is more difficult (e.g., 2010 during the bust).

At the time of switching, the individual faces uncertainty about their own skills for REA and, importantly, the future paths of house prices and REA wages. Similar to home-buyers that take on high leverage, many problems become irrelevant if real estate fundamentals improve and house price growth continues to be positive. However, if either real estate fundamentals decline or current real estate values have been inflated above fundamentals (as many areas experienced during the housing bubble), then the eventual declines associated with the bubble busting can have painful consequences. Motivated by these factors, we examine the wage path of boom-induced switchers as compared to a variety of potential counterfactuals.

We exploit the richness of our employment data combined with wage data at the MSA-year-occupation level from the BLS to test for long-run differences in wages for those induced to switch into REA during the housing boom.[5] Given our first results showing a strong and stable relationship between house price growth and REA entry, we are particularly interested in the long-term effects on individuals that were drawn into REA by non-fundamental house price increases. These are precisely the individuals who might represent a misallocation of labor.

Our empirical specification sorts MSAs based on their house price dynamics over the 2001-2011 time period. We focus on *BoomBust* MSAs, which are areas that experienced a relative boom in house prices (top quintile of house price growth between 2001 and 2006) followed by a relative bust in house prices (bottom quintile of growth between 2007-2011). The price dynamics of these MSAs suggest that at least a portion of the initial boom was unrelated to long-term fundamentals and, therefore, likely experienced some measure of non-fundamental home price increases.[6] The *BoomBust* classification is our proxy for a positive house price deviation from fundamentals. The alternative group, which we designate as *Steady*, are areas that, by construction, did not experience such a high degree of growth and decline in prices. However, as previous literature has suggested, many of these areas likely experienced positive non-fundamental growth as well, implying our aggregate estimates

[5] The BLS use over 1,000 occupation codes, which allow relatively granular discrimination across jobs even within narrowly defined occupations. For example, the wages of business professors are separately reported from economics professors, which are different from professional economists.

[6] Previous literature has documented that house prices may have deviated from fundamental values in particular areas during the run-up (e.g., see Chinco and Mayer, 2015)

may be a lower bound on the overall real effects of non-fundamental house price growth. Moreover, we attempt to hold fixed the long-term fundamental growth (MSA growth from 2001-2017) when comparing labor market outcomes to further isolate the distortion in labor markets caused by the non-fundamental component.

Having already shown that greater increases in house prices is followed by greater probability of entering REA, we use the framework above to estimate the cost borne by those who indeed switch. We sort individuals into two groups: entrants, who are individuals that entered realty during the run-up period of 2002-2006, and non-entrants. We examine wages between 2001-2017. We want to compare the wage path of the entrant to an identical worker who did not enter. We begin with comparing *BoomBust* REA entrants with *BoomBust* non-entrants.[7] When including MSA×Starting Occupation×Year fixed effects, this effectively compares, for example, wage paths for two individuals who were employed as nurses at the start of the sample in a *BoomBust* area, where one switched to REA in the run-up and the other did not. Given the scope of our data, these tight fixed effects will account for the average career progression for that particular occupation in that particular MSA. Hence, this compares average wages for those that switched in an MSA with high, potentially non-fundamental, house price signal to a counterfactual in which they progressed similarly to their occupational peers. While the relative wage of the entrants was only slightly lower before the largest part of the bust, entrants experienced a sharp relative decline after that. The low-point for entrants occurs in 2011 when average wages fall about 20% below the wage of the similar non-entrant in the same MSA before rebounding to about 10-12% lower by the end of the sample in 2017.

We next compare entrants in the *BoomBust* MSAs to entrants in *Steady* MSAs. In this comparison, we can capture any common wage-path components that relate to changing occupations generally, or switching into REA specifically while examining the differential

[7] We classify REA entrants as real estate agents and real estate brokers. We find other occupations are sensitive to entry as well but decide to focus on these occupations for the aforementioned reasons.

effect of doing so in an areas where house price growth more likely had a non-fundamental component. In particular, the difference between the two types of areas is the increase in house prices is more likely non-fundamental in the Boom-Bust MSAs and, therefore, there was a stronger reversion in prices during the crash. Furthermore, this comparison helps to control for the selection concern that individuals REA run-up switchers are of a certain type.

We find *BoomBust* entrants have relatively higher wages during the boom period, and this is driven mostly by a declining average wage for those that enter REA in *Steady* MSAs. However, the 6% relative wage advantage of *BoomBust* entrants over the *Steady* entrants in 2006 is erased by 2007 and ends up around -4% during the years of the bust before regaining parity around 2015. These results highlight that individuals in *BoomBust* MSAs who switched into REA later during the boom period were particularly worse off in the long run than their counterpart that joined at the same time in a *Steady* MSA.

A fundamental idea in finance and economics is that asset prices reveal information and operate as signals to allocate resources. We use the U.S. house-price boom of the early 2000s, which is often characterized by a degree of non-fundamental growth in many areas, and the subsequent house-price bust to examine how variation in these prices affect the (mis)allocation of labor. Overall, our paper uses novel, detailed data to characterize those most affected and then quantify some of the resulting long-term costs.

2 Data and Summary Statistics

Our main data source of educational and employment histories comes from Economic Modeling Specialists International (Emsi).[8] The data includes anonymized histories for over 45 million individuals in the U.S., including a complete history of education and employment

[8]Emsi provides a host of services to recruiters, colleges, and job seekers. Their propriety data come from public and non-public sources. For more information, visit their website: www.economicmodeling.com.

history by unique individual identifier.[9] Emsi's data is sourced from a partnership with CareerBuilder and supplemented with other public sources. The data is largely self-reported and, given the sources, will be slanted towards younger and more skilled labor. The data set contains jobs with start dates as early as 1970 and continues to the present. However, the vast majority of observations are more recent and begin in the late 1990s, commiserate with the uptake of online resumes. For most of our analysis we include data from 2001 onwards.

The data is cleaned to include identifiers for occupation and education which allow us to link to other widely used public databases. For example, we use the occupation code provided in the data to link to the Bureau of Labor Statistics database information using occupation codes. In terms of the BLS data, we gather data on the distribution of wages and total employment figures at the occupation level. The distribution of wages is provided at the national level for occupations dating back to 1998, with the mean dating back even further. At the MSA level, wage data is available going back to 1998 but the majority of data is available 2001 onwards. Not every occupation is covered every year, yet the vast majority of MSA-level year observations are included for real estate agents and real estate brokers. For most of our analysis we use the average wage at the occupation$\times$MSA$\times$year level to proxy for an individual's wage.

From the employment and education data we are able to back out a number of individual level demographic proxies. For instance, we are able to proxy for age by looking at the first job or using the year of graduation for post-secondary education. Using the data, we can also calculate measures of an individual's tenure at their firm, in their occupation and in their industry. Moreover, we observe the location of the individual's college and the location the individual most recently reported (i.e., we do not have historical location data). Ideally, we would rely on higher frequency observations of location but the data do not allow for us to do so.

[9]For the majority of our tests we will use a random sample of either 15% or 10 million individuals due to processing constraints.

House price data is collected largely from FHFA but supplemented with data from Freddie Mac to get more complete coverage. We use the end of quarter 2, or June, data at an annual frequency to calculate house price growth. In Figure 2 we plot the average house price index from 1995 to 2018 for the first, third and fifth quintile of MSAs sorted by boom period (2000-2006) house price growth. As can be seen, most MSAs experienced an increase in house prices during the 2000 to 2006 period that reversed in the 3 to 4 years post-2007. The severity of the boom and bust varied significantly across MSAs. The top quintile of MSAs experienced average house price growth of over 120% during the boom period compared to around 20% for the bottom quintile of MSAs. The areas that experienced the greatest run-up in prices during the boom tended to also experience the greatest decline in prices in the bust, with the top quintile of MSAs experiencing an average decline in home prices of around one-third. The bottom quintile of MSAs experienced a much more modest reduction of around 10%. We use this variation in the severity of the boom and bust to examine how asset price booms affect human capital allocation and the potential long run mis-allocation.

Table 1 summarizes the random sample of data used in the panel regressions. Consistent with data from other sources we find that around 1% of the population is in the real estate agent occupation. Around 16% of individuals switch either firm or occupation in a given year. The average age of an individual is around 35 years old. The average tenure is 6.5 years. Individuals who hold a bachelors degree or higher amount to 36% of the sample. According to the U.S. Census, in 2015 the percentage of Americans who held a bachelors degree or higher amounted to 33.4%, which is quite comparable to our findings. The Census' figure on graduate degree attainment is consistent with our measure, at 12% of the population. The average job zone is 3.7 and the median is 4, implying that the average individual would not be classified as high-skill (≥ 4) yet the median would. Overall, our sample matches well across many dimensions of national averages and thus represents a reasonable sample of the broader U.S. labor market.

Finally, in Panel B of Table 1 we look at the characteristics of the house price dynamics over the period 2000-2017. For 383 different MSAs, we find the average house price increase between 2000 and 2007 is 54%. That amounts to an average annual growth rate of 9%. Next, we identify the peak house price in the the mid-to-late 2000s period and evaluate the house price dynamics following that. For every one of the 383 MSAs, each one experienced a peak which was followed by a decline in that period. The average number of months from peak to trough was 54 months, or 4.5 years. The average decline amounted to 22%, or around 6% per annum over that period. Hence, there were significant declines in house prices. However, when looking at the distribution of that decline, you can see from the $1\%tile$ and median, that the distribution is left-skewed. Our empirical strategy will take advantage of the heterogeneous house price dynamics since 2000.

3 Research Design

Our first objective is to examine the relationship between house price growth and an individual's decision to switch into the real estate agent ("*REA*") occupation. After characterizing that relationship along several dimensions, we examine the long-term wage costs of that decision. We use a panel of individual-level employment data and wages at the MSA-occupation level to examine these issues.

We focus on the REA occupation for a few reasons. REA compensation for a given home purchase/sale is directly a function of the transaction price of the house. There is usually a fixed commission that goes to the REAs in the transaction (e.g., 3% of the home sale price to the buyer's REA and 3% to the seller's REA). All else equal, higher home prices translate to higher commissions for REAs per house sold. Hence, the perceived benefit of switching into the profession would appear highly correlated with house prices.[10] Second, house prices are relatively salient – individuals have relatively accurate perceptions of short-term house

[10]Empirically, there is either no relationship (Hsieh and Moretti, 2003) or a weak positive relationship between house prices and REA wage (Pischke, 2018) since the additional entry in response to house prices dissipates wage gains.

price movements (e.g., see Case et al., 2012). Next, the REA occupation is also attractive because the barriers to entry are relatively low. For example, in Michigan a person can become licensed to be a REA with as little as 40 hours of instruction, passing a written exam, and a fees that amount to less than $150. Finally, REAs represent a non-trivial portion of the labor force – 1.36 million licensed realtors in 2006.[11]

3.1 Switching into Real Estate

Our first set of tests examine the relationship between house prices and an individual's propensity to switch into REA. Our main specification is the following:

$$EnterREA_{i,msa,occ,t+1} = \beta \times GrowthHPI_{msa,t} + \Sigma(Fixed\ Effects)_{i,msa,occ,t} + \varepsilon_{i,t}, \qquad (1)$$

$EnterREA_{i,msa,occ,t+1}$ is an indicator of whether an individual i in an MSA (*msa*) and occupation (*occ*) at time t switches into REA during the next year ($t \rightarrow t+1$), and $GrowthHPI_{msa,t}$ is the past year's growth in MSA house price index (HPI). The coefficient of interest is β, which will capture the the sensitivity of entry into real estate to past one-year house price growth.

In this set of tests, we include all individuals in the panel in year t that are not an REA in year t. In the baseline specification, we control for year and MSA fixed effects to account for aggregate trends in REA employment and geographical variation in average entry rates into REA. In more stringent tests, we also control for unobserved heterogeneity related to an individual's current occupation that may vary geographically or over time. Specifically, we include occupation×MSA fixed effects which captures any time-invariant relationship between entry into REA for a specific occupation in a specific MSA (e.g., nurses in Miami). More broadly, these fixed effects will also capture MSA-specific trends in entry into REA that may be unrelated to house price changes. We also include occupation×year fixed effects

[11] https://www.nar.realtor/membership/historic-report

which capture the common time-variation in switching rates for a specific occupation across all MSAs (e.g., nurses in the year 2004).

Consider an example to illustrate our identifying variation. We are examining the propensity of a nurse switching into REA in Miami in 2004 (sharp HPI growth) compared to a nurse switching into REA in Dallas in 2004 (modest HPI growth) after controlling for the baseline propensity of nurses to switch into REA in their respective MSA and the average overall switching from nurse to REA in 2004. The identifying assumption is that absent variation in house price growth, changes in real estate entry rates across housing markets would follow a similar pattern.

After establishing the baseline relationship between house-price growth and entry into real estate, we examine the source of this entry. The richness of our data allow us to use the worker- and occupation-specific information to understand who and where these new entrants are coming from. While existing literature has been able to examine entry in a broad sense (Pischke, 2018; Gilbukh and Goldsmith-Pinkham, 2018), we provide novel insights into the relationship between house prices and entry by providing some of the first facts and analysis on the full career path of the individual. In particular, since our data have the full history of employment for each individual, we can examine whether there is heterogeneity in the attraction of REA across individuals working in jobs with different characteristics and educational attainment.

We estimate the entry sensitivity to house price growth by characteristic using the following regression specification:

$$\begin{aligned} EnterREA_{i,msa,occ,t+1} =& \Theta(\mathbf{C}_{i,msa,occ,t} \times GrowthHPI_{msa,t}) \\ & + \Sigma(Fixed\ Effects)_{i,msa,occ,t} + \epsilon_{i,t}, \end{aligned} \tag{2}$$

We interact house-price growth with worker characteristic categories, where Θ represents a vector of sensitivities to HPI growth for the categories of the characteristic (e.g., each Job Zone). **C** is a vector of indicator variables for each category of the particular characteristic (e.g., one for each Job Zone). While other papers have examined the quantity of entry, ours is the first to examine the previous occupation and other characteristics of the entrant. We estimate separate regressions for each characteristic category of interest (Job Zone, wage differential, and education). These tests allow us to examine whether entry into REA spans all dimensions (i.e., each element of $\hat{\Theta} > 0$) or is concentrated in a particular type of worker.

3.2 Long-term Wage Dynamics

While our first set of tests examine the entry decision, our next tests examine the long-term costs or benefits of the decision to enter in terms of wages. We are particularly interested in the wage dynamics of workers that were induced to switch by non-fundamental increases in house prices during the boom period. Ideally, we would compare the wage path of a marginal entrant (i.e., entrant drawn away from their job into REA by the house price increase) in an MSA that experienced non-fundamental house price growth to the wage path they would have experienced if house prices in their MSA did not stray from fundamentals during the run-up. This counterfactual is unobservable. However, our data allow us to compare individuals that switch into REA in an MSA with non-fundamental house price growth to individuals in the same MSA with the same previous occupation. Specifically, we compare the wage path of individuals that enter REA during 2002-2006 to non-entrants that had the same occupation in 2001. For example, we examine the difference in the wage paths for two individuals that were nurses in Miami in 2001 where one was drawn into REA during the boom and one was not.

Our goal is to examine the wage paths of individuals drawn into REA by non-fundamental house price growth. It is an exceedingly difficult task to decompose measured house price growth into its fundamental and non-fundamental components, especially in real time. For our tests, we adopt a simple, ex-post heuristic to classify whether an MSA likely experienced substantial non-fundamental growth. Specifically, we classify an MSA as having experienced non-fundamental growth if it was both in the top quintile of house price growth during the housing run-up (2001-2006) and the bottom quintile of house price growth during the housing bust (2007-2011). The idea is that these MSAs most likely had house prices that departed from fundamentals since it is unlikely the underlying fundamentals would experience such large swings at a high frequency. We refer to these MSAs as "*BoomBust*" MSAs. We are also interested in the decisions and wage dynamics in "*Steady*" MSAs that did not experience a boom-bust pattern. These MSAs provide a benchmark in terms of understanding the baseline type and quantity of entrants into REA as well as their wage dynamics. To ensure comparability in long-term fundamental growth rates, we require *Steady* MSAs to have similar long-term house price growth between 2001 and 2017 as our sample of *BoomBust* MSAs. Specifically, we keep in our set of *Steady* MSAs those that had long-term growth less than the maximum long-term growth for *BoomBust* MSAs and greater than the minimum long-term growth for *BoomBust* MSAs.[12]

We use the following regression specification as the starting point for this analysis:

$$
\begin{aligned}
log(Wage_{i,t}) = {} & \Psi_t(\mathbf{Y}_t \times BoomBust_{msa} \times EnterREA_i) \\
& + \Gamma_t(\mathbf{Y}_t \times (1 - BoomBust_{msa}) \times EnterREA_i) \\
& + \Sigma(Fixed\ Effects)_{i,msa,occ,t} + \varepsilon_{i,t},
\end{aligned}
\tag{3}
$$

Since we do not observe individual wages, $Wage_{i,t}$ for individual i is the average wage in their respective occupation in their MSA in year t. $\mathbf{Y}_t$ is a vector of year indicator variables. $BoomBust_{msa}$, as defined above, is an indicator equal to one if the MSA experienced both a

[12]This filter removes over 40% of the non-*BoomBust* MSAs, a vast majority due to their low long-term growth rates.

boom in house prices and a bust, and represents MSAs most likely to have had the highest non-fundamental house price growth during the boom period. $EnterREA_i$ is a indicator variable equal to one if the individual enters REA during the years 2002-2006. Our main tests also include detailed fixed effects at the $MSA \times Year \times Occupation^{2001}$ level, where $Occupation^{2001}$ is the occupation the worker has in 2001. These allow us to control for fixed differences across occupations within and across MSAs over time. By including these high-dimensional fixed effects we are able to compare the wage paths of two individuals that were in the same MSA, in the same occupation in 2001, where one entered realty and one did not.

In terms of long-run wage effects, we focus our efforts on examining two primary groups of workers: (a) those drawn into REA by non-fundamental house prices ("marginal" entrants) and (b) those that would have entered REA in any case ("baseline" entrants), but happened to do so during a non-fundamental price boom in their MSA. The two sets of coefficients of interest are: Ψ_t, which is the wage dynamics of *BoomBust* REA entrant compared to similar workers who did not enter REA in the same MSA, and $\Psi_t - \Gamma_t$, which is the resulting wage dynamics for entrants in *BoomBust* areas compared to entrants in *Steady* MSAs. Relating these estimates to the effects on groups (a) and (b) above has some challenges. Specifically, it is difficult to identify "marginal" versus "baseline" entrants and, therefore, to measure the wage effects separately for each group of entrants. Under the assumption that the effects for "marginal" and "baseline" entrants are the same, then Ψ_t can be interpreted as capturing the effect of entry on marginal entrants (group (a)), and $\Psi_t - \Gamma_t$ the effect of entering REA in a *BoomBust* MSA versus *Steady* MSA for "baseline" entrants (group (b)). In the results section, we further discuss and address these issues and provide additional estimates, which will be properly identified under weaker assumptions.

4 Results

4.1 The housing boom and entry into real estate

Sharp increases in real estate prices characterized the years leading up to the financial crisis for much of the U.S. With increasing house prices, there is also an increase in the per-transaction commission of real estate agents. Our first results examine how variation in house prices relates to the decision to change occupations and become a real estate agent. We then examine heterogeneity in the propensity to enter along several worker dimensions. Later in Section 4.2 we examine the long-term consequences of switching into realty.

4.1.1 Baseline sensitivity to house prices

Figure 1 plots the time series of the Case-Shiller national house price index and the nationwide employment of real estate agents and brokers from the Bureau of Labor Statistics. Panel (a) plots levels and Panel (b) plots growth rates. The figures show that house prices and real estate employment are closely linked. In Table 2 we formally examine the relationship between house price growth and entry into REA using MSA variation in house price growth and REA entry as specified in Equation (1). Specifically, we regress an indicator variable for entry into REA during year $t \to t+1$ on house price growth during years $t-1 \to t$. Because the baseline annual propensity to enter a given profession is small, we report our estimates in basis points. We cluster all standard errors at the occupation $\times$ MSA $\times$ year-level.

We see there is a very strong relationship between past house price growth and entry into realty. In column (1), the coefficient is 6.08 and is significant at the 1% level. This indicates a 20% increase in house prices is associated with a 12% increase in the rate of entry into realty compared to average entry rates (9.80).

In columns (2) and (3), we include occupation $\times$ MSA fixed effects and occupation $\times$ year fixed effects. These fixed effects will capture any time invariant relationship between entry into realty and a specific occupation in a specific MSA and any common time-variation in switching rates for a specific occupation across all MSAs, respectively. These detailed occupation-specific fixed effects along the geographical and time dimensions help draw a sharper relationship between changes in house prices and entry into REA and is our preferred specification. The point estimate in column (2) of 5.85 (t-stat=7.32) is very similar to our base specification in column (1). Column (3) interacts the local house price growth with a run-up-period indicator that takes the value of one if the year is between 2001-2005 (entry in years 2002-2006). In particular, by including the interaction, we allow for the run-up in the early 2000s to have a potentially differential impact between the relationship of entry and house price growth. Given the insignificant coefficient, we interpret this as evidence that the elasticity of REA entry to house prices is fairly constant, regardless of large swings in house price growths.

To study this further, in columns (4) and (5) we examine whether there are nonlinearities in the relationship between house-price growth and REA entry using buckets for past one-year growth. The omitted group are MSAs with past one-year house price growth between 0% and 5%. The estimates in columns (4) and (5) indicate that there is a relatively monotonic relationship between house price growth and entry into realty, with a slightly greater sensitivity for price increases compared to price decreases. Thus, the baseline results are more broad and general as opposed to being solely driven by areas with extreme house price growth.

Earlier, we argued that entry into REA is naturally quite sensitive to house-price changes because of the relatively low barriers to entry into the profession and the compensation per deal is a fixed share of the house price. Since we have the entire spectrum of occupations in our dataset, we next directly test this idea. We run our main regression specification (column (2) of Table 2) for each occupation in our data that has at least 1,000 entrants during the sample period. Figure 3 presents a histogram of the t-statistics for the coefficient estimate on one-year MSA house price growth house for each occupation. We focus on t-statistics given the low likelihood of entry for the vast majority of occupations. This allows us to understand statistical significance without reading too much into point estimates that may be slightly noisier when compared to their mean. The real estate agent occupation t-statistic is clearly an outlier in the far-right tail of the distribution. It is the third highest t-statistic out of 516 occupations.[13] These results suggest that entry into realty is much more sensitive to house prices than entry into other occupations.

These results also ease concerns that an omitted variable is driving the observed relationship between entry into real estate and house price growth. For example, underlying economic activity could be driving house price growth and general labor market churn, in this case it might be that all occupations would see more activity. With REA shown to be especially sensitive relative to most other occupations, explanations such as higher labor market fluidity do not appear to explain our results.

4.1.2 What types of workers are drawn into real estate?

In this section, we further examine the marginal entrants into realty. We begin by examining entry sensitivity across the skill-spectrum. We sort individuals according to the Job Zone of their current occupation and examine entry-to-house price sensitivities for each Job Zone. The U.S. Department of Labor created Job Zone to group occupations based on the education, related experience and on-the-job-training needed to do the work required of the occupation. There are five Job Zone. Job zone 1 occupations require the least amount of preparation (e.g., dishwasher or barista) and job zone 5 occupations require the most preparation (e.g., lawyer or surgeon). Real estate agents are in job zone 3 and real estate brokers are in job zone 4. In our analysis, we group Job Zones 1 and 2 because Job Zone 1 individuals account for less than 1% of our sample.

For individuals currently working high-skilled occupations, the sunk costs of switching are much higher and, most likely, the future rate of depreciation of skills is likely higher as

[13] The two occupations with statistically greater sensitivity are "loan officers" and "loan interviewers and clerks," which are also intimately related to housing market activity.

well. For example, it will be more difficult to transition back to being a lawyer and perform at or near the same level if real estate does not work out, then it would be to transition back to being a barista. These differences entail different trade-offs and potentially different entry-to-house price sensitivities.

We estimate the entry-to-house price sensitivities for each job zone using a pooled regression. We interact Job Zone dummies with last one year house price growth and include the occupation-year and occupation-MSA fixed effects and Job Zone fixed effects. The regression results are reported in column (1) of Panel A of Table 3. The coefficient point estimates are positive across all four Job Zone and significant at the 1% level for Job Zones 3 and 4. The point estimates decrease monotonically with the skill requirements. Individuals in Job Zones 1 & 2 are the most sensitive with a coefficient greater than 10, while individuals in Job Zone 5 are the least sensitive with a coefficient estimate of 3.10. In column (2), we report the average entry rate by Job Zone and in column (3) we report the ratio of the coefficient to the average entry rate. The ratio is equivalent to the percentage increase in the entry rate with a 100% increase in house prices. For example, if house prices were to increase by 100%, the rate of entry for Job Zone 2 individuals would increase by 96%. For Job Zone 5, the increase would be 46%. In general, individuals in lower skilled occupations are more likely to leave to enter real estate when house prices increase.

We next examine sensitivities across wage levels. Specifically, we compare the average wage of the individual's current occupation to the average wage of a real estate agent in their MSA and bin individuals based on the increase or decrease in average wage they would observe by switching into real estate. Individuals in bin 1 have the lowest wage occupations and would experience a 20% or greater increase in average wage if they entered realty, bin 2 individuals would experience between a 20% to 5% increase, bin 3 a 5% increase to 5% decrease, bin 4 a 5% to 20% decrease in average wage and bin 5 individuals have the highest current wage and would experience a 20% or greater decrease in average wage. It is not clear ex ante which type of wage earner should be more sensitive to house prices.

The results are presented in Panel B of Table 3. We find positive coefficient estimates across all 5 groups. The coefficient estimate is is significant for all groups except for individuals that would experience a 5% to 20% wage increase. Individuals in group 4 have the highest estimated sensitivity with a coefficient of 9.36. These results suggest individuals from across the wage spectrum are drawn into real estate in response to house price increases with the exception of those that would experience only a slight increase in wage.

We further examine sensitivities across individuals' type by cutting on education level. Results are presented in Panel C of Table 3. We find positive coefficient point estimates for all degree levels except individuals with associate's or vocational degrees. Individuals with a bachelor's and individuals with no post-secondary degree information are the most sensitive in terms of point estimates, which are 8.26 and 7.00, respectively. The coefficient on bachelor's degree is only borderline significant at the 10% level. Even individuals with graduate degrees are sensitive with point estimates above 3.5 for both master's degree (p-value< 0.01) and doctorate degree holders (p-value< 0.05).

Taken together these results highlight the breadth of the relationship between house price growth and entry into realty. Individuals across the wage, skill and education spectrum are more likely to enter realty when house prices rise.

4.1.3 Entry into Realty and Non-Fundamental House Price Growth

The previous results highlight the strong positive relationship between entry into realty and general house price growth. We next examine if individuals are more likely to enter realty specifically in response to non-fundamental house price growth. To do so, we compare entry rates in *BoomBust* MSAs to entry rates in *Steady* MSAs in the run-up period. The *BoomBust* MSAs experienced extreme house price growth in the run-up and extreme declines in the crash, while *Steady* MSAs did not experience the boom-bust pattern to the same degree. For these tests, we regress entry into REA on an indicator equal to one if the individual lives in a

BoomBust MSA, while controlling for the MSA's long-term growth in house prices between 2001 and 2017. Specifically, we estimate:

$$EnterREA_{i,msa,t+1} = \alpha + \beta \times BoomBust_{msa,t} + \gamma \times zLTGrowth_{msa} + \varepsilon_{i,t}, \tag{4}$$

where $zLTGrowth_{msa}$ is the standardized overall house price growth for an MSA between 2001 and 2017 and $BoomBust_{msa,t}$ is an indicator variable for a *BoomBust* MSA. We estimate this regression only during the run-up period (2001-2005, entrants in 2002-2006). The coefficient β is the additional entry rate in *BoomBust* MSAs relative to *Steady* MSAs after controlling for the long-term growth rate in the area.[14]

Results are presented in Table A2. In columns (1) and (2), we include all individuals. In column (1) we do not control for long-term growth rates. The estimated coefficient on the *BoomBust* indicator is 7.20 with a t-statistic of 15.98. For comparison, the intercept estimate – the entry rate in *Steady* MSAs – is 10.8. Compared to *Steady* MSAs, individuals living in *BoomBust* MSAs were 66% more likely to enter realty during the run-up period. In column (2), we control for long-term growth rates and find similar differences in entry between *BoomBust* and *Steady* MSAs. The coefficient on *BoomBust* is 6.74 and remains highly statistically significant. Examining the Job Zone-level results, we see individuals were much more likely to enter realty in *BoomBust* MSAs than *Steady* MSAs across all Job Zones. All coefficient estimates are greater than 5 and highly statistically significant. Job Zone 4 individuals exhibit the greatest differential in entry rate with a coefficient estimate of 8.44. Overall, these results suggest marginal entrants either believed the price increases during the boom were permanent or the probability of a price reversal (i.e., a crash) in the near-term was low. In the next section, we examine the consequences of entering realty in *BoomBust* MSAs.

[14] Results are very similar if we do not control for long-term growth.

4.2 Entry Into Realty and the Path of Wages

In this section, we examine the short- and long-term consequences of entry into realty in response to non-fundamental past house price growth. Our first step is estimating regression (3), which traces out the relative wage paths of workers that enter REA during the run-up period as compared to those that do not for both *BoomBust* MSAs as well as *Steady* MSAs. To sharpen our comparisons, our estimation includes MSA × Year × 2001 Occupation fixed effects to account for differences in wages across MSAs, over time and across initial occupation. We are effectively comparing the wage paths of two individuals in the same location and occupation in 2001 over time, where one enters realty during the run-up period and one does not. For computational purposes, we restrict our regressions to a random sample of 10 million individuals.[15] Because of the large number of estimated coefficients, we present our results graphically, with the regression tables in the Appendix.

Figure 4 presents the results. The logarithm of wage is on the y-axis and year is on the x-axis. Panel (a) in Figure 4 plots the relative wage of *BoomBust* REA entrants ($\hat{\Psi}_t$) compared to *BoomBust* non-entrants. The figure shows a stark difference in the wage path for workers in *BoomBust* MSAs that entered REA during the house price run-up relative to those that did not. Initially, entrants into realty are only slightly worse-off. Their relative wage is between 0% to -3% during the run-up period (2002-2006). In 2007, with the onset of the decline in the housing market, the relative wage of REA entrants declines sharply to approximately -7%. The relative wage of entrants continues to decline through the crisis and recession, reaching its nadir in 2011. In 2011, individuals that entered realty during the run-up period in a *BoomBust* MSA earned 20% less than similar individuals that did not enter realty. The gap begins to narrow again later in the sample, but remains large. Even in 2017, the wage of entrants is more than 10% below the wage of non-entrants that were observationally similar pre-housing boom.

[15]To ensure maximum power in our regressions, we include all individuals who are classified as "REA entrants."

We next examine if REA entrants in *BoomBust* MSAs faired better or worse than REA entrants in *Steady* MSAs in the short- and long-run. Panel (b) in Figure 4 plots the difference between the relative wage of *BoomBust* entrants and the relative wage of *Steady* entrants, with both being relative to non-entrants in the same MSA (i.e., $\hat{\Psi}_t - \hat{\Gamma}_t$). We find *BoomBust* entrants are relatively better off during the run-up period, with a 6% higher relative wage in 2006. During the bust, the relative wage of *BoomBust* entrants declines dramatically relative to *Steady* entrants. By 2008, the premium experienced by *BoomBust* entrants disappeared. In 2010 to 2014, *BoomBust* entrants are statistically significantly worse off with 2% to 4% lower relative wage each year. Between 2006 and 2010, relative wages decline 10%. This is a significant shock to relative income for these individuals. From 2015 onwards, the difference in relative wage is near zero.

The overall effect of entering realty in a *BoomBust* MSA relative to a *Steady* MSA will depend on the year the individual entered. If an individual entered realty in 2006, they only enjoyed one year of relatively higher wage before the bust and the ensuing negative relative wages between 2010 and 2014. For early entrants, the positive wage premium likely offset the negative premiums in the long-run. Overall, these results suggest REA entrants in areas with a non-fundamental shock to house prices are relatively better off than entrants in *Steady* areas in the short-run, but in the long-run they are significantly worse-off.

4.3 Heterogeneity in the Wage Effect

The effect of entering realty in the run-up on wages likely differs across types of individuals. For example, individuals leaving higher paying jobs will experience a larger initial wage decrease than individuals leaving lower paying jobs. Additionally, individuals leaving occupations with greater skill requirements may have greater employment opportunities and, therefore, be better able to mitigate the potential wage declines during the bust period by switching into another occupation.

We examine heterogeneity in the wage effect by estimating Equation 3 for each job zone. In Panel A of Figure 5, we report the relative wage path for *BoomBust* entrants compared to *BoomBust* non-entrants ($\hat{\Psi}_t$) by job zone.

A number of interesting patterns emerge. First, there is significant heterogeneity in the initial wage effect from entry into realty. Individuals from lower skilled job zones experience an increase in wage and individuals from higher skilled job zones experience a decrease in wage. These differences are not necessarily surprising given occupations in higher job zones are paid more on average, so individuals leaving higher paying job zones will likely take a larger pay cut when switching into real estate.[16] Second, across all four job zone groupings, the relative wage of entrants decreases sharply with the onset of the crash. For the lowest skill job zone the relative wage drops from 32% in 2006 to around 7% in 2011, a drop in relative wage of 25%. Job Zone 3 individuals experience a similar 23% decrease in wages during this time as well. Even the higher skilled entrants experience declines in relative wages although the effect is smaller in magnitude. Entrants from job zones 4 and 5 experience a 15% and 9% decline, respectively, during the 2006 to 2011 period. Relative wages remain below their 2006 value for a number of years across all job zones. For job zones 1-4, relative wages never return to their 2006 value even as markets recover. For job zone 5 individuals, the relative wage returns to its 2006 level 7 years after the market peak. These are significant, likely unexpected, declines in relative wages that take effect over a short time period and persist for a decade or longer.

For job zone 3 individuals, the relative wage falls below zero in 2010 and remains below zero until 2014. Their relative wages remain slightly above zero for the remainder of the sample. For individuals in job zones 4 and 5, relative wages are less than zero throughout the entire sample period. By 2017, the relative wage of job zone 4 individuals was -20% and for

[16] An important caveat to these level shifts is that we are using average wage for the given occupation, which may lead to an over-estimate of the initial wage for new entrants (Gilbukh and Goldsmith-Pinkham (2018)). Also, if initial wage in real estate is positively correlated with job zone, then we are likely overestimating the positive (negative) effect for the lower (higher) job zones.

job zone 5 individuals it was -40%. Considering over 80% of entrants into realty in *BoomBust* areas are from job zones 3-5, these results further confirm the average entrant into realty in the *BoomBust* areas was worse off in the long-run (in terms of wages).

The second effect of interest is the effect of entering realty in an area that experienced non-fundamental house price increases (*BoomBust* areas) relative to entering in a *Steady* area. We plot this effect by job zone in Panel B of Figure 5. The patterns are similar across job zones. In the *BoomBust* areas the relative wage of entrants into realty is higher during the run-up (2002-2006) for all job zones except job zone 5. In 2007, with the onset of the crash, the relative wage of *BoomBust* entrants begins to decline. For all, but Job Zone 4, the relative wage is less than zero in 2007. For all four groups, the relative wage reaches its nadir in the 2010-2012 time period and all four job zones have point estimates below zero through 2015. In 2016, individuals in job zones 1-4 have relative wages near zero or slightly positive. Job zone 5 individuals never return to zero with a relative wage of -7% even in 2017. For three of the four job zones, the negative relative wage effect persisted for 8+ years after the onset of the crash in house prices. Overall, all suffered relative declines during the bust, but the highest skilled individuals are the most negatively impacted by entering realty in a *BoomBust* area relative to a *Steady* area.

4.4 Effect for the average marginal entrant

The main wage effect of interest is the effect for the marginal entrants in *BoomBust* areas. The marginal entrants are the individuals that entered realty in response to the non-fundamental house price growth. The effect for the marginal entrant may be different from the effect for the baseline entrant (i.e., an individual that would enter realty if house prices did not experience non-fundamental growth) and, therefore, the effect for the average entrant. We do not observe which individuals are marginal entrants and which individuals are baseline entrants, so we cannot directly estimate the effect for marginal entrants only. Instead, we make an assumption that marginal entrants and non-marginal entrants of the same type (e.g., job zone) experience a similar wage effect. Under this assumption, we can then calculate the average marginal effect by estimating the wage effect by type and then weighting the wage effect by the composition of the marginal entrants. Specifically, we calculate:

$$MarginalEntrantWage_t = \sum_{j=1}^{J} \frac{\text{Marginal Entrants of Type j}}{\sum_{j=1}^{J} \text{Marginal Entrants of Type j}} \times \hat{\Psi}_{t,j}, \tag{5}$$

where $\hat{\Psi}_{t,j}$ is the effect of entering REA during the run-up in a *BoomBust* MSA for type j (see Equation 3).

We use job zone as the main type classification. We previously calculated the wage effect for each job zone ($\hat{\Psi}_{t,j}$), which is reported in Panel A of Figure 5. To estimate the number of marginal entrants from each Job Zone, we multiply the Job Zone-specific *BoomBust* coefficient estimate from Table A2 by the number of individuals in that job zone. Armed with these sets of estimates, we can then calculate the average wage effect for marginal entrants according to Equation 5.

We plot the estimated average wage effect for the marginal entrants in Figure 6. We find the average wage effect for the marginal entrant follows a similar pattern as the effect for the average entrant. Compared to the average entrant, the marginal entrants are slightly better off for most of the sample period. This difference is because a greater proportion of marginal entrants are from the lower job zones, which were relatively better off. Still, marginal entrants are much worse off than if they had not entered REA during the run-up period. They never enjoy a wage premium compared to non-entrants and suffer striking declines in relative wage in the bust that never return to their pre-bust level.

5 Conclusion

House prices across the country rose at an unprecedented pace in the early 2000s. We find this increase led to a dramatic increase in the allocation of labor to the real estate agent occupation. Individuals from across the skill, education and wage spectrum are more likely to leave their current job and enter realty when house prices increase. Moreover, we show individuals in areas characterized by significant, non-fundamental house price increases were much more likely to enter realty than similar individuals in other areas. In hindsight, the entry related to non-fundamental house price growth may have distorted labor allocations.

We find that this reallocation had an overwhelming negative effect on entrants. In particular, individuals who responded to non-fundamental growth in the price signal by entering realty were significantly worse off in the long run. Using individual level career paths, we provide evidence that these individuals suffered long term costs as compared to non-switchers, as well as to those who switched in areas that did not experience as pronounced of a decline. We hypothesize that this could be related to human capital depreciation, the compensation of real estate agents, and the employment opportunities available after the shock.

A fundamental concept in finance and economics is that prices, and the information contained within, act as signals to allocate resources. However, there is little evidence on how systemically important assets may affect the allocation of labor. Using the U.S. housing market cycle of the early 2000s, which is often characterized by speculation, we ask how asset prices affect the (mis)allocation of labor. Overall, our paper helps to characterize and quantify the costs associated with the misallocation of labor that resulted from housing prices deviating from fundamentals.

References

Adelino, Manuel, Antoinette Schoar, and Felipe Severino, 2015, House prices, collateral, and self-employment, *Journal of Financial Economics* 117, 288–306.

Barwick, Panle Jia, and Parag A Pathak, 2015, The costs of free entry: an empirical study of real estate agents in greater boston, *The RAND Journal of Economics* 46, 103–145.

Case, Karl E, Robert J Shiller, and Anne K Thompson, 2012, What have they been thinking? homebuyer behavior in hot and cold markets, *Brookings Papers on Economic Activity* 265–299.

Charles, Kerwin Kofi, Erik Hurst, and Matthew J Notowidigdo, 2018, Housing booms and busts, labor market opportunities, and college attendance, *American Economic Review* 108, 2947–94.

Chinco, Alex, and Christopher Mayer, 2015, Misinformed speculators and mispricing in the housing market, *The Review of Financial Studies* 29, 486–522.

Gao, Zhenyu, Michael Sockin, and Wei Xiong, 2016, Economic consequences of housing speculation, *Working paper* .

Gilbukh, Sonia, and Paul Goldsmith-Pinkham, 2018, Heterogeneous real estate agents and the housing cycle, *Working paper* .

Han, Lu, and Seung-Hyun Hong, 2011, Testing cost inefficiency under free entry in the real estate brokerage industry, *Journal of Business & Economic Statistics* 29, 564–578.

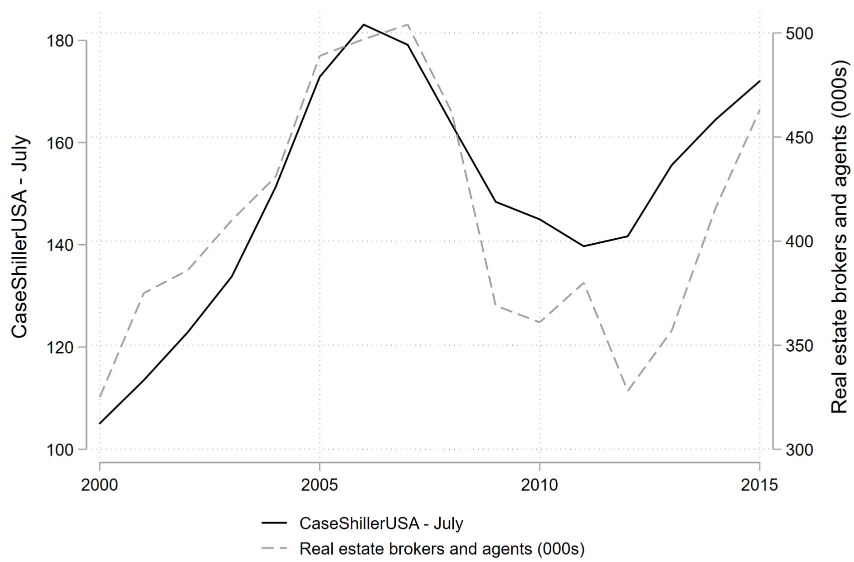
Hsieh, Chang-Tai, and Enrico Moretti, 2003, Can free entry be inefficient? fixed commissions and social waste in the real estate industry, *Journal of Political Economy* 111, 1076–1122.

Mian, Atif, Kamalesh Rao, and Amir Sufi, 2013, Household balance sheets, consumption, and the economic slump, *The Quarterly Journal of Economics* 128, 1687–1726.

Pischke, Jörn-Steffen, 2018, Wage flexibility and employment fluctuations: evidence from the housing sector, *Economica* 85, 407–427.

Stroebel, Johannes, and Joseph Vavra, forthcoming, House prices, local demand, and retail prices, *Journal of Political Economy* .

(a) National House Prices and REA Employment



(b) National House Price Growth and REA Employment Growth

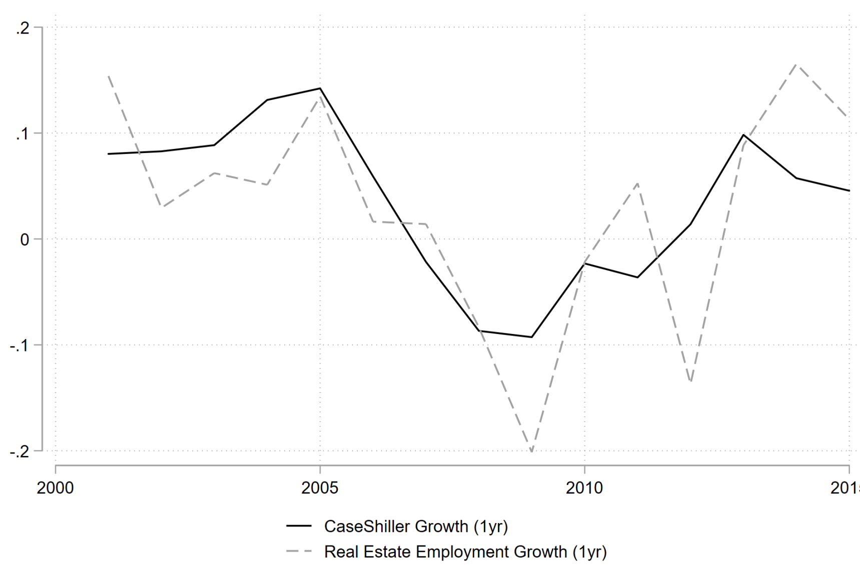


Figure 1: House Prices and REA Employment
Panel A of the figure presents the national Case-Shiller index and number of real estate agents in the United States between 2000 and 2015. The July data point of the monthly Case-Shiller index is represented on the left-hand side y-axis. The number of real estate agents and brokers is taken from the Federal Reserve Economic Data (FRED) side, hosted by the Federal Reserve of St. Louis. The corresponding axis for employment data is on the right-hand side y-axis. Panel B performs the same exercise but compares growth rates instead of levels.

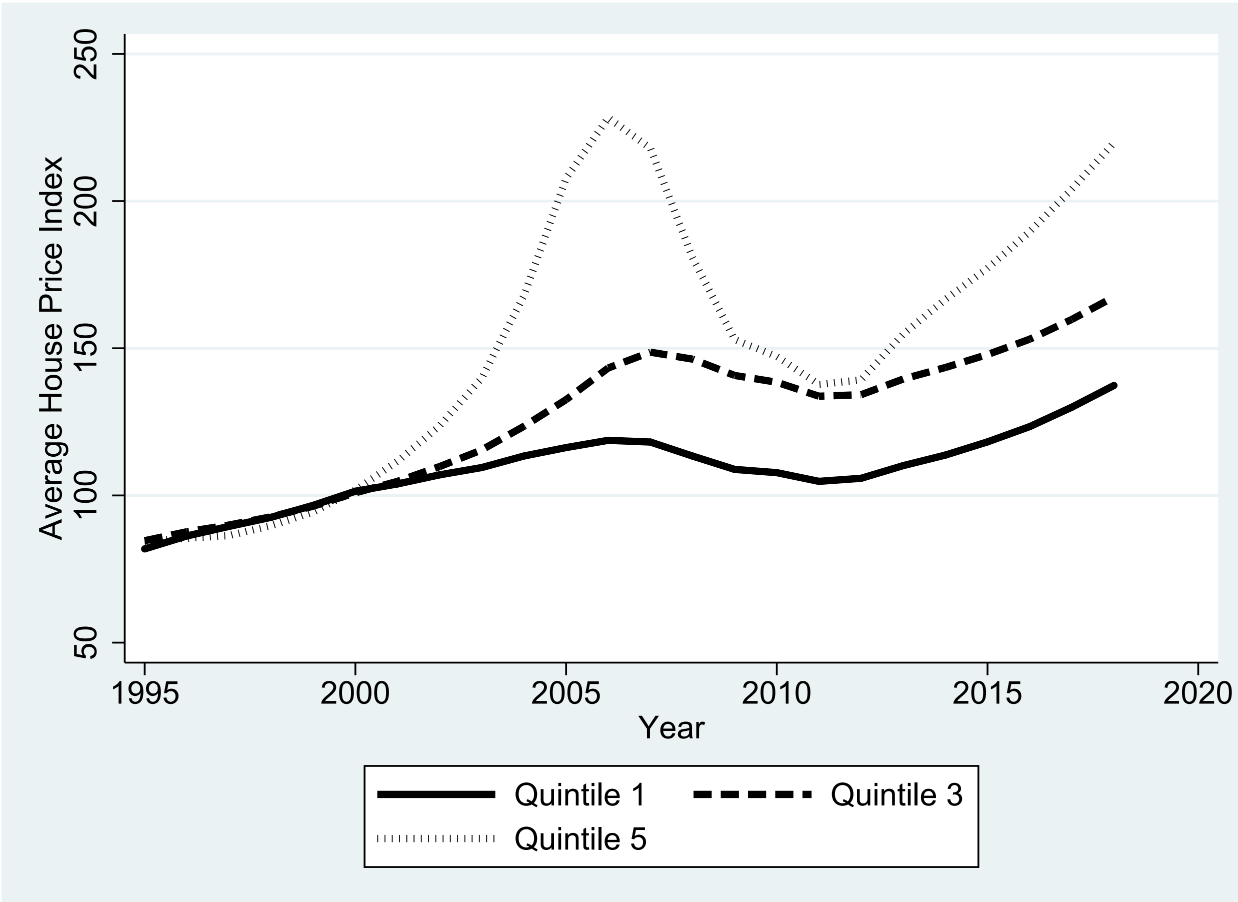


Figure 2: House Prices by Boom Period Growth Quintile (1995-2018)
This figure plots the average house price index across boom period MSA growth quintiles from 1995 to 2018. We sort MSAs into quintile bins based on 2000-2007 house price growth and report the average within-quintile house price index for quintiles 1 (low growth), 3 and 5 (high growth). The index equals 100 in 2000 for all MSAs.

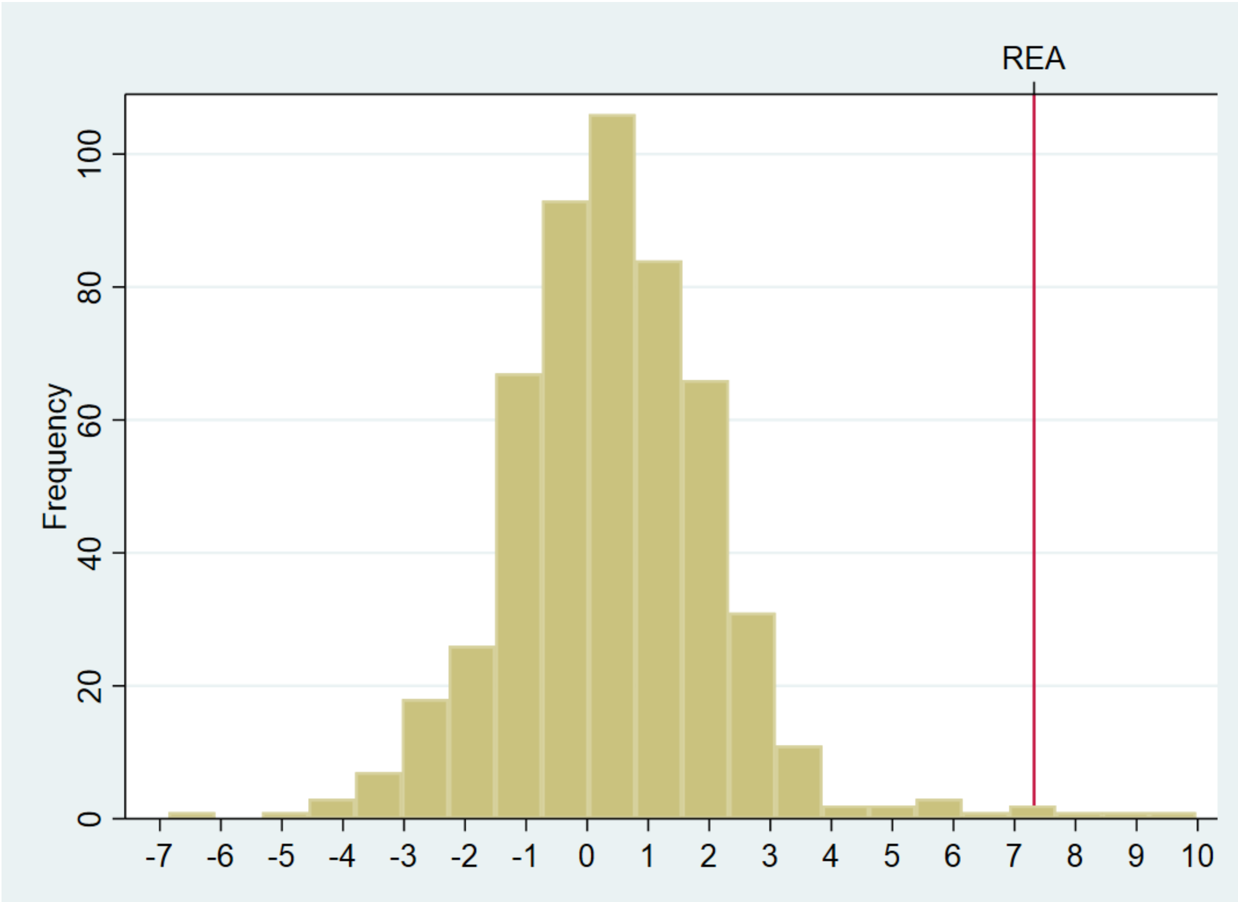
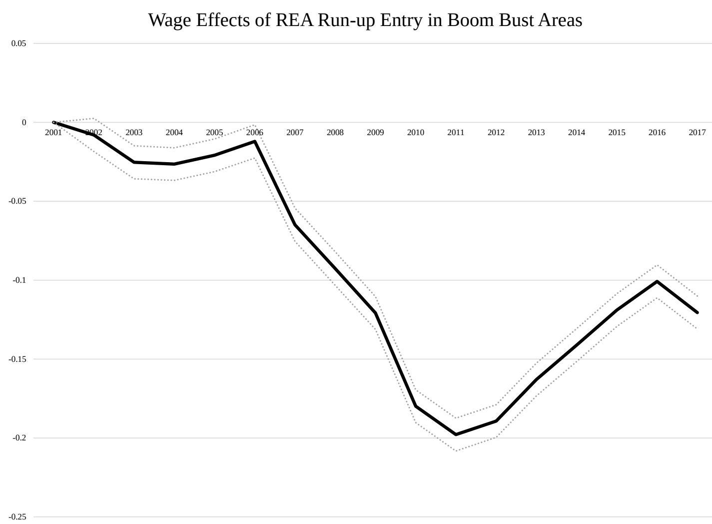


Figure 3: House Prices Growth and the Propensity to Enter an Occupation
This figure plots the t-statistics of the sensitivity of entry into each occupation on past one year house price growth. More specifically, we run the same regression as in Table 2, but the outcome variable is entry into a particular occupation. We do this for each occupation in our dataset, and plot a histogram of the resulting t-statistics below. The vertical line in the figure marks the t-statistic for the relationship between house price growth and entry into the real estate agent (REA) occupation. We include occupation×MSA (Occ.×MSA) fixed effects and occupation×year (Occ.×MSA) fixed effects. Standard errors are clustered by Occupation×Year×MSA.

(a) Wages for REA Entrant vs Non-Entrant in BoomBust MSAs



(b) Relative Wages for REA Entrants; BoomBust vs Steady MSAs

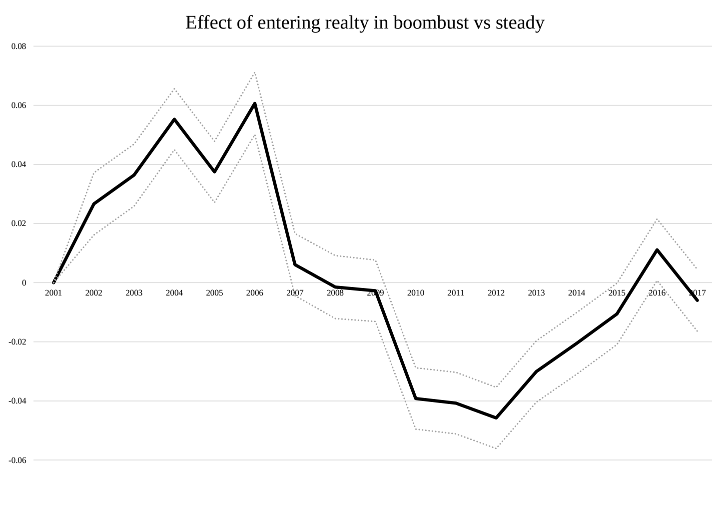
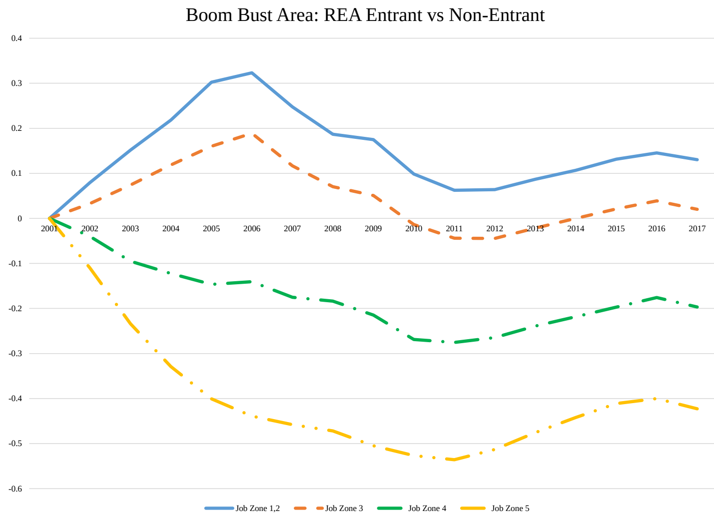


Figure 4: Real Estate Entry and Long-Term Wages

Panels A and B of the figure presents regression coefficients from Equation (3). The outcome variable is the average log-wage at the MSA-occupation-year level. An MSA is classified as *BoomBust* if it experienced a relative boom in house prices (top quintile of house price growth between 2001 and 2006) followed by a relative bust in house prices (bottom quintile of growth between 2007-2011). We refer to non-*BoomBust* MSAs as *Steady* MSAs. An *entrant* is an individual who entered the real estate profession for the first time between 2002 and 2006. Panel A compares *BoomBust* MSA Entrants against *BoomBust* MSA Non-Entrants. Panel B compares relative wage paths for entrants in *BoomBust* MSAs against *Steady* MSA, after differencing out the wage path or non-entrants in their respective MSAs. We include occupation×MSA (Occ.×MSA) fixed effects and occupation×year (Occ.×MSA) fixed effects in all regressions. Standard errors are clustered by Occupation×Year×MSA. The corresponding table can be found in the Online Appendix

(a) Wages for BoomBust MSA Entrants vs Non-Entrants by Job Zone



(b) Wages for Entrants; Boom-bust vs Steady MSA by Job Zone

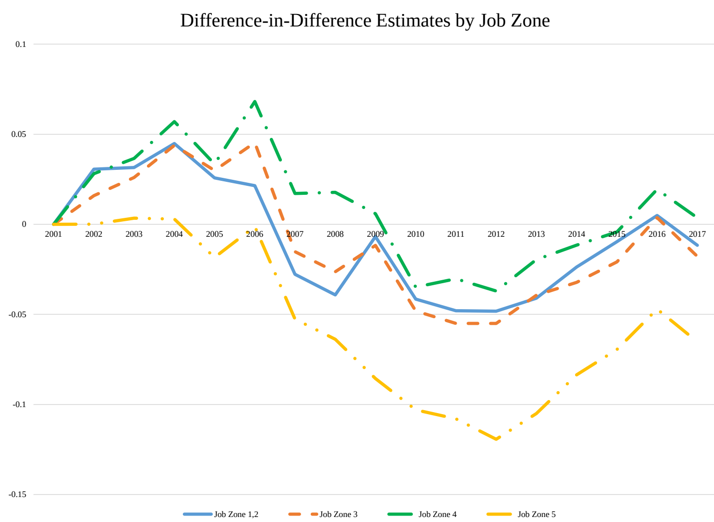


Figure 5: Relative Wages of Boom-Bust REA Entrants By Job Zone Type
Panels A and B of the figure presents regression coefficients from Equation 3 estimated for each job zone. The outcome variable is the average log-wage at the MSA-occupation-year level. An MSA is classified as a Boom area if it falls in the top quintile of house price growth over the period 2000-2007. Analogously, Bust areas are those that were in the bottom quintile of house price decline in the subsequent deterioration of the housing market. An entrant is an individual who entered the real estate profession for the first time between 2002 and 2006. Panel A compares Boom-Bust Entrants against Non-Entrants, as well as the omitted group (Non-Boom, Non-Bust Non-Entrants). Panel B compares average wage paths for entrants in Boom-Bust areas against Boom-No Bust areas. We include occupation×MSA (Occ.×MSA) fixed effects and occupation×year (Occ.×MSA) fixed effects in all regressions. Standard errors are clustered by Occupation×Year×MSA. The corresponding table can be found in the Online Appendix

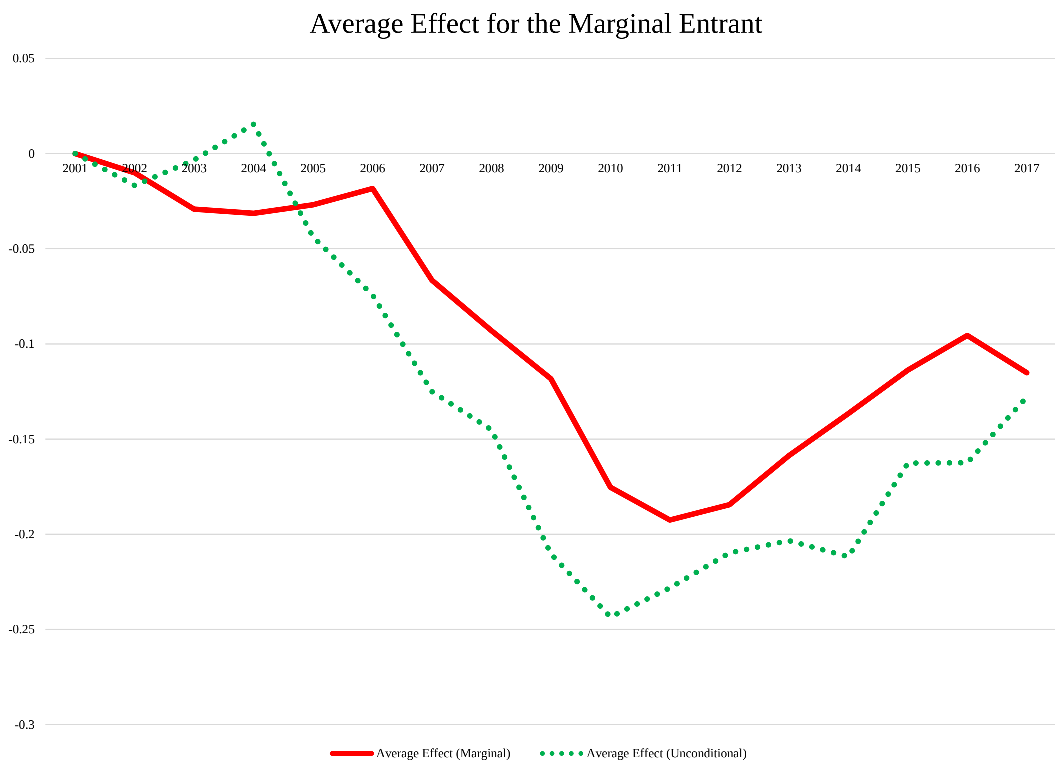


Figure 6: MSA Wages for the Marginal Entrant vs Non-Entrant in Boom-Bust MSAs

This figure presents estimates of the wage effect for the average marginal entrant in a Boom-Bust MSA. We calculate the wage effect for the marginal entrant as outlined in Section 4.4. For comparison, we include the wage effect for all Boom-Bust entrants (same plot as Figure 4 Panel A).

Table 1: Summary Statistics

The table presents summary statistics for our sample, constructed using data from Emsi, BLS, FHFA, and Freddie Mac. The level of observation is at the individual-year for the panel section while the MSA-level observation is the cross-section of all MSAs included in the panel. The panel spans 2001-2017. Real Estate Agent is an indicator that takes the value of one if the person is in the real estate agent profession, and zero otherwise. Enter REA is an indicator variable that takes the value of one when an individual enters the REA occupation the first time, zero otherwise. REA Run-up Switch indicates an individual where Enter REA was one at some point between 2002 and 2006. Switch jobs is an indicator variable which takes the value of one if the individual switches occupations or firms from the previous year, and zero otherwise. Wages are are the average wage of their listed occupation at the MSA-year or National level. Controls, discussed in the Empirical Strategy section, include age, age squared, tenure, tenure squared, and an indicator variable if you are switching occupations. Age is proxied for by taking the difference between the current year and the year of the first job and adding 18. Tenure is calculated as the year of the observation less the year of the start date for the current job. Bachelor or above takes the value of one if the individual currently has a bachelors degree or a higher degree, zero otherwise. Graduate degree takes the value of one if the individual holds a graduate degree and zero otherwise. Job zone, as defined by the BLS, is an occupation-level variable which captures the level of training and education required. High-skill takes the value of 1 if job zone is four or five, zero otherwise. Boom equals one if the area was in the top quintile of house price growth between 2000 and 2007. Bust takes the value of one if the area was in the bottom quintile of house price decline in the period following peak house prices. The final two columns calculate the mean for those inidividual-year observations where the person switched occupations or entered the real estate agent profession, respectively. MSA level variables include the percentage growth in the Run-up (2000-2007). We also perform break-point analysis and find the growth and time period between the break point and the peak house price index. We annualize the growth rate so we can compare across MSAs. We perform the analog analysis to calculate peak-to-trough decline in percentage and months and ultimately annualize the percentage decline as well.

	Panel Level Observation							
	Num. Obs.	Mean	Std. Dev.	1%*tile*	Median	99%*tile*	Switch Occupations	Enter REA
Real Estate Agent	58,857,394	0.02	0.13	0.00	0.00	1.00	0.02	1.00
Enter REA	58,857,394	0.00	0.06	0.00	0.00	0.00	0.02	1.00
REA Run-up Switch	58,857,394	0.03	0.16	0.00	0.00	1.00	0.04	0.68
Avg. Wage (MSA)	34,694,328	85646.22	46878.04	21672.00	75504.42	224138.05	82321.15	64131.75
Age	58,857,394	34.67	9.31	19.00	34.00	61.00	32.96	32.33
Bachelor or Above	58,857,394	0.36	0.48	0.00	0.00	1.00	0.34	0.32
Graduate Degree	58,857,394	0.12	0.32	0.00	0.00	1.00	0.11	0.06
Job Zone	51,411,797	3.68	0.93	2.00	4.00	5.00	3.62	3.18
High Skill	58,857,394	0.56	0.50	0.00	1.00	1.00	0.51	0.18
Boom	58,857,394	0.41	0.49	0.00	0.00	1.00	0.42	0.48
Bust	58,857,394	0.33	0.47	0.00	0.00	1.00	0.34	0.42

	MSA Level Variables					
	Num. Obs.	Mean	Std. Dev.	1%*tile*	Median	99%*tile*
Run-up Increase	383	54%	34%	4%	43%	148%
Break-point to Peak Months	383	46.3	18.8	12.0	43.0	97.0
Annual Growth Pct.	383	9%	7%	1%	6%	28%
Peak-to-Trough Decline	383	-22%	15%	-62%	-18%	-2%
Peak-to-Trough Months	383	53.7	20.9	6.0	55.0	112.0
Annual Decline Pct.	383	-6%	4%	-17%	-4%	-1%

Table 2: House Price Growth and Entrance Into Realty

This table presents OLS estimates from the regression of entry into real estate agent on local house price growth. The dependent variable is a dummy variable equal to 10,000 if an individual entered realty between June of year t and June of year t+1, zero otherwise (i.e., a scaled dummy variable). Growth in HPI is the growth in the local MSA house price index from June of year t-1 to June of year t. In columns (3) and (4), we include dummy variables based on Growth in HPI. Only individuals that are not realtors as of June of year t are included in the regressions. In columns (1) and (4), we include MSA fixed effects and year fixed effects. In columns (2), (3), and (4), we include occupation×MSA (Occ.×MSA) fixed effects and occupation×year (Occ.×MSA) fixed effects. Standard errors are clustered by Occupation×Year×MSA.

	(1)	(2)	(3)	(4)	(5)
Growth in HPI	6.08***	5.85***	5.34***		
	(5.69)	(7.32)	(5.37)		
Growth in HPI × Boom Period			1.37		
			(0.77)		
<-10%				-0.42	-0.45*
				(-1.17)	(-1.73)
-10% to 0%				-0.36*	-0.36**
				(-1.86)	(-2.56)
5% to 15%				0.68***	0.68***
				(4.71)	(6.19)
>15%				1.25***	1.15***
				(4.16)	(5.23)
Constant	9.80***	9.80***	9.79***	9.82***	9.83***
	(167.40)	(225.12)	(202.65)	(96.80)	(132.43)
Observations	69,751,526	69,737,815	69,737,815	69,751,526	69,737,815
R^2	0.00017	0.0044	0.0044	0.00017	0.0044
Fixed Effects	MSA, Year	Occ.×MSA, Occ.×Year	Occ.×MSA, Occ.×Year	MSA, Year	Occ.×MSA, Occ.×Year
Omitted Group				0% to 5%	0% to 5%

Table 3: House Price Growth and Entrance Into Realty By Type
This table presents OLS estimates from the regression of entry into real estate agent on local house price growth. The dependent variable is a dummy variable equal to 10,000 if an individual entered realty between June of year t and June of year t+1, zero otherwise (i.e., a scaled dummy variable). Growth in HPI is the growth in the local MSA house price index from June of year t-1 to June of year t. Only individuals that are not realtors as of June of year t are included in the regressions. In Panel A, we focus on previous occupation's job by interacting Job Zone, as defined by BLS, with Growth in HPI. The regression is a fully saturated pooled regression so there are no omitted groups. Panel B repeats the same exercise but focuses on the wage differential between the previous occupation's average wage and the average wage of a REA, at the MSA-level. Finally, in Panel C, we classify individuals by their level of educational attainment and interact with Growth in HPI. We include occupation×MSA (Occ.×MSA) fixed effects and occupation×year (Occ.×MSA) fixed effects in all regressions. Standard errors are clustered by Occupation×Year×MSA.

Panel A: Job Zone

	Regression Results	Average Entry Rate by Job Zone	Ratio
Job Zones 1 & 2 × Growth in HPI	10.3*	10.69	0.96
	(5.28)		
Job Zone 3 × Growth in HPI	7.63***	9.47	0.81
	(4.05)		
Job Zone 4 × Growth in HPI	5.69***	10.39	0.55
	(4.40)		
Job Zone 5 × Growth in HPI	3.10*	6.75	0.46
	(1.81)		
Observations	64,001,925		
R^2	0.0049		

Panel B: Wage Difference

	Regression Results	Average Entry Rate by Wage Group	Ratio
> 20% Wage Increase × Growth in HPI	7.24***	10.97	0.66
	(4.04)		
5% to 20% Wage Increase × Growth in HPI	0.94	11.60	0.08
	(0.57)		
-5% to 5% Wage Increase × Growth in HPI	6.92**	10.93	0.63
	(3.03)		
5% to 20% Wage Decrease × Growth in HPI	9.36***	12.49	0.75
	(3.48)		
> 20% Wage Decrease × Growth in HPI	5.65*	8.64	0.65
	(3.05)		
Observations	34,917,928		
R^2	0.0045		

Panel C: Education Level

	Regression Results	Average Entry Rate by Degree	Ratio
No Degree × Growth in HPI	7.00***	9.81	0.71
	(7.83)		
Associate/Vocational × Growth in HPI	-0.76	11.81	-0.06
	(-0.34)		
Bachelor's × Growth in HPI	8.26*	11.34	0.73
	(1.78)		
Master's × Growth in HPI	3.59***	6.80	0.53
	(2.65)		
Doctorate × Growth in HPI	3.69**	3.96	0.93
	(2.16)		
Observations	69,737,815		
R^2	0.0045		

Table 4: Relative Entry into Realty During the Run-Up Period in *BoomBust* MSAs
This table presents OLS estimates from the regression of entry into real estate agent during the run-up on an indicator variable if an individual lives in a *BoomBust* MSA. The dependent variable is a dummy variable equal to 10,000 if an individual entered realty between June of year t and June of year t+1, zero otherwise (i.e., a scaled dummy variable). *BoomBust* is a dummy variable equal to one if the MSA was in the top 20% of MSAs in terms of house price growth during the run-up period and the bottom 20% during the bust period. Only individuals that are not realtors as of June of year t are included in the regressions. zLTGrowth$_{01-17}$ is the MSA's standardized long-term growth rate of house prices between 2001 and 2017. Only observations for the years 2001-2005 are included to capture the run-up period. In columns (1) and (2), all observations are included. In columns (3)-(6), the sample is restricted to a specific Job Zone indicated in the column heading. We do not include fixed effects. Standard errors are clustered by Occupation×Year×MSA.

	(1)	(2)	(3)	(4)	(5)	(6)
			Job Zone			
Job Zone(s):	All	All	1 & 2	3	4	5
BoomBust	7.20***	6.74***	6.31***	5.21***	8.44***	5.56***
	(15.98)	(14.37)	(5.42)	(5.28)	(10.53)	(5.86)
zLTGrowth$_{01-17}$		0.71***	1.22***	1.00**	0.45	0.38
		(3.77)	(2.59)	(2.46)	(1.47)	(0.92)
Constant	10.8***	10.9***	11.9***	10.8***	11.7***	6.90***
	(54.07)	(52.91)	(21.11)	(24.40)	(34.85)	(16.43)
Observations	4,737,362	4,737,362	768,798	1,014,017	1,926,327	644,679
R^2	0.000086	0.000089	0.000094	0.000069	0.00011	0.000082

Table A1: Relative Entry into Realty During the Run-Up Period in *BoomBust* MSAs By Degree

This table presents OLS estimates from the regression of entry into real estate agent during the run-up on an indicator variable if an individual lives in a *BoomBust* MSA. The dependent variable is a dummy variable equal to 10,000 if an individual entered realty between June of year t and June of year t+1, zero otherwise (i.e., a scaled dummy variable). *BoomBust* is a dummy variable equal to one if the MSA was in the top 20% of MSAs in terms of house price growth during the run-up period and the bottom 20% during the bust period. Only individuals that are not realtors as of June of year t are included in the regressions. zLTGrowth$_{01-17}$ is the MSA's standardized long-term growth rate of house prices between 2001 and 2017. Only observations for the years 2001-2005 are included to capture the run-up period. For each regression, the sample is restricted to individuals with a specific level of education (indicated in the column heading). We do not include fixed effects. Standard errors are clustered by Occupation×Year×MSA.

	(1) < Bachelor's	(2) Bachelor's	(3) Master's	(4) Doctorate
BoomBust	6.64***	6.95***	4.80***	4.24**
	(12.34)	(7.03)	(3.26)	(2.30)
zLTGrowth$_{01-17}$	0.69***	0.69*	1.23**	0.18
	(3.09)	(1.81)	(2.30)	(0.30)
Constant	11.5***	11.3***	7.10***	3.19***
	(46.18)	(27.41)	(12.28)	(5.12)
Observations	3304246	1033973	291507	107636
R^2	0.000085	0.000084	0.000085	0.000082

Table A2: Relative Entry into Realty During the Run-Up Period in *BoomBust* MSAs By Wage Differential

This table presents OLS estimates from the regression of entry into real estate agent during the run-up on an indicator variable if an individual lives in a *BoomBust* MSA. The dependent variable is a dummy variable equal to 10,000 if an individual entered realty between June of year t and June of year t+1, zero otherwise (i.e., a scaled dummy variable). *BoomBust* is a dummy variable equal to one if the MSA was in the top 20% of MSAs in terms of house price growth during the run-up period and the bottom 20% during the bust period. Only individuals that are not realtors as of June of year t are included in the regressions. $zLTGrowth_{01-17}$ is the MSA's standardized long-term growth rate of house prices between 2001 and 2017. Only observations for the years 2001-2005 are included to capture the run-up period. For each regression, the sample is restricted based on the difference between an individual's current wage and the local average real estate agent wage (indicated in the column heading). We do not include fixed effects. Standard errors are clustered by Occupation×Year×MSA.

	(1)	(2)	(3)
		Wage Growth	
	>20%	-20% to 20%	<-20%
BoomBust	4.05***	7.08***	5.81***
	(3.04)	(3.14)	(4.82)
$zLTGrowth_{01-17}$	1.72***	1.41*	0.18
	(2.98)	(1.68)	(0.35)
Constant	13.3***	13.1***	11.3***
	(18.76)	(12.75)	(19.28)
Observations	600,547	392,422	721,755
R^2	0.000069	0.00011	0.000054