Wage Flexibility and Employment Fluctuations: Evidence from the Housing Sector

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August 2017

Abstract:

Many economists suspect that downward nominal wage rigidities in ongoing labor contracts are an important source of employment fluctuations over the business cycle but there is little direct empirical evidence on this conjecture. This paper compares three occupations in the housing sector with very different wage setting institutions, real estate agents, architects, and construction workers. I study the wage and employment responses of these occupations to the housing cycle, a proxy for labor demand shocks to the industry. The employment of real estate agents, whose pay is far more flexible than the other occupations, indeed reacts less to the cycle than employment in the other occupations, although specific estimates are noisy. I show that the aggregate implications of the estimates depend also on the aggregate labor demand elasticity, which captures how easily laid off workers can find employment in alternative sectors.

JEL classifications: E24, J20, J44

Keywords: Wage setting, wage rigidity, commissions, real estate agents

Email address: s.pischke@lse.ac.uk. I thank Alexander Lembke, Georg Graetz, and Felix Koenig for excellent research assistance, and two referees, Alan Manning, Guy Michaels, Albert Saiz, and Orie Shelef for helpful comments. This research has been supported by a grant from the ESRC to the Centre for Economic Performance at the LSE.

1 Introduction

In the traditional Keynesian model, unemployment occurs during recessions because nominal wages are downwardly rigid. Firms lay off works rather than lowering their wages in recessions. Such explanations for employment fluctuations over the business cycles retain their appeal in modern discussions (e.g. Bewley, 2002). While downward wage rigidity is well documented (see below), there is much less evidence linking wage rigidity directly to employment fluctuations or unemployment. This paper intends to contribute to this debate by comparing the employment response of three different housing market related occupations, real estate agents, architects, and construction workers, to the housing market cycle.

The focus on three such narrow occupations is interesting because pay arrangements differ substantially across these occupations. Real estate agents receive most or all of their pay in the form of commissions. As a result, the "wage" implicit in their employment arrangement is very flexible. If the housing market turns down and prices fall or transactions dry up, the earnings of real estate agents drop commensurately. There is no a priori reason for brokerages (the employers of agents) to lay off agents; the same number of agents could stay in their job at the new lower wage. Of course, agents may decide to quit when employment is becoming less attractive as these workers move along their labor supply curve. Architects and construction workers, on the other hand, are largely paid on standard wage and salary contracts, although overtime pay and bonuses, which provide some degree of flexibility, are common in these occupations. As these occupations should also be affected by the housing cycle, they serve as a useful control group for the real estate agents.

Apart from the different contractual arrangements, another attraction for studying the housing market are the large booms and busts, which have taken place in the market over the past 15 years. Moreover, there are large differences in the amplitude of housing market cycles across different parts of the United States. Figure 1 shows house prices in California, Indiana, and New York. States on both coasts saw large run ups in prices during the 2000s while price increases were modest in in the Midwest. The figure also shows that the bust in the housing market after 2006 was much more pronounced in California than in New York.

In this paper, I am exploiting this variation in fluctuations in house prices and transactions across states and time in the 2000s. I utilize these fluctuations as a proxy for labor demand shocks to the occupations under study. The connection for real estate agents is a very direct one: their commission is a percentage of the transactions value so that the product of prices and transactions directly affects their earnings. For architects and construction workers the connection is more indirect but new housing starts tend to be closely related to the housing cycle.

I interpret fluctuations in the housing market as shocks to the labor demand for the occupations I study. The compensation of both real estate agents and architects is small compared to the total value of houses or housing transactions so that shocks originating from the labor markets for these workers are unlikely to play any significant role in overall movements of the housing market. For construction workers this may be more problematic as the costs of construction are a larger portion of new housing costs. Nevertheless, the perception of most observers is that housing market fluctuations primarily stem from demand side pressures. For example, Glaeser, Gyourko and Saks (2005) and Glaeser, Gyourko and Saiz (2008) explain the divergent housing cycles across US cities by an interaction of increasing housing demand and land use regulations. Gyourko and Saiz (2006) find that construction costs did not contribute to the recent observed housing price cycles.

Combining data from the American Community Survey (ACS) and the Quarterly of Workforce Indicators (QWI) with real estate prices and transactions mostly for the first decade in the 2000s, I estimate the response of wages and employment in each of the occupations with respect to the value of transactions in the housing market. Since the scaling of these responses will naturally differ depending on how directly the occupation is affected by these market fluctuations, my preferred measure is to divide the employment response by the wage response to obtain an elasticity which can be thought of as the labor supply or inverse wage setting elasticity for the occupation. These estimates are effectively IV estimates of employment on wages instrumenting with housing market fluctuations. These estimated elasticities line up according to the flexibility with which wages are set in the different occupations. The estimated elasticities are around 2.5 for real estate agents, 2 to 4 for architects, and 4 to 23 for construction workers. However, the elasticity, particularly for construction workers, is estimated imprecisely because their wage response is very modest.

I use a simple demand and supply framework of the labor market to interpret these results. This suggests that apart from the role of wage rigidity, the labor demand elasticity is an important factor determining to what degree demand shocks translate into employment losses. One way of interpreting the demand elasticity is the ease with which workers in a specific sector might find other employment in the face of a downturn. I present evidence that this might be easier for real estate agents than for the other occupations. This effectively more elastic demand means that wage rigidity matters more for real estate agents then it does for construction workers.

This paper relates to a large literature documenting pervasive downward nominal wage rigidity. Prominent examples are Card and Hyslop (1997), Kahn (1997), and Altonji and Devereux (2000) for the US and Dickens et al. (2007), who report results from a consortium assessing wage rigidity in 16 countries.[1] While these papers are motivated by the importance of wage rigidity for employment fluctuations they focus on documenting the relative absence of negative nominal wage changes and how these relate to inflation. On the other hand, this literature does not relate wage rigidity directly to employment fluctuations or labor demand shocks.

An exception is the paper by Fehr and Goette (2005) for Switzerland, who correlate estimates of wage rigidity across different inflation regimes and cantons to unemployment rates. They find that unemployment is higher when there is more "wage sweep up" due to nominal wage rigidity. Inflation creates implicit variation in the bite of nominal wage rigidity but does not directly distinguish more or less flexible contracting arrangements. Hence, their paper demonstrates a link between wage rigidity and unemployment but does not show directly whether more flexible wage contracts would lead to less unemployment.

Card (1990) relates employment fluctuations directly to contracts with more or less flexibility. He exploits the wage indexing provisions of Canadian union contracts to estimate the employment response to unexpected price changes. Union contracts which do not specify any indexing to future price changes fix nominal wages in either direction. Unexpected inflation then resets the wage. Card (1990) interprets the resulting employment fluctuations as movements along a labor demand curve. This differs somewhat from the exercise I am interested in here, which is focused on the response of employment to labor demand shocks under different wage contracting regimes. Instead of a labor demand curve I am trying to estimate the wage setting schedule under different contracting regimes.

[1] Despite this evidence, there is considerable debate about the importance of nominal wage rigidity. For example, the absence of wage cuts may be due to measurement error in survey data. Elsby, Shin, and Solon (2016) show that wage cuts are much more frequent in administrative data (which have their own problems) than in survey data, and conclude that wages of many job stayers were reasonably flexible during the Great Recession.

Holzer and Montgomery (1993) are interested in the response of wages and employment to firm level demand shocks. Using firm level data, they proxy demand shocks by sales growth. However, in a broad cross-section of firms, sales might reflect both demand and supply conditions. Kaur (2014) studies agricultural labor markets in India, which allows her to construct a more credible measure of demand shocks due to rainfall. However, her market is one for day laborers. As a result, there is no context of a "layoff" in her setting. Rather, she shows that an increase in the spot market wage due to favorable conditions in one year persists into the subsequent year when the reasons for the higher wage have dissipated, and this translates into lower employment. This notion of rigid wages is more closely associated with rigidity in starting wages rather than the wages in ongoing employment contracts. But wages in new jobs are believed to be relatively responsive to labor market conditions in the US, see for example Beaudry and DiNardo (1991), Baker, Gibbs, and Holmstrom (1994), and Pissarides (2009).

Most closely related to my investigation is a paper by Lemieux, MacLeod, and Parent (2012). They separate workers into those who work on standard fixed wage contracts and those whose who receive part of their compensation as bonus pay. Regressing wages, hours and earnings on a bonus pay dummy interacted with the unemployment rate (as a cyclical indicator) they find larger cyclical effects on wages in bonus jobs and larger effects on hours in fixed wage jobs. However, bonus pay is a relatively minor component of total compensation in many jobs, and my paper uses occupations with bigger differences in pay setting regimes. Housing market fluctuations are also likely a better labor demand indicator than the unemployment rate.

Also related is the study by Card, Kramarz, and Lemieux (1999) who correlate relative employment changes to changes in the cross-sectional wage distribution over time in a particular country. This more aggregate investigation ranks three countries, the US, Canada, and France, by the relative rigidity of their wage setting institutions. This is close in spirit to the informal ranking of three different occupations in my study.

An important prior analysis focusing on real estate agents is the closely related exercise by Hsieh and Moretti (2003). They also regress changes in real estate agent employment and earnings on changes in house prices. They find an elasticity close to 1 for employment and almost no response of earnings. However, in contrast to my investigation they look at relatively long run (10 year) changes during a period when the housing market in the US was mostly booming. They interpret their results as inefficient entry of workers into an industry where the commission rates on sales tend to be fixed irrespective of house price levels. A relative elastic supply of real estate agents absorbs any potential wage gains as the proceeds are being spread across more workers. My study focuses on year-to-year changes which are more likely to capture business cycle fluctuations. In particular, my sample period includes the sharp downturn in many housing markets after 2006, which is relevant for the wage flexibility story. Unlike my study, Hsieh and Moretti don't compare wages and employment to any other housing related occupations.

2 Institutional Arrangements and Analytical Framework

Real estate agents and brokers facilitate transactions between buyers and sellers in the housing market. An individual has to obtain a state license after completing some coursework in order to act as a real estate agent; the entry requirements for this occupation are not large. After some experience and/or with additional education, individuals can qualify as a broker, which allows them to set up their own brokerage.[2] A broker typically employs various agents, who will execute the sales of individual properties. In most states and transactions, a seller enters a legal relationship with a brokerage. The designated agent will carry out a number of specified services related to the transaction for the client. These services include finding a buyer but typically also involve various legal obligations associated with the sale. Clients pay a fee in the form of a commission on the sales price to the brokerage for these services.

Agents are employed by brokers on a variety of contracts. The most common ones involve agents receiving a share of the commission revenue for their sales; this is often referred to as percentage commission splits. Shares of 50 to 80 percent are common in the industry. Few agents receive a fixed base salary or are paid solely on a salaried basis. However, it is not uncommon for an agent to actually *pay* the broker a monthly fee while receiving a large share of their commission revenue, often 100 percent in this case. In industry parlance these agents "pay for their desk." In addition to desk fees these agents typically cover their own business expenses (NAR RealtorMag, 2014a; NAR 2014; Shelef and Nguyen-Chyung, 2015).

There is little precise information on the exact prevalence of flexible components of pay like commissions. Various labor market surveys contain some coarse information, typically combining payments such as bonuses, commissions, and overtime pay. The top panel in Table 1 displays the share of workers receiving pay from overtime, tips, and commissions from the Current Population Survey (CPS) for the three occupations analyzed here.[3] Potentially, all these pay components are related to performance and the amount of work available. More than half the real estate agents respond to receive such flexible pay

[2] Specific regulations and nomenclature differ across states.

[3] The CPS asks "(Do / Does) (name/you) usually receive overtime pay, tips, or commissions at (your/his/her) MAIN job?"

compared to 10 – 15 percent of architects and construction workers. For construction workers this is presumably mostly overtime, which will lose its relevance once hours fall below the threshold for overtime pay. As a result, overtime pay provides some wage flexibility in a downturn but wages eventually turn rigid.

I augment the CPS results with information from industry sources. According to the Member Profile of the National Association of Realtors, 95 percent for agents and brokers receive some flexible pay component, which in most cases will be commissions. It is unclear why the CPS fraction is much lower. NAR members are more likely brokers or more experienced and higher earning agents. These groups tend to be on more high powered contracts but these agents are also more likely to receive a salary. However, if anything, this suggests that the fraction reporting commissions in the more representative CPS should be even higher.

The second panel in Table 1 collates information on the share of pay that is due to the flexible pay components. Unfortunately, I have only been able to locate such information from industry sources for architects and construction workers, for whom only 5 percent is due to such pay components. The last number for construction workers on fringe costs of 19 percent is probably an overstatement for my purposes, as a large proportion of fringe costs is likely part of fixed pay, like employer contributions to health insurance premia. Unfortunately, detailed information is not available for real estate agents but the numbers are likely to be substantially higher as commission shares below 50 percent are rare. NAR (2014) reports that 13 percent of agents are on 100 percent commissions and 73 percent on percentage commission splits.

One issue is whether we should think of agents as actually employed by brokers at all, or as effectively self-employed. The IRS has rules as to when agents should be classified as independent contractors or employees. States have their own rules, often based on common law guidelines, to determine whether agents are covered by unemployment insurance and workers compensation (NAR RealtorMag, 2014b). For example, NAR (2014, exhibit 4-4) reports that 83 percent of their members are independent contractors and hence effectively self-employed. However, it is important to keep in mind that almost half of the responses in this industry survey come from brokers rather than agents.

On the other hand, 49 percent of real estate agents self-identify as employed in the sample from the ACS I use below. This compares to 72 percent of architects and 75 percent of construction workers. In practice, many real estate agents seem to think of themselves as employees.

Even if employed, the relationship of real estate agents to their employers may be a looser one than that of architects and possibly even construction workers to their firms. As workers move in and out of their jobs more frequently, contracts are more likely to resemble spot market contracts while more attached workers may have (possibly implicit) long term contracts with their employers. The current wage in a long term contract may not be the relevant value of compensation which matters for market clearing. Unfortunately, we know relatively little about the nature of contracts in labor markets in general, and I am not aware of any relevant data for the occupations under consideration here. However, in Table 2 I compare average tenure in the three occupations to get at least a view as to whether the differences in attachment are large. The tenure data are from the CPS Tenure Supplements and the Displaced Worker Surveys.

Both columns in the table display results from regressions of tenure on a constant and dummies for architects and construction workers. The constant in these regressions reflect the average tenure for real estate agents, while the coefficients for the other occupations measure the difference in average tenure of that occupation from realtors. Column 1 uses the

Job Tenure Supplements to the CPS. Tenure here refers to the incomplete tenure in the current ongoing employment spell. Real estate agents have about 5.7 years of tenure. Architects stay in their jobs about 20 percent longer with an average tenure around 7 years. Construction workers have more similar tenures to real estate agents; their point estimate is slightly negative. Column 2 shows results using data from the Displaced Worker Survey. Here, tenure refers to completed tenure in the job from which a worker has been laid off. Average tenure for these workers is shorter, and the differences across the occupation are smaller and not significant, given the noisier estimates in this smaller sample. But the general pattern is the same: real estate agents fall in between architects and construction workers. Overall, realtors do not seem to be big outliers in terms of their attachment to their employers.

The wage contracts of real estate agents closely approximate a simple, optimal agency contract we are used to seeing in a textbook. Such a contract involves a negative intercept and a slope of 1. Figure 2 illustrates how agent earnings are a function of the total value of transactions. These values are the product of the average sales price of a property in market m (P_m) and the number of transactions (sales) agent i completes in a month (S_{im}). Agent earnings are

$$Y_{im} = \gamma_{im} + \delta c \, P_m \, S_{im} \tag{1}$$

where γ_{im} is the base salary or desk fee, δ is the share of the commission the agent receives (say 0.5), and c is the commission rate (e.g. 0.06) on the transactions value. I use $\ln(P_m \, S_m)$ as my measure of labor demand shocks in the empirical analysis below, where S_m are market level sales. As Figure 2 illustrates, agent earnings and wages fluctuate directly with transactions values in the housing market.

Note that market level transactions are $S_m = \Sigma S_{im}$, where the sum is over the L_m real estate agents working in market m. Fluctuations in the housing market will directly affect P_m and S_m. Hsieh and Moretti (2003) have shown that the number of active real estate agents L_m responds strongly to price booms, at least at a decadal horizon. Hence, S_m tends to rise when prices rise but S_{im} could well fall if L_m expands enough. Every agent simply sells fewer houses in a boom so that agent earnings stay the same. In fact, Hsieh and Moretti (2003) find that average earnings of agents don't rise in booming markets. I am using the market level $\ln(P_m S_m)$ as my cyclical indicator and I want this to affect agent earnings. However, unlike Hsieh and Moretti, I am looking at annual data and I will show below that agent earnings are responsive to $\ln(P_m S_m)$ at that frequency.

The analysis in this paper is based on a simple demand and supply framework analogous to Card, Kramarz, and Lemieux (1999), where the wage setting institutions differ across occupational labor markets. Figure 3 illustrates this for two occupations, say real estate agents and construction workers. Each occupation has a wage setting (or labor supply) curve and a labor demand curve. The wage setting curve for construction workers is inelastic, reflecting the relatively rigid wages for this group of workers. The wage setting curve for real estate agents is elastic as the wages for this group adjust flexibly to changes in the labor market. Figure 3 shows a common labor demand curve for each of the two groups. When labor demand shifts inwards, as during the housing bust from 2006 – 09, wages fall little for construction workers, while there is a large adjustment in employment. The opposite happens for real estate agents where wages fall more and employment adjusts less.

I treat the market indicator $\ln(P_m S_m)$ as a labor demand shifter, and interpret the ratio of the employment to the wage response to shocks as the inverse wage setting elasticity of the occupation. One issue with using $\ln(P_m S_m)$ as a labor demand shifter for the first decade in

2000s is that the boom and bust cycles in the housing market correlate strongly with the financial crisis and the general downturn of the economy. Since labor demand and supply in Figure 3 are those to an occupation, supply depends crucially on job prospects for workers outside the occupation. An inward shift in labor demand due to the housing bust during the 2006 – 2009 period may therefore coincide with an outward shift of labor supply (or wage setting) because job prospects also deteriorated in other occupations at the same time.

I deal with this in two ways. All regression models are estimated at the state level and control for aggregate time effects. I.e. I only use the within state variation in $\ln(P_m S_m)$. To the degree that the recession due to the financial crisis affected all states similarly this will be washed out by the time effects. To address within state correlations of labor demand and supply shifts I also control for an "alternative wage" for the occupations under analysis. This is given as the wage of all workers in the state with similar characteristics as the workers in the occupation under analysis, and described in more detail in the data section below. It is not a perfect solution as this alternative wage is clearly an equilibrium object.

3 Data

The analysis combines labor market data for real estate agents, construction workers and architects with data on the economic cycle in the housing sector. Data on the labor market come from the American Communities Survey (ACS) and from the Quarterly Workforce Indicators (QWI), housing sales transaction data are from the National Associations of Realtors (NAR) and sales prices from the Federal Housing Finance Agency (FHFA). Details about the data and variable construction are in Appendix 1.

The ACS is a large-scale annual survey of the US population starting in 2000. I select real estate agents, architects, and construction workers and construct annual employment, average hourly wages, weeks worked per year, and usual hours worked per week for these occupations. The hourly wage measure divides wage and salary income by annual hours worked. Since the aim of this paper is to analyze the effect of rigidity in contracted wages, I exclude the self-employed in the analysis. The main analysis uses data aggregated at the state and year level. While metropolitan areas might be preferable, longer time series of house prices are available at the state level.

To control for potential shifts in labor supply that coincide with demand shifts I construct a measure of workers' "alternative wage." This variable is meant to proxy for the outside option of workers. It is constructed as a weighted average of the wage of similar individuals working outside a given occupation. The weights are derived from a probit regression of working in that occupation on demographics. To illustrate the process consider the "alternative wage" of a real estate agent. I first estimate a probit model for working as a real estate agent on seven education dummies, race, a squared term in age, and an interaction of gender and marriage dummies. Next I calculate the weighted average wage of all *non*-real estate agents using the predicted probability of being a real estate agent as weight. This procedure creates an average wage for workers in other occupations who look most similar to real estate agents in terms of observables.

One drawback of the ACS is that samples for specific occupations at the state-year level can be small, leading to imprecise cell averages. I therefore complement the ACS data with data from the QWI, which is mainly based on administrative records of the state unemployment insurance (UI) systems. While the QWI covers almost the universe of employment contracts in the US, its main drawback is that it excludes jobs outside of the UI system. This excludes the self-employed but potentially also other real estate agents because the commission-based contracts prevalent in the industry are exempted from UI coverage in a number of states. Apart from this under-coverage, the QWI inclusion rules will most likely capture the agents with the least flexible contracts.

A second drawback is that the QWI only contains information by industry and not occupation of the workers. Therefore, I use the industries for Offices of Real Estate Agents and Brokers; Architectural, Engineering, and Related Services; and for Residential Building Construction to mimic the three occupation groups in the ACS. This introduces some measurement error as I also capture wages and employment of other occupations like secretaries who are likely on different contracts. The QWI data start at different points in time for different states mostly in the 1990s and early 2000s. This leads to an unbalanced panel but allows me to extend the time period for some states.

The labor market data is linked to data on the regional housing cycle. The data for the total value of housing transactions comes from two sources. The price data is taken from the annual series of house prices by the FHFA (formerly OFHEO). This data is based on mortgages bought by Freddie Mac and Fannie Mae. The index is calculated using two mortgages on the same property and aggregating the data using the Case and Shiller (1989) method. The data used here use single-family residential properties only, the state level data start in 1991, and are published annually. Housing sales transactions are obtained from NAR for the years 1989 to 2010. This data is based on reports of local membership groups and again covers existing single-family homes. Combining the labor market and housing data leads to a panel spanning the years of 2000 to 2010 when using the ACS and an unbalanced panel for the years 1991 to 2010 when using the QWI.

The data on fluctuations in the housing market should capture swings in the demand for the three occupations. My preferred measure is the annual value of house sales given by the product of the number of transactions and the average sales price. For real estate agents, this variable directly tracks the transactions values on which commissions are based. For the other two occupations, demand might be thought to be more closely related to the number of new construction projects. To address this point I collected data on the value of new housing permits issued in each year and state from the Census Bureau's "Building Permits Survey." A regression of the ln of Construction Permits on ln Housing Prices and ln Transactions separately yields an R^2 of 0.3 within states and years, and 0.2 when the regression is run on the product of prices and transactions (see Appendix 1 Table A2). This suggests some differences in new construction and sales of existing homes but the value of housing sales should also capture demand shifts in architecture and construction fairly well.

4 Empirical Results

Table 3 shows regression results from running wage and employment regressions of the form

$$\ln(Y_{st}) = \alpha + \beta_p \ln(P_{st}) + \beta s \ln(S_{st}) + \phi_s + \lambda_t + e_{st} \qquad (2)$$

where Y_{st} is the wage or employment outcome for realtors in state s and year t, P_{st} is the housing price index, S_{st} is the number of home sales, and ϕ_s and λ_t are state and year fixed effects, respectively. Regressions are weighted by the number of working age individuals in a state. Column (1) shows that a 10 percent increase in prices or sales translates into about 1.5 percent higher hourly wages for real estate agents. Even though the wage elasticity is well below 1, this seems like a substantial effect and is statistically significant. We would expect an elasticity of 1 if the contracts for all agents were simply proportional (i.e. $\gamma = 0$ in eq. (1) above), agent employment would not react to labor demand shocks, and transactions volumes $P_{st}\ S_{st}$ were completely accurately measured. None of these are likely to hold. Moreover, the regression is based on repeated cross-sections, and entry and exit effects will tend to bias the estimates of β down if less productive agents enter in booms. In any case, the estimates are large compared to the zero effect found by Hsieh and Moretti (2003).

Since the coefficients on prices and sales are very similar as expected (although the p-value for equality is only about 0.04) it makes sense to restrict them and work with the transactions value $\ln(P_{st}\ S_{st})$ as in column (2) instead. Adding the alternative wage for real estate agents in column (3) makes little difference to the result. The estimate for the alternative wage is positive as expected but imprecise.

Columns (4) to (6) repeat the same regressions for the number of realtors employed. Elasticities are around 0.5 to 0.6, suggesting substantial employment responses of realtors over the cycle. This mirrors the result of Hsieh and Moretti (2003) that realtors respond to the housing cycle through entry and exit, and this will mute some of the wage effects of market fluctuations. To gauge the size of this response we will have to compare realtors to other occupations, as we will do shortly. The result in column (6) shows that the employment result is also relatively insensitive to entering the alternative wage, which is now negative.

Columns (7) to (9) show results for the average number of weeks worked, and columns (10) to (12) for hours worked per week. There seems to be no adjustment at the intensive margin as housing markets fluctuate. If realtor wages are relatively flexible, we might expect a smaller employment response for this group but some adjustment on the intensive margin. One reason for the absence of an hours response might be the presence of desk fees in agent contracts, as illustrated in Figure 2. Since these fees constitute a fixed cost of work, agents may not want to reduce their hours (very much) in response to housing busts but may still react by leaving the occupation or employment entirely. However, many more agents are on percentage commission splits and may not pay any desk fees. It is also surprising that there is not more of a response at the weeks margin.

It is difficult to gauge whether the wage and employment responses of real estate agents to labor demand shocks are large or small by looking at this occupation in isolation. Therefore, I run similar regressions to (2) for architects and construction workers. Workers in these occupations are on much more standard fixed wage contracts with comparatively minor flexible components like overtime or bonuses. One complication in comparing the β coefficients for different occupations is that house price and sales shocks may affect real estate agents much more directly than the other occupations. To circumvent this problem, I concentrate on the wage setting elasticity, given by the ratio $\beta_{empl}/\beta_{wage}$. This ratio is free from these scaling problems, since scaling should affect wage and employment results proportionally. Notice that the inverse wage setting elasticity can be obtained from the regression of employment on wages

$$\ln(L_{st}) = \theta_0 + \theta \ln(W_{st}) + \phi^1{}_s + \lambda^1{}_t + \eta_{st}, \tag{3}$$

instrumenting the wage by the demand shock $\ln(P_{st}\, S_{st})$.

Table 4 displays the results for the three occupations. Column (1) repeats the estimates of the employment, weekly hours and wage elasticities with respect to $\ln(P_{st}\, S_{st})$ for real estate agents; these are the estimates from columns (5), (11), and (2) from Table 3, respectively. The fourth row gives the inverse wage setting elasticity, which is the ratio of the employment and wage estimates. This comes out to 2.8 for the real estate agents. Columns (2) and (3) display the estimates for architects and construction workers. Both employment and wage responses are lower for these occupations, as expected. What is of more interest is the ratio in row (4) which is 2.0 for architects and 23 for construction workers. The wage setting elasticity is imprecisely estimated because the wage effect in the denominator of the ratio is small for both these occupations. The reduced form estimate for weekly hours in row (2) is uniformly small for all occupations; indicating little intensive margin response to labor demand shocks for any of the occupations.

Columns (4) to (6) of Table 4 repeat the same estimates with the QWI data. Both the ACS and the QWI data have advantages and disadvantages. The main strength of the QWI data is that they capture the universe of workers covered by the UI system, while the ACS samples are small for the specific occupations analyzed here. Indeed, the QWI estimates are generally more precise. The inverse wage setting elasticities are 2.2 for real estate agents, 4.3 for architects, and 3.5 for construction workers.[4]

One caveat with these results is that the cyclical patterns of wage and employment responses may differ in the three occupations, and differences in the estimates might reflect this. In Table 5, I also enter leads and lags of house transactions values in the regressions. Because of the short time dimension of the panel at hand I limit the analysis to one lead and one lag. Even the estimates with one lead and lag are very noisy. To the degree that a pattern emerges, it suggests that employment and wage responses are either contemporaneous or happen with a one year lag. Maybe the employment responses of architects are slightly faster than for the other two occupations. This would make sense as this occupation is engaged in the earliest stages of a building project and new construction plans may react first to changes in housing demand.[5] In order to interpret the coefficients from the specification with leads

[4] In Appendix 1 Table A3 I replicate the ACS results using industries as in the QWI data. However, little specific insight emerges from this comparison.

[5] In Appendix Table A2 I probe the dynamic relationship between building permits and transactions and prices in a similar way. No clear evidence emerges that permits lead the housing cycle.

and lags I also present the sum of the coefficients. This is an estimate of the long-run response in a dynamic model. The estimated inverse wage setting elasticities from this exercise are very close to those from the contemporaneous specification.

Another issue with the estimates is that employment fluctuations may imply selection in who works over the business cycle. As a result, changes in average wages may reflect both changes in wages for the employed individuals as well as this changing composition (see e.g. Solon, Barsky, and Parker, 1994). If the worst workers leave their jobs in a downturn and join in a boom then wages will look less cyclical than they truly are. This composition bias will be worse the larger the employment fluctuations in an occupation. Table 4 suggested that employment of realtors reacts most strongly to the transactions value indicator, and hence this occupation may suffer more from the composition bias in wages. The true wage effect should therefore be larger, and the resulting inverse wage setting elasticity would be overestimated.

In order to investigate whether this is potentially an important issue, I turn to data from the Current Population Survey Merged Outgoing Rotation Groups (CPS-MORG). Wages are collected twice from each surveyed household one year apart. I match individuals across the two outgoing rotation groups where wages are collected. This allows me to look at wages for entrants, leavers, and stayers in an occupation.

Table 6 presents a regression of wages from the matched CPS sample on occupation entrants and leavers (with stayers as the base group and controlling for age). Using hourly wages in the top panel suggests that entrants have broadly similar wages to stayers while leavers are slightly negatively selected. The bottom panel uses weekly earnings, which are available for a slightly bigger sample at the cost of conflating wage and hours information. The estimates are now consistently negative and larger in absolute value than for wages. This suggests that there is some selection both on wages and on hours, and the selection is most heavily concentrated on leavers. Selection turns out to be smallest for real estate agents but the differences are not massive.

Unfortunately, occupation transitions are notoriously poorly measured in panel datasets (see Kambourov and Manovskii, 2013). An incorrect coding of the occupation in one period will lead to spurious entry and exit from the occupation. Realtors may have more spurious transitions. Annual entry and exit rates for realtors in the matched CPS data are 56 and 47 percent, respectively. This is much higher than what we would expect from the tenure data in Table 2. If entry and exit followed a Poisson process, average incomplete tenure of 5.7 years in the CPS Tenure Supplements suggests completed tenure of 11.4 years, which translates into annual steady state flows of 9 percent. This means less than 20 percent of the observed transitions in the merged CPS data may be true transitions, and the estimates in Table 6 may be substantially attenuated as a result. However, the estimates for the other occupations would be attenuated as well. While spurious transitions are somewhat less important for architects and construction workers, using similar calculations for the other occupations suggests that this phenomenon does not reverse the conclusions from Table 6. Wages and earnings of entrants and leavers seem to be lower than those of stayers but the differences across occupations are slight.

Time Series Results

An important issue for the macroeconomic implications of these results is whether employment flows to and from the housing occupations is to non-employment or to other occupations. If workers who lose their jobs because of rigid wages quickly find employment elsewhere then the aggregate implications of rigid wages may not be very important. The story is different if most of these job losses result in unemployment.

The ACS and QWI data are not suited for addressing this question because they do not allow me to measure flows directly. I therefore use the longitudinal data on individuals from the CPS constructed above to build a time series of employment and employment flows from 1980 to 2016. I am turning to a national time series because the sample size in the CPS is too small to analyze occupations within state (and it is small even to analyze these occupations at the national level).

Note that employment at time t obeys the flow equation $L_t - L_{t-1} = Entry_t - Exit_t$. Approximating $\ln(L_t) - \ln(L_{t-1})$ by $(L_t - L_{t-1})/L_{t-1}$, we can write the time series version of eq. (2) in first differences as

$$
\begin{aligned}
(L_t - L_{t-1})/L_{t-1} &= Entry_t/L_{t-1} - Exit_t/L_{t-1} \\
&\approx \lambda + \beta_P\{\ln(P_t) - \ln(P_{t-1})\} + \beta_S\{\ln(S_t) - \ln(S_{t-1})\} + e_t
\end{aligned}
\tag{4}
$$

It is possible to estimate this equation either for the total employment change or for inflows and outflows separately. Moreover, inflows and outflows can be further disaggregated into flows to and from other occupations and flows between the occupation in question and non-employment. Because of the spurious transitions problem I will only show results for total employment change and for entry and exit between the occupation and non-employment. As a result, entry and exit coefficients will not add up to those for total employment changes. Finally, I only use the price term on the right hand side of the equation because the transactions data do not go back into the 1980s, and the time series has few observations as it is. The quality of these time series does not seem to be high. Apart from the spurious transitions problem discussed above, the series for entry from other occupations and—as a result—total employment changes seem extremely volatile from year to year.

With these caveats in mind, Table 7 displays the results. Overall employment elasticities are much larger than those in Table 4 but remember that we are now using the entire time variation including national time effects in the estimation.[6] More interesting than the overall employment elasticities is how much of these effects is accounted for by entry and exit. For construction workers, exit from employment accounts for all of the cyclical fluctuations in employment change while entry is not cyclical. For architects, entry is also not cyclical and exit accounts for about half the total employment elasticity. For realtors, both entry and exit is cyclical. Exit accounts for about 15 percent of the total and entry another 10 percent. This means 75 percent of the employment flows for realtors are to and from other employment.

The results suggest that exits matter for all three occupations but real estate agents may have more flows to and from other occupations and self-employment as well. Some of these may be spurious but note that unsystematic occupation miscoding should lead to attenuation here as well and not produce the large estimates in the first row of Table 7. The estimates suggest that real estate agents have more flows to other employment which are related to the housing cycle.

5 Interpretation

I will interpret the differences in employment responses of real estate agents and the other occupations through the lens of a very simple, competitive labor market model. The estimates for the wage setting elasticity are not particularly precise and the specific results

[6] Employment effects in Table 4 without time effects are generally larger as well but not to the same extent.

differ between the ACS and QWI estimates, so I will consider a range of estimates. The inverse wage setting or labor supply elasticity for real estate agents is most consistently estimated at a value around 2.5. The most rigid occupation seems construction workers but their elasticity varies between 4 in the QWI and 23 in the ACS.

Consider the most standard supply and demand model of the labor market. If wages were completely fixed, a labor demand shock would translate one for one into a change in employment. I will use this as the benchmark of a most rigid labor market. Consider the same labor market model but now set the inverse wage setting or supply elasticity to $\theta < \infty$. Employment then would contract by a fraction $\theta/(\theta + \eta)$ for a one unit shock to labor demand, where η is minus the elasticity of labor demand. Column (4) of Table 8 displays values for this employment response for a labor demand elasticity of $\eta = 0.5$ as in Card (1990).[7] For realtors with a $\theta = 2.5$, employment would decline by 83 percent of the benchmark case. For a more rigid occupation with $\theta = 4$ the employment decline is 89 percent and with $\theta = 23$ it is 98 percent. Low and behold, the employment responses are not very different because labor demand is inelastic. With perfectly inelastic demand, the supply elasticity plays no role for the employment response at all; employment always contracts by the full amount. $\eta = 0.5$ is small enough that we are close to the inelastic case.

But the standard one sector model is likely too simple, particularly for real estate agents, who may be moving to employment in other sectors when they leave realtor jobs. Augment this model with a second sector so that labor demand is now η_0 in the own sector and η_1 in the alternative sector.[8] The estimated supply elasticity is the supply to the own sector, θ_0.

---

[7] Hamermesh (1993) puts the consensus estimate of the own elasticity of labor demand even lower at 0.35

[8] Details about the setup of the model and the derivations are in Appendix 2.

Workers move between sectors freely, so wages are the same in both sectors. In this case, a fraction $(\theta_0 - \eta_1)/(\theta + \eta_0)$ of workers would move to non-employment for a one unit labor demand shock to the own sector. Results for this calculation are shown in the last column of Table 8. In the first three rows I set $\eta_1 = \eta_0 = 0.5$. This makes little difference when wages are rigid like in the $\theta = 23$ case but it mutes the employment response for more flexible wages, like the $\theta = 2.5$ case for real estate agents in the first row. Only 67 percent of workers become unemployed compared to 83 percent without an outside sector. The demand and supply elasticities interact here, and some workers gain employment in the alternative sector as wages are now allowed to fall in response to the labor demand shock in the initial sector.

But the alternative sector may not simply be a single sector similar in size to the first. For example, real estate agents may have various possibilities of alternative employment. They could work as mortgage brokers, they may sell insurance, or take a clerical job and each of these alternative occupations could be considered a single sector. In other words, there could be multiple alternative sectors. Adding a third sector would simply replace the labor demand elasticity for sector 1 by the sum the demand elasticities for both alternative sectors. As a result, it is possible to think of additional sectors simply as more elastic labor demand in sector 1: this “sector” more easily absorbs additional workers.

It is now possible to think of the one sector responses as the employment losses in the own sector. Some of the workers affected by the decline in labor demand in the own sector find employment in other sectors in the multi-sector model. The multi-sector response shows the actual loss of employment. These two parts can be mapped into the total employment response in line 1 of Table 7, and the sum of entry and exit from the labor market in lines 2 and 3.[9]

Table 8 shows calculations for values of η_1 of 1 and 1.9. I chose these values so that the ratios of the one to multiple sector employment response in the $\theta = 2.5$ case (real estate agents) are about 60 percent and 25 percent, respectively. The 25 percent number is taking the estimates in Table 7 at face value that only 25 percent of employment fluctuations of real estate agents are to and from non-employment. The 60 percent number asserts that roughly half of the remaining estimate is non-sensical, and hence presents an intermediate case.

In the most extreme case if the outside demand elasticity were 1.9, real estate agents would find it easy to find other jobs. Only 20 percent of the initial job losses would translate into non-employment. In contrast, in the rigid construction sector, 90 percent of workers would still become unemployed. But construction workers may have fewer outside opportunities (and this was suggested by the results in Table 7) so the one sector response of 98 percent might still be the relevant one. Even in the intermediate case of $\eta_1 = 1$, the capacity of other sectors to absorb employment losses for real estate agents is sizeable.

This discussion suggests that the comparison of real estate agents and construction workers suffers from the drawback that these occupations differ not just in terms of the flexibility of their wage setting institutions but also in terms of the alternatives available to workers in the face of a job loss. The model allows us to separate these two effects. Instead of comparing an employment response of 20 and 98 percent, we want to compare either within the one sector or the multiple sector model only. In the one sector case, moving from very inflexible

[9] In steady state, employment losses that occurred in recessions have to be made up by employment gains in booms. As a result, in this simple model adding the entry and exit rates is the correct metric to assess the flows with non-employment.

wage setting as for construction workers ($\theta = 23$) to a flexible scenario as for real estate agents ($\theta = 2.5$) would not reduce employment losses very much. 85 percent of workers (0.83/0.98) would still become unemployed even with more flexible wages. Doing the opposite calculation for real estate agents in the multiple sector case means that flexibility helps a lot. In the most extreme scenario with $\eta_1 = 1.9$, wage flexibility reduces employment losses to 22 percent (0.20/0.90). Even the intermediate scenario with $\eta_1 = 1$ means a reduction to 53 percent (0.50/0.94). This highlights an important role of alternative job opportunities in mediating the effect of flexibility on employment outcomes.

6 Conclusion

There is a sizeable literature on downward nominal wage rigidity and many economists believe that this is a source of employment fluctuations over the business cycle. Nevertheless, there is not much evidence linking rigid wages directly to employment outcomes as I have done here. I do indeed find that the wages of real estate agents react relatively more and employment relatively less to labor demand shocks than they do for architects and construction workers, who tend to have more rigid wage setting institutions. Comparing narrow occupations which work in a highly cyclical industry is attractive because we have a good sense how pay setting institutions differ across these occupations.

But focusing on narrow occupations also has shortcomings. Neither the ACS nor the QWI are ideal data sources for this exercise and results are noisy. It is therefore comforting that a fairly consistent pattern of results still emerges from both data sets. The data sets are repeated cross-sections rather than true panels, so the estimates likely suffer from composition bias. However, this does not seem to impact the three occupations differentially.

A more important issue is that real estate agents seem to have many outside job opportunities, and many of their employment flows are to and from employment in other occupations or in self-employment. I use a very simple supply and demand framework to show that this is an important issue. More generally, the discussion highlights that the employment response to demand shocks depends heavily on the labor demand elasticity as well. This is not a quantity this research strategy is able to assess directly but it is a crucial part of the aggregate consequences of wage rigidity.

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Figure 1: Housing Market Fluctuations in Three States

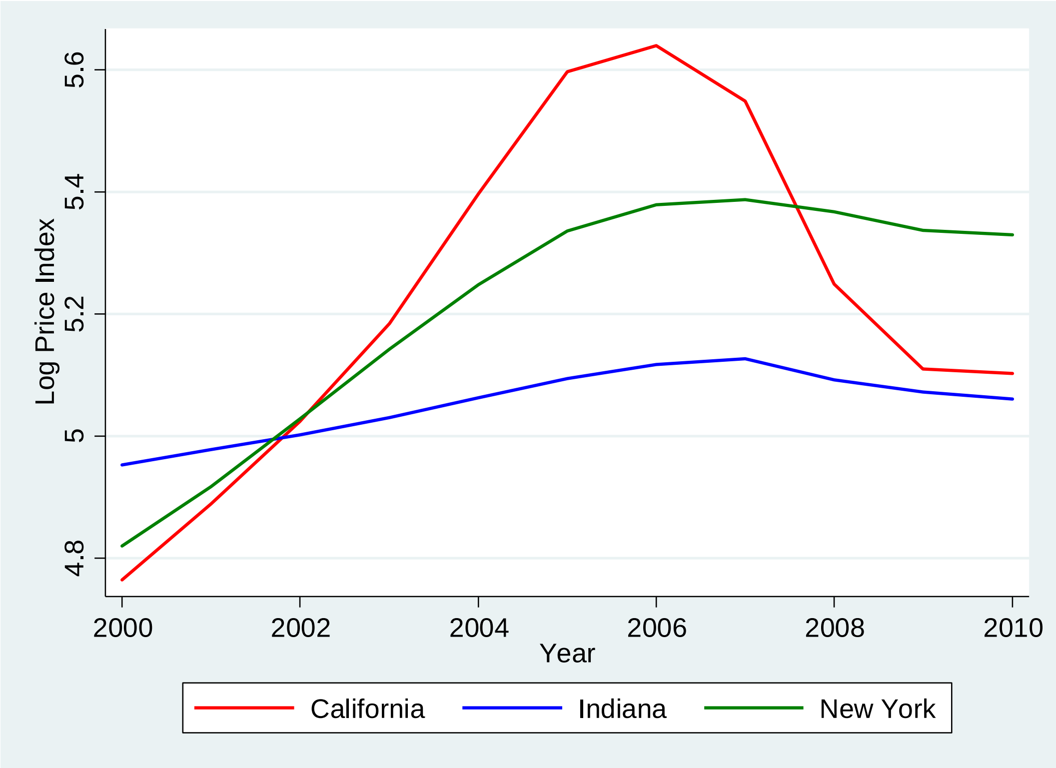

Figure 2: Contract for a Real Estate Agent

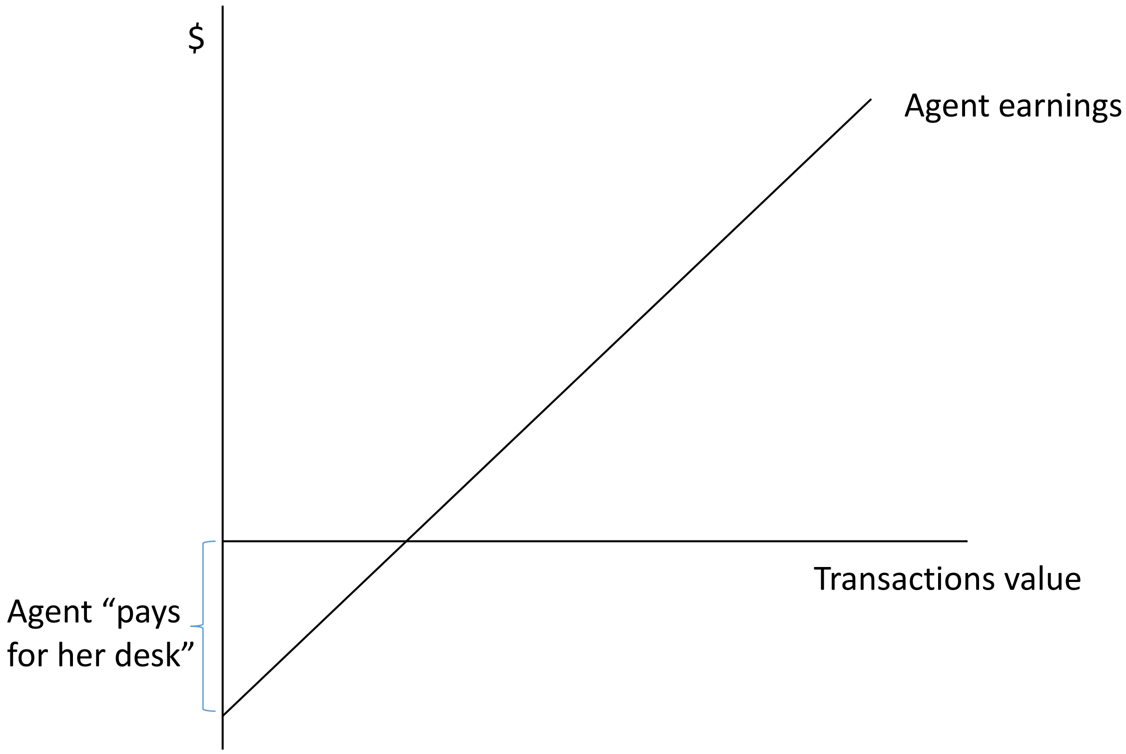

Figure 3: The Labor Market for Housing Related Occupations

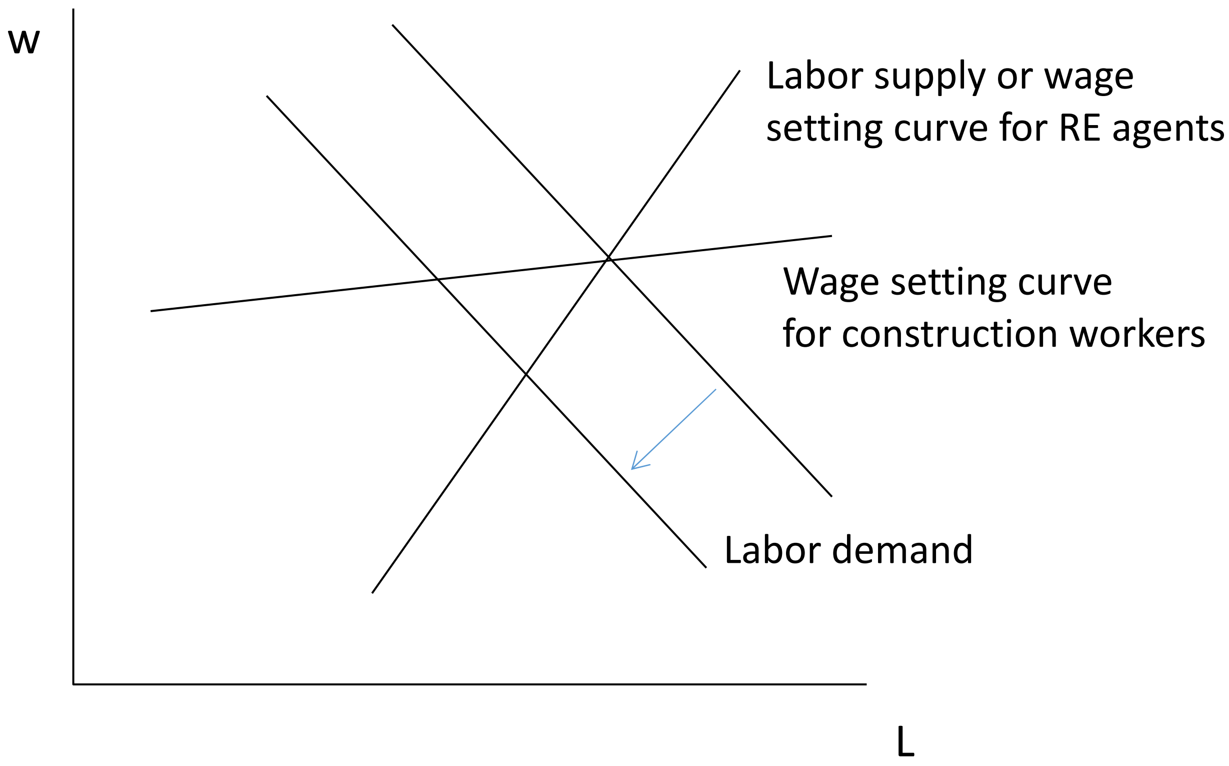

Table 1: Prevalence of Flexible Pay in Housing Related Occupations

Occupation	Source	Year	Occupation definition	Flexible pay definition	Value (Percent)
	(1)	(2)	(3)	(4)	(5)
Share of workers receiving flexible pay					
Real estate agents	CPS MORG	1991-2010	Census Code	Overtime, tips, commissions	51
Real estate agents	NAR	2013	Sales Agents & Brokers	Workers with flexible pay component	95
Architects	CPS MORG	1991-2010	Census Code	Overtime, tips, commissions	12
Construction workers	CPS MORG	1991-2010	Census Code	Overtime, tips, commissions	13
Share of flexible pay in income for workers receiving it					
Architects	AIA	2011	Architect excl. managerial roles	Overtime, bonus, and incentive compensation	5
Construction workers	Dietrich Surveys	2014	Construction coordinator and field engineer	Diff between base pay and all earnings (excl. overtime)	5
Construction workers	PAS	2014	Journeymen All trades	Fringe costs to firms (excl. overtime)	19

Sources: NAR: NAR (2014), Exhibit 3-1: sales agents with commissions or profit sharing; AIA: AIA (2011), Exhibit 1-5: architects and designers in all firms; Dietrich Surveys: Personal email correspondence with Wayne Dietrich on July 31, 2014; PAS: PAS (2014), p. 7, average fringe.
Notes: CPS percentages in the top panel refer to employed workers only; percentage from the NAR refers to sales agents.

Table 2: Job Tenure in Housing Related Occupations

Occupation	CPS Tenure Supplements	DWS
	(1)	(2)
Average tenure real estate agents (constant)	5.70	4.04
	(0.17)	(0.44)
Architects	1.28	0.51
	(0.38)	(1.05)
Construction workers	-0.15	-0.77
	(0.18)	(0.45)
No. of observations	13,361	2,346

Note: Coefficients from a regression of years of tenure with the current employer on a constant and dummies for architects and construction workers in a sample representing the three occupations. Samples from the CPS for 1996-2016 using the Tenure Supplements and the Displaced Worker Surveys. Regressions are weighted using the provided sampling weights.

Table 3: Wage and Employment Cyclicality of Real Estate Agents

	Dependent variable											
	ln hourly wage			ln employed individuals			ln average weeks			ln average weekly hours		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ln HPI (P)	0.144			0.674			-0.002			-0.032		
	(0.066)			(0.135)			(0.025)			(0.023)		
ln sales volume (S)	0.158			0.292			0.010			-0.004		
	(0.075)			(0.102)			(0.025)			(0.019)		
ln HPI x sales		0.153	0.121		0.425	0.426		0.006	0.007		-0.014	-0.011
		(0.060)	(0.070)		(0.089)	(0.097)		(0.022)	(0.026)		(0.017)	(0.024)
ln alternative wage			0.539			-0.009			-0.018			-0.052
			(0.494)			(0.708)			(0.178)			(0.225)
No. of observations	559	559	559	555	555	555	559	559	559	559	559	559
p-value for equality of *P* and *S*	0.038			0.000			0.861			0.360		

Notes: The regressions are based on state-year observations spanning the period from 2000 to 2010. All models include year and state fixed effects and are estimated using weighted least squares, with the number of working age individuals in a state as weights. The dependent variable is constructed by aggregating individual data from the ACS at the state-year level. Standard errors in parentheses are clustered at the state level.

Table 4: Wage and Employment Cyclicality of Different Housing Related Occupations

	ACS by occupation			QWI by industry		
	Realtor	Architect	Construction	Realtor	Architect	Construction
	(1)	(2)	(3)	(4)	(5)	(6)
Employment effect	0.425	0.188	0.288	0.386	0.293	0.497
	(0.089)	(0.137)	(0.066)	(0.082)	(0.065)	(0.094)
Weekly hours effect	-0.014	-0.073	0.030			
	(0.025)	(0.031)	(0.007)			
Wage effect	0.153	0.095	0.012	0.173	0.069	0.140
	(0.060)	(0.058)	(0.016)	(0.039)	(0.022)	(0.051)
Inverse wage setting	2.77	1.97	23.54	2.23	4.27	3.55
Elasticity	(1.04)	(1.54)	(28.88)	(0.73)	(0.90)	(1.34)
No. of observations (see note)	559	539	559	667	667	667

Note: Sample period is 2000-2010 for the ACS and 1991-2010 for the QWI. ACS groups are based on occupation, QWI groups based on industry. The employment regressions have 555, 515, 559 observations for realtors, architects and construction workers respectively due to empty cells. Cycle variable is total value of house transactions (price x volume). Average wage is the hourly wage for ACS, the monthly wage for QWI. Regressions are weighted with the number of working age individuals in a state as weight. Standard errors in parentheses are clustered at the state level.

Table 5: Wage and Employment Regressions with Leads and Lags in the ACS

	Realtor		Architect		Construction	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: ln employed individuals						
Lagged ln HPI x sales		0.399		0.093		0.346
		(0.140)		(0.242)		(0.075)
ln HPI x sales	0.425	0.158	0.188	0.277	0.288	-0.031
	(0.089)	(0.167)	(0.137)	(0.383)	(0.066)	(0.068)
Lead ln HPI x sales		-0.056		-0.226		0.076
		(0.149)		(0.261)		(0.079)
Sum of effects	0.425	0.501	0.188	0.144	0.288	0.392
	(0.089)	(0.131)	(0.137)	(0.178)	(0.066)	(0.083)
No. of observations	555	502	515	468	559	506
Dependent variable: ln hourly wage						
Lagged ln HPI x sales		0.009		0.177		0.045
		(0.073)		(0.123)		(0.024)
ln HPI x sales	0.153	0.110	0.095	-0.140	0.012	-0.013
	(0.060)	(0.093)	(0.058)	(0.176)	(0.016)	(0.045)
Lead ln HPI x sales		0.076		0.115		-0.016
		(0.075)		(0.138)		(0.033)
Sum of effects	0.153	0.195	0.095	0.152	0.012	0.017
	(0.060)	(0.085)	(0.058)	(0.082)	(0.016)	(0.018)
No. of observations	559	506	539	490	559	506
Inverse wage setting elasticity	2.77	2.56	1.97	0.95	23.54	23.41
	(1.04)	(1.12)	(1.54)	(1.17)	(28.88)	(23.25)

Note: Sample period is 2000-2010. Regressions are weighted with the number of working age individuals in a state as weights. Standard errors in parentheses are clustered at the state level.

Table 6: Regression of Earnings on Transition Status

	Realtor (1)	Architect (2)	Construction (3)
Dependent variable: ln hourly wage			
Entrant	0.028	-0.021	-0.065
	(0.018)	(0.026)	(0.005)
Leaver	-0.021	-0.089	-0.085
	(0.020)	(0.032)	(0.005)
No. of observations	13,081	3,891	83,837
Dependent variable: ln weekly earnings			
Entrant	-0.029	-0.040	-0.095
	(0.020)	(0.029)	(0.006)
Leaver	-0.078	-0.120	-0.113
	(0.022)	(0.035)	(0.006)
No. of observations	14,453	4,006	79,624

Note: Reported results are coefficients of weighted least squared regressions of outcome variable on a quartic in age, entry and exit dummies (stayers are the omitted category) using the CPS sample weights. Samples are based on longitudinal matches of CPS merged out-rotation groups. Data span 1980-2016. Wages are log hourly wages in 1983 dollars. Standard errors are clustered at the individual level.

Table 7: Transitions in and out of Employment

	Realtor	Architect	Construction
	(1)	(2)	(3)
$\Delta Employment_t/Employment_{t-1}$	1.342	0.527	0.779
	(0.582)	(0.414)	(0.301)
$Entry_t/Employment_{t-1}$	0.212	0.013	-0.052
	(0.091)	(0.102)	(0.122)
$Exit_t/Employment_{t-1}$	-0.267	-0.252	-0.584
	(0.092)	(0.138)	(0.104)

Note: Regressor is $\ln(HPI_t)$- $\ln(HPI_{t-1})$. Samples are based on longitudinal matches of CPS merged out-rotation groups. There are 37 annual observations from 1980-2016. Regressions are unweighted and standard errors are heteroskedasticity robust.

Table 8: Employment Impacts as a Fraction of Completely Rigid Wage Case

Own sector supply elasticity	Demand elasticity		Employment response	
	Own sector	Other sectors	One sector	Multiple sectors
(1)	(2)	(3)	(4)	(5)
2.5	0.5	0.5	0.83	0.67
4	0.5	0.5	0.89	0.78
23	0.5	0.5	0.98	0.96
2.5	0.5	1	0.83	0.50
4	0.5	1	0.89	0.67
23	0.5	1	0.98	0.94
2.5	0.5	1.9	0.83	0.20
4	0.5	1.9	0.89	0.47
23	0.5	1.9	0.98	0.90

Note: Employment responses based on a supply and demand model of the labor market with one or multiple sectors (see text for details).

Appendix 1: Data and Supplementary Results

ACS

The ACS sample consists of employed (EMPSTAT = 1) respondents age 22 to 65, working for wages (CLASSWKR = 2) as real estate agents (1990 OCC code 254), architects (43), and construction workers ([OCC codes 563 – 599 or 844 – 873] and IND code 23). In addition to this employment information, which pertains to the reference week, the ACS reports weeks worked, usual hours per week, and income from wages and salaries in the previous 12 months. I construct an hourly wage by dividing wage and salary income (INCWAGE) by the product of the midpoints of the brackets for weeks worked (WKSWORK2) and usual hours per week (UHRSWORK). Following Baum-Snow and Neal (2009), I winsorize the resulting hourly wage variable at the 99th percentile because usual hours are often underreported in the ACS, leading to inflated wages. Using variables that refer to the previous year assumes that individuals employed in the survey year were working in the same occupation and lived in the same state in the previous year.

I construct annual employment in year t by counting the number of employed workers in an occupation in each state and survey year t. I construct average hourly wages, weeks worked per year, and usual hours worked per week for year t from the respondents in survey year t+1. These calculations use the variable PERWT as weight.

In order to construct the outside wage I use a sample of employed respondents in all occupations including the self-employed. For each of the three housing related occupations j, I run a probit regression for working in that occupation on six education dummies (attended grade 12, high school diploma, some college, college degree, Masters degree, and PhD, dropping out below grade 12 as the omitted category, aggregated from the variable EDUCD), a race indicator (RACE=1), a squared term in age, and an interaction of sex and a dummy for married (MARST = 1 or 2). I calculate the weighted average wage of everybody not working in occupation *j* using the predicted probability of being in occupation *j* as weight.

QWI

The source data for the QWI is the Longitudinal Employer-Household Dynamics (LEHD) linked employer- employee microdata. The LEHD data is a massive longitudinal database covering over 95 percent of U.S. private sector jobs. The QWI data start at different points in time for different states mostly in the 1990s and early 2000s. This leads to an unbalanced panel but allows me to extend the time period for some states (see Table A1 for details on the coverage of the QWI data by state). The wage variable in the QWI is EARNS and reports average monthly earnings of employees with stable jobs (i.e., worked with the same firm throughout the quarter). The employment variable is EMP and estimates the total number of jobs on the first day of the reference quarter. I take the average of the values for the four quarter to construct an annual series.

Since the QWI only contains industry information, I use the NAICS industry codes 5312 for Offices of Real Estate Agents and Brokers, 5413 for Architectural, Engineering, and Related Services, and 2361 for Residential Building Construction. To facilitate the comparison of the ACS and QWI results I also construct a sample using industry classifications from the ACS. The industry classifications in the ACS are however coarser than in the QWI. I use industry codes 53 for real estate offices, 5413 for architectural services and 23 for the construction industry. Table A3 shows a comparison of the results from Table 4 with those obtained from the ACS based on industries rather than occupations.

CPS Data

Occupations in the CPS data are defined as follows: Realtors are pre-2003 occupation code 254, then 4920, architects pre-2003 code 43, then 1300, and construction workers pre-2003 occupation codes 563-599, 844-859 and 865-874 in industry 60, then occupation codes 6200-6260 in industry 770. All samples use workers ages 22 to 65. I use data from three different sources, the Tenure Supplements, the Displaced Worker Supplements, and the Outgoing Rotation Groups.

Tenure Supplements

The results in column (1) of Table 2 are based on the Job Tenure and Occupational Mobility Supplements to the CPS conducted in January or February of the even years from 1996 to 2016, obtained from IPUMS-CPS. The data yields 13,361 observations on realtors, architects, and construction workers. Occupation is identified in the main survey variable OCC for the current main job. Tenure in years is reported in the variable JTYEARS. The results in Table 2 use the weight JTWT.

Displaced Worker Supplements

The results in column (2) of Table 2 are based on the Displaced Worker Supplements to the CPS for the even years from 1996-2016 (run in conjunction with the Tenure Supplement above), obtained from IPUMS-CPS. The sample has 2,346 observations referring to respondents who lost their job due to a layoff within three years prior to the interview. Occupations and tenure refer to the job from which the displacement occurred. Occupations are based on variable DWOCC. Tenure in years is reported in the variable DWYEARS. The results in Table 2 use the weight DWWT. Note that the respondents in the DWS sample are the same respondents as in the Tenure Supplements but the DWS tenure refers to a different job.

Longitudinal Matched Data from the CPS Outgoing Rotation Groups

The longitudinal CPS samples are based on the Outgoing Rotation Groups from 1979 to 2016 from the NBER website. Individuals in interview months 4 and 8 were matched using the procedure from Madrian and Lefgren (1999) updated based on Rivera Drew et al. (2014) to improve matching accuracy. Matching is not possible between January to September 1985 and 1986, between July to December 1984 and 1985, between June to December 1994 and 1995, and between January to August 1995 and 1996 because of sample redesigns. Matches are dropped if the reported sex or race differs or if age is not consistent across interviews.

For the analysis in Tables 6 and 7 I construct employment in the three occupations as well as entry and exit to these occupations. Employment is defined ESR = 1 or 2 (before 1989), LFSR = 1 or 2 (from 1989 to 1993) and LFSR94 = 1 or 2 (from 1994); self-employment is defined as CLASS = 5 and 6 until 1994 and class94 = 6 and 7 thereafter. In Table 6 an individual is classified as Stayer if they work in the occupation in both interviews and are not self-employed, they are classified as Entrants if they work in the respective occupation and are not self-employed in the second interview but not the first, and as Leavers if they work in the respective occupation and are not self-employed in the first interview but not the second. Entrants and Leavers may be transitions to and from non-employment as well as to and from other occupations and self-employment. For the analysis in Table 7, Entry is entry into the occupation only from non-employment, and exit is exit from the occupation only to non-employment.

Weekly earnings in Table 6 are EARNWKE and hourly wages are calculated as EARNWKE/UHOURSE without adjustments for top-coding. The regressions in table 6 use the weight EARNWT. The employment counts for the time series used in Table 7 use the weight WGT. Annual wage series are deflated using the January values from the BLS price data series CUSR0000SA0.

Housing Data

Annual house prices for the US as a whole are retrieved from the Federal Housing Finance Agency (FHFA) for the years 1979-2015. The FHFA price index uses mortgage data from the Federal Home Loan Mortgage Corporation (Freddie Mac) and the Federal National Mortgage Association (Fannie Mae). Using an adapted version of the weighted-repeat sales method (Case and Shiller, 1989), the price index is estimated using repeated observations of housing values for individual single-family residential properties on which at least two mortgages were originated and subsequently purchased by either Freddie Mac or Fannie Mae. The series reports prices for all transactions at the quarterly level, not seasonally adjusted. To match the annual frequency of the outcome data, I take the average price for the four quarters.

Housing transactions are from the NAR series “Single-Family Existing-Home Sales,” which is based on closed home sales and captures about 30-40 percent of all home sales in the US. The data is collected from local realtor associations and multiple listing services. This data is not available after 2010. Data is missing in New Hampshire in 2004 and 2005. The data were obtained through personal communication with T. Doyle at NAR on Aug 4, 2014.

Table A1: Availability of QWI data by state

State	Start year	Start quarter	State	Start year	Start quarter
AK	2000	1	MT	1993	1
AL	2001	1	NC	1992	4
AR	2002	3	ND	1998	1
AZ	2004	1	NE	1999	1
CA	1991	3	NH	2003	1
CO	1993	2	NJ	1996	1
CT	1996	1	NM	1995	3
DC	2005	2	NV	1998	1
DE	1998	3	NY	2000	1
FL	1997	4	OH	2000	1
GA	1998	1	OK	2000	1
HI	1995	4	OR	1991	1
IA	1998	4	PA	1997	1
ID	1991	1	RI	1995	1
IL	1993	2	SC	1998	1
IN	1998	1	SD	1998	1
KS	1993	1	TN	1998	1
KY	2001	1	TX	1995	1
LA	1995	1	UT	1999	3
MA	NA		VA	1998	3
MD	1990	1	VT	2000	1
ME	1996	2	WA	1990	1
MI	2000	3	WI	1990	1
MN	1994	3	WV	1997	1
MO	1995	1	WY	2001	1
MS	2003	3			

Table A2: Value of Housing Construction Permits and House Sales

	Ln(*value of construction permits*)			
	(1)	(2)	(3)	(4)
Lagged ln HPI (P)			-0.187	
			(0.317)	
Lagged ln Sales (S)			-0.0190	
			(0.108)	
Ln HPI (P)	1.332		0.405	
	(0.086)		(0.535)	
Ln Sales (S)	0.517		0.143	
	(0.068)		(0.127)	
Lead ln HPI (P)			1.226	
			(0.308)	
Lead ln Sales (S)			0.166	
			(0.0988)	
Lagged ln HPI x Sales				0.351
				(0.101)
Ln HPI x Sales		0.786		0.324
		(0.065)		(0.137)
Lead ln HPI x Sales				0.302
				(0.102)
Within R^2	0.31	0.21	0.38	0.24
No. of observations	559	559	455	455

Note: Coefficients are from an OLS regression of ln(construction permit value) on ln(house price values) for the years 2000-2010. All variables are residuals of a regression on state and year fixed effects and thus purged of year and state fixed effects.

Table A3: Wage and Employment Cyclicality of Different Housing Related Occupations

	ACS by occupation			ACS by industry			QWI by industry		
	Realtor	Architect	Construction	Realtor	Architect	Construction	Realtor	Architect	Construction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
employment effect	0.425	0.188	0.288	0.030	0.211	0.275	0.386	0.293	0.497
	(0.089)	(0.137)	(0.066)	(0.045)	(0.049)	(0.029)	(0.082)	(0.065)	(0.094)
weekly hours effect	-0.014	-0.073	0.030	-0.000	0.004	0.029			
	(0.025)	(0.031)	(0.007)	(0.015)	(0.009)	(0.005)			
wage effect	0.153	0.095	0.012	0.111	0.059	0.020	0.173	0.069	0.140
	(0.060)	(0.058)	(0.016)	(0.025)	(0.023)	(0.012)	(0.039)	(0.022)	(0.051)
inverse wage setting elasticity	2.77	1.97	23.54	0.27	3.57	14.02	2.23	4.27	3.55
	(1.04)	(1.54)	(28.88)	(0.34)	(1.56)	(9.08)	(0.73)	(0.90)	(1.34)
No. of observations	559	539	559	559	559	559	667	667	667

Note: Sample is as Table 4. Cycle variable is total value of house transactions (price x volume). Average wage is the hourly wage for ACS, the monthly wage for QWI. Regressions are weighted with the number of individuals in a state as weights. Columns 4-9 use averages over industries rather than occupations as outcome variable. QWI industry NAICS codes are respectively realtors 5312, architects 5413, and construction 2361. ACS industries are realtors 531, architects 5413, and construction 23. Standard errors in parentheses are clustered at the state level.

Appendix 2: Model

Consider a competitive model of the labor market for a particular type of worker, who can work in either one of sectors 0 or 1. Sector 0 is the occupation of interest, say real estate agent; sector 1 stands for other occupations the worker could work in, say insurance sales person. Labor demand is

$$L_0 = D_0(w) + A$$
$$L_1 = D_1(w)$$

where A is a shock to labor demand in the sector of interest. The empirical exercise in the paper, isolating the response to shocks to the housing sector, corresponds to comparative statics with respect to A. Workers move freely between sectors, so there is a single wage which clears both markets. Supply to the labor market by the type of worker who we observe in sector 0 is

$$L_0 + L_1 = S(w).$$

Labor market equilibrium is given by

$$S(w) = D_0(w) + D_1(w) + A.$$

Totally differentiating the equilibrium condition yields

$$\frac{dw}{dA} = \frac{1}{S' - D_0' - D_1'} \tag{1}$$

$$\frac{dw}{dA}\frac{L}{w} = \frac{1}{\theta + \eta_0 + \eta_1}$$

where θ is the elasticity of labor supply to the market and η_i is minus the demand elasticity in sector i. The employment response in sector 0 can be obtained by differentiating the sector's demand function

$$dL_0 = D_0' dw + dA$$

and combining this with eq. (1) yields

$$\frac{dL_0}{dA} = \frac{\theta + \eta_1}{\theta + \eta_0 + \eta_1}. \tag{2}$$

We are interested in the total employment response to a labor demand shock, which is given by

$$d\left(L_0 + L_1\right) = \left(D_0' - D_1'\right) dw + dA = \frac{\theta}{\theta + \eta_0 + \eta_1} dA. \tag{3}$$

Comparison of eqs. (2) and (3) shows that the total response is smaller; some workers who lose their jobs in sector 0 find alternative employment in sector 1.

The supply elasticities estimated in the paper are the elasticities of labor supply to sector 0. The comparative statics with respect to A represent a labor demand shock to sector 0 and therefore move us along the sector specific supply curve. Hence, the sector's supply elasticity is

$$\theta_0 = \frac{dL_0}{dw}\frac{w}{L} = \frac{dL_0}{dA}\frac{dA}{dw}\frac{w}{L},$$

which can be obtained by combining the results in eqs. (1) and (2):

$$\theta_0 = \frac{\theta + \eta_1}{\theta + \eta_0 + \eta_1}\left(\theta + \eta_0 + \eta_1\right) = \theta + \eta_1. \tag{4}$$

This allows us to state the total employment response in eq. (3) in terms of θ_0:

$$\frac{d\left(L_0 + L_1\right)}{dA} = \frac{\theta_0 - \eta_1}{\theta_0 + \eta_0}. \tag{5}$$