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Lisa B. Kahn
Erika McEntarfer

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of Labor

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Lisa B. Kahn
Yale University,
NBER and IZA

Erika McEntarfer
U.S. Census Bureau

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

Employment Cyclicality and Firm Quality*

Who fares worse in an economic downturn, low- or high-paying firms? Different answers to this question imply very different consequences for the costs of recessions. Using U.S. employer-employee data, we find that employment growth at low-paying firms is less cyclically sensitive. High-paying firms grow more quickly in booms and shrink more quickly in busts. We show that while during recessions separations fall in both high-paying and low-paying firms, the decline is stronger among low-paying firms. This is particularly true for separations that are likely voluntary. Our findings thus suggest that downturns hinder upward progression of workers toward higher paying firms – the job ladder partially collapses. Workers at the lowest paying firms are 20% less likely to advance in firm quality (as measured by average pay in a firm) in a bust compared to a boom. Furthermore, workers that join firms in busts compared to booms will on average advance only half as far up the job ladder within the first year, due to both an increased likelihood of matching to a lower paying firm and a reduced probability of moving up once matched. Thus our findings can account for some of the lasting negative impacts on workers forced to search for a job in a downturn, such as displaced workers and recent college graduates.

JEL Classification: E24, E32, J23, J3, J63

Keywords: recessions, wages, firm quality

Corresponding author:

Lisa Kahn
Yale School of Management
165 Whitney Ave
PO Box 208200
New Haven, CT 06511
USA
E-mail: lisa.kahn@yale.edu

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1 Introduction

Worker sorting across firms has long been thought to play a central role in labor market efficiency. Despite frictions that can inhibit this sorting process, such as search costs or imperfect learning, workers are thought to gradually move towards jobs of better overall- or match-specific quality.[1] At the same time, recessions may impede worker sorting. Several papers have noted that worker churn and job-to-job mobility declined during recent recessions and that this decline was particularly severe during the Great Recession.[2] This suggests that a worker's ability to move on from poor job matches or bad jobs is curtailed in times of high unemployment. A natural question, then, is in what types of jobs are workers – at least temporarily – saddled? If the business cycle has differential impacts on jobs or firms of varying quality, the consequences of reduced mobility could be very different. In this paper, we ask who fares worse in an economic downturn, low- or high-paying firms?

The classic Schumpeter (1939) cleansing effect posits that in recessions resources are reallocated to more productive firms, since, after a negative productivity shock, the least productive endeavors are no longer worthwhile.[3] Because productivity and pay are typically positively correlated (see for example Serafinelli 2012), cleansing predicts that in recessions workers flow to high-paying firms. However, there are also reasons to expect employment to contract by relatively more among high-paying firms during recessions. For example, the notion of a job ladder suggests that workers tend to flow from bad jobs to good, i.e., from low- to high-paying jobs (Burdett and Mortensen 1998). If during recessions higher paying firms choose not to expand, then lower paying firms might find it easier to hold on to productive employees and might thus shrink by relatively less than high-paying firms.[4] It is also possible that high-paying firms produce goods for whom demand is more sensitive to the business cycle, maybe because they tend to produce goods that are more highly priced.[5] Empirically, it is therefore an open question whether the job ladder effect or differential product market cyclicality will outweigh any Schumpeterian cleansing. If so, then during recessions, employment in low-paying firms would decline less rapidly than that in high

[1] This idea goes at least as far back as the canonical work of Jovanovic (1979); for empirical work on job mobility see Farber's 1999 survey.

[2] See in particular Lazear and Spletzer (2012), Hyatt and McEntarfer (2012a).

[3] Many theoretical papers seek to explain this phenomenon by exploiting a friction that inhibits resources from being allocated optimally. Recessions can produce large enough shocks to overcome any frictions inhibiting optimal reallocation. See for example Hall (1991), Mortensen and Pissarides (1994), Caballero and Hammour (1994, 1996) and Gomes, Greenwood and Rebelo (2001).

[4] Moscarini and Postel-Vinay (2013) write down a dynamic Burdett and Mortensen-style search model with a job ladder with exactly this implication, that in a downturn firms at the bottom of the job ladder fare relatively better since their workers are less likely to be poached away by firms at higher rungs.

[5] For example, Bils and Klenow (1998) show that consumer demand for luxury goods is more cyclically sensitive than for other products such as non-durables. The cyclical upgrading literature (Okun 1973, Bils and McLaughlin 2001) shows that jobs in high-paying industries (such as durable goods manufacturing) are more sensitive to the business cycle than jobs in low-paying industries (such as non-durable goods manufacturing), likely because products in these industries have more cyclically sensitive demand. This implies that opportunities to move into these jobs become relatively less prevalent in contractions.

paying firms.

In this paper we investigate the employment effects of the business cycle across high- and low-paying firms. We use data from the Longitudinal Employer Household Dynamics (LEHD) program, a U.S. employer-employee matched database, from 1998 to 2011. We first show that employment growth at low-paying firms is *less* sensitive to the business cycle, as measured by the state unemployment rate, than that at higher paying firms. This is important because it implies that the quality of jobs erodes in a downturn. We next provide evidence that the growth rate effect is likely driven by a partial collapse of movement up the job ladder in a bust, as opposed to differences in product market cyclicality and other possible factors. This implies that low-paying firms fare relatively better in a downturn because workers who would like to move on to better opportunities get stuck there. We estimate that movement up the job ladder is 20% slower for those working at the lowest-paying firms in a large bust, compared to a boom. We also estimate that the distribution of new job matches shifts towards these lower-paying firms in a downturn. The combination of a worse initial match and a reduced likelihood of upgrading implies that new job matchers are particularly scarred by recessions. We estimate that firm quality a year after matching, as measured by average firm pay, is 2.6% lower for those matching in a large recession compared to a boom. Thus the dynamics presented in this paper have important implications for the literature on the long-lasting effects of recessions on workers, which tends to find that those forced to search for jobs in a downturn, e.g., recent college graduates and displaced workers, are particularly damaged.

The growth rate result is surprising, since it is inconsistent with Schumpeterian cleansing. However it does line up with a small, recent body of work examining employment growth rates over the business cycle as a function of firm size. Moscarini and Postel-Vinay (2012) show in a number of countries including the U.S. that differential growth rates of small-, compared to large-, firms are positively related to the unemployment rate. Fort, Haltiwanger, Jarmin and Miranda (2013) analyze firm growth over the business cycle as a function of firm age and size, using U.S. data. They find that small, young, firms typically fare relatively better in cyclical contractions, although this relationship reversed in the 2007-09 recession. This recent literature thus supports the notion that low-quality firms (small or low-paying) are somewhat sheltered by the business cycle, but has so far been unable to empirically pinpoint the underlying mechanisms.[6] We devote the bulk of this paper to disentangling mechanisms and quantifying the impacts on workers.

Net growth in a given quarter equals hires minus separations in that quarter. It is well known that both hiring and separations decline during periods of high unemployment, and

[6] The recent work on firm size is at odds with an older literature, interested in establishing whether small firms face credit constraints and whether these are exacerbated in recessions. The literature had been inconclusive on this question but tended to find empirical support for a greater sensitivity to credit constraints among small firms. See for example Gertler and Gilchrist (1994), Chari, Christiano and Kehoe (2007), and Sharpe (2004).

we show that this holds across all firms. However, we find that separations decline by more in lower paying firms than higher paying firms. This relatively larger decline in separations among low-paying firms accounts for the relatively higher growth rates in employment among low-, compared to high-, paying firms in economic downturns. In addition, we find that the relative difference in separations between low- and high-paying firm is driven by job-to-job transitions rather than by separations that are followed by at least a full quarter of non-employment. We believe that separations directly to another employer are more likely to represent voluntary moves. Thus, we interpret our result as evidence that low-paying firms grow relative to high-paying firms in recessions predominantly because they experience a greater decline in voluntary quits.[7] It is then likely that a reduction in moves up the job ladder during downturns drives our result.

We do find, in addition, that differential impacts on moves to non-employment play a small role: higher-paying firms experience small increases in separations to non-employment in downturns, while low-paying firms do not. A separation to at least a full quarter of non-employment is unlikely to be a voluntary move on the part of a worker and more likely signifies a layoff. Therefore high-paying firms shrink in downturns predominantly because they do not experience as large a decline in voluntary exits (as mentioned above) but also because they have a small increase in layoffs. High-paying firms could face a greater need to lay off workers because demand for their products is more cyclically sensitive or because they had an easier time hiring workers during the preceding boom (being at the top of the job ladder) and now have become too large for production in a downturn. We test for the former by measuring whether revenues are differentially cyclical across high- and low-paying firms and do not find evidence of such an effect, though our test is imperfect since we can only obtain revenue data for publicly traded firms. We also find no evidence that high-paying firms suffer more from downward earnings rigidities (and therefore would have to layoff workers in tough times rather than cutting pay).

We view this body of results as being most consistent with a job ladder model where workers tend to use jobs at low-paying firms as stepping stones to better opportunities elsewhere. In an economic downturn those opportunities do not present themselves and workers are forced to stay put. Firms higher up on the job ladder will naturally experience this impact of a downturn less, because workers are more likely to see those jobs as final destinations, regardless of economic conditions. In particular, the Moscarini and Postel-Vinay (2013) poaching model predicts this set of findings. In their model, firms at the top of the job ladder poach workers away from firms at lower rungs, enabling them to grow in a boom. In a bust, they stop poaching because they do not need to produce at the same scale (and may indeed need to trim the fat off their existing workforce), enabling firms at

[7] Hyatt et al. (2014) find a high correlation between separations to non-employment in the LEHD data and layoffs in the Job Openings and Labor Turnover Survey (JOLTS), and an even higher correlation (just under 1) between separations to employment in the LEHD and quits in the JOLTS.

lower rungs to retain their workers. This results in more cyclically sensitive employment at high-paying firms, while low-paying firms fare relatively better in a bust.[8]

Our results are very much in the spirit of Barlevy (2002) who shows that the decline in job-to-job transitions seen in recessions has a quantitatively important negative effect on match quality, terming this the "sullying effect" of recessions.[9] We find that workers at low-paying firms suffer more from this decline in voluntary mobility, implying a further sullying effect of recessions: workers get stuck in worse overall quality (lower paying) jobs. Our estimates imply that in a large recession, average earnings decline by 0.1% ($4/month) due solely to the shifting composition of workers across firms. We also estimate that workers in the lowest paying firms are 20% less likely to upgrade to a better firm in a large recession, compared to a boom.

Finally, our results have important implications for the long-lasting consequences of recessions on workers. A growing body of evidence suggests that recessions have vastly different impacts on workers in the long run, depending on what stage of their career the recession hits them in. First, labor market conditions at the beginning of a worker's career have long-lasting scarring effects (Kahn 2010, Oreopoulos, von Wachter and Heisz 2012, Altonji, Kahn, and Speer 2014). Second, the consequences of job displacement have been shown to be much larger when displacement occurs in a recession (Davis and von Wachter 2011). It therefore seems that being forced to search and match during an economic downturn can be incredibly damaging to a worker's career. We conclude the paper with some evidence on this dimension. We show that workers matching in a large recession are both more likely to match to a low-paying firm, and, one year later, less likely to have upgraded to a better firm. Therefore, a year after matching, a worker is in a firm that pays 2.6% less, on average, when matching in a bust compared to a boom.

The remainder of the paper proceeds as follows. Section 2 describes the data, while section 3 details our methodology. Section 4 presents our core regression results on net and gross worker flows. Section 5 provides a discussion of the results, and tests for the underlying mechanisms. Section 6 shows how firm upgrading and the careers of new matchers are impacted by the mechanisms uncovered in the previous sections. Section 7 concludes.

2 Data

We analyze employment changes within firms and over the business cycle using data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program. The

[8]In a recent paper, Haltiwanger, Hyatt and McEntarfer (2014) use the LEHD to measure the cyclicality of poaching across large and small firms. Counterintuitively, they do not find evidence that large firms poach from small firms, on net. However, motivated by our findings in this paper, they provide additional results categorizing firms by pay (as we do), rather than by size. Here they do find strongly pro-cyclical net employment reallocation of workers from low- to high-paying firms, consistent with our results.

[9]See also Bowlus (1993) and Davis, Haltiwanger, and Schuh (1996) for empirical evidence on the decline in match quality in recessions.

LEHD program maintains a variety of survey and administrative data from several state and federal agencies. For this paper, we chiefly use state unemployment insurance (UI) wage records and the Quarterly Census of Employment and Wages (QCEW) data. Both UI and QCEW data are available for states in partnership with the LEHD program, currently all 50 states and the District of Columbia. A thorough discussion of the LEHD data is provided in Abowd et al. (2006); a brief description follows.

State-level unemployment insurance (UI) data contain quarterly earnings for employees covered by state unemployment insurance systems, over 96% of private sector employment. A firm, as defined in this analysis, is a collection of workers who share a common unemployment insurance system identifier (SEIN). Individual wage records can be linked across quarters to create individual work histories, worker flows, and earnings dynamics. The firm identifier on the UI records is used to link to information on the firm available in the QCEW data (we principally use employment size and industry measured with the North American Industry Classification System, hereafter NAICS). Worker demographics, namely sex and date of birth, are available from links to the Census administrative and survey data. For this paper we restrict attention to the 34 states that have UI and QCEW data for every quarter of our sample period 1998:Q1-2011:Q4. This sample period was chosen to maximize the number of states for which a balanced panel of data exists over a reasonably long time period.

These data are advantageous in that they allow us to observe both gross and net worker flows for a substantial fraction of firms in the U.S. labor market. Furthermore, we can create a rich set of firm characteristics to measure employer quality. Finally, the time period over which we can exploit a balanced panel consisting of a large number of states allows us to capture both the 2001 and 2007-09 recessions. We take advantage of prototype data on job-to-job flows developed from the LEHD by Hyatt and McEntarfer (2012b).[10]

Our exercise in this paper is to analyze how firms of different qualities are impacted by the business cycle. Our measure of quality is based on average pay in the firm. Since one goal of this paper is to better understand the experiences of workers in recessions, we would ultimately like our quality measure to correlate with properties of a desirable job. Obviously pay is an important dimension of worker satisfaction. Furthermore, firms that can pay higher wages are likely more productive. Serafinelli (2012), for example, presents evidence using detailed administrative data in Italy that high paying firms are indeed more productive. We construct time-invariant pay measures by taking average wage within an establishment over our entire sample period (1998-2011). This avoids the well-known reclassification bias

[10] These data link primary jobs across quarters, using the timing of hires and separations to infer which worker moves are job-to-job moves (with little-to-no time in non-employment) versus moves to and from longer spells of unemployment. The sample is restricted to primary jobs only, to clean out noise in the job-to-job flows data. However, our results on net employment growth and gross hires and separations are fully robust to including all jobs. These data are also used in Hyatt and McEntarfer (2012a), who document aggregate patterns in worker flows over the last 15 years and compare changes in earnings for different types of moves, and Haltiwanger, Hyatt, and McEntarfer (2014), who measure the extent of poaching behavior by large firms away from small firms.

problem (for example, that a firm is reclassified into a higher pay bin as the economy grows; see Moscarini Postel-Vinay (2012)), though our results are robust to other measures.[11]

Figure 1 shows an employment-weighted kernel density of firm-level average monthly earnings (for employees who work an entire quarter, in 2008 dollars). This distribution has a long right tail and to avoid potential data disclosure issues, we cap earnings at $12,000. As can be seen, we have substantial variation across firms over this time period. In our subsequent analysis we divide firms into employment-weighted quintiles, based on this measure. We use state-industry-specific cut points (measured at the two-digit NAICS level). Our categories thus define firms as high- or low-paying relative to other firms in the same state and industry. Workers in the lowest paying quintile earn on average $1,842/month, while workers in the highest paying quintile earn on average $6,665/month (see table 2 discussed below).

We subsequently analyze the impact of the unemployment rate on growth rates as a function of firm quality, measured by the pay quintiles. We have a number of reasons for making these pay quintiles state-industry specific. First, our definitions are not sensitive to different costs-of-living across states. Second, firms may have different average labor bills for reasons unrelated to the quality of the job. For example, a greater reliance on part-time workers would lower the overall labor bill (we cannot measure hours); a greater reliance on sub-contractors for particular roles would shift the pay distribution within a firm (we cannot measure occupation); a different mix of base pay, benefits, bonuses, tips, could also alter the level and distribution of pay within a firm. Making our cutpoints industry-specific should at least help hold constant these factors. However, we cannot distinguish whether our measure identifies high-paying firms, or firms that tend to employ highly-paid workers. We therefore interpret our results as being applicable to either margin. Finally, we identify the impact of the business cycle using local labor market conditions, as measured by the state unemployment rate. This measure is likely less relevant for traded sectors and will vary across states with different natural rates of unemployment. The fact that our cutpoints our comparisons across firms are within state and industry helps here as well.

The key dependent variables in this paper are net employment growth rates as well as gross flow rates. To calculate these rates, we aggregate our firm-level data to the state-year-quarter-industry-wage quintile category, by summing employment and worker flows in each cell.[12] This level of aggregation allows us to control for industry, while still enabling us to capture employment dynamics driven from firm births and deaths.[13]

[11]In particular, we have experimented with using a two-quarter moving average as in Fort et al. (2013). Our results are also robust to categorizing based on average pay at the establishment, rather than firm (the LEHD imputes workers in a close geographic region to the same establishment within an SEIN).

[12]We aggregate to the three-digit NAICS industry level here so that we can both control for two-digit industry fixed effects, and experiment with other controls at a more disaggregated level.

[13]While in principle, we could conduct our analysis at the individual firm level, that would produce growth, hire and separations rates that are quite a bit noisier. These rates are misleadingly large in the period in which a firm starts or closes and outliers can be generated by seasonal employers or non-reporting events (or

Specifically, the quarterly growth rate in a given quarter, t, for a firm pay type, q, is defined in equation 1, where B is beginning of quarter employment, E, is end of quarter employment, in a firm, f. The growth rate is the net employment change among all firms, f, of type q (firms are indexed 1 to F_q) divided by average employment over the quarter, t, among these firms.[14]

$$\text{growth rate}_{tq} = \frac{\sum_{f=1}^{F_q}(E_{tf} - B_{tf})}{.5 * \sum_{f=1}^{F_q}(E_{tf} + B_{tf})} \tag{1}$$

Hire and separation rates are defined in equations 2 and 3, respectively, as the total number of hires (A) or separations (S) in quarter, t, at firms of quality, q, divided by average employment over the quarter. Our results are robust to an alternative denominator, total employment over the quarter, which is sometimes used in the literature. However, our definitions are convenient because the common denominator across the three rates means that the hire rate minus the separation rate must add up to the growth rate (see Lazear and Spletzer 2012).

$$\text{hire rate}_{tq} = \frac{\sum_{f=1}^{F_q} A_{tf}}{.5 * \sum_{f=1}^{F_q}(E_{tf} + B_{tf})} \tag{2}$$

$$\text{separation rate}_{tq} = \frac{\sum_{f=1}^{F_q} S_{tf}}{.5 * \sum_{f=1}^{F_q}(E_{tf} + B_{tf})} \tag{3}$$

We further decompose both separations and hires into those directly to/from employment and those to/from non-employment. A separation is categorized as a move directly to another employer if the worker has pay from another employer in the same quarter as the separation or the quarter immediately following. Because our data only come at a quarterly frequency, a worker must have at least a full quarter without earnings to be categorized as a mover to non-employment. See Hyatt and McEntarfer (2012b) for more detail. Information on gross

in principle mergers and acquisitions, though the LEHD use an algorithm to exclude these events). At the individual firm level, these outliers create problems for our estimation, so we prefer the slightly aggregated analysis presented here. This aggregation is particularly important given an LEHD data limitation: that it is difficult to link firms consistently over time due to periodically changing SEIN's.

[14]Note this formula implies that the growth rate is well defined for firm births and firm deaths (or, more precisely, cells made up entirely of firm births or cells made up entirely of firm deaths) and equals 2 or -2, respectively.

hires and separations, as well as decompositions across source or destination of the worker are not available in most data sets, even those containing measures of net employment growth, and herein lies much of our contribution.

Table 1 presents employment-weighted summary statistics by firm category for our rates of interest. Again, the unit of observation is a date-industry-state-pay quintile cell. Growth rates are fairly similar across pay quintiles, ranging from 0.0014 to 0.003.[15] Hire and separation rates are highly correlated within firm category, reflecting the fact that most hiring serves to replace workers who have separated, but rates vary widely across firm category. For example, gross hire and separation rates in the lowest pay quintile are, on average, over double the rates in the highest pay quintile. Across our whole sample period and for all types of firms, separation rates are roughly evenly split between separations to employment and non-employment. Hires are also roughly evenly split across those from employment and those from non-employment, except that at lower paying firms workers are relatively more likely to be hired from non-employment, while the opposite is true at higher paying firms. Jobs at higher paying firms could be more difficult to obtain, consistent with a job ladder, so such firms tend to hire from a higher quality pool of workers, the employed.

Equation 4 defines the excess churn rate in a given time period, t, as hires and separations in excess of the net employment change in the period $(E-B)$, divided by average employment in the period. A firm with a high-churn rate has a high number of worker flows in excess of job flows. We take this definition, which is now standard in the literature, from Burgess, Lane, & Stevens (2000). Campbell et al. (2005) show that high churn is associated with lower productivity and lower survival rates for a select set of industries.

$$churn_{tf} = \frac{A_{tf} + S_{tf} - |E_{tf} - B_{tf}|}{.5 * (E_{tf} + B_{tf})} \tag{4}$$

We place firms into quintiles based on the average excess churn rate over the entire sample period, and report this distribution for each pay quintile. From column 1 of table 1, about a third of firms in the lowest pay quintile are in the highest churn quintile, while only a tenth are in the lowest churn quartile. These ratios are almost exactly reversed in column 5, the highest pay quintile. This illustrates the strong negative correlation between pay and churn. In some specifications we will control for the churn distribution within pay quintiles.

Table 1 also shows the firm size distribution in each pay quintile. Firm size is defined as the number of employees in the SEIN on the 12th day of the first month of the quarter,

[15] Based on our categorization, high-paying firms have double the growth rate of the other quintiles. One might have expected lower paying firms to grow more quickly because of positive correlations between pay, size, and age. Haltiwanger, Jarmin and Miranda (2013) show that small firms grow faster than large firms, but this is driven by the fact that small firms are also younger.) By generating quintile cutpoints that are state-industry-specific, we make firms across categories much more similar to each other. For example, while a third of low paying firms (based on our categorization) are small, another third are very large. Overall the lowest paying firms (unconditional on state and industry) are much more likely to be small and are also the fastest growing.

averaged over the life of the SEIN.[16] Larger firms have been shown to have higher pay, better working conditions, a greater degree of benefits provision, increased productivity, and increased probability of firm survival (Brown and Medoff 1989, Hurst and Pugsley 2011). In our data, the lowest paying firms are predominantly found in either the smallest (less than 20) or largest (500+) size categories. The majority of higher paying firms are in firms with at least 500 employees. Again, in some specifications, we will control for the firm size distribution underlying the pay quintile.

3 Methodology

In order to understand the differential impact of the unemployment rate on growth, hire, and separation rates across firm pay quintiles, we estimate regressions of the form specified in equation 5.

$$(5)\ \ rate_{sItq} = \alpha_0 + \alpha_1 st\_unemp_{st} + W_q\alpha_2 + [st\_unemp_{st} * W_q]\alpha_3 + f(t) + I^{industry} + I^{state} + \varepsilon_{sItq}$$

We regress $rate_{sItq}$, a growth, separation, or hire rate among firms of quality, q, in state, s, in industry (three-digit NAICS), I, in time period, t, on the state unemployment rate (st_unemp_{st}), a vector of firm quality indicators (W_q) corresponding to pay quintiles, and their interactions. We weight by average employment over the quarter. The coefficient, α_1, yields the impact of a 1 percentage point (ppt) increase in the state unemployment rate on $rate_{sItq}$ for the omitted firm quality category, the lowest pay bucket. The vector of interaction terms, α_3, indicates whether the impact of st_unemp is different for higher pay buckets. The main effects of firm quality (W_q) and the industry fixed effects ($I^{industry}$, at the two-digit NAICS level) control for level differences in $rate_{sItq}$ across different types of firms or industries (for example, some industries may on average be shrinking and others growing).

It is important for st_unemp to isolate random shocks to a local labor market, rather than general differences across locations or broad time periods, because we are interested in understand how firms are impacted by business cycle shocks. We therefore additionally control for state fixed effects, and include flexible controls for time period, $f(t)$, in two forms. First we control for quarter fixed effects and a linear time trend. These allow us to control for seasonality and secular changes over this time period (for example, the marked decline in churn during the 2000s), while still exploiting time-series variation in economic conditions at both the national and state levels. However, since we only have a short time

[16] Both Fort et al. (2013) and Moscarini Postel-Vinay (2012) use firm size data from the BDS, which contains information on both establishment-level employment and national employment. Our measure of firm size is correlated with the national size of the firm (0.75) but is not an exact match, more closely approximating the size of the firm in the state, the same level at which we are classifying firms into pay quintiles.

period we would like to ensure that our results are not driven by spurious correlations due to anomalies that coincided with business cycle movements. Therefore, in an alternative specification, we control for date fixed effects, absorbing all variation in the national time series and identifying purely off of cross-sectional variation in economic conditions.

Our key identifying assumption is that st_unemp and its interactions with W_q are exogenous in equation 5. A problem for us would be if a $sItq$-cell were so large that the growth rate of firms in that cell had a mechanical link to the state unemployment rate. However, we do not find such reverse causality plausible, given that our level of observation is fairly disaggregated, at the three-digit NAICS level. Another problem would be if labor market shocks were mis-measured by the state unemployment rate, and especially if this was differential across firm type. For example, for firms producing non-traded goods, the local unemployment rate is likely highly correlated with whether the firm experiences a shock, while for firms producing traded goods, the local unemployment rate may be less indicative. First, we point out that in some specifications we exploit both local and national variation in economic conditions, and these will be most relevant for firms producing traded goods. Second, this kind of measurement error in economic conditions will bias α_3 downward in magnitude, especially for pay buckets with a higher share of firms producing traded goods. It is well known in the trade literature that exporting firms are higher paying.[17] Thus this should be a larger problem for higher pay buckets, biasing us against our finding that growth rates at higher paying firms are more sensitive to the business cycle.

We experiment for controls for the average distribution of size and churn within a pay bucket. Given both variables are highly correlated with firm pay, it is useful to know whether either pay or churn are the underlying drivers of the dynamics reported in the paper, or whether these dynamics exist within size and churn. We can understand this to the extent that there is variation within pay bucket in these variables.

Finally, we cluster our standard errors by state. Our key explanatory variable, the state-specific unemployment rate, varies at the state-level and over time, but is likely serially correlated within state. We have also clustered at the state-date-firm quality level and obtained very similar results in terms of statistical significance.

[17]See Bernard, Jensen, Redding, and Schott (2007) for a survey. They cite a wealth of evidence documenting that exporters tend to be larger, more productive, more skill- and capital-intensive, and higher paying, relative to non-exporters.

4 Regression Results on Growth, Hire, and Separation Rates

4.1 Growth Rate

To gain a general sense of the time series relationships among economic conditions and growth across firm quality, we first look at the differential growth rate across our lowest and highest quintiles. We simply subtract the rate in the highest pay bucket from that in the lowest. Moscarini and Postel-Vinay (2012) do a similar exercise comparing growth rates at large and small firms. This differential growth rate is plotted in figure 2 along with the national unemployment rate (dashed line). Both lines have been detrended using a Hodrick-Prescott filter, and seasonally adjusted by residualizing on quarter dummies (therefore the levels are not that meaningful).[18]

Though noisy, the differential growth rate very closely tracks the national unemployment rate. That is, when unemployment is high, low-paying firms grow relative to high-paying firms, while when unemployment is low, low-paying firms shrink relative to high-paying firms. Note these effects are symmetric across booms and busts.

The time series evidence presented in figure 2 is suggestive, however with such a short panel of data, we cannot perform any sort of reliable statistical inference based solely on this time series. We now turn to a regression framework where we exploit cross-sectional variation in unemployment rates across our 34 states and 56 quarters. Results are reported in table 2. The dependent variable is the growth rate (net change in employment divided by average employment over the quarter) in the state-date-industry-wage quintile. We focus first on panel A, which reports the point estimates and standard errors from equation 5. The specifications in columns I and II control for time period with quarter fixed effects and a time trend, while columns III and IV instead control for date fixed effects. Columns II and IV augment the preceding specification with controls for churn and size distributions. Results are extremely similar across all four specifications. We tend to focus on column IV, since the date fixed effects absorb any coincidental trends that are correlated with the unemployment rate, and the churn and size controls to some extent allow us to isolate firm pay as the primary mechanism.

From column IV, the main effect of the unemployment rate, shown in the top row, is negative, though very small in magnitude (0.00019) and not statistically significant. This coefficient can be interpreted as the impact of the unemployment rate on the growth rate for the lowest pay quintile – the omitted category in each regression. This regression suggests, then, that the employment growth rate at low paying firms is acyclical. The interaction terms show the differential impact of the state unemployment rate on the growth rate at

[18] We first filter the differential growth rate and the unemployment rate, using a smoothing parameter of 1600, then regress the filtered series on quarter dummies and obtain residuals.

higher paying establishments. They are all negative and statistically significant at the 1% level. This means the state unemployment rate has a more negative impact on the growth rate at higher paying establishments. For example, a coefficient of -0.0011 (with a standard error of 0.00009) among the highest paying firms, indicates that for each percentage point increase in the unemployment rate, these firms shrink by 0.0011 more than the tiny effect seen in the lowest paying establishments. Multiplying this coefficient by 6 yields the predicted impact of the Great Recession on the growth rate.[19] This effect is quite large considering the mean growth rate for this group was roughly 0.003. Coefficients are fairly similar for the 3rd through 5th wage quintiles, while smaller in magnitude for the 2nd quintile but still highly significant.

Because firm types differ in their baseline growth rates (for example, the growth rate in the highest paying firms is nearly double that in the lowest paying firms), we convert our estimates to elasticities. This also helps interpret the magnitudes of these effects. Panel B reports the total impact of a 1% increase in the state unemployment rate on the growth rate at each firm-quality bucket (adding an interaction term to the main effect of the unemployment rate for higher paying firms).[20] From the first column, in response to a 1% increase in the state unemployment rate, the growth rate among the lowest paying firms does not change while the growth rate for the highest paying firms declines by 2.2%. Elasticities are substantially larger in magnitude for the 2nd-4th pay quintiles, declining by 2.9%, 4.0%, and 4.4%, respectively. These are again quite similar across specification.

Thus from table 2, we conclude that growth rates at the lowest paying firms are acyclical. In contrast, growth rates at higher paying firms are counter-cyclical, though in terms of elasticities, the highest paying firms are also a bit sheltered. These results have implications for the distribution of jobs over the business cycle, since low-paying firms grow relative to high-paying firms in busts. To put a magnitude on that, we can take average monthly earnings in each type of firm, reported in table 1, and predict average pay in the economy based on the implied distribution of workers across firms. Starting from a point when workers are evenly distributed across the quintiles, the average worker is in a firm paying \$3815/month. Our estimates imply that after the Great Recession, the average worker is in a firm paying \$4/month less, or almost 0.1% less. During the Great Recession, real gross domestic income fell by 3.8%. Compared to this benchmark, the impact on the distribution of workers across firms is modest, but not unsubstantial.

[19] The national unemployment rate rose from 4.2 in 2006:Q4 to a peak of 10.4 in 2010:Q1.

[20] To obtain these elasticities we add α_1 to the relevant interaction term in α_3 (or nothing in the case of the lowest quintile), multiply and divide by the quintile-specific averages for the state unemployment rate and the growth rate (respectively) reported in table 1.

4.2 Hire and Separation Rates

The regressions in table 2 show that growth rates at higher paying firms are more negatively impacted by the unemployment rate. By definition, the growth rate equals the gross hire rate minus the gross separation rate. We can thus decompose the impact of the unemployment rate on the growth rate into effects on these two margins. First, to get a general sense of how these fluctuate differentially across firms over the business cycle, we plot the differential rates in figure 3. The left panel shows the differential gross separation rate (the separation rate in the lowest paying firms minus that in the highest paying firms), while the right panel shows the differential gross hire rate. These gross flow rates look roughly pro-cyclical, exhibiting very different patterns than the differential net growth rate from figure 1. When the unemployment rate is low, low-quality firms hire and separate at greater rates than high-quality firms, while the opposite is true in times of high unemployment. These effects are largely symmetric across booms and busts, though more so for the differential separation rate than for the hire rate.

Table 3 presents regression results for separation rates (left panel) and hire rates (right) for four specifications (the same as those presented above). Both dependent variables show quite similar patterns to each other, though like the figures, opposite patterns to the growth rate. From panel A, the main effect of the unemployment rate is negative and a similar magnitude for both hires and separations, while the interaction effects are positive and significant. That is, the negative impact of the unemployment rate on both hires and separations at the lowest paying firms is somewhat offset at higher paying firms.[21] The magnitude of the offset increases with pay quintile, as might be expected, though the contrasts are stronger for separation rates than for hire rates. Our estimates from column IV imply that in the Great Recession, separation rates would have declined by 1.7 ppts at the lowest paying firms and by 0.25 ppts at the highest paying firms, while hire rates would have declined by 1.6 and 0.8 ppts, respectively.[22]

Panel B reports elasticities, analogous to table 2. Converting to elasticities is particularly important here because the average separation and hire rates at the lowest paying firms is double that at the highest paying firms (from table 1), making the units difficult to compare. For example, it would be much easier for a firm to reduce its separation rate by a third of a ppt off a base of 20% than off a base of 10%. For separation rates, these elasticities generally

[21] That separation rates decline in times of higher unemployment might be surprising given we expect firms to make more layoffs in a worse economy. However, this finding is consistent with a more-than-offsetting decline in voluntary quits (e.g., Shimer 2005, Hall 2005b).

[22] Results are again quite similar across specification. The biggest difference across specifications is that the main effect of the unemployment rate on both hires and separations declines in magnitude (by about a third to a fifth) when we control for date fixed effects. The date fixed effects absorb any variation in national economic conditions, leaving only local deviations to the national economy to identify the unemployment rate effect. Thus some of the overall effect from columns I and II is due to sensitivity to national economic conditions, which probably makes sense, while the magnitudes of the interaction effects remain fairly constant across specification.

hold up to the patterns presented in panel A; elasticities at lower paying firms are larger than those at higher paying firms. Elasticities for hire rates, show different patterns across specifications; in columns I and II elasticities are actually smaller in magnitude at lower paying firms, while in columns III and IV elasticities are similar in magnitude across all firms.

4.3 Discussion

The growth rate equals the hire rate minus the separation rate. Table 2 showed that growth rates were less impacted by the business cycle at low paying firms. Table 3 indicates that this effect is driven by the separations margin. The lowest paying firms have a dramatic decline in worker exits in a downturn, which allows them to maintain their workforce in spite of a large reduction in hiring. Higher paying firms do not see such a decline in separations but they still have relatively large declines in hiring (in percent changes they see a fairly similar decline to lower paying firms).

Figure 4 illustrates this result. Here we plot the total impact of a one percentage point increase in the unemployment rate on growth (solid blue), hire (red), and separation (green) rates across firm pay quintile (ignore for the moment the dashed green lines).[23] The growth rate effect is close to zero for the lowest quintile, and exhibits a shallow decline (increase in magnitude) across higher quintiles, before leveling off at the highest quintiles. In contrast, the separation and hire rate impacts are large in magnitude and negative for the lowest wage quintile and steadily increase (decrease in magnitude) across higher quintiles. The separation rate effect is very close to zero for the highest paying firms. Thus, while net employment changes are more cyclical at high-paying firms, gross worker flows are more cyclical at low-paying firms.

The gap between the hire and separation and rate effects (which will add up to the growth rate effect) is largest among the highest paying firms. In busts, hires and separations decrease by roughly the same amount at the lowest paying firms, so net employment remains roughly constant, while at higher paying firms separations do not decline by as much as hires do, so they shrink. In boom times, low-paying firms have relatively more separations, with a commensurate increase in hires, resulting again in a constant size, while high-paying firms increase their hires by more than their separation rate increases by, resulting in faster growth.

5 Distinguishing among theories

We have shown that employment growth rates at low-paying firms are less sensitive to the business cycle than those at high-paying firms. This is inconsistent with Schumpeterian

[23]Using the specification from columns labeled IV (which control for date fixed effects and size and churn distributions), we take the main effect of the unemployment rate as the impact for the lowest wage firm. We then add this coefficient to the interaction terms for quintiles 2-5.

cleansing, which predicts that resources would be reallocated from low- to high-paying firms in recessions, since the former are likely less productive. In the introduction, we emphasized that other factors could drive worker flows in the opposite direction. For example, a temporary collapse in the job ladder in a downturn would generate a relative reduction in moves from low- to high-paying firms (Moscarini and Postel-Vinay 2013). Also, if high-paying firms are more sensitive to the business cycle because demand for their products is more cyclically sensitive (perhaps because they sell luxury, or otherwise more expensive, goods), we should see relative declines in employment for these firms (Bils and Klenow 1998). In this section, we try to distinguish between these, and other stories that could be generating our results.

5.1 Types of Mobility

The employment advantage afforded to low-paying firms in downturns is driven by a large reduction in worker separations, and exists despite an equally large decline in hiring at these firms. Why do separation rates decline by more at lower paying firms in a bust? Is it that high-paying firms lay off more workers when times are tough? Or, is it because low paying firms benefit more from the reduced mobility of their workforce, as a job ladder model would predict? Or it could be a combination. In this subsection we decompose separations (and hires) based on the destination (source): employment or non-employment. This is useful because it gives us an indication of why the separation occurred. A separation where a worker moves directly to another job is more likely to be a voluntary quit than one where the worker had a complete quarter with no earnings. If a partial collapse of the job ladder is a primary driver of the growth rate result then voluntary separations should be the most important margin.

Table 4a shows impacts of the unemployment rate on separations to employment and non-employment rates, reporting regression results of the form specified in equation 5. The regression coefficients in panel A show that for separations to employment, the lowest paying firms experience a large negative drop in response to a 1 ppt increase in the state unemployment rate. The positive interaction terms, most of which are significant at the 1% level, show that this effect is offset somewhat at higher paying firms, mirroring the gross separation rate results from table 3. For example, in column IV, impacts on the highest paying firms are three-quarters smaller in magnitude, than for the lowest-paying firms. Elasticities in panel B also mirror this result, though here there are some differences across specification.[24]

The separations to non-employment results show that while the lowest paying firms have negligible impacts, the higher paying firms have larger, positive effects. Interaction terms are typically significant at the 5% level, and elasticities tend to produce the same patterns.

[24] In columns III and IV, elasticities are larger in magnitude for lower paying firms than for higher paying firms, while in columns I and II, elasticities are fairly similar in magnitude across firm type. We tend to prefer the former since those specifications have date fixed effects. So the bulk of evidence in table 4a is that declines in the types of moves that are more likely to be voluntary are much larger at lower paying firms.

Thus the gross separations margin is driven by a large decline in separations-to-employment among the lowest paying firms, and a modest increase in separations to non-employment among the higher paying firms. This can be seen in figure 4, which decomposes the separation rate effect into separations to employment (long-dash green) and non-employment (short-dash green). Again we plot the total impact of a 1 ppt increase in the state unemployment rate on these separations rates for each pay quintile. Clearly from the figure, the level impact of the separation rate effect is driven primarily by the impact on separations to employment. The impact of the unemployment rate on these is large and negative for the lowest paying firms, but becomes smaller in magnitude for higher paying firms. Also, higher paying firms see a small positive impact on separations to non-employment.

The inference that a separation to employment was more likely a voluntary move on the part of a worker, while a separation to a full quarter of non-employment was more likely a layoff, is imperfect in that this mapping likely varies across firms and over the business cycle. For example, there is some evidence that monthly job finding rates are lower for skilled workers, likely because they have higher returns to search. Thus a skilled worker might be more likely to be observed without pay for a full quarter following a layoff. Workers laid off from a low-paying firm may not show up as a separation to non-employment if they find another bad job quickly. Thus the separations-to-employment rate might include more layoffs at low-paying firms, especially in downturns. However, we find an overall large *decline* in separations-to-employment in the lowest paying firms. Any such misclassification of layoffs, which would imply an increase in separations-to-employment in a downturn (when firms lay off more workers) is clearly not large enough to offset this decline.

There are a few reasons why we might see relative increases in separations-to-non-employment among the higher paying firms. First, these firms may be in more distress because of either more cyclical sensitivity in the product market or because of frictions inhibiting them from adjusting on other margins (such as wage or price rigidities). Both are explored in the next subsection. An increase in layoffs at firms at the top of the job ladder is also in spirit consistent with the Moscarini Postel-Vinay (2013) poaching model. These firms grow large in a boom because they have a large queue of potential workers to choose from. They may grow too large in scale for a downturn and need to shed workers. Further confirmation of the poaching model might be obtained by looking at hires. If good firms poach away from bad firms in boom times, and a reduction in this poaching behavior is what allows bad firms to retain their workforce in busts, then we should see large declines in hires from employment for the high-paying firms.

Table 4b shows impacts on hire rates decomposed into those that came from employment (left panel) and non-employment (right). In magnitude, hires from employment decline by most at the lowest paying firms (the first and second quintiles). Impacts are about 20-40% smaller in magnitude for the highest paying firms. Once converting to elasticities, however, we see the effects are roughly similar across groups.

Impacts on hires from non-employment are pretty small, and even slightly positive for the highest-paying firms, though the latter are only marginally significant.

Figure 4 decomposes the hire rate into these two components, showing the total impact of a 1 ppt increase in the state unemployment rate on hires from employment (long-dash red) and non-employment (short-dash red). This decomposition mirrors that for separation rates. The level impact of the hire rate effect is driven primarily by the impact on hires to employment, where the effects of the unemployment rate are most negative for the lowest paying firms.

Thus high-paying firms do exhibit reductions in hires from employment (poaching) in a recession, consistent with Moscarini Postel-Vinay (2013). However, even though magnitudes are similar in terms of percent changes, the lower paying firms experience relatively larger reductions in levels. Why do low paying firms also have such a large reduction in hires? A natural interpretation is that after a large decline in voluntary worker exits, low-paying firms respond with a commensurate decline in hires, targeting roughly the same size workforce. It is plausible, then, that a reduction in poaching in a downturn drives the impact on the hires-from-employment rate at high paying firms, while a response to a reduction in attrition drives that at lower paying firms.

5.2 Labor Demand Explanations

High-paying firms might have a greater need to cut on their labor bill because of a greater product demand cyclicality. Or, for a given need to cut the labor bill, high-paying firms might suffer more from rigidities. Either could explain why higher paying firms seem to respond to a downturn by laying off workers, more so than lower paying firms. We explore these explanations empirically in this subsection.

Cyclicality of product demand

Firms may differ in how a recession impacts their profitability because of differential product demand cyclicality. For example, consider an inexpensive chain restaurant and a five-star restaurant. The latter most likely pays their employees more and also might have more cyclical demand. Indeed, Bils and Klenow (1998) showed that luxury products indeed have more cyclical demand. If there is a positive correlation between worker pay and prices then we might expect higher paying firms to be more sensitive to business cycle fluctuations.

To investigate differential product demand cyclicality, we need information on firm performance other than employment changes. The LEHD has a measure of revenue at the firm level but it is unreliable. Instead, we turn to Compustat North America by Standard & Poors, the most complete database of U.S. accounting data.[25] Compustat has reliable balance sheet data for publicly-traded firms. We can therefore ask whether fundamental

[25] We obtain these data via Wharton Research Data Services.

accounting data are more sensitive to the business cycle at high-quality firms, among those that are publicly traded.

The disadvantage of Compustat data is that it is made up of publicly traded firms, all of whom may be considered reasonably high-quality. The low-paying firms in Compustat may be a poor representation of low-paying firms in the LEHD and the economy as a whole. We therefore first present evidence on whether the patterns presented above that exist in the LEHD also exist in Compustat firms. Though Compustat does not have comparable earnings or gross worker flows data, it does have annual employment. We can therefore perform our net growth rate analysis using firm size as a proxy for firm pay.[26]

We define size based on average employment in the firm over its lifetime in Compustat (analogous to our pay measures). We then divide firms by size quintile, where the cut points are within industry.[27] Figure 5 presents the differential net growth rate (blue line) of the lowest minus highest size quintile, by year, analogous to those presented in figure 2. The national unemployment rate is also shown (red dashed line). As can be seen the lines track each other very closely; when the unemployment rate increases, small firms grow relative to large firms, and vice versa when the unemployment rate decreases. Figure 5 is useful since it shows that even among firms within Compustat, all of whom must be reasonably high quality, the same basic dynamics hold. We hope, then, that analyzing the balance sheet data in Compustat can tell us something about the financial pressures high- and low-paying firms face over the business cycle.[28]

We use the rate of change of quarterly revenue as a proxy for a firm's incentive to hire. Profit maximizing firms will set employment such that marginal cost equals marginal revenue product. Presumably firms with more cyclical product demand will experience accompanying revenue declines. We link the Compustat revenue change data to the LEHD by aggregating quarterly revenue change to the three-digit NAICS level. This allows us to ask whether LEHD pay quintiles are made up of firms in sub-sectors which typically experience more or less business cycle volatility, as measured by Compustat.[29] Figure 6 plots these percent revenue changes for firms in the lowest quintile (dashed red line), firms in the highest quintile (dash-dot green line), and the average for firms in the 2nd through 4th quintiles (solid blue line). We also include recession bars. Reassuringly, revenue change has a strongly cyclical pattern, falling in recessions and rising in booms. However, the graph shows little difference across low- and high-paying firms over the business cycle. Low-paying firms experienced

[26]Size is a common proxy for pay since the two variables are highly correlated. Moscarini Postel-Vinay (2012) show in a large number of countries that small firms grow relative to large firms in slack labor markets, while the opposite is true in tight labor markets.

[27]Since most firms in Compustat have a larger, national presence, we do not use geographic location information.

[28]Though not shown here, in regression analysis, the relationship between net employment changes and the national unemployment rate is statistically significantly larger in magnitude (more negative) at firms in the largest size quintile compared to the smallest.

[29]We are not permitted to link Compustat data to the LEHD at the firm level because of confidentiality concerns.

a slightly larger decline in revenue change during the 2001 recession, while high-paying firms experienced a slightly larger decline in the Great Recession.[30] This figure is therefore inconsistent with the notion that high-paying firms are more sensitive to the business cycle.

Based on the evidence presented here, we think it unlikely that differential business cycle sensitivity in the product market is driving our results. The sub-sectors where low- and high-paying firms are typically found do not experience differential sensitivities, as reported by Compustat. Though we should caution that this exercise needs to be taken with a grain of salt, since it is based on an unrepresentative set of firms.

Downward earnings rigidities

A long-standing literature (see for example Shimer (2004) or Hall (2005a) among many others) points to nominal wage rigidities as an explanation for larger employment fluctuations than fluctuations in other market fundamentals. The degree to which nominal wages are downwardly rigid remains a completely open empirical question with evidence on all sides (see Pissarides 2009 for a survey). Furthermore, to our knowledge no one has examined pay rigidity as a function of average firm pay. On the one hand, low-paying firms likely pay more of their workforce on an hourly basis, so may have an easier time cutting take-home pay through hours reductions.[31] Also, the fact the high-paying firms continue to hire relatively more than low-paying firms, despite an increase in layoffs, is consistent with the literature showing that starting wages are more pro-cyclical than incumbent wages (Martins, Solon and Thomas 2010). At the same time, high-paying firms may pay a higher share of salaries in the form of bonuses, which are likely much easier to adjust.

We investigate downward earnings rigidities in the LEHD using total quarterly earnings for a worker from a given firm. This measure has both advantages and disadvantages. On the one hand, we cannot measure whether there exist nominal reductions in pay *rates*, the variable most discussed in the literature. However, our measure incorporates a number of dimensions along which a firm can adjust labor costs besides lowering the base rate of pay, for example hours, overtime and bonuses. This is certainly the more relevant measure for our purposes, since we are trying to explain whether some firms have a greater need to cut labor costs by firing workers rather than by lowering pay.

To test whether the strength of downward pay rigidities vary with firm quality, we follow

[30] A plot of differential revenue change across low- and high-quality firms, analogous to our figure 2, shows no systematic relationship with the unemployment rate. We prefer to present the figure in levels instead since it generates more intuition for the measure itself.

[31] The queuing literature also suggests that high-paying firms will have more rigid pay, relative to low-paying firms. High-quality firms post a high wage, which results in a long queue of workers who wish to work there, driven for example by an efficiency wage (Akerlof and Yellen 1985), imperfect information (Weiss 1980) or explicit personnel policies (Okun 1973). They would then find it easier to adjust the size of their workforce without adjusting wages. A corroborating piece of evidence comes from the cyclical upgrading literature which finds that wages are more cyclical in low-paying industries (Bils and McLaughlin 2001). This would nicely explain why high-quality firms need not increase wages in expansions, however, is it less compelling for explaining why a firm would not lower wages in a contraction.

a similar methodology to Dickens et al. (2007). We measure nominal annual pay changes in earnings, Δp_{it}, for job stayers.[32] For a firm, f, in time period t, we then estimate the nominal pay rigidity as per equation 6. That is, for a firm with N workers who have a valid pay change measure, we take the number whose annual pay change was equal to 0 and divide that by the number whose pay change was less than or equal to 0. In practice, we define a pay change to be equal to 0 if it is within $\pm 1\%$, to allow for some noise, and results are robust to larger bounds.

$$\text{nominal pay rigidity}_{ft} = \frac{\sum_{i=1}^{N} \mathbf{1}(\Delta p_{it} = 0)}{\sum_{i=1}^{N} \mathbf{1}(\Delta p_{it} \leq 0)} \tag{6}$$

This measure proxies for the following: Among workers who were at risk of receiving a nominal pay decrease, what share did NOT receive one? We find that on average over our time period, this share is roughly 0.25. We then average these within our firm-pay buckets, weighting by average employment at a given date, to gain a sense of whether firms of varying quality experience differential pay rigidities over the business cycle.

Figure 7 plots these estimates over time for firms in the lowest wage quintile (dashed red line), firms in the highest wage quintile (dash-dot green line), and for the average of firms in the 2nd through 4th quintiles (solid blue line). We also include recession bars. As can be seen, pay rigidity has a cyclical pattern, falling in recessions and rising in booms.[33] However, the graph very clearly shows that high-paying firms have a much larger drop in rigidities in recessions. Also, the middle-quintile firms seem to be a bit more cyclical themselves with earnings rigidities increasing during the boom years between the two recessions.

This measure of downward nominal pay rigidities is far from perfect. For example, we can only estimate the rigidity among stayers at a firm, while we have already shown that high- and low-paying firms differ in their gross separation rates over the business cycle. For example, a high-paying firm might layoff its workers whose pay cannot be adjusted, leaving only those whose pay can be adjusted. However, the evidence presented here suggests that high-paying firms are able to adjust labor costs in recessions, relative to low-paying firms, by cutting earnings. Therefore, we do not believe differential earnings rigidities can be driving our results.[34]

[32] A worker must have 10 continuous quarters of earnings to be included in the sample. At the quarterly level, issues arise such as differences in the number of pay cycles within a quarter that vary across firm and across calendar year. To avoid additional noisiness, we measure annual pay changes. We also trim the distribution of earnings changes to those who had more than $\pm 50\%$ changes, since these presumably represent errors in reporting.

[33] The data show rigidity for pay changes that occur over the next year. Thus the cyclical pattern looks as though it leads the recession bars.

[34] Analyzing differential rigidities (analogous to our figure 1), similarly reveals that high-paying firms become differentially less rigid in times of high unemployment. We again prefer to present the figure in levels to help build intuition for our metric itself.

5.3 Alternative explanations

Managerial practices at high- and low-paying firms surely differ along a variety of dimensions. Differences might arise if low-paying firms are always closer to the margin of survival. For example, the "pit stop" model of management (Koenders and Rogerson 2005) says that in booms managers are focused on growth and in busts must focus on efficiency and cut workers. Given positive correlations between pay, productivity, and size, it could be that low-paying firms are always closer to the margin of survival and therefore always focused on efficiency. This would result in a relatively greater need for high-paying firms to lay off workers in downturns. However, such a theory suggests the counter-intuitive notion that low-paying firms manage more efficiently. This seems on the surface unlikely, given that low-paying firms are on average smaller, have higher churn, and are probably less productive.

In contrast, one might suppose that given their lower productivity, smaller size, and likely lower probability of survival, low-paying firms manage inefficiently. While, high-paying firms layoff workers in economic downturns, low-paying firms do less of this, even though they should. This seems unlikely for a couple of reasons. First, such poor management should result in relatively more firm deaths in bad times at low-paying firms. Our employment measures include firm deaths yet we still find that on average, low-paying firms grow relative to high-paying firms in busts, including and despite any shrinkage from firm deaths. Second, reinspecting figure 4, and noting the *larger* adjustment in gross flows at low-quality firms, it does seem as though managers at low-paying firms respond. Faced with a large decline in voluntary quits, low-paying firms respond with a commensurate decline in hiring. This suggests that low-paying firms do respond to their business environment and target a particular sized workforce.

It could be that because low-paying firms are on average smaller, they cannot lay off workers without stopping production. That is, there might be a divisibility problem where a large firm could shut down a fraction of its production by laying off that fraction of workers, while a small firm does not have that many whole bodies to work with. To address this, we have performed our analysis restricting the sample to firms with at least 50 workers, and obtained very similar results.[35] These are available upon request.

Finally, we point out that a simple compensating differentials framework can yield our results. In equilibrium, volatile jobs need to be higher paying in order to make the marginal worker indifferent between working there and a low-paying job with stable employment. However, this is also on the surface at odds with some evidence in the data. From table 1, the lowest paying firms have 20% turnover each period, while the highest paying firms have half that. They also have larger rates of separation-to-non-employment, a more negative

[35] This robustness also helps dress the concern that small businesses (to the extent size is correlated with pay) manage differently in other ways. For example, Hurst and Pugsley (2011) show that most small business owners intend to serve an existing customer base and do not intend to grow. This would imply less growth in booms and as a result possible less shrinkage in busts.

risk. Thus the lower paying jobs are on average much more unstable.

6 Impacts on the job ladder

We find that employment growth at high-paying firms is pro-cyclical, while growth at the lowest paying firms is acyclical. The latter is accompanied by a sharp decline in worker churn in recessions. We have shown that the most likely driver of these results is that the job ladder to some extent breaks down in a bust, allowing low-paying firms to retain their workforce. In this section we quantify the size of this breakdown in the job ladder, based on data on individual workers and their transitions across firms. We also estimate impacts for new job matches in light of the fact that job seekers seem to be particularly scarred by recessions.

6.1 All Workers

To asses both the level of worker mobility up the job ladder in normal times, and how this changes over the business cycle, we estimate ordered logit models of the form specified in equation 7. $W_{it+1} \in [1,5]$ is the pay quintile of an individual's primary employer in $t+1$. We allow this to be a function of the state unemployment rate in t, dummies for pay quintile of the firm in t (W_{it}), interactions between the two, and a set of controls which mirror those from our main specification in equation 5.

(7)

$$W_{it+1} = \alpha_0 + \alpha_1 st\_unemp_{st} + W_{it}\alpha_2 + [st\_unemp_{st} * W_{it}]\alpha_3 + f(t) + I^{industry} + I^{state} + X_{it}\beta + \varepsilon_{it+1}$$

Regression results are reported in appendix table 1. Coefficients are quite similar across four specifications; we control for either quarter fixed effects and a time trend or date fixed effects, and sometimes include controls for worker characteristics (age, gender and job duration in t). Across all specifications, we find that a higher unemployment rate in t reduces the likelihood of being at a higher pay quintile in $t+1$, and this effect is significant at the 1% level. This represents the effect for the omitted category, workers in the lowest quintile in t. The interaction terms show that for workers in higher quintiles in t the unemployment rate effect is almost completely offset.

A more natural interpretation is presented in table 5, where we report implied transition matrices from this regression for a boom (4.2% unemployment rate) and a bust (10.4% unemployment rate), in the left and right panels, respectively. We use regression coefficients from column IV, which includes date fixed effects and worker characteristics.

Focusing first on a boom and for workers who were in the lowest quintile in t (left panel, first column), we estimate that nearly 89.9% of these workers remain in the lowest paying firms one quarter later (this could be their firm in t or a different firm in the same pay quintile). This means that 10.1% move up the job ladder, with the vast majority moving up only one rung. One way to quantify the magnitude of this chance of upgrading is to assign average pay to each quintile (from table 1) and predict what kind of firm the average worker will be in one quarter later in terms of average pay at that firm. This is shown in the bottom row. Those beginning in the lowest quintile in t will on average be at a firm whose average pay is \$1,936 in $t+1$. This represents 5% advancement above their starting point which was \$1,842 (average pay at the lowest quintile).

Workers starting at higher rungs of the ladder could upgrade, downgrade or stay put. For example at the second rung workers stay in their current rung 72% of the time, and upgrade or downgrade with roughly equally probabilities, around 14%. Workers in the highest run in t are most likely to survive in their current rung, at 94%.

The right panel reports what our estimates imply for these transition probabilities in a bust. The largest impacts are on workers in the lowest paying firms. Only 8% of these workers upgrade firms over the quarter, one-fifth fewer than in a boom. In $t+1$ these workers have only upgraded to a firm paying \$1,917/month, \$19 less (or a 20% smaller expected advancement) than in a boom. Transitions for incumbents in rungs 2-4 are essentially unaffected by the bust, while workers in the top rung in t are a bit less likely to hold onto their position until $t+1$.

These results are quite consistent with what we found above. They imply a substantial breakdown of the job ladder for workers in the lowest rung, as well as a small loss of position for workers in the highest rung, and not much change for those in the middle. However, it is worth pointing out that these results are selected since they restrict to those working in $t+1$. Though not shown, we estimate that on average, those in lower rungs in t are less likely to be working in $t+1$, a higher unemployment rate in t also implies a smaller chance of working in $t+1$, but that those in higher rungs in t face a greater negative impact of the unemployment rate. They are differentially less likely to be working in $t+1$, consistent with our finding earlier that higher paying firms are more likely to make layoffs in a downturn. Thus table 5 cannot fully quantify the regressive effects of a recession on a worker's position when starting at higher rungs, since these workers are substantially more likely to be out of work for at least a full quarter.[36]

6.2 New Entrants

The relative advantage low-paying firms retain in a downturn might help to explain why the two groups mentioned in the introduction, recent college graduates and those displaced from a job where they had high tenure, face substantial earnings losses when these events occur

[36]Our estimates imply that in the Great Recession workers in the top rungs of the ladder had a 2 ppt increased probability of transitioning to non-employment in the next quarter, while workers in the bottom rung were unaffected.

in a downturn.[37] Our estimates imply that the distribution of jobs shifts towards the lower paying firms in a downturn and that these jobs become stickier. How much of the long-term earnings losses for each of the groups mentioned above can be accounted for by this shift in the distribution of jobs and a short-term break down of the job ladder?

To answer this question, we estimate two ordered logit regressions, shown in equations 8 and 9.

$$W_{it} = \alpha_0 + \alpha_1 st\_unemp_{st} + f(t) + I^{industry} + I^{state} + X_{it}\beta + \varepsilon_{it+1} \tag{8}$$

$$W_{it+3} = \alpha_0 + \alpha_1 st\_unemp_{st} + W_{it}\alpha_2 + [st\_unemp_{st} * W_{it}]\alpha_3 + f(t) + I^{industry} + I^{state} + X_{it}\beta + \varepsilon_{it+1} \tag{9}$$

Equation 8 estimates the likelihood of matching to a higher paying quintile as a function of economic conditions at the time of the match and controls. Appendix table 2 reports logit coefficients for four specifications analogous to those that have been reported throughout the paper. We estimate a significant reduction in the likelihood of matching to a better firm when the unemployment rate is higher, across all specifications.

Table 6 reports fitted probabilities implied by the specification in column IV (which controls for date fixed effects and worker age and gender) for both a boom and a bust. In a boom (first column), 42.2% of new matches are to the lowest paying firms. These firms are overrepresented in job starts compared to the stock of workers (which is by construction evenly distributed across firm type). This is because of the especially high churn rates at the lowest paying firms. In contrast only 4.6% of new matches are to the highest paying quintile. The bottom row shows that the average worker matching to a firm in a boom is at a firm paying \$2,782, on average. This is lower than the \$3,811 average for the stock of workers.

In a bust (second column), the firm quality distribution shifts downward. Workers are about 4 ppts more likely to match to the lowest paying firms and about a point less likely to match to each of the higher quintiles. This amounts to a nearly \$90 reduction in firm quality (average firm pay for the average matching worker) or 3% less than those matching in booms. Of course this exercise is merely descriptive in the sense that we have not adjusted for ability differences across those matching in booms versus busts. There could be negative selection of workers matching to firms in recessions, since those with a good current position stay put (see Kahn (2013) for evidence on this). However, it is also at least consistent with

[37] Davis and von Wachter (2011) estimate that the impact of job displacement for those with at least 3 years of tenure is a 20% drop in the present discounted value of lifetime earnings, for those displaced in a recession. The impact for those displaced in a boom is a 12% drop. Altonji, Kahn, and Speer (2014) estimate that those graduating from college into a large recession in the U.S. experience an average drop in annual earnings of roughly 2% per year over the first decade of a career, and similar impacts on wage rates. Oreopoulos, von Wachter and Heisz (2012) find similar losses in Canada and show they manifest through initial matches to worse (smaller) firms.

the relative shift of jobs towards lower paying firms, demonstrated above.

Next, to understand whether workers are differentially likely to upgrade from their initial match, as a function of the economy at the time of that match, we estimate equation 9. This ordered logit predicts the location of a worker (in terms of firm pay quintile) 3 quarters later, for workers matching to a firm in t, as a function of the economy in t, the type of firm matched to, and the interaction, as well as some controls. Regression coefficients for four specifications are reported in appendix table 3. We find that the unemployment rate at time of match is negatively related to firm quintile 3 quarters later, for workers matching to the lowest quintile (the omitted category). This effect is fully offset for workers matching to the 2nd and 3rd quintiles, and halfway offset for those matching to the 4th quintile. The effect is exacerbated for those matching to the highest quintile in t, and in total is 5 times larger than the base effect.

We again report transition matrices for the final specification (which includes date fixed effects, a quadratic in age, and a gender dummy) in table 7. Workers who match to the lowest ranked firms in a boom (left panel, first column) do tend to upgrade in the first year following the match. Only 62.5% of these workers remain in a low paying firm, while a quarter have upgraded to the 2nd pay quintile and more than 10% have actually moved up to an even higher quintile. On average, a worker matching to the lowest paying firms in a boom is at a firm whose average pay is $2,346 three quarters later. This is a $500 advancement above the average pay at the lowest paying firms ($1,842) or 27%. Workers starting out in higher rungs are also slightly more likely to hold their position or advance, than to backslide. For example, 27% of workers matching to the 3rd quintile remain at that quintile, while another 27% advance to the 4th or 5th quintiles. Among those matching to the highest paying firms, 65% retain their position 3 quarters later, when matching in a boom. However, a quarter slide back to the 4th quintile and 10% slide back further than that.

For those matching in a bust, these figures look fairly similar, with some important differences. Above, we estimated that in busts there is a substantial decline in exits-to-employment from the lowest paying firms. This effect means that workers matching to the lowest paying firms in a bust will probably be less likely to upgrade, initially. Indeed, the right panel of table 7 shows that 63.8% of those matching to the lowest paying firms in a bust retain their position; thus only 36.2% advance, 1.4 ppts less than for those matching in a boom. In dollar terms, the average worker moves to a firm whose average pay is $2,325 when matching in a bust, or $20 less advancement (4.2%) than those matching in a boom.

Above, we also estimated that the highest paying firms are more likely to make layoffs (i.e., separations to non-employment) in a bust. From table 7, it looks as though these layoffs hit new entrants especially hard. Workers matching to a top paying firm in a bust are far less likely to maintain their position, 57.5%, compared to 65% in a boom. In dollar terms, this amounts to a $214 lower average firm pay in $t + 3$. It is thus much worse to match to a high-paying firm in a bust than a boom. Perhaps these firms look to clean out some of their incumbent workforce in a bust, but still need some temporary, lower skilled workers, to squeak by with their production needs.

Workers matching to firms in the middle of the pay distribution do not see much of a change in mobility when matching in a bust compared to a boom.

Overall, how do workers fare when matching to a firm in a bust compared to a boom? If we assume the matching probability does not change over the business cycle (that is, ignore the results from equation 8), and instead fit the boom match probabilities, we get that the average worker is at a firm paying $2,946 3 quarters later, if matching to a boom, and only $2,929 if matching in a bust. These are both advancements relative to the initial match, which we reported above as $2,782 in a boom. This nearly $20 difference or 10% smaller advancement for those matching in a bust is attributed solely to the reduced probability of upgrading after matching. If we also factor in that workers are more likely to match to low paying firms in a recession, we get the combined effect. The average worker, 3 quarters later, is at a firm paying on average $2,871. Thus the full effect of matching in a bust, compared to a boom, is a $75 lower average firm quality 3 quarters later. This is 2.6% of the average earnings in $t+3$ for someone matching in t in a boom, or half of their typical advancement.

The same disclaimer on causality applies here. However, we find these results interesting, consistent with the reduction in voluntary mobility estimated above, and useful for considering the possible magnitudes the dynamics presented above can have in terms of impacts on workers and the job ladder.

7 Conclusion

In this paper, we use employer-employee matched U.S. data to study net and gross worker flows over the business cycle as a function of firm pay. We find that low-paying firms fare relatively better in downturns; their growth rates are unaffected by the business cycle. The evidence suggests that in normal times, low-paying firms suffer from a large worker separation rate, and therefore also do a lot of replacement hiring. In bad times, separations decline substantially at these firms and they aim for a commensurate reduction in hires. This keeps the growth rate relatively constant over the business cycle. The decline in separations exhibited in a recession look to be a decline in voluntary separations on the part of the worker since the largest effect is for separations to employment. Higher paying firms experience less of an impact on their separations to employment but still a large reduction in hires. The highest paying firms also increase separations to non-employment, which most likely represent layoffs. As we have said, these findings are consistent with the Moscarini Postel-Vinay (2013) poaching model, though we cannot completely rule out a small role for differential sensitivity to the business cycle driven by consumer demand.

While previous research has emphasized that match quality may decline in recessions due to a lack of workforce reallocation (Barlevy termed this the "sullying" effect of recessions in his 2002 paper), our evidence here suggests an additional sullying effect. The types of jobs workers get stuck in are more likely to be low quality. Our results suggest that the reduced ability to move on to better matches caused by a recession has a greater impact on workers in low-quality firms compared to those in high-quality firms. We estimate that a large recession reduces the probability of advancing out of the lowest paying firms by 20%.

These results also have important implications for the literature on the differential impact of recessions on workers. The literature has shown that entering the labor market in a recession (Kahn (2010), Oreopoulos, von Wachter and Heisz (2012), Altonji, Kahn and Speer (2014)) and being displaced from a long-term job in a recession (Davis and von Wachter 2010) each have particularly long-lasting, negative earnings impacts. Both groups were forced to search for, and likely accept, a job in a downturn. Our results indicate that workers matching in recessions are more likely to go to a low-paying firm, and more likely to stay there once matched. These effects combine to an estimated 2.6% drop in average firm quality a year after matching, for those matching in a recession compared to a boom, or $75/month lower average firm pay. These workers thus lose out on roughly half of the advancement made by workers matching in a boom. Our estimates are based solely on typical pay in these firms, and do not reflect any heterogeneity within firm. Also, they do not pick up any scarring effects from spending time at a low-paying firm. These could include both how a worker is perceived to potential employers, but also impacts on human capital accumulation and the development of networks. These impacts could be large and long-lasting.

References

[1] Abowd, John, Bryce Stephens, Lars Vilhuber, Fredrik Andersson, Kevin L. McKinney, Marc Roemer, and Simon Woodcock (2006). "The LEHD Infrastructure Files and the Creation of the Quarterly Workforce Indicators" LEHD Technical Paper No. 2006-01.

[2] Akerlof and Yellen (1985), "A Near Rational Model of the Business Cycle, with Wage and Price Inertia," *Quarterly Journal of Economics*, 100, suppl., pp. 823-38.

[3] Altonji, Joseph G., Lisa B. Kahn, and Jamin D. Speer (2014) "Cashier or Consultant? Entry Labor Market Conditions, Field of Study, and Career Success," NBER working paper #20531.

[4] Barlevy, Gadi (2002), "The Sullying Effect of Recessions," *The Review of Economic Studies*, 69(1), pp. 65-96.

[5] Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding, and Peter K. Schott (2007), "Firms in International Trade," *Journal of Economic Perspectives,* 21(3), pp. 105-130.

[6] Bils, Mark and Peter Klenow (1998), "Using Consumer Theory to Test Competing Business Cycle Models," *Journal of Political Economy*, 106(2).

[7] Bils, Mark and Kenneth J. McLaughlin (2001), "Inter-Industry Mobility and the Cyclical Upgrading of Labor," *Journal of Labor Economics*, 19(1), pp. 94-135.

[8] Bowlus, Audra. (1993), "Matching Workers and Jobs: Cyclical Fluctuations in Match Quality," *Journal of Labor Economics*, 13(2), pp. 335-350.

[9] Brown, C. and J. Medoff (1989), "The Employer Size-Wage Effect," *Journal of Political Economy*, 97(5).

[10] Burdett, K. and D. Mortensen (1998), "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, 39(2), pp. 257-273.

[11] Burgess, Simon, Julia Lane and David Stevens (2000), "Job Flows, Worker Flows, and Churning," *Journal of Labor Economics*, 18(3): pp. 473-502.

[12] Caballero, R. and Hammour, M. (1994), "The Cleansing Effect of Recessions, *American Economic Review*, 84, pp. 1350-1368.

[13] Caballero, R. and Hammour, M. (1996), "On the Timing and Efficiency of Creative Destruction," *Quarterly Journal of Economics*, 111, pp. 805-852.

[14] Campbell, B., H. Chiang, J. Haltiwanger, L. Hunter, R. Jarmin, N. Nestoriak, T. Park, and K. Sandusky (2005), "Firm Performance, Workforce Quality, and Workforce Churn," mimeo.

[15] Chari, V. V., L. Christiano and P. Kehoe (2007), "The Gertler-Gilchrist Evidence on Small and Large Firm Sales," mimeo.

[16] Davis, Stephen J., John Haltiwanger and Scott Schuh (1996), *Job Creation and Destruction*, MIT Press.

[17] Davis, Stephen and Till von Wachter (2011), "Recessions and the Cost of Job Loss," *Brookings Papers on Economic Activity*, Fall.

[18] Dickens, W., L. Goette, E. Groshen, S. Holden, J. Messina, M. Schweitzer, J. Turunen, M. Ward, (2007), "How Wages Change: Micro Evidence from the International Wage Flexibility Program," *Federal Reserve Bank of New York Staff Reports*, staff report no. 275.

[19] Farber, Henry (1999), "Mobility and Stability: the Dynamics of Job Change in Labor Markets," in O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics*, vol. 3, North Holland, pp. 2439-2483.

[20] Fort, Teresa, John Haltiwanger, Ron Jarmin and Javier Miranda (2013), "How Firms Respond to Business Cycles: The Role of Firm Age and Firm Size," NBER working paper #19134

[21] Gertler and Gilchrist (1994), "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *The Quarterly Journal of Economics*, 109 (2), 309-340.

[22] Gomes, J., J. Greenwood, and S. Rebelo (2001), "Equilibrium Unemployment," *Journal of Monetary Economics*, 48(1), pp. 109-152.

[23] Hall, Robert (1991), "Labor Demand, Labor Supply and Employment Volatility," in NBER Macroeconomics Annual (Cambridge: MIT Press)

[24] Hall, Robert (2005a), "Employment Fluctuations with Equilibrium Wage Stickiness," *American Economic Review*, 95(1), pp. 50-65.

[25] Hall, Robert (2005b), "Job Loss, Job Finding, and Unemployment in the U.S. Economy over the Past Fifty Years," *NBER Macroeconomics Annual 2005*, pp. 101-137.

[26] Haltiwanger, John, Henry Hyatt, and Erika McEntarfer (2014), "Cyclical Reallocation of Workers across Employers by Firm Size and Firm Wage," mimeo.

[27] Haltiwanger, John, Ron Jarmin and Javier Miranda (2013), "Who Creates Jobs? Small vs. Large vs. Young," *Review of Economics and Statistics*, 95(2), pp. 347-361.

[28] Hurst, Erik and Benjamin Pugsley (2011), "What Do Small Businesses Do?", *Brookings Papers on Economic Activity*, Fall.

[29] Hyatt, Henry and Erika McEntarfer (2012a) "Job-to-Job Flows and the Business Cycle" *American Economic Review Papers and Proceedings*, 103(3), pp. 580-583.

[30] Hyatt, Hentry, and Erika McEntarfer (2012b), "Job-to-Job Flows and the Business Cycle," US Census Bureau Center for Economic Studies Paper No. CES-WP-12-04.

[31] Hyatt, Henry, Erika McEntarfer, Kevin McKinney, Stephen Tibbets, and Doug Walton (2014), "Job-to-Job Flows: New Labor Market Statistics from Linked Employer-Employee Data," *Joint Statistical Meetings Papers and Proceedings*, forthcoming.

[32] Jovanovic, Boyan (1979), "Job Matching and the Theory of Turnover," *The Journal of Political Economy*, 87(October), pp. 972-90.

[33] Kahn, Lisa (2010), "The Long-Term Consequences of Graduating from College in a Recession," *Labour Economics*, 17(2): pp. 303-316.

[34] Kahn, Lisa (2013), "Asymmetric Information between Employers," *American Economic Journal: Applied Economics*, 5(4): pp. 165-205.

[35] Koenders, K. and R. Rogerson (2005), "Organizational Dynamics Over the Business Cycle: A View on Jobless Recoveries," Federal Reserve Bank of St. Louis Review.

[36] Lazear, Edward and Jim Spletzer (2012), "Hiring, Churn and the Business Cycle" *American Economic Review Papers and Proceedings*, 102(3): pp. 575-579.

[37] Martins, P., G. Solon and J. Thomas, "Measuring What Employers Do About Entry Wages Over the Business Cycle: A New Approach," *American Economic Journal: Macroeconomics*, forthcoming.

[38] Mortensen, D. and C. Pissarides (1994), "Job Creation and Job Destruction in the Theory of Unemployment," *Review of Economic Studies*, 61, pp. 397-415.

[39] Moscarini, Giuseppe and Fabien Postel-Vinay (2013), "Stochastic Search Equilibrium," *Review of Economic Studies*, 80(4), pp. 1545-1581.

[40] Moscarini, Giuseppe and Fabien Postel-Vinay (2012), "The Contribution of Large and Small Employers to Job Creation in Times of High and Low Unemployment," *American Economic Review*, 102 (6), pp. 2509-2539.

[41] Okun, Arthur (1973), "Upward Mobility in a High Pressure Economy," *Brookings Papers on Economic Activity*, 207-52.

[42] Oreopoulos, Phil, Till von Wachter and Andrew Heisz (2012), "The Short- and Long-Term Career Effects of Graduating from College in a Recession," *American Economic Journal: Applied Economics*, 4(1) pp. 1-29.

[43] Pissarides, C. (2009), "The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?" *Econometrica*, 77(5), pp. 1339-69.

[44] Schumpeter, J. (1939), *Business Cycles* (New York: McGraw-Hill).

[45] Serafinelli, M. (2012), "Good Firms, Worker Flows and Productivity," mimeo.

[46] Sharpe, Stephen (1994), "Financial Market Imperfection, Firm Leverage, and the Cyclical of Employment," *American Economic Review*, 84 (4), pp. 1060-74.

[47] Shimer, R. (2004), "The Consequences of Rigid Wages in Search Models," *Journal of the European Economic Association*, 2 (2-3), pp. 469-79.

[48] Shimer, R. (2005), "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 95(1), pp. 25-49.

[49] Weiss, Andrew (1980), "Job Queues and Layoffs in Labor Markets with Flexible Wages," *Journal of Political Economy*, 88(June), pp. 526-38.

Figure 1:

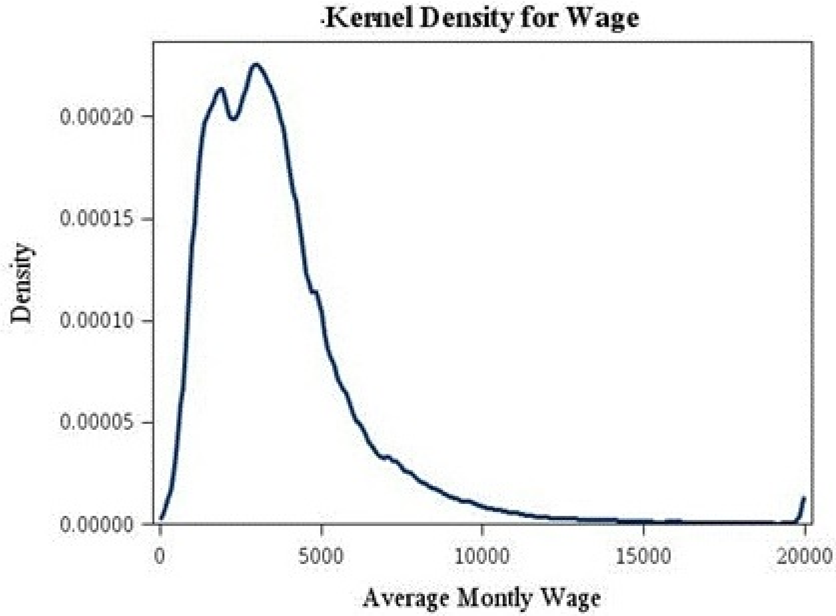
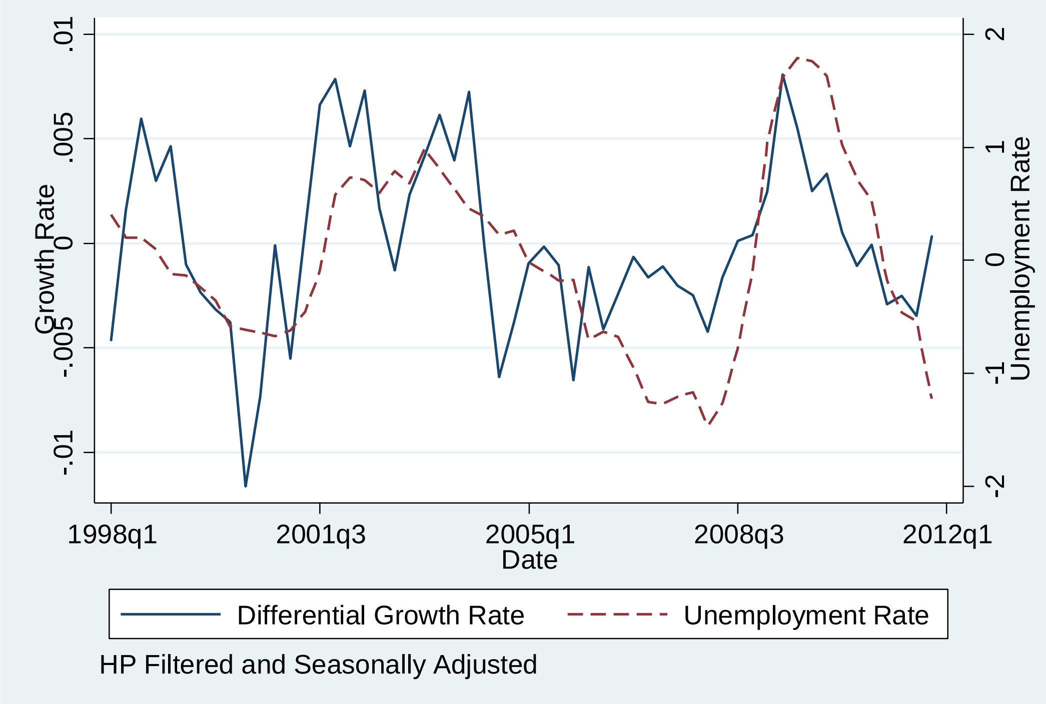


Figure 2: Differential Growth Rates: Low-High Wage Firms



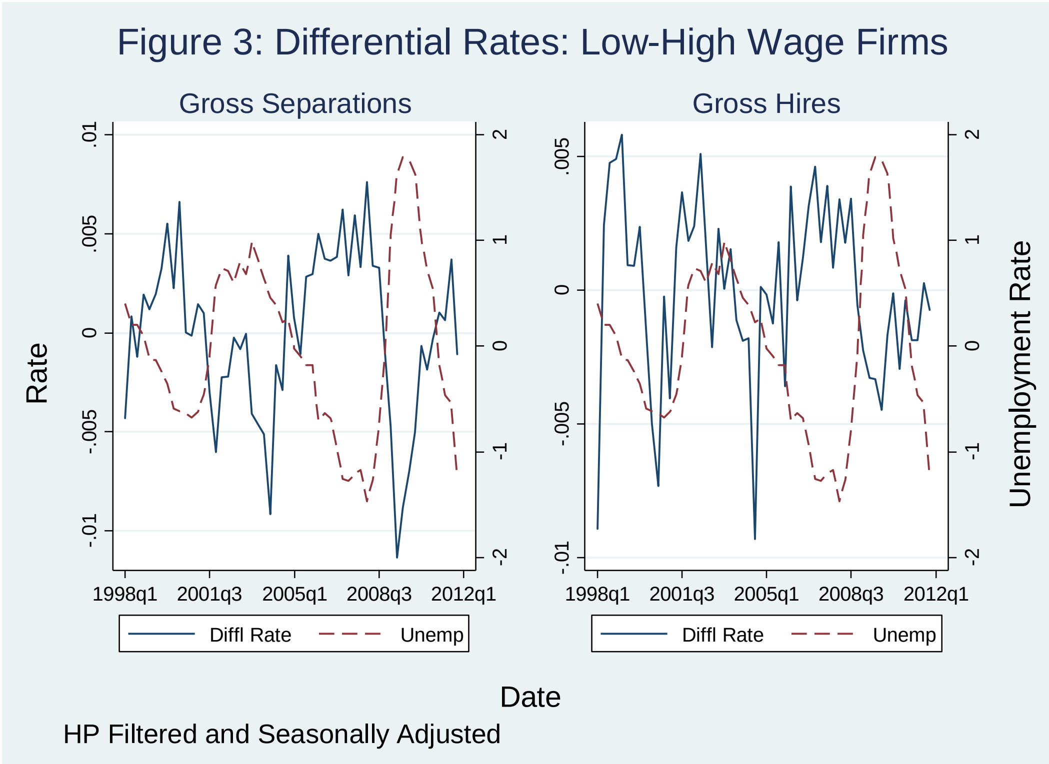


Figure 3: Differential Rates: Low-High Wage Firms
Gross Separations
Gross Hires
Rate
Unemployment Rate
1998q1
2001q3
2005q1
2008q3
2012q1
Diffl Rate
Unemp
Date
HP Filtered and Seasonally Adjusted

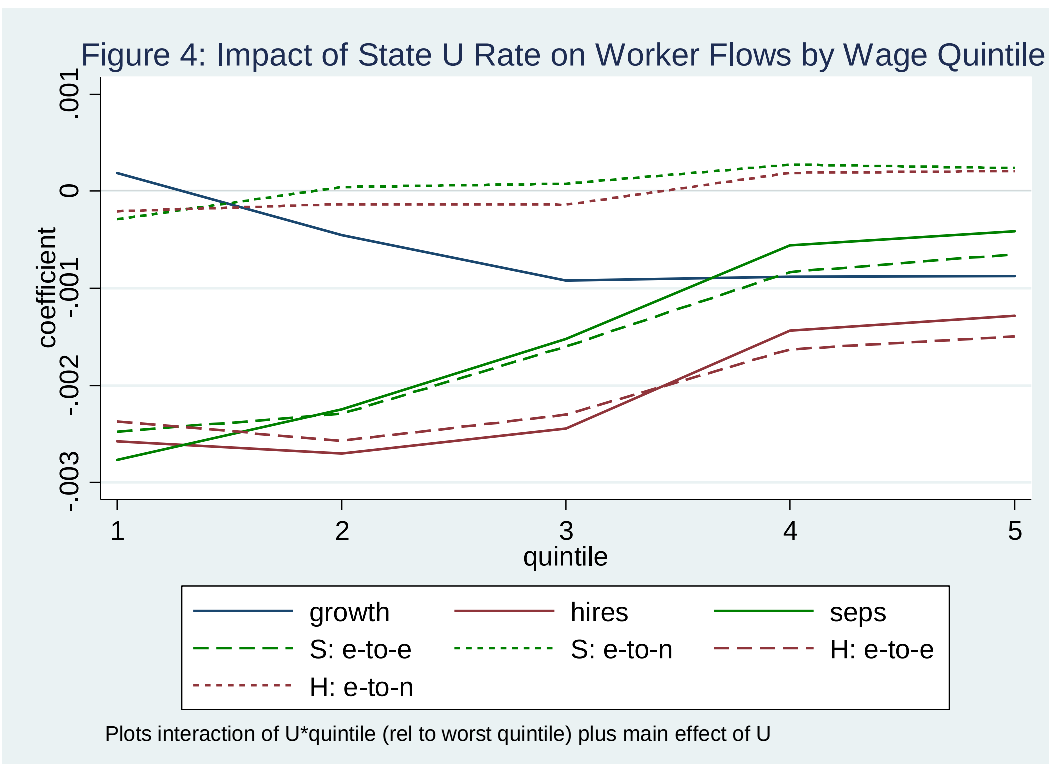


Figure 4: Impact of State U Rate on Worker Flows by Wage Quintile
coefficient
quintile
growth
hires
seps
S: e-to-e
S: e-to-n
H: e-to-e
H: e-to-n
Plots interaction of U*quintile (rel to worst quintile) plus main effect of U

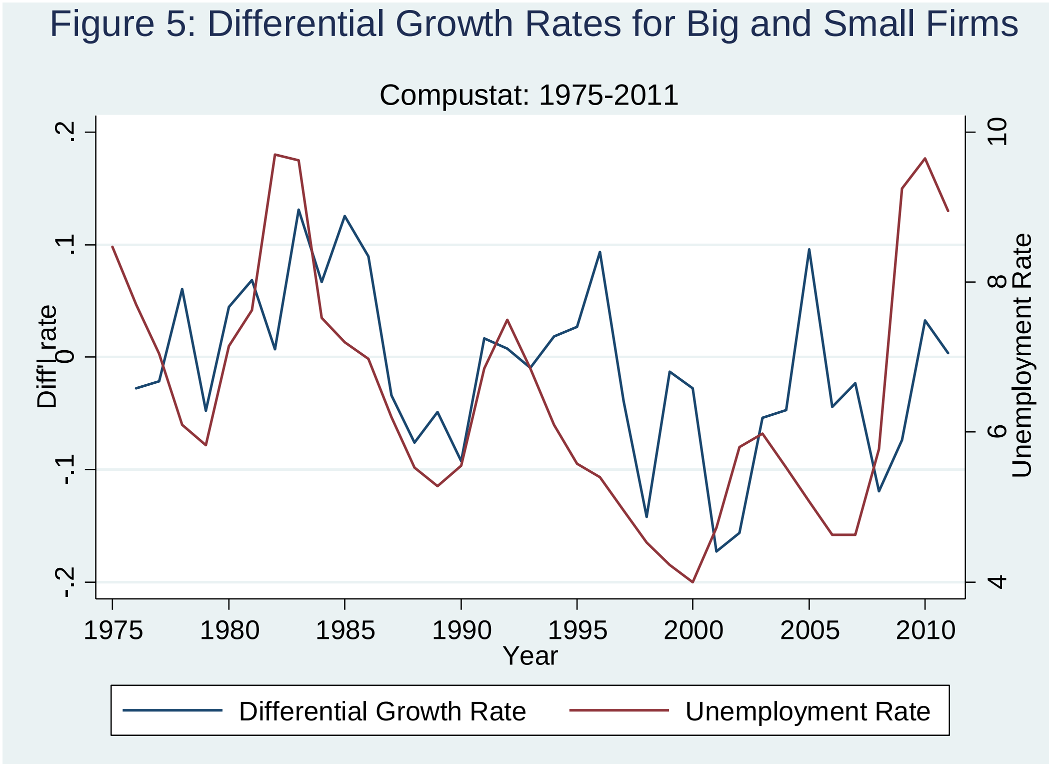


Figure 5: Differential Growth Rates for Big and Small Firms
Compustat: 1975-2011
Diff'l rate
Unemployment Rate
Year
-.2
-.1
0
.1
.2
4
6
8
10
1975
1980
1985
1990
1995
2000
2005
2010
Differential Growth Rate
Unemployment Rate

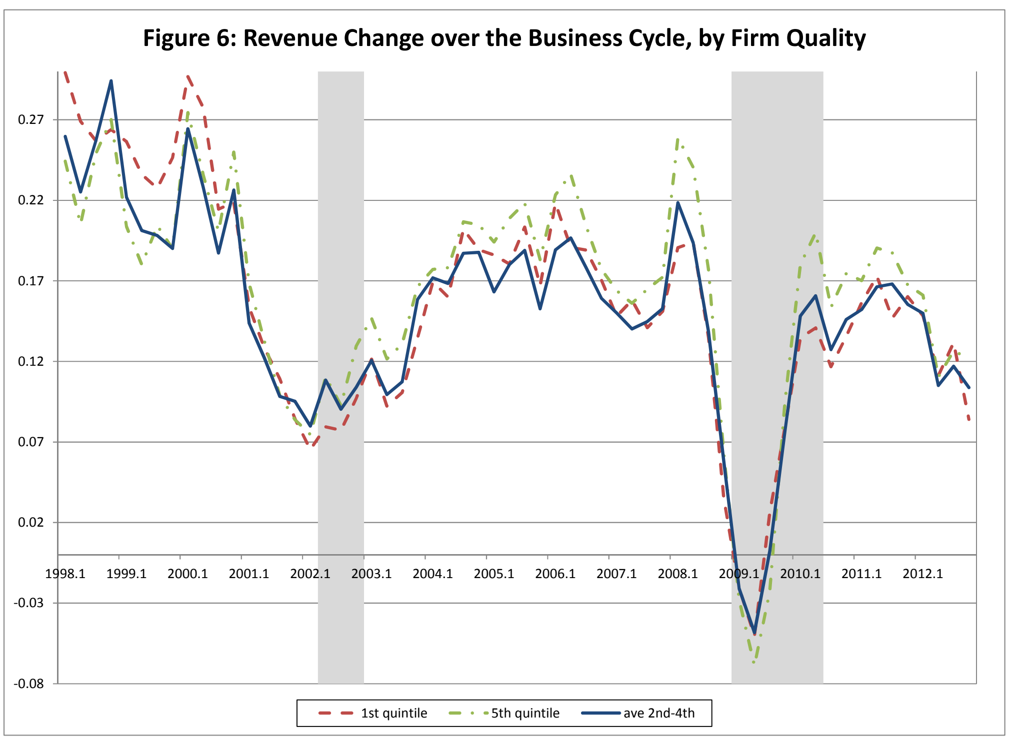


Figure 6: Revenue Change over the Business Cycle, by Firm Quality
0.27
0.22
0.17
0.12
0.07
0.02
-0.03
-0.08
1998.1
1999.1
2000.1
2001.1
2002.1
2003.1
2004.1
2005.1
2006.1
2007.1
2008.1
2009.1
2010.1
2011.1
2012.1
1st quintile
5th quintile
ave 2nd-4th

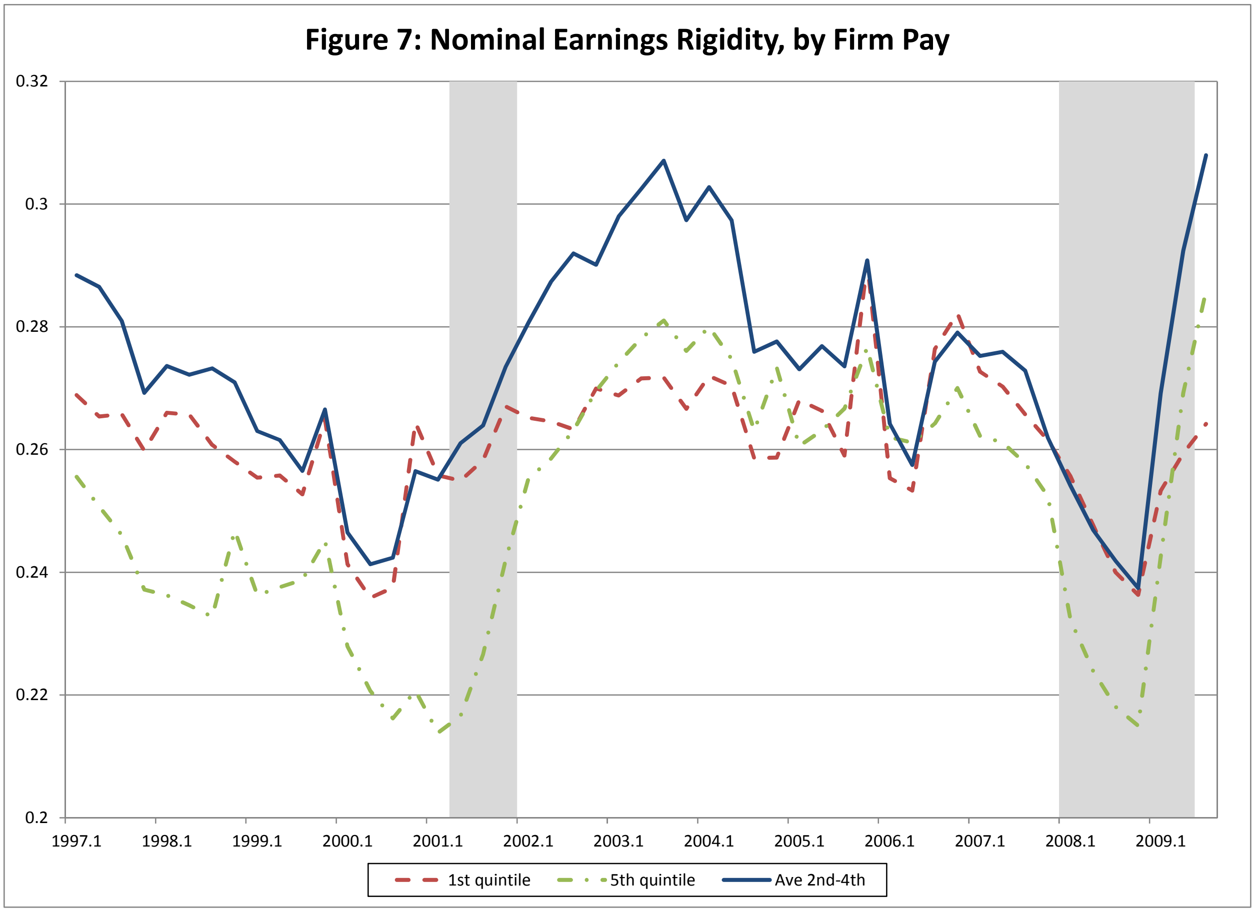


Figure 7: Nominal Earnings Rigidity, by Firm Pay
0.32
0.3
0.28
0.26
0.24
0.22
0.2
1997.1
1998.1
1999.1
2000.1
2001.1
2002.1
2003.1
2004.1
2005.1
2006.1
2007.1
2008.1
2009.1
1st quintile
5th quintile
Ave 2nd-4th

Table 1: Summary Statistics by Pay Quintile

	Wage Quintile				
	Lowest	2nd	3rd	4th	Highest
Growth Rate	0.0017	0.0014	0.0017	0.0015	0.0030
Separation Rate	0.203	0.158	0.130	0.117	0.107
Hire Rate	0.205	0.160	0.132	0.118	0.110
Sep-to-Employment	0.098	0.083	0.069	0.062	0.057
Sep-to-Non-Employment	0.106	0.075	0.061	0.055	0.050
Hire-from-Employment	0.092	0.081	0.070	0.065	0.063
Hire-from-Non-Employment	0.113	0.079	0.062	0.054	0.047
State U Rate	5.98	5.95	5.96	5.94	6.01
Average Monthly Earnings	$1,842.16	$2,754.87	$3,458.19	$4,354.70	$6,665.13
Churn distribution:					
Lowest	0.103	0.132	0.195	0.248	0.299
2nd	0.117	0.170	0.222	0.253	0.235
3rd	0.175	0.205	0.194	0.193	0.209
4th	0.239	0.228	0.213	0.154	0.155
Highest	0.366	0.264	0.177	0.152	0.102
Size distribution:					
<20	0.319	0.168	0.116	0.105	0.109
20-50	0.112	0.090	0.074	0.075	0.077
50-250	0.157	0.155	0.124	0.115	0.135
250-500	0.055	0.060	0.050	0.043	0.047
500+	0.358	0.526	0.637	0.662	0.632

Notes: Weighted by average employment over the quarter. Quintile cutpoints are state-industry (two-digit NAICS) specific.

Table 2: Growth Rates as a Function of Economic Conditions and Firm Characteristics	**I**	**II**	**III**	**IV**
Panel A: Regression Coefficients				
State Unemp Rate (U)	-0.000012	-0.000018	0.000189	0.000189
	[0.00020]	[0.00020]	[0.00036]	[0.00036]
U * 2nd pay quintile	-0.0007	-0.0007	-0.0007	-0.0006
	[0.00006]**	[0.00006]**	[0.00006]**	[0.00006]**
U * 3rd pay quintile	-0.0011	-0.0011	-0.0011	-0.0011
	[0.00010]**	[0.00010]**	[0.00010]**	[0.00010]**
U * 4th pay quintile	-0.0011	-0.0011	-0.0011	-0.0011
	[0.00011]**	[0.00011]**	[0.00011]**	[0.00011]**
U * 5th pay quintile	-0.0011	-0.0011	-0.0011	-0.0011
	[0.00009]**	[0.00009]**	[0.00009]**	[0.00009]**
Panel B: Elasticities				
1st wage quintile	-0.04	-0.06	0.65	0.65
2nd wage quintile	-2.91	-2.88	-2.00	-1.95
3rd wage quintile	-3.98	-3.96	-3.23	-3.20
4th wage quintile	-4.44	-4.41	-3.57	-3.52
5th wage quintile	-2.22	-2.20	-1.81	-1.78
Quarter fixed effects + time trend	X	X		
Churn and size controls		X		X
Date fixed effects			X	X

+ significant at 10%; * significant at 5%; ** significant at 1%

Notes: Regressions weighted by average employment over the quarter. All regressions control for quintile fixed effects, as well as state and two-digit NAICS industry fixed effects. Quintiles are obtained by averaging quarterly pay over the lifetime of the firm and fitting into the two-digit NAICS industry-state distribution weighted by employment. Standard errors in brackets are clustered at the state level. Coefficients from panel A are converted to elasticities in panel B by adding th emain effect of U to the relevant interaction term then multiplying and dividing by the quintile-specific average state unemployment rate and growth rate, respectively, from table 1.

Table 3: Hire and Separation Rates as a Function of Economic Conditions and Firm Characteristics								
	Dependent Variable:							
	Separation Rate				**Hire Rate**			
	I	II	III	IV	I	II	III	IV
Panel A: Regression Coefficients								
State Unemp Rate (U)	-0.00419	-0.00410	-0.00345	-0.00277	-0.00420	-0.00411	-0.00327	-0.00258
	[0.00051]**	[0.00033]**	[0.0012]**	[0.00086]**	0.00024	[0.0002]**	0.00031	[0.0003]**
U * 2nd quintile wage	0.00001	0.00051	0.00002	0.00052	-0.00065	-0.00014	-0.00063	-0.00013
	[0.00036]	[0.00017]**	[0.00036]	[0.00017]**	0.00029	[0.0003]	0.00026	[0.0002]
U * 3rd quintile wage	0.00101	0.00124	0.00101	0.00124	-0.00013	0.00012	-0.00010	0.00014
	[0.00042]*	[0.00033]**	[0.00042]*	[0.00033]**	0.00029	[0.0003]	0.00025	[0.0002]
U * 4th quintile wage	0.00210	0.00219	0.00211	0.00221	0.00100	0.00111	0.00103	0.00114
	[0.00050]**	[0.00037]**	[0.00050]**	[0.00037]**	0.00029	[0.0002]**	0.00025	[0.0002]**
U * 5th quintile wage	0.00236	0.00235	0.00237	0.00236	0.00129	0.00129	0.00129	0.00129
	[0.00056]**	[0.00036]**	[0.00056]**	[0.00036]**	0.00031	[0.0003]**	0.00027	[0.0002]**
Panel B: Elasticities								
1st wage quintile	-0.12	-0.12	-0.10	-0.081	-0.12	-0.12	-0.10	-0.075
2nd wage quintile	-0.16	-0.13	-0.13	-0.084	-0.18	-0.16	-0.15	-0.101
3rd wage quintile	-0.15	-0.13	-0.11	-0.070	-0.20	-0.18	-0.15	-0.110
4th wage quintile	-0.11	-0.10	-0.07	-0.028	-0.16	-0.15	-0.11	-0.072
5th wage quintile	-0.10	-0.10	-0.06	-0.023	-0.16	-0.15	-0.11	-0.070
Quarter FE's + time trend	X	X			X	X		
Churn and size controls		X		X		X		X
Date FE's			X	X			X	X

+ significant at 10%; * significant at 5%; ** significant at 1%

Notes: See notes to table 2.

Table 4a: Separation Rates as a Function of Economic Conditions and Firm Characteristics								
	Separations to Employment				**Separations to Non-Employment**			
	I	II	III	IV	I	II	III	IV
Panel A: Regression Coefficients								
State Unemp Rate (U)	-0.00425	-0.00420	-0.00286	-0.00248	0.000061	0.000104	-0.000591	-0.000289
	[0.00027]**	[0.00024]**	[0.00050]**	[0.00036]**	[0.00035]	[0.00027]	[0.00083]	[0.00068]
U * 2nd quintile wage	-0.00014	0.00017	-0.00012	0.00019	0.000150	0.000341	0.000141	0.000332
	[0.00019]	[0.00013]	[0.00018]	[0.00013]	[0.00022]	[0.00013]*	[0.00022]	[0.00013]*
U * 3rd quintile wage	0.00071	0.00086	0.00073	0.00088	0.000294	0.000374	0.000286	0.000366
	[0.00025]**	[0.00023]**	[0.00025]**	[0.00023]**	[0.00023]	[0.00018]*	[0.00023]	[0.00018]*
U * 4th quintile wage	0.00156	0.00162	0.00159	0.00164	0.000541	0.000577	0.000528	0.000563
	[0.00029]**	[0.00027]**	[0.00029]**	[0.00027]**	[0.00030]+	[0.00022]*	[0.00030]+	[0.00012]*
U * 5th quintile wage	0.00182	0.00183	0.00182	0.00183	0.000541	0.000523	0.000546	0.000527
	[0.00029]**	[0.00026]**	[0.00029]**	[0.00026]**	[0.00036]	[0.00024]*	[0.00036]	[0.00024]*
Panel B: Elasticities								
1st wage quintile	-0.260	-0.257	-0.175	-0.152	0.003	0.006	-0.033	-0.016
2nd wage quintile	-0.314	-0.289	-0.214	-0.164	0.017	0.035	-0.035	0.003
3rd wage quintile	-0.305	-0.288	-0.184	-0.138	0.035	0.047	-0.030	0.007
4th wage quintile	-0.259	-0.249	-0.123	-0.080	0.065	0.073	-0.007	0.030
5th wage quintile	-0.255	-0.249	-0.110	-0.068	0.073	0.076	-0.005	0.029
Quarter FE's + time trend	X	X			X	X		
Churn and size controls		X		X		X		X
Date FE's			X	X			X	X

+ significant at 10%; * significant at 5%; ** significant at 1%

Notes: See notes to table 2.

Table 4b: Hire Rates as a Function of Economic Conditions and Firm Characteristics								
	Hires from Employment				Hires from Non-Employment			
	I	II	III	IV	I	II	III	IV
Panel A: Regression Coefficients								
State Unemp Rate (U)	-0.00387	-0.00382	-0.00273	-0.00237	-0.000334	-0.000295	-0.000541	-0.000207
	[0.00033]**	[0.00031]**	[0.00062]**	[0.00048]**	[0.00037]	[0.00028]	[0.00072]	[0.00054]
U * 2nd quintile wage	-0.00047	-0.00021	-0.00045	-0.00020	-0.000186	0.000070	-0.000181	0.000074
	[0.00018]*	[0.00014]	[0.00017]*	[0.00014]	[0.00020]	[0.00012]	[0.00020]	[0.00012]
U * 3rd quintile wage	-0.00008	0.00006	-0.00007	0.00007	-0.000047	0.000061	-0.000040	0.000067
	[0.00019]	[0.00018]	[0.00020]	[0.00018]	[0.00024]	[0.00017]	[0.00024]	[0.00017]
U * 4th quintile wage	0.00066	0.00072	0.00069	0.00074	0.000337	0.000389	0.000344	0.000396
	[0.00026]*	[0.00025]**	[0.00025]*	[0.00025]**	[0.00030]	[0.00020]+	[0.00030]	[0.00020]+
U * 5th quintile wage	0.00084	0.00088	0.00084	0.00088	0.000450	0.000414	0.000451	0.000415
	[0.00027]**	[0.00027]**	[0.00027]**	[0.00027]**	[0.00034]	[0.00020]+	[0.00034]	[0.00021]+
Panel B: Elasticities								
1st wage quintile	-0.251	-0.248	-0.177	-0.154	-0.018	-0.016	-0.029	-0.011
2nd wage quintile	-0.318	-0.295	-0.233	-0.188	-0.039	-0.017	-0.055	-0.010
3rd wage quintile	-0.335	-0.320	-0.237	-0.196	-0.037	-0.023	-0.056	-0.013
4th wage quintile	-0.295	-0.285	-0.188	-0.150	0.000	0.010	-0.022	0.021
5th wage quintile	-0.291	-0.283	-0.181	-0.144	0.015	0.015	-0.011	0.027
Quarter FE's + time trend	X	X			X	X		
Churn and size controls		X		X		X		X
Date FE's			X	X			X	X

+ significant at 10%; * significant at 5%; ** significant at 1%

Notes: See notes to table 2.

Table 5: Worker Reallocation over the Business Cycle

Transistion Matrix in Boom							**Transistion Matrix in Bust**					
firm in t+1:	firm in t:						firm in t+1:	firm in t:				
	1	2	3	4	5			1	2	3	4	5
5	0.000	0.000	0.002	0.077	0.940		5	0.000	0.000	0.002	0.080	0.938
4	0.000	0.005	0.125	0.777	0.059		4	0.000	0.005	0.127	0.779	0.061
3	0.003	0.131	0.696	0.140	0.001		3	0.002	0.130	0.697	0.136	0.001
2	0.098	0.721	0.171	0.005	0.000		2	0.078	0.721	0.168	0.005	0.000
1	0.899	0.144	0.006	0.000	0.000		1	0.920	0.144	0.005	0.000	0.000
Expected Firm Pay in t+1:	$1,936	$2,724	$3,447	$4,399	$6,527			$1,917	$2,723	$3,452	$4,409	$6,520

Notes: Transition probabilities estimated based on ordered logit regressions from appendix table 1, column IV. Sample includes all workers with earnings in t and t+1. A boom is a 4.2% unemployment rate and a bust is a 10.4% unemployment rate.

Table 6: Firm Quality of New Matches over the Business Cycle

firm in t:	Boom	Bust
5	0.046	0.039
4	0.081	0.071
3	0.146	0.133
2	0.304	0.296
1	0.422	0.461
Expected Firm Pay:	\$2,782	\$2,695

Notes: Estimates based on ordered logit regressions from appendix table 2, column IV. Sample includes all workers who matched to firms in t. A boom is a 4.2% unemployment rate and a bust is a 10.4% unemployment rate.

Table 7: Worker Reallocation for New Matches over the Business Cycle

Transistion Matrix in Boom							Transistion Matrix in Bust					
firm in t+3:	firm in t:						firm in t+3:	firm in t:				
	1	2	3	4	5			1	2	3	4	5
5	0.010	0.031	0.072	0.181	0.650		5	0.010	0.032	0.073	0.176	0.575
4	0.036	0.099	0.194	0.326	0.246		4	0.034	0.101	0.194	0.322	0.288
3	0.088	0.192	0.269	0.258	0.069		3	0.084	0.194	0.269	0.261	0.089
2	0.241	0.325	0.281	0.161	0.026		2	0.234	0.325	0.281	0.165	0.035
1	0.625	0.352	0.184	0.074	0.009		1	0.638	0.348	0.183	0.076	0.013
Expected Firm Pay in t+3:	$2,346	$2,849	$3,369	$4,097	$5,730			$2,325	$2,859	$3,372	$4,071	$5,515

Notes: Transition probabilities estimated based on ordered logit regressions from appendix table 3, column IV. Sample includes all workers who matched to firms in t, with earnings in t+3. A boom is a 4.2% unemployment rate and a bust is a 10.4% unemployment rate.

Appendix Table 1: Worker Reallocation over the Business Cycle
Dependent variable: Firm pay quintile in t+1

	I	II	III	IV
State Unemp Rate (U)	-0.0429	-0.0423	-0.0392	-0.0403
	[0.0053]**	[0.0054]**	[0.0047]**	[0.0049]**
U * 2nd pay quintile	0.0401	0.0397	0.0403	0.0399
	[0.0064]**	[0.0064]**	[0.0064]**	[0.0064]**
U * 3rd pay quintile	0.0440	0.0433	0.0444	0.0438
	[0.0077]**	[0.0075]**	[0.0076]**	[0.0075]**
U * 4th pay quintile	0.0463	0.0455	0.0468	0.0461
	[0.0067]**	[0.0067]**	[0.0067]**	[0.0067]**
U * 5th pay quintile	0.0329	0.032	0.0333	0.0325
	[0.0084]**	[0.0084]**	[0.0084]**	[0.0084]**
2nd pay quintile	3.8164	3.8093	3.8156	3.8082
	[0.038]**	[0.038]**	[0.038]**	[0.038]**
3rd pay quintile	7.1956	7.1842	7.1939	7.1819
	[0.058]**	[0.058]**	[0.058]**	[0.058]**
4th pay quintile	10.887	10.8744	10.8851	10.8718
	[0.147]**	[0.148]**	[0.147]**	[0.148]**
5th pay quintile	16.1864	16.1712	16.1848	16.1692
	[0.19]**	[0.189]**	[0.188]**	[0.189]**
Intercept 5	-13.2991	-13.3564	-13.325	-13.3602
	[0.19]**	[0.195]**	[0.194]**	[0.195]**
Intercept 4	-9.0486	-9.1041	-9.0745	-9.1077
	[0.11]**	[0.115]**	[0.113]**	[0.115]**
Intercept 3	-5.5852	-5.6392	-5.6110	-5.6427
	[0.042]**	[0.041]**	[0.039]**	[0.040]**
Intercept 2	-1.9467	-1.9988	-1.9724	-2.0022
	[0.039]**	[0.039]**	[0.034]**	[0.035]**
Quarter fixed effects + time trend	X	X		
Worker Characteristics		X		X
Date fixed effects			X	X

+ significant at 10%; * significant at 5%; ** significant at 1%

Notes: Sample is all workers with earnings in t and t+1. We report estimates from ordered logits. Regressions also include state and industry fixed effects. When included, worker characteristics are a quadratic in age, a gender dummy, and job duration in quarters. Standard errors are clustered at the state level.

Appendix Table 2: Job Matches over the Business Cycle
Dependent variable: Firm pay quintile in t

	I	II	III	IV
State Unemp Rate (U)	-0.0173	-0.0173	-0.0257	-0.0257
	[0.0023]**	[0.0023]**	[0.0071]**	[0.0071]**
Intercept 5	-2.9008	-2.9017	-2.8321	-2.8328
	[0.059]**	[0.058]**	[0.092]**	[0.091]**
Intercept 4	-1.7933	-1.7943	-1.7245	-1.7252
	[0.077]**	[0.076]**	[0.104]**	[0.103]**
Intercept 3	-0.8431	-0.8441	-0.7741	-0.7748
	[0.119]**	[0.118]**	[0.142]**	[0.140]**
Intercept 2	0.4482	0.4473	0.5174	0.5166
	[0.147]**	[0.145]**	[0.165]**	[0.163]**
Quarter fixed effects + time trend	X	X		
Worker Characteristics		X		X
Date fixed effects			X	X

+ significant at 10%; * significant at 5%; ** significant at 1%

Notes: Sample is all new matches in t. We report estimates from ordered logits. Regressions also include state and industry fixed effects. When included, worker characteristics are a quadratic in age and a gender dummy. Standard errors are clustered at the state level.

Appendix Table 3: Firm Upgrading for New Matches
Dependent variable: Firm pay quintile in t+3

	I	II	III	IV
State Unemp Rate in t (U)	-0.00608	-0.00607	-0.00959	-0.00959
	[0.0039]	[0.0039]	[0.0026]**	[0.0026]**
U * 2nd pay quintile	0.0117	0.0117	0.0124	0.0124
	[0.0047]*	[0.0047]*	[0.0047]**	[0.0047]**
U * 3rd pay quintile	0.00943	0.00943	0.0102	0.0102
	[0.0073]	[0.0073]	[0.0073]	[0.0073]
U * 4th pay quintile	0.00313	0.00313	0.00402	0.00402
	[0.0058]	[0.0058]	[0.0058]	[0.0058]
U * 5th pay quintile	-0.0419	-0.0419	-0.0413	-0.0413
	[0.0099]**	[0.0099]**	[0.0099]**	[0.0099]**
2nd pay quintile	1.0684	1.0684	1.065	1.065
	[0.034]**	[0.034]**	[0.034]**	[0.034]**
3rd pay quintile	1.9609	1.9609	1.9569	1.9569
	[0.047]**	[0.047]**	[0.047]**	[0.047]**
4th pay quintile	3.0269	3.0269	3.0224	3.0224
	[0.073]**	[0.073]**	[0.073]**	[0.073]**
5th pay quintile	5.3448	5.3448	5.3422	5.3422
	[0.11]**	[0.11]**	[0.11]**	[0.11]**
Intercept 5	-4.4175	-4.4167	-4.3714	-4.3703
	[0.082]**	[0.082]**	[0.075]**	[0.075]**
Intercept 4	-2.8802	-2.8793	-2.8339	-2.8328
	[0.041]**	[0.042]**	[0.034]**	[0.035]**
Intercept 3	-1.7269	-1.726	-1.6806	-1.6795
	[0.041]**	[0.041]**	[0.045]**	[0.045]**
Intercept 2	-0.3759	-0.3751	-0.3294	-0.3284
	[0.047]**	[0.047]**	[0.044]**	[0.043]**
Quarter fixed effects + time trend	X	X		
Worker Characteristics		X		X
Date fixed effects			X	X

+ significant at 10%; * significant at 5%; ** significant at 1%

Notes: Sample is all new matches in t. We report estimates from ordered logits. Regressions also include state and industry fixed effects. When included, worker characteristics are a quadratic in age and a gender dummy. Standard errors are clustered at the state level.