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## ABSTRACT

In this paper, we use linked employer-employee data to study the reallocation of heterogeneous workers between heterogeneous firms. We build on recent evidence of a cyclical job ladder that reallocates workers from low productivity to high productivity firms through job-to-job moves. In this paper we turn to the question of who moves up this job ladder, and the implications for worker sorting across firms. Not surprisingly, we find that job-to-job moves reallocate younger workers disproportionately from less productive to more productive firms. More surprisingly, especially in the context of the recent literature on assortative matching with on-the-job search, we find that job-to-job moves disproportionately reallocate less-educated workers up the job ladder. This finding holds even though we find that more educated workers are more likely to work with more productive firms. We find that while more educated workers are less likely to match to low productivity firms, they are even less likely to separate from them, with less educated workers both more likely to separate to a better employer in expansions and to be shaken off the ladder (separate to nonemployment) in contractions. Our findings underscore the cyclical role job-to-job moves play in matching workers to higher productivity and better paying employers.

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# 1 Introduction

Economists have shown that large and persistent differences in productivity across producers prevail even within narrowly defined industries.[1] Accompanying this dispersion is a high pace of reallocation of outputs and inputs across firms within industries. In advanced economies like the United States, this reallocation has been shown to be productivity enhancing.[2] This is evident in the common finding that high productivity firms grow and low productivity firms contract and exit. A plausible explanation for the persistence of productivity dispersion across producers is that when there are intrinsic productivity differences across firms, adjustment frictions allow high and low productivity firms to co-exist in equilibrium. Search and matching frictions in the labor market are potentially one important source of these frictions.

Recent evidence (see Haltiwanger, Hyatt, and McEntarfer (2016), hereafter HHM)) suggests that job-to-job moves of workers play a substantive role in productivity enhancing reallocation of workers, especially during booms. They find that net employment growth is substantially higher for high productivity firms than low productivity firms, and on average most of this growth differential is accounted for by job-to-job flows. However, when a contraction occurs, it is flows between employment and nonemployment that play an important role in productivity enhancing reallocation. During recessions, job-to-job flow reallocation generally halts and firms shed employment through net nonemployment flows, with greater employment losses at lower productivity firms. Thus, the channel through which productivity enhancing reallocation of workers occurs varies over the cycle. During booms, the reallocation is mostly through job-to-job flows. In recessions, it is mostly through the nonemployment margin.

In this paper, we investigate who is moving up the job ladder. By job ladder, we mean the general tendency of job-to-job flows to move workers to more productive and higher

[1]New sources of producer-level data have resulted in a wealth of empirical research on productivity. While these papers are too numerous to cite here, Syverson (2011) provides an excellent overview.

[2]Some recent contributions to the macro development literature (see, e.g., Restuccia and Rogerson (2009), Hsieh and Klenow (2009) and Bartelsman, Haltiwanger, and Scarpetta (2013)) have investigated the hypothesis that misallocation accounts for much of the cross country variation in GDP per capita, as distortions in some countries yield a much weaker link between productivity and reallocation. This issue is not the focus of the current paper, but these findings highlight the importance of understanding the connection between productivity and reallocation.

paying firms. To do this, we study the reallocation of heterogeneous workers between heterogeneous firms using linked employer-employee data. By examining what types of workers are reallocated from less productive to more productive firms, we shed insight into the role job-to-job moves play in the labor market. Given the cyclical nature of the job ladder, this analysis also provides evidence on what types of workers are principally impacted when the job ladder collapses in recessions. We also investigate what types of workers fall off the ladder (i.e., exit to nonemployment) in contractions.

Our findings can also be used to assess the predictions of key macro models of the labor market. A useful starting point is to compare and contrast the approaches of Mortensen and Pissarides (1994, hereafter MP) relative to those of Burdett and Mortensen (1998) and more recently Moscarini and Postel-Vinay (2009, 2012, 2013, 2016, hereafter MPV). MP and subsequent extensions of their framework with multiple worker firms (see, e.g., Cooper, Haltiwanger, and Willis (2007) and Elsby and Michaels (2013)) emphasize the role of idiosyncratic productivity shocks in inducing productivity enhancing reallocation via flows to and from nonemployment. Firms with low productivity draws contract, while those with positive productivity draws (as well as entering firms) expand. In these models, productivity enhancing reallocation is countercyclical. Low productivity firms are more likely to contract in recessions leading to a burst of job destruction, and the decline in labor market tightness in contractions dampens the decline in job creation that would otherwise occur given the economic contraction.[3]

In contrast, the models of Burdett and Mortensen (1998) and MPV focus on the reallocation of workers through job-to-job flows. These models usually abstract from idiosyncratic productivity shocks but rather focus on permanent productivity differences across firms.[4] Such permanent productivity differences yield an equilibrium size distribution that is the result of exogenous separations along with search and matching frictions. These models yield an equilibrium where unemployed workers find it advantageous to take any job offer.

[3] These models are closely connected to canonical firm dynamic models such as Hopenhayn (1992) and Hopenhayn and Rogerson (1993) but with explicit focus on search and matching frictions. It is the latter that provides insights about the nonemployment margin and the cyclicality of productivity enhancing reallocation.

[4] One exception is the model proposed by Coles and Mortensen (2016), who incorporate firm entry and exit, as well as productivity shocks, into a random search framework. While they develop idiosyncratic firm-specific uncertainty, they do not incorporate aggregate uncertainty and so do not consider business cycles.

As such, workers may find themselves at small, low wage, low productivity firms and seek to move up the job ladder if they can obtain an offer from a large, high wage, high productivity firm. MPV show that this movement up the ladder will be procyclical. During booms, all firms want to expand, but high productivity firms are less constrained in their ability to expand because they can poach workers from firms lower on the ladder through higher wage offers. An implication is that such productivity enhancing reallocation via the ladder will be procyclical. These models have richer labor market dynamics than the MP type models since on-the-job search is incorporated but variants of these models that include business cycles such as MPV and Lise and Robin (2017) have so far not incorporated endogenous job destruction due to firm-specific productivity shocks.[5]

In our earlier paper, we show that both of these perspectives have some support in the data. Job-to-job flows do tend to move workers from low productivity firms to high productivity firms. Moreover, such movements up the job ladder are highly procyclical.[6] However, HHM also find that reallocation from low productivity firms to high productivity firms via the nonemployment margin increases in recessions. This is mostly driven by sharp contractions at low productivity firms in recessions. This sharp increase in job destruction at low productivity firms yields a flow into nonemployment during economic contractions is consistent with the predictions of MP models.

Both MP and MPV assume worker homogeneity and thus are silent about what types of workers move up the job ladder. But recent search and matching papers such as Bagger and Lentz (2016), Lopes de Melo (2016), Lise and Robin (2017), and Hagedorn, Law, and Manovskii (2017) present model estimates that imply that worker flows will be characterized by positive assortative matching, i.e., more matching between high type workers and high type firms. These papers have generally found that there is little to be gained or even much to be lost from lower type workers moving to higher type firms. In this rich and developing literature, Lise and Robin (2017) is especially interesting because of its predictions concerning how match quality varies over the business cycle (most search and matching models of

[5]Schaal (2015) incorporates idiosyncratic firm-specific uncertainty and aggregate uncertainty into a model of on-the-job search, but uses a directed search framework, as opposed to the random search framework that is more of our focus in this paper. His model also does not incorporate worker heterogeneity in productivity and therefore does not generate predictions regarding labor market sorting.

[6]Haltiwanger et al. (2016) present related evidence that movements up the firm wage ladder are procyclical, but find relatively little evidence of a firm size ladder.

assortative matching lack a cyclical component). They propose a model of random search in which initial matches coming out of unemployment are relatively poor, and workers move into better matches over time. This movement into better matches intensifies in booms, but the relatively high movements of workers out of unemployment has an offsetting effect in that more relatively poor matches are also created during booms. Downturns also have a "cleansing" effect in that it is the least productive workers, the least productive firms, and the most marginal matches that are no longer viable.[7]

Our results can help to assess the implications of such search and matching models. Overall, our findings are generally consistent the predictions generated by this family of models. We find that within detailed industries, high productivity firms have a larger share of college-educated workers than low productivity firms, a finding that is consistent with positive assortative matching in labor markets. In booms, the propensity of all workers to move up the ladder increases, while matches at the least productive firms are more likely to terminate in recessions. Our results by worker age suggest that lifecycle dynamics are quite important, with job-to-job moves reallocating young workers disproportionately from lower rungs of the job ladder. We also find that less-educated and younger workers more likely flow into nonemployment during downturns, especially at low productivity firms.

However, we do not find evidence that job-to-job moves increase assortative matching between worker and firm types. Surprisingly, we find instead that job-to-job moves play a relatively more important role in reallocating less-educated workers up the job ladder, particularly during expansions. This reallocation is most dramatic at the bottom of the job ladder, where job-to-job moves reallocate a disproportionate number of less-educated workers from low productivity firms to better performing employers. While highly educated workers as well as less-educated workers are poached, much of the growth dispersion between high and low productivity firms during expansions is fueled by workers without college degrees moving up from lower rungs of the ladder. In contractions, the growth dispersion is fueled through greater job destruction at low productivity firms, where job destruction is concentrated

[7] These "cleansing" and "sullying" features of Lise and Robin (2017) are similar to those of Barlevy (2002), although the latter paper focused only on worker-firm complementarity and did not assume that any workers or firms were more intrinsically more productive than any others. By contrast, Lise and Robin (2017), like several other recent models of labor market sorting, rank workers and firms based on a univariate dimension of productivity, treating the nature of the complementarity between workers and firms of different ranks as a question of interest.

among less-educated workers. Our findings here may indicate that high productivity firms have an absolute advantage for workers regardless of type; that is, most workers are more productive when matched to better firms.

The greater propensity of less-educated workers to move up the ladder may seem counterintuitive, given that we also find evidence of positive assortative matching (more highly educated workers at highly productive firms). But workers with college degrees have lower rates of turnover generally, even at less productive employers. So although they are less likely to be matched with less productive firms, they are also less likely to leave less productive firms (relative to their less-educated coworkers) for other employers in expansions, leading to lower reallocation rates. One possibility is that workers with college degrees are more specialized (i.e., their productivity has larger job-specific match effects) making them less likely to find a better match simply by moving to a more productive firm.

In canonical models of the labor market, more productive firms also pay higher wages. Thus we might expect similar patterns of worker reallocation if we instead rank firms by pay instead of productivity. However, there are reasons to expect a less than perfect correspondence between productivity rank and wage rank in our data. In particular, our ranking of firm productivity is within narrowly-defined industries. A worker moving between a low productivity retail job and a higher productivity retail job may remain a low wage worker, even if wages are higher at the more highly-ranked firm. In an online appendix, we repeat our analysis, this time ranking firms by average worker pay, across all industries. Our main results ranking firms by productivity are robust to ranking firms instead by wages. Younger and less-educated workers are more likely to remain stuck in low-paying firms in recessions, and employment growth in higher paying firms in expansions is fueled disproportionately by younger and less-educated workers moving up from lower-paying employers.

The paper proceeds as follows. Section II describes the data. Section III presents empirical results on the who has been moving up the job ladder in recent years. Section IV presents concluding remarks.

## 2 Data

We use linked employer-employee data from the Longitudinal Employer-Household Dynamics (LEHD) program at the U.S. Census Bureau to examine the flows of workers across firms. The LEHD data consist of quarterly worker-level earnings submitted by employers for the administration of state unemployment insurance (UI) benefit programs, linked to establishment-level data collected for the Quarterly Census of Employment and Wages (QCEW) program. As of this writing, all 50 states, DC, Puerto Rico, and the Virgin Islands have shared QCEW and UI wage data with the LEHD program as part of the Local Employment Dynamics federal-state partnership. LEHD data coverage is quite broad; state UI covers 95 percent of private sector employment, as well as state and local government.[8] The unit of observation in the UI wage data is the state-level employer identification number, which typically captures the activity of a firm within a state in a specific industry.

The LEHD data allow us to decompose employment growth by worker hires and separations. We use an exact decomposition of hires and separations due to a job-to-job flow (what we equivalently call a "poaching flow") and hires and separations from nonemployment. This approach links the main job in each quarter of an individual worker's employment history. When a worker separates from a job and begins work at a new job within a short time period, we classify it as a job-to-job flow. Transitions between jobs which involve longer spells of nonemployment are classified as flows to and from nonemployment.[9]

A challenge for the identification of job-to-job flows in the LEHD data is that the administrative data do not provide enough information to identify why a worker left one job and began another. We only have quarterly earnings, from which we infer approximately when workers left and began jobs. Although information on precise start and end dates would be helpful, it would be insufficient to identify voluntary flows between jobs since workers switching employers may take a break between their last day on one job and their first day on a new job. Our definition of job-to-job flows includes all job transitions where the

[8] For a full description of the LEHD data, see Abowd et al. (2009).

[9] Our data universe differs slightly from that used in the recently released public use Census Job-to-Job Flows data, which publishes quarterly worker flows for workers employed on the first day of the quarter, see Hyatt et al. (2014). By using all workers employed during the quarter in our sample, our worker flows have higher levels but almost identical trends as the public use data.

corresponding job end and job start are within the same quarter or in adjacent quarters.[10]

For firm productivity, we use a new firm-level database on productivity from Haltiwanger et al. (2017) based on the revenue and employment data from the Census Business Register and the Longitudinal Business Database.[11] Since the underlying revenue and employment data are from the Census Business Register, this database offers much wider coverage of labor productivity at the firm level than earlier studies that focused on sectors like manufacturing or retail trade. These data allow us to measure the log of real revenue per employee on an annual basis with wide coverage of the private, non-farm (for profit) firms. Revenue is deflated with the GDP price deflator.

Our measure of productivity is gross output per worker, which is commonly used to measure productivity at the micro and macro level, but a relatively crude measure compared to Total Factor Productivity (TFP). However, this measure of labor productivity has been shown to be highly correlated with TFP measures within industries. Specifically, Foster, Haltiwanger, and Krizan (2001) and Foster, Haltiwanger, and Syverson (2008) find that the correlation between TFP and gross output (revenue) per worker within detailed industry year cells is about 0.6. In our analysis, we use revenue labor productivity deviated from industry by year means, and also the percentile and quintile rank of revenue labor productivity within detailed industries. We show later in this paper that the former is highly predictive of the growth and survival of firms.

While our revenue data offers much wider coverage than earlier studies, there are some gaps. One reason is that, for non-profits, revenue data coverage is incomplete and erratic.[12] Another reason is the complexity of matching revenue data to the Census business frame, which is based on federal payroll tax records. Most of the matches between the payroll

[10] Haltiwanger, Hyatt, and McEntarfer (2015) compare this definition to two alternative definitions of job-to-job moves that are more restrictive: including only transitions where the job end and start are in the same quarter, and an alternative definition which uses the worker's earnings history to identify job-to-job transitions with earnings gaps (and recode them to nonemployment flows). They find that each of the different measures is highly correlated (pairwise correlations of about 0.98) and each of the LEHD based job-to-job flow series has a correlation of about 0.96 with CPS based job-to-job flows. Based upon the robustness analysis in our earlier paper, we are confident our main results are not sensitive to which set of rules we use to distinguish between employment flows and job-to-job moves.

[11] For additionaldetails of the link between LEHD and the Longitudinal Business Database, see Haltiwanger et al. (2014).

[12] We are using the first vintage of the data from Haltiwanger et. al. (2017), which explicitly excludes NAICS 81, which is Other Services. This industry is very heterogeneous, including non-profits such as religious organizations where productivity is not well defined.

tax and revenue data are via Employer Identification Numbers (EINs). Firms, however, can use different EINs for filing income taxes and filing quarterly payroll taxes.[13] For such firms, name and address matching is required. Haltiwanger et al. (2017) also show that the missingness of revenue is only weakly related to industry, firm size, or firm age characteristics. We are able to construct measures of labor productivity at the firm (operational control) level given that the Census Business Register has a complete mapping of all EINs owned by any given parent firm.

Even with these limitations, we have revenue per worker matched to the LEHD data for more than 4 million firms in each year. For the firms in the LEHD data with no match to the productivity data, we create a missing productivity category (we find no systematic patterns of workers to and from the firms with missing productivity). To mitigate concerns about the effect of other sources of measurement error on our results we use within-industry productivity ranks for our main analysis, defined at the 4-digit NAICS level. Specifically, we compute the employment-weighted quintiles of the (within-industry year) productivity distribution. Using these quintiles, we define high productivity firms as those in the top quintile and low productivity as those in the bottom quintile.[14]

Information on the characteristics of the workers moving across firms comes from the LEHD data. The worker characteristics that are the focus of this paper are age and educational attainment. Worker age in the LEHD data is sourced from the 2000 Decennial Census and Social Security administrative data. These two rich sources of data provide age (and sex) for over 98 percent of workers in the LEHD data. In our analysis, we use four age categories: less than 25 years old, 25-34, 35-44, and age 45 or older. The rate of job change declines quite rapidly as workers age, with the highest rates of job change in workers' teens and twenties, and dropping off quite sharply once workers are in their thirties. Thus we have

[13] Another source of mismatch is sole proprietors file income taxes on their individual income tax returns while payroll taxes are filed via their EIN. Administrative data are available that links the EINs to the filers via the SS-4 form (application for EINs). While this information is incorporated in the Census Business Register, it is imperfect.

[14] Another limitation of our firm-level productivity measure is that it only reflects relative productivity of the firm within an industry. We know that there are high degrees of industry switching in the job-to-job flows that may reflect movements up the productivity ladder based on inter-industry differences in productivity. To capture such inter-industry productivity differences, HHM use data from the Bureau of Economic Analysis on value added per worker on an annual basis. They rank industries in each year by employment-weighted quintiles of the value added per worker at the industry level. They find that workers also move up the between industry productivity ladder and that such moves are procyclical.

more age categories in the early stages of workers' careers.

Our source data for educational attainment is the 2000 Decennial Long Form, a one-in-six person sample of individuals in the United States. For respondents who are age 25 or older on April 1, 2000 (the reference date for the Census 2000), we use the reported educational attainment in our analysis; this is approximately 10 percent of workers in the LEHD data. For the remaining 90 percent of workers, educational attainment at age 25 is imputed into four categories (less than high school, high school, some college, and Bachelor's degree or more, the latter of which we abbreviate as "college graduate" in what follows) using all available information about the worker in the administrative data - in particular, race, ethnicity, gender, demographics of their neighbors and co-workers, and complete earnings history.[15] While this is admittedly a very large share of workers with imputed education, analysis of the LEHD education variable shows that it performs quite well within-sample. The education classification we use is the same as that used for the public domain Quarterly Workforce Indicators (QWI) data product released by the Census Bureau.[16]

There are some additional limitations of the LEHD data that should be noted. First, employment coverage in the LEHD data is broad, but not complete, and in some cases regardless of approach we will erroneously classify a job-to-job transition as a flow to (or from) nonemployment. This includes flows to and from federal employment (approximately 2 percent of employment) and to parts of the non-profit and agriculture sectors. We will also misclassify some transitions that cross state boundaries. We start our time-series of the decomposition of net job flows in 1998, when there is data available for 28 states, and states continue to enter the LEHD frame during our time series.[17] Our 28 states include

[15]While workers can, of course, return to school after the age of 25, Bachelor's degree attainment drops offs sharply after age 25; the overwhelming majority of workers who obtain a Bachelor's degree have done so by this age.

[16]While this is the classification used for the QWI, the share of workers by age and educational attainment in the QWI deviates from the patterns of alternative sources such as the CPS or ACS in recent years. In particular, the QWI has lower educational attainment for young workers compared to the CPS and ACS. This is possibly due to the Great Recession lowering returns to education for young workers. We don't think this is a substantial issue for our analysis since we are mostly interested in the relative ranking of workers by education and we think the impute is likely to get the relative ranking of education right if not the absolute level. We also note that workers who have not yet reached age 25 by 2013 (the last year of our data) are dropped from all of our reported education analysis. We keep track of such workers in a separate category but don't report the patterns for this group.

[17]Our 28 states are CA, FL, GA, HI, ID, IL, IN, KS, ME, MD, MN, MO, MT, NC, NJ, ND, NM, NV, PA, OR, RI, SC, SD, TN, VA, WA, WI, and WV. Other states have data series that start in subsequent years. While we restrict our analysis to a pooled 28-state sample, we do allow flows into and out of that

many of the largest states so that our sample accounts for 65 percent of national private sector employment. This implies that our analysis is based on tracking more than 65 million workers every quarter – given the large sample any differential flow estimates across firm type, worker type and time are very precisely estimated. We note that our analysis of job-to-job flows using firm size and firm wage are for the entire 1998-2011 period. When we use firm productivity data, our analysis is restricted to the 2003-2011 period given the productivity data are only available starting in that period on a year-to-year basis.

# 3 Results

## 3.1 Firm-Level Productivity Dispersion and Firm Dynamics

We begin by exploring the nature of firm-level differences in productivity across firms in the same industry. Our measure of revenue labor productivity exhibits a number of the key features that Syverson (2011) emphasized are common in the literature on firm productivity and dynamics. First, we find tremendous dispersion of revenue labor productivity within narrowly defined industries. The within-industry/year standard deviation of log real revenue per worker is about 0.75. This is in the range of labor productivity dispersion indices reported by Syverson (2004). Second, we find that while the productivity differences across firms are persistent they are subject to innovations each period. Estimating a first order AR1 specification on the annual firm-level data of log real revenue per worker yields an persistence coefficient of 0.70 (with a standard error of 0.00001) and a standard deviation of innovations of 0.50. Third, we find that log real revenue per worker is highly predictive of firm growth and survival. Table 1 reports simple regressions of the relationship between productivity, growth and survival.[18] We consider two dependent variables for all incumbents in period $t-1$. The first dependent variable is the Davis, Haltiwanger, and Schuh (1996)

sample to be identified as poaching flows as data for states becomes available. For example, data for Ohio becomes available in 2000 so that if a worker changes employers from a firm in Ohio to one in New Jersey after 2000 this will be classified as a poaching hire in New Jersey, even though Ohio is not in the sample. By 2004 almost all states have data available so one might be concerned that the time series patterns may be noisier in the early years of our sample. Our analysis presented below suggests otherwise and more thorough analysis by Henderson and Hyatt (2012) shows that the omission of states has a discernible but small effect on job-to-job flow rates.

[18] For this analysis, we don't restrict the sample to those firms that match to the LEHD data infrastructure. These regressions use more than 40 million firm-year observations from the Census Business Register.

firm-level growth rate of employment that is inclusive of firm exit from $t-1$ to $t$.[19] The second dependent variable is an exit indicator that takes on the value of one if the firm exits between $t-1$ and $t$ and is zero otherwise. We use a linear probability model for this second specification. Firm exit and growth is organic growth and exit in the manner defined by Haltiwanger, Jarmin, and Miranda (2013) (i.e., it abstracts from changes in ownership or merger and acquisition activity).

We regress these two outcomes on the deviation of within-industry log productivity in $t-1$ and on log size in $t-1$ (i.e., log firm employment in $t-1$). While these are simple reduced form specifications, these specifications are consistent with standard models of firm growth and survival since these are proxies for the two key state variables for the firm in making growth and survival decisions. The canonical model implies that, holding initial size constant, a firm with higher productivity is more likely to grow and less likely to exit. We find overwhelming evidence in support of these predictions in Table 1. A one standard deviation increase in within-industry productivity yields a 21 percentage point increase in net employment growth and 5 percentage point decrease in the likelihood of exit. This evidence gives us confidence to proceed with our measure of revenue labor productivity since we produce patterns that others have found using TFP measures in sectors such as manufacturing. In line with the existing literature, our findings on the tight relationship between firm productivity, growth and survival are consistent with the hypothesis that there are intrinsic differences in productivity across firms that help account for the ongoing high pace of jobs across firms. In addition, such intrinsic differences in productivity have implications for worker reallocation including the potential role of a productivity job ladder.

Before turning to the implications for worker reallocation, we investigate the relationship between productivity differences across firms in the same industry and differences in the mix of workers across firms. As noted above, in what follows we use quintiles of the employment-weighted within-industry firm productivity distribution to classify firms. Consistent with that approach, in Table 2 we report the results of regressing the percentile rank of a firm in the within-industry firm productivity distribution on the shares of workers in age, gender and

[19] This measure is given by $g_{it} = (E_{it} - E_{it-1})/(0.5 * (E_{it} + E_{it-1}))$. As discussed by Davis, Haltiwanger, and Schuh (1996), it is a second order approximation to a log first difference that accommodates entry and exit.

education cells. Since we are interested in the employment-weighted distribution we estimate a weighted regression using employment weights of the firm. We find that firms with a higher share of more educated workers, young workers (less than 45), and males are more productive. For example, a one percentage point increase in the share of college graduates at a firm is associated with a 0.64 increase in the percentile rank. Overall, these observable worker characteristics account for only 11 percent of the within-industry dispersion in productivity across firms measured using these percentile ranks. These findings are broadly consistent with related findings in the literature (see, e.g., Abowd et. al. (2005) and Lentz and Mortensen (2010)) that show that only a small fraction of within-industry productivity differences across firms is accounted for by variation in indicators of worker quality. Our approach only uses observable characteristics across firms but Abowd et. al. (2005) use unobservable characteristics based on AKM-style decompositions of worker wages into worker and firm fixed effects.[20]

We draw a number of related inferences from this last exercise and related findings in the literature. First, since most of the variation in productivity across firms is not accounted for by worker characteristics, we interpret this as additional evidence that there are intrinsic differences across firms. The evidence that measured productivity and growth and survival are so closely associated is, as noted, also relevant evidence for this inference. Second, the positive association with measured productivity and worker education is consistent with some positive assortative matching.[21] Third, we also note that we find that the classification of firms into quintiles is robust to using either the original distribution of productivity across firms or using the residuals from the regressions in Table 2 to classify firms. In the results that follow, we examine the patterns of flows of workers by education and age across firms ranked by productivity. Since this ranking is robust to using the residuals from Table 2, this implies that we can interpret our findings as showing the direction and propensity of flows by worker type to firm rankings that are orthogonal to the overall shares of observable

[20] Barth, Davis, and Freeman (2016) provide evidence that more skilled workers are at larger and more capital intensive firms. They also present evidence that workers move up the firm wage job ladder over a five-year horizon. Their focus is more on the lower frequency, cross sectional patterns in the data so they, for example, do not examine the patterns of high frequency direct job-to-job flows.

[21] Of course, our estimates may suffer from the problem of attribution, and so high productivity firms may only appear to be high productivity because of an aspect of worker or firm productivity that we do not measure, see Eeckhout and Kircher (2011).

worker characteristics by age, gender, and education at the firm. Put differently, this permits interpreting our findings in what follows as capturing the direction and nature of flows of workers by worker type to firms by firm type (where the latter is the firm productivity differences that are orthogonal to observable worker characteristics).

## 3.2 Worker Reallocation and Productivity Differences Across Firms

To understand how job-to-job moves reallocate workers from one set of firms to another, we start with the following identity:

$$NetJobFlows(NJF) = H - S = (H_p - S_p) + (H_n - S_n) \tag{1}$$

where $H$ is hires, $S$ is separations, $H_p$ is poaching (job-to-job) hires, $S_p$ is poaching separations (workers that separate via a job-to-job flow), $H_n$ is hires from nonemployment and $S_n$ is separations into nonemployment.[22] In implementing this decomposition empirically, we convert all flows to rates by dividing through by employment. All of the aggregate series we use in this section have been seasonally adjusted using X-11.

In the aggregate economy, net job flows are driven by flows to and from employment, $H_n$ - $S_n$, and poaching hires and poached separations are equal, so $H_p$ - $S_p = 0$. However, across groups, net poaching can be positive or negative. Both job-to-job flows and nonemployment flows are important components of overall worker reallocation. About half of total worker reallocation (hires plus separations) is due to job-to-job flows; the remainder is due to hires from nonemployment and separations to nonemployment.[23] Since the overall pace of worker reallocation is very large (about one fourth of employment each quarter) both components are important for understanding the dynamics of the labor market. We now turn to their respective contributions to productivity enhancing reallocation.

[22] We use the term "poaching" to describe job-to-job flows since it is consistent with the terminology of wage posting job ladder models, and it also facilitates recognizing that a given type of firm (e.g., high productivity) may have workers that are hired by that firm via a job-to-job flow and separate from that firm via a job-to-job flow. It is convenient expositionally to refer to the former as a poaching hire and the latter as a poaching separation.

[23] The fraction of worker reallocation due to job-to-job flows is sensitive to the definitions of job-to-job flows. The alternative definitions yield a level shift in job-to-job flows but as shown in HHM the alternatives are very highly correlated. Across the methods, job-to-job flows account for on the order of one third (within quarter only) to half (within/adjacent quarter) of worker reallocation.

To investigate productivity enhancing reallocation, we consider the above decomposition for high vs. low productivity firms. For firms of type $Y$, we compute $H_p(Y) - S_p(Y)$ and $H_n(Y) - S_n(Y)$ where $Y$ is either high or low productivity firms. We express these flows as rates by dividing through by employment for firms of type $Y$. Using this approach, Table 3 provides time series averages of the components of this decomposition for high and low productivity firms.[24] The most productive firms have overall positive net employment growth on average and net poaching $H_p$ - $S_p$ is positive. In contrast, the least productive firms have overall negative employment growth on average and poaching is negative. Net hires from nonemployment is also slightly negative for the lowest productivity firms. Taking the differential in the net job flows, Table 3 implies that net employment growth for high productivity firms is 1.5 percentage points per quarter higher than low productivity firms on average. More than 80 percent is due to job-to-job flows.

HHM show that these average patterns mask important cyclical fluctuations. The net job flow differential between high and low productivity firms during the boom of 2004-2006 was 1.5 percentage points per quarter with virtually all accounted for by job-to-job flows. During that boom period, low productivity firms lost 1 percent of workers to more productive firms each quarter but only contracted by about -0.7 percent since such firms had positive net hiring from nonemployment. During the sharp contraction of 2007:4-2009:2, the net job flow differential between high and low productivity firms was about 1.4 percentage points. However, in this period, about half of this was due to differentials in net hiring from nonemployment. Both high and low productivity firms shed workers to nonemployment during that period, but low productivity firms shed more.

Before proceeding to the main focus of this paper, it is instructive to emphasize that, for the most part, we focus on the net poaching flows and net nonemployment flows across firm types and worker types. However, as is evident from Table 3, there are large and important gross poaching flows and gross flows to and from nonemployment. The gross flows are very large relative to the net flows. Moreover, gross flows are higher at low productivity compared to high productivity firms. Low productivity firms are not only net losers of jobs but they are much more volatile in terms of a high pace of hires and separations. Also, as emphasized in HHM, the gross poaching flows largely reflect a within firm type flow. That

[24] These results are time series averages of quarterly patterns reported in HHM.

is, high productivity firms poach heavily from high productivity firms and the same holds for low productivity firms. For our purposes, we are mostly interested in the directional patterns of the net poaching flows (i.e., are workers on net moving up the ladder and, if so, what types of workers are on net moving up the ladder) and the directional patterns of the net nonemployment flows (i.e., how these net flows vary by firm type, the cycle, and worker type). While we focus on the net poaching and net flows from nonemployment, it is useful to understand the respective roles of the hires and separations margins especially with respect to the flows to and from nonemployment. In what follows, we provide some evidence of the cyclical patterns of these flows. In so doing, we are able to explore whether firm and worker types that exhibit net flows to nonemployment in recessions are doing so via an increase in separations or a decline in hires.

## 3.3 Who Moves from Low Productivity to High Productivity Firms?

With these patterns as background, we now turn to decomposing the net poaching and net hires from nonemployment by worker education and worker age. For firm type $Y$ and worker type $X$, we compute the net employment gain of type $X$ workers at type $Y$ firms as the sum of two components:

$$NetPoachingFlows(Y, X) = H_p(Y, X) - S_p(Y, X) \tag{2}$$

$$NetNonemploymentFlows(Y, X) = H_n(Y, X) - S_n(Y, X), \tag{3}$$

where $Y$ indicates either high or low productivity firms and $X$ is a specific worker age or education group. For most of our analysis, we express these flows as rates. We calculate these rates both as fractions of employment at $Y$ type firms and as fractions of type $X$ group employment. For example, for net poaching flows, the corresponding rates are:

$$NetPoachingRate(Y, X) = [H_p(Y, X) - S_p(Y, X)]/Emp(Y) \tag{4}$$

$$NetPoachingPropensity(Y, X) = [H_p(Y, X) - S_p(Y, X)]/Emp(X). \tag{5}$$

Equation (4) shows the rate of employment growth at firm type $Y$ due to job-to-job moves of worker type $X$. For example, a net poaching rate of 0.05 percent for high school graduates at high productivity firms means that high productivity firms grew by 0.05 percent that quarter by poaching high school graduates away from less productive firms. Equation (5) shows the propensities of each $X$ group to be engaged in such flows. This allows us to see which groups are contributing disproportionately to net employment growth relative to the size of their group. For example, we might see high school graduates contributing more to employment growth simply because they are a larger group than non-high school graduates. In this case, a net poaching propensity of 0.05 percent for high school graduates at high productivity firms means that, on net, 0.05 percent of high school graduates were reallocated into high productivity firms in that quarter via job switching. Equation (4) describes the contribution of different groups to employment growth at the firm, while equation (5) describes the propensity of different groups to be reallocated across firms controlling for their size. For most of our results, we analyze rates as calculated in (5).

We begin with the poaching flows as fractions of employment by firm type $Y$ groups (equation 4). The first column of each panel of Table 4 reports the time series average contribution of each group to net poaching at high and low productivity firms. For ease of interpretation, we report these rates as shares of the total. To provide perspective for the shares reported in the first column, the second column reports the share of each worker characteristic group in the population. The third column is the ratio of the first and second columns. Groups with ratios above one disproportionately account for the $Y$ specific flows.

As seen in Table 4, while workers with college degrees account for a sizable share (22 percent) of worker reallocation into high productivity firms, this is less than their overall share of the workforce (27 percent). Surprisingly, given our earlier finding that high productivity workers have higher shares of college graduates generally, job-to-job flows have a greater tendency to move less-educated workers into high productivity firms. All education groups other than college graduates account for a higher share of employment growth via poaching workers from less productive firms than they are a share of the workforce. This table demonstrates the importance of accounting for group size in interpreting worker reallocation across firms, which is why for the remainder of the paper we will focus on propensity rates. Table 4 also shows that the role of lifecycle dynamics in reallocating workers up the job ladder is very pronounced. Workers less than 35 years of age account for a very large fraction of worker reallocation across firm types via job-to-job moves. Workers younger than 25 account for 29 percent of flows to high productivity and 37 percent of flows from low productivity firms even though they only account for 16 percent of the workforce.

Figure 1 shows how worker reallocation at high and low productivity firms varies over the cycle, where the flows are measured as shares of the respective education group (equation 5). First, note that net poaching to high productivity firms is positive for all groups in all periods (panel 1(a)) while net poaching to low productivity firms is negative for all groups in all periods (panel 1(b)). Less-educated workers have a higher propensity to be engaged in such net poaching flows especially away from low productivity firms.[25] This result may seem counterintuitive given our earlier finding that high productivity workers are more concentrated at high productivity firms. However, turnover of highly educated workers is lower, even for highly educated workers matched to less productive firms. So while highly educated workers are less likely to be matched to low productivity firms, they are also less likely to separate to a better employer, leading to lower reallocation rates for this group. Workers with more education may be more specialized, making them less mobile across firm types. Figure 2 shows the analogous patterns for net flows to nonemployment, i.e. net hires from and separations to nonemployment. During expansions, net hires from nonemployment are positive for all education groups at both high and low productivity firms, with less-educated workers slightly more represented (panels 2(a) and 2(b)). In contractions, net hires from nonemployment are negative, but especially more so for workers with lower educational attainment at low productivity firms (panel 2(b)).

Figure 3 shows the combined effect of net poaching and net nonemployment flows on net employment growth for high and low productivity firms, as shares of the respective groups. Panel 3(a) shows that in expansions, high school graduates, some college, and college graduates contribute to employment growth at high productivity firms at similar rates, controlling

[25] The magnitudes in Figure 1 are small but it is important to remember these are shares of the entire education group in the workforce and that these shares have not been annualized. Over the course of a year in booms, almost 1 percent of workers with less than high school and high school graduates are engaged in either flowing out of the lowest productivity quintile or flowing into the highest productivity quintile. Recall from Table 3 that over the course of a year about 3.2 percent of workers at low productivity firms get poached away to higher productivity firms and 1.6 percent of workers at high productivity firms are poached from lower productivity firms.

for the size of the prospective groups. Workers who did not finish high school are slightly more likely to be contributing to employment growth at high productivity firms compared to other groups in expansions. This reflects the combined effect of job-to-job flows and nonemployment flows at high type firms, both of which slightly favor reallocation of less-educated workers in expansions. Panel 3(b) shows net employment flows for the lowest quintile of firm productivity. Here the combined effect of net job-to-job flows and net nonemployment flows is that employment losses at low productivity firms are disproportionately from less-educated workers. However, as seen in panel (b) of Figures 1 and 2, the channel through which these employment losses occur differs in expansions and contractions. In expansions, it is through worker separations up the job ladder. In contractions, it is through worker separations to nonemployment.

Table 5 quantifies the differential cyclical responses across worker groups illustrated in panel (c) of Figures 1-3, estimating the following equation:

$$NetDifferential(High - Low, X) = \alpha + \gamma t + \beta \Delta U + \epsilon \tag{6}$$

where the left-hand side variable is the difference between worker reallocation at high vs. low productivity firms, and $\Delta U$ is the change in the unemployment rate with marginal effect $\beta$, $\alpha$ is a constant, and $\gamma$ captures a linear time trend.[26] There are three left-hand side variables, one for each component of net employment growth (net growth, net poaching, net nonemployment flows) and regressions are run separately for each education group.[27] First, note the negative sign on the change in unemployment rate for all groups when the dependent variable is the net poaching rate, shown in column 2 of Table 5. This indicates that when unemployment rises, net poaching rates at high and low productivity firms move closer together. As is evident in Figure 1, this convergence is largely due to pronounced cyclicality of the bottom of the job ladder, relative to the top. This cyclicality is especially pronounced

[26]These regressions are intended to provide quantitative evidence on the covariance between the net differentials and a cyclical indicator. Tables 5 and 7 provide such evidence from 24 specifications across education and age groups. Tables 6 and 8 report related specifications regressing the gross poaching and nonemployment flows on the cyclical indicator for 32 specifications. Tests for the presence of autocorrelation cannot reject the null of zero autocorrelation at the 5 percent level for 90 percent of the specifications.

[27]Even though we have an enormous micro dataset to compute our flows, appropriate caution is called for in interpreting these results especially by firm productivity groups as we have a relatively short times series and one major cyclical downturn – the Great Recession.

for workers without college degrees, with the gap in net poaching flows falling more rapidly with increases in the unemployment rate. The third column of Table 5 shows the differential cyclicality of the net nonemployment margin for different groups. Here differential net hires from nonemployment between high and low productivity firms increases with the unemployment rate for all groups except college graduates. The positive coefficient on the change in the unemployment rate indicates greater layoffs at low productivity firms in contractions, and the range of coefficients indicates that less-educated workers at low productivity firms are more likely to be "shaken off the ladder," or moving to nonemployment, in contractions, relative to other groups. Column 3 examines the differential cyclicality of net employment growth by group. As can be seen in panel 3(a), the net effect of the poaching and nonemployment margins is that the differential growth rates between high and low productivity firms are disproportionately driven by less-educated workers at all points of the business cycle. In column 1 of Table 5, the only statistically significant effect is for workers with less than a college degree, indicating that it is only for this group that differential is disernably more pronounced when the unemployment rate increases.

Table 6 examines gross worker flows to see if either the hires or separation margin is driving the worker reallocation patterns shown in Figures 1-3. Specifically, Table 6 shows estimates from the following regression:

$$Z(Y, X) = \alpha + \gamma t + \beta \Delta U + \epsilon \tag{7}$$

where $Z$ is hires or separations. The coefficients on changes in the unemployment rate show that within education groups, both hires and separations at low productivity firms are more cyclically sensitive than those at high productivity firms. Within firm productivity groups, hires and separations are more cyclically sensitive for less-educated workers. Taken together, the results imply that in recessions less-educated workers at low productivity firms are hit especially hard through *both* higher separations and fewer hires.

We now turn to the lifecycle dynamics of worker reallocation across firms, segmenting workers by age instead of education. Figure 4 shows the analog of Figure 1 with workers grouped by age instead of education. Panel 4(a) shows that high productivity firms grow by disproportionately poaching younger workers away from less productive firms. Panel 4(b) shows that the cyclical job ladder away from low ranked firms is almost entirely driven by the youngest workers in the economy. Both panels show that poaching flows to high productivity firms and away from low productivity firms are sharply reduced in the Great Recession, especially for young workers. The analogous patterns for net hires to nonemployment are illustrated in Figure 5. Both high (panel 5(a)) and low productivity (panel 5(b)) firms grow disproportionately by hiring young workers from nonemployment.

Figure 6 shows the combined effect of poaching and nonemployment margins, showing net employment growth rates by age, calculated again as shares of the workforce. As high productivity firms disproportionately poach and hire from nonemployment younger workers, they not surprisingly also grow by adding young workers to their firms (panel 6(a)). Low productivity firms, however, are lose employment among all groups except the youngest workers. While low productivity firms lose many young workers through poaching (panel 4(b)), they also hire a great many others from nonemployment (panel 5(b)) more than offsetting the employment losses of the youngest workers moving up the ladder (panel 6(b)). This pattern holds only during economic expansions, however. In contractions, the ladder collapses and net hiring of young workers from nonemployment collapses as well. The net effect is a contraction that disproportionately impacts younger workers at low productivity firms.

Table 7 quantifies the differential cyclical responses illustrated in panel (c) of Figures 4-6, showing estimates from the regression shown in equation (6). For all age groups, we find that the differential net poaching between high and low productivity firms declines with an increase in the unemployment rate (column 2). Consistent with Figure 4, this is especially pronounced for the youngest workers. In contrast, the differential net hires from nonemployment between high and low productivity firms increases with an increase in the unemployment rate for all age groups (column 3). This decline in net hires from nonemployment relative to high productivity firms in contractions is much more pronounced for younger workers. The net effect of the poaching and nonemployment margins is that while the differential net growth rates between high and low productivity firms are largely driven by reallocation of younger workers, this effect is more pronounced when the unemployment rate increases for workers less than 25.

The cyclical patterns for hires and separations of high and low productivity firms by worker age are presented in Table 8. Within age groups, separations at low productivity firms are more cyclically sensitive than those at high productivity firms. In contrast, hires at low productivity firms have about the same cyclicality as high productivity firms, holding age group constant. Within firm productivity groups, hires and separations tend to be more cyclically sensitive for less-educated workers. An exception is separations into nonemployment for high productivity firms. Here we find that separations to nonemployment are actually more cyclically sensitive for 25-44 year old workers. Overall, though, these results are similar to those by education since they highlight that it is young workers at low productivity firms who are most likely to get shaken off the ladder during recessions. Young workers are also much less likely to get hired at low productivity firms during recessions.

### 3.4 Implications for Inequality

As more productive firms generally pay higher wages, our results ranking firms by productivity have implications for matching between workers and better paying employers. Recent work suggests that a substantial fraction of the rise in earnings inequality over the last thirty years can be attributed to increased pay dispersion across firms (Barth et al. (2016); Card et al. (2016)). However, there are reasons to expect that our ranking of firms by productivity may not necessarily correspond to firms ranked by pay. Specifically, our ranking of firm productivity is within narrowly defined industries. Workers moving between low and high productivity firms in a low wage industry may still be stuck in low wage work, even if the new employer pays better wages.

In an online appendix we repeat our analysis, ranking firms instead by average pay across all industries. Our results for the job ladder are robust to ranking firms by pay instead of productivity. Younger and less-educated workers are more likely to remain struck in low-paying firms in recessions, and job-to-job moves of workers favor the reallocation of less-educated workers into higher paying firms. In contractions, it is matches between less-educated and younger workers that are disproportionately severed. The key difference between the two results is that there is overall less reallocation between high- and low-paying firms compared to the analogous patterns for firm productivity. The principal reason for this is that high wage firms do not grow as fast as high productivity firms. Factors such as technological change and pressures from international trade impact some industries more than others, with high wage sectors like manufacturing are not growing as fast as many low wage sectors of the economy.

We draw a number of inferences from this empirical exercise and related findings on the importance of the employer in wage determination. First, as the rate of reallocation into better firms varies in expansions and contractions, the cyclical job ladder indicates an important role for frictions (or "luck") in matching workers to better paying firms. The ability of younger and less-educated workers to move up the ladder is strongly impacted by the business cycle. Not only are young and less-educated workers less able to move up the ladder in slack labor markets, but they are more likely to be knocked off ladder in contractions. Second, our finding that labor market churn plays a more important role in matching less skilled workers to employers may indicate that frictions play a larger role in explaining wage dispersion among less-educated workers. Lastly we note that the job ladder mitigates the impact of growing pay dispersion across firms, with less-educated workers disproportionately reallocated to better employers through job-to-job moves. Davis and Haltiwanger (2014) argue that labor market fluidity has been declining in recent years, a worrisome trend if this a primary means of matching less skilled workers to higher paying employers.

# 4 Concluding Remarks

Who moves up the job ladder? Using rich matched employer-employee data for the U.S., we find that younger and less-educated workers have the highest propensity to be reallocated from low productivity, lower paying firms to high productivity, higher paying firms. This greater propensity stems from multiple factors that differ somewhat for young workers and for less-educated workers. Young workers are much more likely to begin employment spells at the bottom of either job ladder. Young workers then disproportionately move up the ladder via job-to-job flows from the bottom rung of the ladder in economic booms. Economic contractions disproportionately affect young and less-educated workers through both margins, as these workers are more likely to be shaken off the job ladder through separations to nonemployment, while movements up the job ladder through job-to-job moves collapse.

Young and less-educated workers are also less likely to become hired from nonemployment in economic downturns. Our findings indicate that the ability of less-educated workers to match to higher productivity, higher paying employers is disproportionately impacted by the business cycle, relative to more highly educated workers. Much of the literature on entering labor markets in recessions has focused on impacts for college graduates; our results hint that consequences for job mobility and earnings growth may be even more consequential for less-educated workers entering labor markets in contractions.

Both job-to-job flows and flows to and from nonemployment contribute to productivity enhancing reallocation but they do so with very different channels and consequences for workers. During booms, productivity enhancing reallocation of net jobs away from low productivity to high productivity firms is dominated by job-to-job flows. During booms, low productivity firms are engaged in substantial net hires from nonemployment which mitigates their loss of net jobs during booms. During such boom periods, workers of all education and age groups move up these job ladders but with the greater propensities of young and less-educated workers. During recessions, the job ladders collapse – net reallocation of jobs to high productivity firms via job-to-job flows drops dramatically. However, productivity enhancing reallocation continues in that low productivity firms have much larger flows into nonemployment than high productivity firms. In this respect, there is reallocation via subtraction – namely that of jobs at low productivity relative to high productivity firms. The workers who bear the brunt of this subtraction are young and less-educated workers.

Our findings imply that it is not simply "high type" workers who move up the job ladder (at least high type as measured by worker education). Thus, extreme forms of positive assortative matching where only high type workers work together and only at the most productive and highest paying firms is not supported by the evidence. Instead our findings are consistent with all types of workers moving up the ladder. The greater propensity for low type workers to move up the ladder in booms might seem to be inconsistent with positive assortative matching until one also realizes that low type workers are much more likely to be shaken off the ladder during downturns. We do find that the more productive firms have more high type workers (as measured by education) but only a relatively small fraction of the differences in measured productivity across firms can be accounted for by worker characteristics.

We regard our results as providing new basic facts that should help in motivating, calibrating, estimating and ultimately testing hypotheses that emerge from models of job and worker reallocation. Our decomposition of net job flows at the firm level into hires and separations via job-to-job flows and hires and separations via nonemployment highlights the importance of both of those margins. Interestingly, we find evidence of strong directionality of these flows by firm productivity and firm wage that also vary systematically over the cycle. These directional patterns also vary systematically by worker age and education.

Our findings suggest challenges for the existing models of worker and job reallocation we discussed in the introduction. The general finding that job-to-job flows move workers up the firm productivity and firm wage ladders on average and more strongly in booms is consistent with existing job ladder models. However, our findings have some implications for the developing literature that incorporates assortative matching into a job ladder framework, which has suggested that low productivity workers are likely to be stuck at the bottom of the job ladder because they are better matched there than at a more productive firm. In particular, our finding that workers of all age and education groups move up the firm productivity and firm wage ladders can be reconciled by introducing models where high productivity and high wage firms have an absolute advantage for all worker types. It will be a challenge to account for the especially high propensities of the young and less-educated to move up the ladders. Life cycle dynamics surely will help account for the patterns by worker age, but the patterns by worker education raises questions about the reason highly productive workers are more likely to be employed at highly productive firms. The systematic pattern of young and less-educated workers being shaken off the ladder in recessions via increases in separations will be another challenge for existing job ladder models. Job ladder models with or without worker heterogeneity focus on the hiring margin as the primary margin of adjustment. The MP model does focus on the separations margin into nonemployment for low productivity, low wage firms. However, that paradigm neglects the job ladder (on-the-job search) and worker heterogeneity. We think it will be difficult to account for our findings without bringing elements of both the job ladder and MP paradigms together. Moreover, a successful merger of those models will also require incorporating worker heterogeneity to account for our systematic patterns of flows by both firm and worker characteristics.

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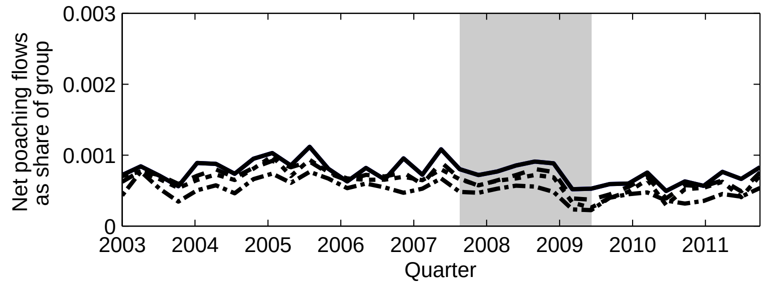
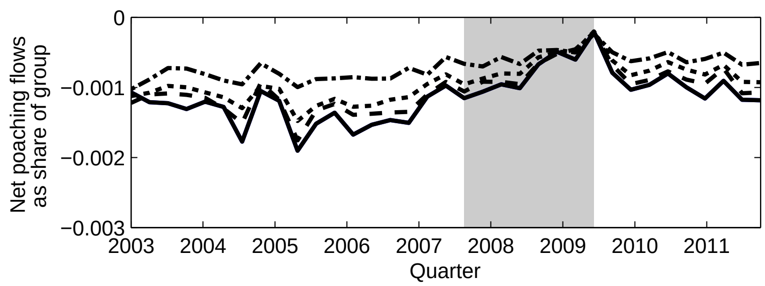
Figure 1: Net Poaching Flows by Within-Industry Firm Productivity and Worker Education

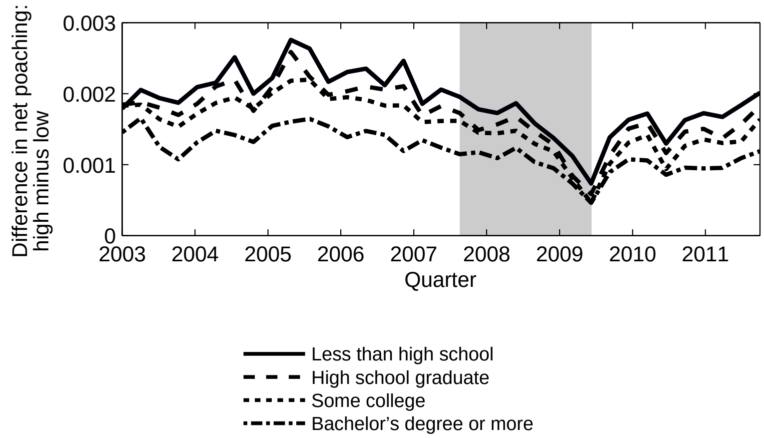
(a) High Productivity




(b) Low Productivity



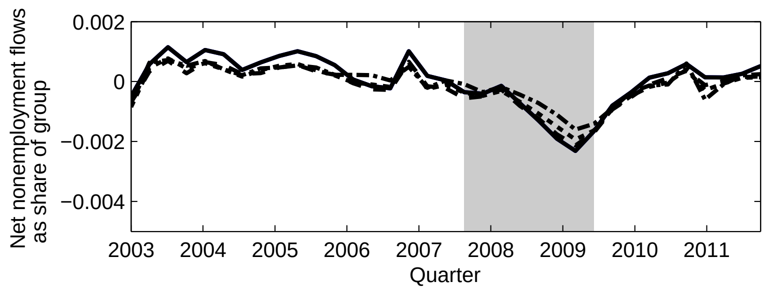

(c) Net Differential



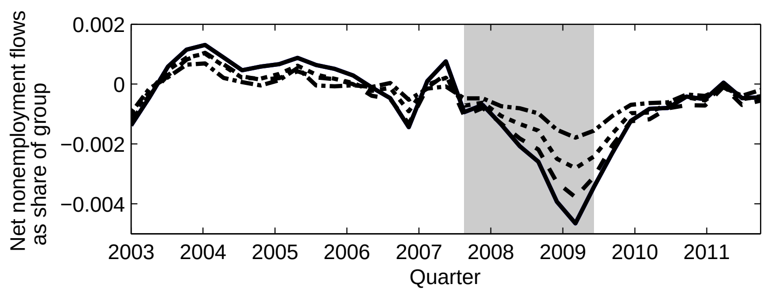

Notes: Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11. "High Productivity" indicates that a firm is in the top quintile of the productivity distribution within a 4-digit NAICS industry, and "Low Productivity" indicates that a firm is in the bottom quintile of the productivity distribution within a 4-digit NAICS industry.

Figure 2: Net Nonemployment Flows by Within-Industry Firm Productivity and Worker Education

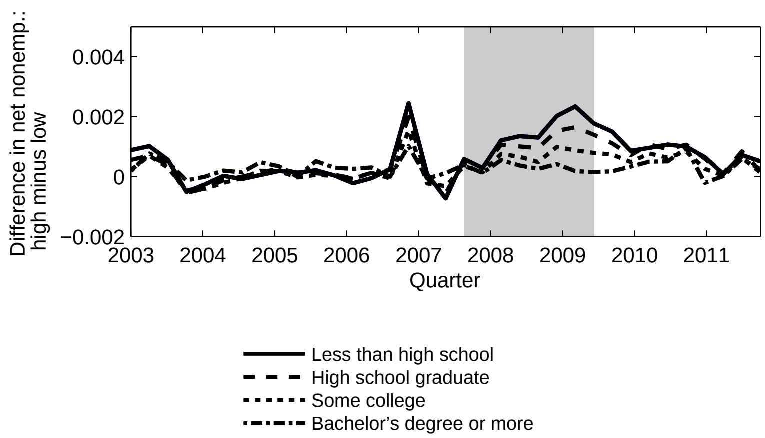
(a) High Productivity




(b) Low Productivity



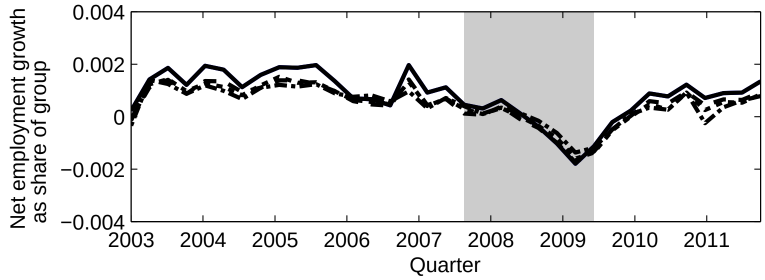

(c) Net Differential



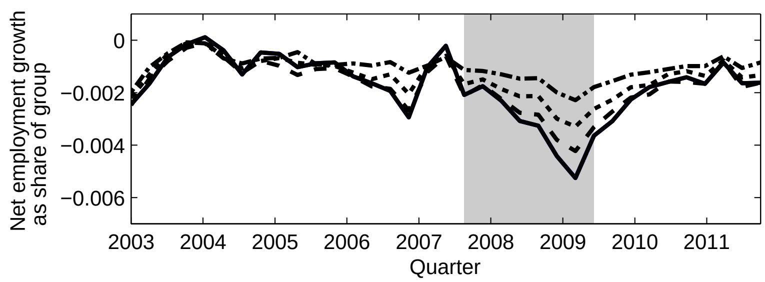

Notes: Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11. "High Productivity" indicates that a firm is in the top quintile of the productivity distribution within a 4-digit NAICS industry, and "Low Productivity" indicates that a firm is in the bottom quintile of the productivity distribution within a 4-digit NAICS industry.

Figure 3: Net Employment Growth (Sum of Net Poaching and Net Nonemployment Flows) by Within-Industry Firm Productivity and Worker Education

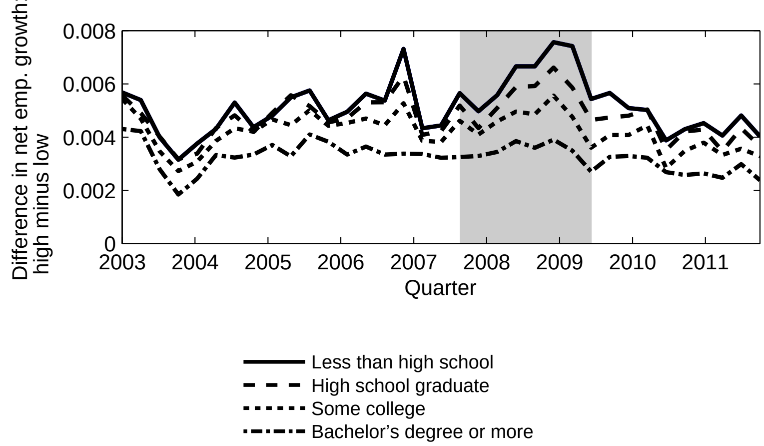
(a) High Productivity




(b) Low Productivity



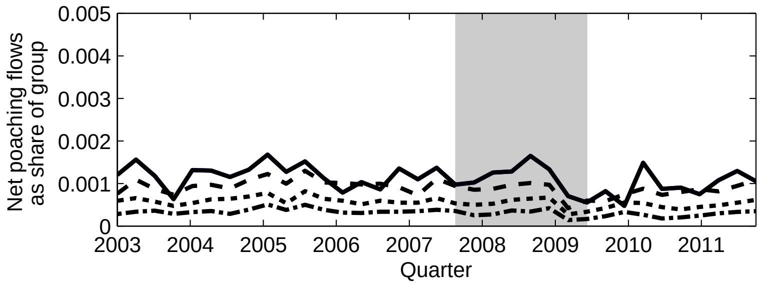

(c) Net Differential



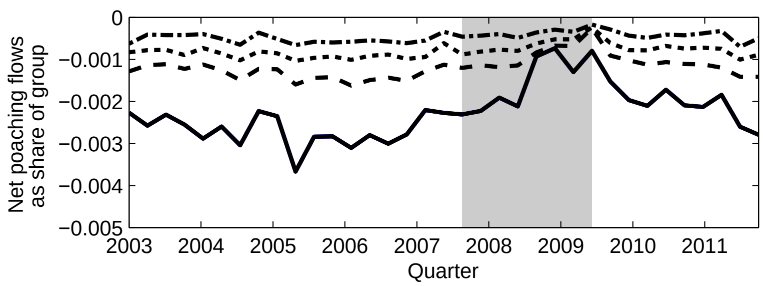

Notes: Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11. "High Productivity" indicates that a firm is in the top quintile of the productivity distribution within a 4-digit NAICS industry, and "Low Productivity" indicates that a firm is in the bottom quintile of the productivity distribution within a 4-digit NAICS industry.

Figure 4: Net Poaching Flows by Within-Industry Firm Productivity and Worker Age

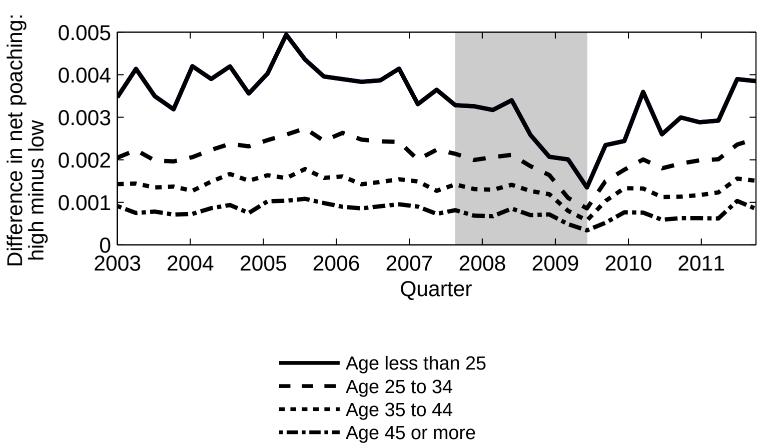
(a) High Productivity




(b) Low Productivity



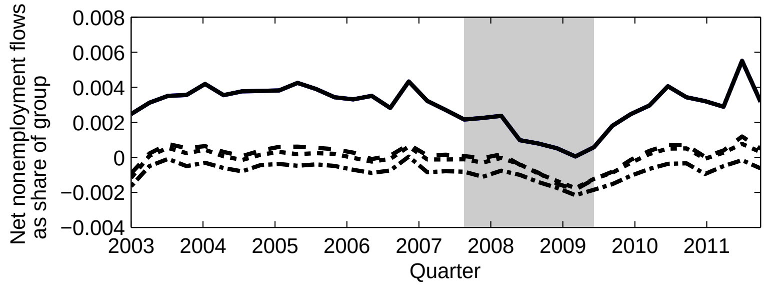

(c) Net Differential



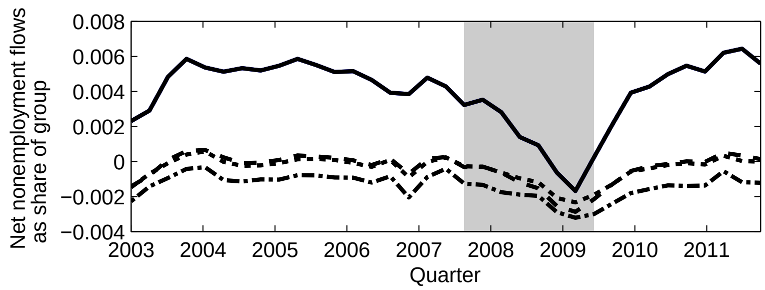

Notes: Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11. "High Productivity" indicates that a firm is in the top quintile of the productivity distribution within a 4-digit NAICS industry, and "Low Productivity" indicates that a firm is in the bottom quintile of the productivity distribution within a 4-digit NAICS industry.

Figure 5: Net Nonemployment Flows by Within-Industry Firm Productivity and Worker Age

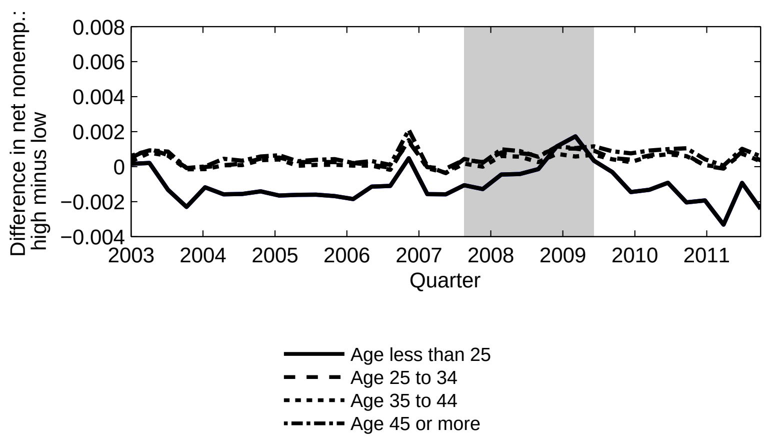
(a) High Productivity




(b) Low Productivity



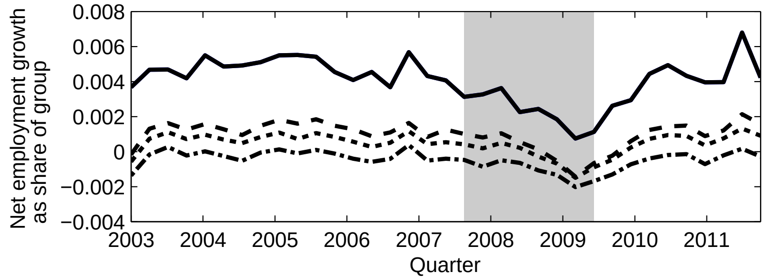

(c) Net Differential



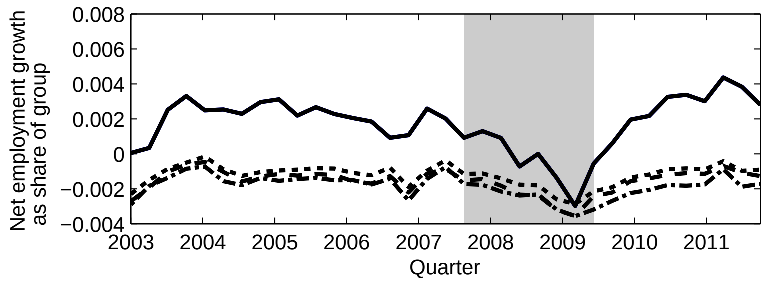

Notes: Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11. "High Productivity" indicates that a firm is in the top quintile of the productivity distribution within a 4-digit NAICS industry, and "Low Productivity" indicates that a firm is in the bottom quintile of the productivity distribution within a 4-digit NAICS industry.

Figure 6: Net Employment Growth (Sum of Net Poaching and Net Nonemployment Flows) by Within-Industry Firm Productivity and Worker Age

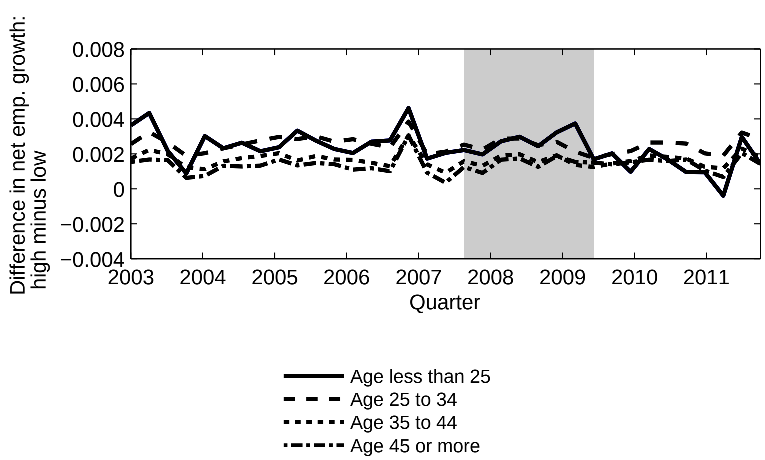
(a) High Productivity




(b) Low Productivity




(c) Net Differential




Notes: Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11. "High Productivity" indicates that a firm is in the top quintile of the productivity distribution within a 4-digit NAICS industry, and "Low Productivity" indicates that a firm is in the bottom quintile of the productivity distribution within a 4-digit NAICS industry.

Table 1: The Relationship Between Productivity Growth and Survival

| Dependent Variable | Lagged Productivity | Lagged Log(Employment) |
|---|---|---|
| Net Growth Rate | 0.2643*** | 0.0583*** |
| | (0.0002) | (0.0001) |
| Exit | −0.0739*** | −0.0454*** |
| | (0.0001) | (0.0000) |

Notes: Parameter estimates from two firm-level regressions. Standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. This regression is based on more than 40 million firm-year observations. Productivity is measured as log real revenue per worker deviated from 6-digit NAICS industry by year means.

Table 2: Within-Industry Firm Percentile Rank

| | Parameter Estimate |
|---|---|
| Intercept | 6.2024*** |
| | (0.0715) |
| Share of Employment | |
| Male | 0.1918*** |
| | (0.0002) |
| Age less than 25 | 0.1994*** |
| | (0.0008) |
| Age 25 to 34 | 0.0359*** |
| | (0.0005) |
| Age 35 to 44 | 0.1183*** |
| | (0.0005) |
| High school graduate | −0.3359*** |
| | (0.0010) |
| Some college | 0.4723*** |
| | (0.0010) |
| Bachelor's degree or more | 0.6642*** |
| | (0.0007) |
| $R^2$ | 0.127 |

Notes: Parameter estimates from a firm-level regression, weighted by employment. Standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Firm productivity ranks are calculated within a 4-digit NAICS industry.

Table 3: Hiring and Separation Rates by Within-Industry Productivty

| Firm Prod. Type | Poaching Rates | | Nonemp. Rates | | Net Poaching Rate | Net Nonemp. Rate | Net Emp. Rate |
|---|---|---|---|---|---|---|---|
| | Hires | Separations | Hires | Separations | | | |
| High | 0.065 | 0.060 | 0.057 | 0.057 | 0.004 | 0.000 | 0.005 |
| Low | 0.072 | 0.080 | 0.077 | 0.079 | -0.008 | -0.002 | -0.010 |

Notes: All statistics are calculated as averages across time for 2003:Q1 to 2011:Q3. "High" indicates that a firm is within the top quintile of the productivity distribution within a 4-digit NAICS industry. "Low" indicates that a firm is in the bottom quintile of the productivity distribution within a 4-digit NAICS industry.

Table 4: PRODUCTIVITY LADDER BY WORKER EDUCATION AND AGE

| WORKER CATEGORY | SHARE OF NET POACHING FLOWS | SHARE OF WORKFORCE | RATIO |
|---|---|---|---|
| | HIGH PRODUCTIVITY FIRMS | | |
| Less than high school | 0.16 | 0.13 | 1.23 |
| High school graduate | 0.30 | 0.28 | 1.06 |
| Some college | 0.32 | 0.32 | 1.01 |
| Bachelor's degree or more | 0.22 | 0.27 | 0.81 |
| | LOW PRODUCTIVITY FIRMS | | |
| Less than high school | 0.17 | 0.13 | 1.24 |
| High school graduate | 0.31 | 0.28 | 1.12 |
| Some college | 0.32 | 0.32 | 1.00 |
| Bachelor's degree or more | 0.21 | 0.27 | 0.76 |
| | HIGH PRODUCTIVITY FIRMS | | |
| Age less than 25 | 0.29 | 0.16 | 1.75 |
| Age 25 to 34 | 0.30 | 0.22 | 1.40 |
| Age 35 to 44 | 0.20 | 0.23 | 0.85 |
| Age 45 or above | 0.21 | 0.38 | 0.54 |
| | LOW PRODUCTIVITY FIRMS | | |
| Age less than 25 | 0.37 | 0.16 | 2.24 |
| Age 25 to 34 | 0.26 | 0.22 | 1.18 |
| Age 35 to 44 | 0.18 | 0.23 | 0.79 |
| Age 45 or above | 0.19 | 0.38 | 0.50 |

NOTES: For education results, workers less than 25 are dropped, as they have not completed their education. Shares of poaching flows and employment are calculated as the average across time for 2003:Q1 to 2011:Q3. "Ratio" divides the share of net poaching by the share of the workforce.

Table 5: Net Difference: High Minus Low Productivity, by Worker Education

| | Net Employment Differential | Poaching Differential | Nonemployment Differential |
|---|---|---|---|
| | **Less than high school** | | |
| Change in unemployment rate | 0.064** | −0.059*** | 0.124*** |
| | (0.028) | (0.013) | (0.024) |
| Time trend | 0.000 | −0.002*** | 0.002** |
| | (0.001) | (0.000) | (0.001) |
| $N$ | 35 | 35 | 35 |
| | **High School Graduate** | | |
| Change in unemployment rate | 0.028 | −0.055*** | 0.083*** |
| | (0.024) | (0.011) | (0.020) |
| Time trend | 0.000 | −0.002*** | 0.002*** |
| | (0.001) | (0.000) | (0.001) |
| $N$ | 35 | 35 | 35 |
| | **Some College** | | |
| Change in unemployment rate | −0.000 | −0.048*** | 0.048*** |
| | (0.020) | (0.010) | (0.016) |
| Time trend | −0.000 | −0.002*** | 0.002*** |
| | (0.001) | (0.000) | (0.001) |
| $N$ | 35 | 35 | 35 |
| | **Bachelor's Degree or More** | | |
| Change in unemployment rate | −0.025 | −0.025*** | 0.001 |
| | (0.016) | (0.008) | (0.013) |
| Time trend | −0.001** | −0.002*** | 0.000 |
| | (0.001) | (0.000) | (0.000) |
| $N$ | 35 | 35 | 35 |

Notes: Point estimates are taken from national-level regressions run separately by education and dependent variable (net employment differential, poaching differential, and nonemployment differential). All regressions use 35 quarterly observations from 2003:Q1 to 2011:Q3. Standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Hires and Separations at High vs. Low Productivity Firms, by Worker Education

| | High Productivity | | Low Productivity | |
|---|---|---|---|---|
| | Hires | Separations | Hires | Separations |
| Less than high school | −0.126*** | 0.048*** | −0.170*** | 0.129*** |
| | (0.015) | (0.012) | (0.024) | (0.021) |
| High school graduate | −0.112*** | 0.036*** | −0.138*** | 0.094*** |
| | (0.016) | (0.011) | (0.021) | (0.016) |
| Some college | −0.103*** | 0.028** | −0.112*** | 0.069*** |
| | (0.015) | (0.012) | (0.017) | (0.013) |
| Bachelor's degree or more | −0.089*** | 0.020* | −0.072*** | 0.039*** |
| | (0.014) | (0.011) | (0.012) | (0.011) |
| $N$ | 35 | 35 | 35 | 35 |

Notes: Point estimates are taken from national-level regressions run separately by education and dependent variable: Hires (High productivity), Separations (High productivity), Hires (Low productivity), Separations (Low productivity). All regressions use 35 quarterly observations from 2003:Q1 to 2011:Q3 and include a linear time trend (not reported). Standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Net Difference: High Minus Low Productivity, by Worker Age

| | Net Employment Differential | Poaching Differential | Nonemployment Differential |
|---|---|---|---|
| | **Age less than 25** | | |
| Change in unemployment rate | 0.118*** | −0.114*** | 0.232*** |
| | (0.037) | (0.023) | (0.026) |
| Time trend | −0.005*** | −0.003*** | 0.002** |
| | (0.001) | (0.001) | (0.001) |
| *N* | 35 | 35 | 35 |
| | **Age 25 to 34** | | |
| Change in unemployment rate | −0.016 | −0.069*** | 0.053*** |
| | (0.021) | (0.012) | (0.015) |
| Time trend | −0.001 | −0.001* | 0.000 |
| | (0.001) | (0.000) | (0.001) |
| *N* | 35 | 35 | 35 |
| | **Age 35 to 44** | | |
| Change in unemployment rate | −0.005 | −0.034*** | 0.030* |
| | (0.019) | (0.008) | (0.016) |
| Time trend | −0.000 | −0.001** | 0.001 |
| | (0.001) | (0.000) | (0.001) |
| *N* | 35 | 35 | 35 |
| | **Age 45 or Above** | | |
| Change in unemployment rate | 0.026 | −0.018*** | 0.045*** |
| | (0.022) | (0.006) | (0.020) |
| Time trend | 0.000 | −0.001** | 0.001 |
| | (0.001) | (0.000) | (0.001) |
| *N* | 35 | 35 | 35 |

Notes: Point estimates are taken from national-level regressions run separately by education and dependent variable (net employment differential, poaching differential, and nonemployment differential). All regressions use 35 quarterly observations from 2003:Q1 to 2011:Q3. Standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Hires and Separations at High vs. Low Productivity Firms, by Worker Age

| | High Productivity | | Low Productivity | |
|---|---|---|---|---|
| | Hires | Separations | Hires | Separations |
| Age less than 25 | −0.227*** | 0.018 | −0.328*** | 0.146*** |
| | (0.037) | (0.021) | (0.043) | (0.027) |
| Age 25 to 34 | −0.115*** | 0.035*** | −0.115*** | 0.089*** |
| | (0.017) | (0.013) | (0.017) | (0.015) |
| Age 35 to 44 | −0.089*** | 0.040*** | −0.081*** | 0.078*** |
| | (0.014) | (0.012) | (0.014) | (0.013) |
| Age 45 or above | −0.074*** | 0.030** | −0.082*** | 0.067*** |
| | (0.013) | (0.011) | (0.016) | (0.013) |
| $N$ | 35 | 35 | 35 | 35 |

Notes: Point estimates are taken from national-level regressions run separately by age and dependent variable: Hires (High productivity), Separations (High productivity), Hires (Low productivity), Separations (Low productivity). All regressions use 35 quarterly observations from 2003:Q1 to 2011:Q3 and include a linear time trend (not reported). Standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

# Web Appendix (Not for Publication)

## A Ranking Firms by Wage Instead of Productivity

In many models of the labor market, more productive firms also pay higher wages. Thus we should find similar patterns of worker reallocation if we instead rank firms by pay instead of productivity. If true, this means that younger and less-educated workers are more likely to remain stuck in low-paying firms in recessions, and that employment growth in higher paying firms in expansions is fueled disproportionately by younger and less-educated workers moving up from lower-paying employers. However, there are reasons to suspect a less than perfect correspondence between productivity rank and wage rank in our data. In particular, our ranking of firm productivity is within narrowly-defined industries. A worker moving between a low productivity retail job and a higher productivity retail job may remain a low wage worker, even if wages are higher at the more highly-ranked firm. To check and see if our results ranking firms by productivity are robust to ranking firms by wages, in this appendix we repeat our analysis, this time ranking firms by pay.

In ranking firms by wage, we follow the approach taken in Haltiwanger et al. (2016). Specifically, we use the average real quarterly earnings for workers who worked the entire quarter at the employer (what we call full-quarter workers), where the employer is the state payroll tax entity.[28] We then calculate employment-weighted quintiles of the firm earnings per worker in each quarter. We classify firms as high wage if they are in the top two quintiles, and low wage if they are in the bottom quintile.[29] Note that this measure ranks firms by pay not within industries but across all industries. Full-quarter workers are those employed

[28] Note that firm wage is defined at the state-employer level, while our productivity measure is defined at the federal employer level. This apparent inconsistency is due to the mixing of the state-provided LEHD job data and the federal Census business data, see Haltiwanger et al. (2014). As a robustness check, HHM investigate the relationship between the state-level firm wage and the national firm wage and find they are highly correlated.

[29] We define high wage firms as the top two quintiles to be consistent with the definition we used in Haltiwanger et al. (2016). In that paper, we pooled the top two quintiles of the employment-weighted firm wage distribution in our analysis to balance the flows of workers in our high wage and low wage groups - low wage firms generally having very high hire and separation rates relative to the employment in their wage class. Note that in our productivity measure, flows across high and low productivity groups are much more balanced, as productivity is defined within-industry.

in the prior, current and subsequent quarter by the firm. Using full-quarter workers has the advantage of excluding the workers who are hired or separate in the current quarter (including workers engaged in job-to-job transitions) from being included in the firm wage measure. As such, this mitigates concerns of reverse causality.

A potential concern is that our average earnings per worker is not controlling for hours per worker, and so it is a potentially noisy proxy for the desired measure of the average wage at the firm, however, We think this is not likely to be an important source of measurement error given our use of quintiles of the earnings per worker distribution especially since we focus on the difference between high wage (top two quintiles) and bottom quintile. In our view, it is unlikely that this source of measurement error would reverse firms being in the high and low wage categories. Moreover, we think this is a form of classical measurement error implying that if anything this would imply we are understating differences between the high and low wage firm types. In addition, the use of full quarter workers mitigates these concerns.

Table A.1 summarizes the average rates of net job flows and the components of our decomposition into net poaching and net hires from nonemployment when firms are ranked by pay. Table A.1 shows less overall reallocation from low wage to high wage firms compared to the analogous patterns for firm productivity in Table 3. A principal reason for this is that high wage firms on the whole do not grow as fast as higher productivity firms within the same industry. This is a reminder that between industry reallocation is likely driven by a number of factors other than productivity (and in turn wages). For example, technological change and pressures from international trade may cause jobs in a relatively high-paying sector like manufacturing to decline while service sector growth remained fairly robust.

We now turn to who moves up the job ladder, continuing to rank firms by average worker earnings. The first column of Table A.2 reports the average share of net poaching flows accounted for by each reported age/education group. The second column reports the propensity of each age/education group to be reallocated across firm types, using the employment in each worker group as the denominator. The third column is the ratio of the first and second columns. Groups with ratios above one disproportionately account for net worker reallocation across high and low wage employers. Similar to what we find when we rank firms by productivity, younger and less-educated workers disproportionately account for worker reallocation up the job ladder via job-to-job moves. Ratios for less than high school, high school graduates, age less than 25 and age 25-34 are all above one. In terms of the absolute shares, high school and some college account for a large fraction of these flows since they are groups with a larger share of the workforce compared to less than high school or college graduates. Workers age less than 25 account for a very large fraction of job-to-job flows to high wage firms and from low wage firms. Workers age less than 25 account for 41 percent of flows to high wage firms and 58 percent of flows from low wage firms even though they only account for 16 percent of the workforce.

Figure A.1 shows the net poaching flows for high wage (panel A.1(a)), low wage (panel A.1(b)) and the differential net poaching flows between high and low wage flows (panel A.1(c)) where the flows are measured as shares of the respective education group. High wage firms gain workers from all education groups through poaching, while low wage firms lose employment from every education group as their workers are poached away. While high wage firms disproportionately poach highly educated workers, they largely poach such workers from other high-paying firms, and net employment growth at high wage firms via poaching is disproportionately from less-educated workers moving up the ladder. At low wage firms, employment losses via poaching are larger and more cyclical than for high wage firms, and again, are disproportionately less-educated workers moving up the job ladder. Net poaching flows to high wage firms and away from low wage firms are sharply reduced in the Great Recession. This decline in the Great Recession is particularly pronounced for less-educated workers.

As illustrated in Figure A.2, net hires from nonemployment are positive during periods of economic expansion and negative during economic contractions for low wage firms. High wage firms tend to be losing workers to nonemployment in most periods but especially during economic contractions. In times of economic expansion, net hires from nonemployment for low wage firms are positive especially for less-educated workers. It is during such times that high wage firms are actively poaching from low productivity firms.

Table A.3 quantifies the differential cyclical responses illustrated in Figures A.1 and A.2. For all education groups, we find that the differential net poaching between high and low wage firms declines with an increase in the unemployment rate. Consistent with Figure A.1, this is especially pronounced for the less-educated workers. In contrast, the differential net hires from nonemployment between high and low wage firms increases with an increase in the unemployment rate for less than high school and for some college. For college graduates, we find that the differential net hires from nonemployment falls more for high wage than low wage firms.

The patterns for education groups by firm wage are largely similar to those by firm productivity. All education groups move up the firm wage ladder via job-to-job flows but it is the less-educated workers with especially high propensity to be moving up the firm wage ladder. Moving up the firm wage ladder is highly procyclical. As with the results by firm productivity, less-educated workers have higher propensities to move up the firm wage ladder in booms because they are much more likely to be shaken off the firm wage ladder during contractions (and also are less likely to get on the firm wage ladder at such times). At both high and low wage firms, less-educated workers experience sharp net flows into nonemployment during contractions. This is especially true for less-educated workers at low wage firms.

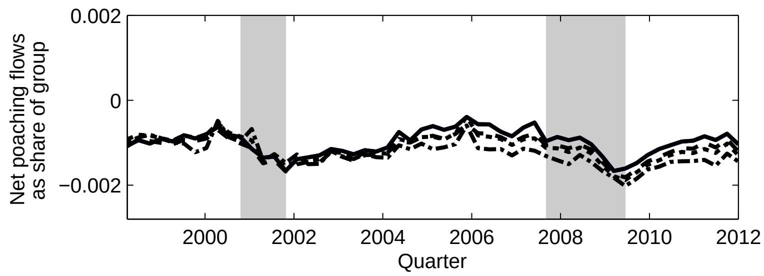
Figure A.3 shows the net poaching flows for high firm wage (panel A.3(a)), low firm wage (panel A.3(b)) and the differential net poaching flows between high and low firm wage flows (panel A.3(c)) where the flows are measured as shares of the respective age group. Net poaching to high wage firms is positive for all age groups in all periods while net poaching to low productivity firms is negative for all age groups in almost all periods. Younger workers have a much higher propensity to be engaged in such net poaching flows especially away from low wage firms. The net differential highlights the higher propensity of young workers to be engaged in such net poaching flows from low wage and to high wage firms. The magnitude of such flows is substantial. Over the course of a year in boom times as much as 8 percent of workers less than 25 are engaged in flows from the lowest wage firms or towards the highest wage firms or both. The net poaching flows to high wage firms and away from low wage firms are sharply reduced in the Great Recession. This decline in moving up the ladder in the Great Recession is particularly pronounced for young workers.

The analogous patterns for net hires to nonemployment are illustrated in Figure A.4. Net hires to nonemployment are positive for young workers at both high and low wage firms in almost all periods but especially during economic expansions. The positive net hires to nonemployment for young workers are especially high at low wage firms. Such net hires to nonemployment are more than 5 times larger than high productivity firms during boom period from 2004-2006. The decline in net hires to nonemployment for young workers in downturns is especially pronounced at low wage firms. The high propensity of young workers to be hired from nonemployment in all times is consistent with young workers entering the labor market. However, the sharp decline in such flows in downturns for young workers especially at low wage firms is consistent with young workers being more likely to get shaken off the ladder. It is also consistent with young workers being less likely to enter the labor market in economic downturns. For older workers, at both high and low wage firms, there is a net loss of jobs to nonemployment in periods of both expansion and contraction. This is consistent with worker retirements but it is also evident that this propensity increases in economic downturns.

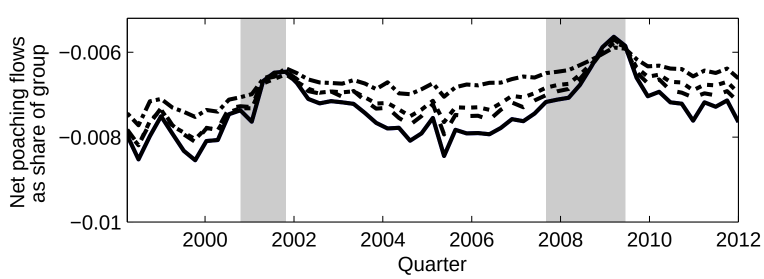
Table A.4 quantifies the differential cyclical responses illustrated in Figures A.3 and A.4. For all age groups, we find that the differential net poaching between high and low wage firms declines with an increase in the unemployment rate. Consistent with Figure 7, this is especially pronounced for the youngest workers. In contrast, the differential net hires from nonemployment between high and low wage firms increases with an increase in the unemployment rate for all age groups except the 35-44 age group. This decline in net hires from nonemployment at low wage firms relative to high wage firms in contractions is much more pronounced for younger workers.

Figure A.1: Net Poaching Flows by Firm Wage and Worker Education

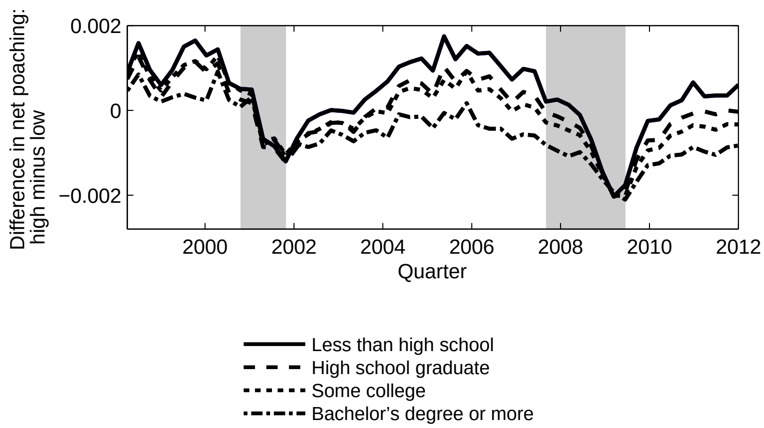
(a) High Wage




(b) Low Wage



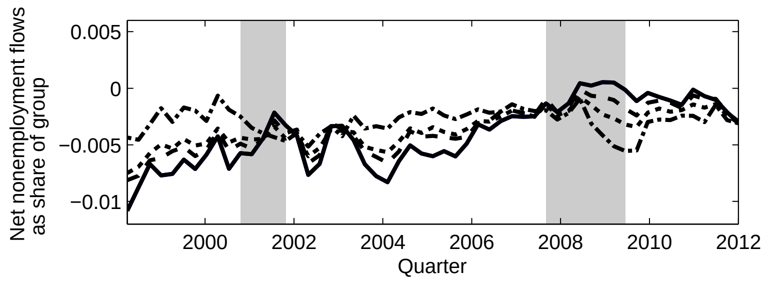

(c) Net Differential



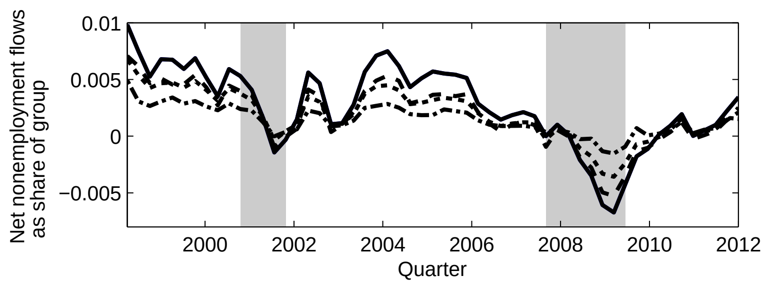

Notes: Transition rates are calculated on a quarterly basis from 1998:Q2 to 2011:Q4. Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11. "High Wage" indicates that a firm is within the top two quintiles of the firm wage distribution. "Low Wage" indicates that a firm is in the bottom quintile of the firm wage distribution.

Figure A.2: Net Nonemployment Flows by Firm Wage and Worker Education

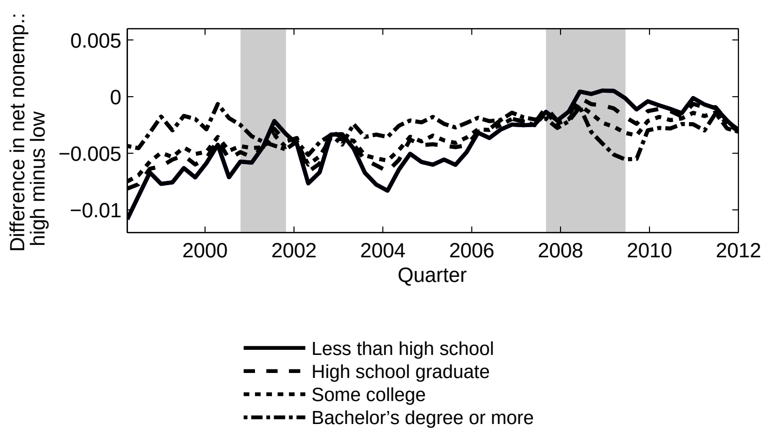
(a) High Wage




(b) Low Wage



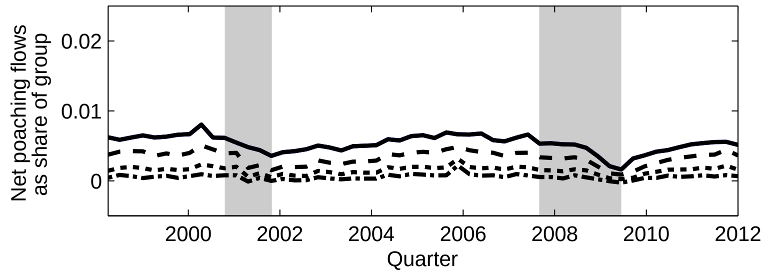

(c) Net Differential



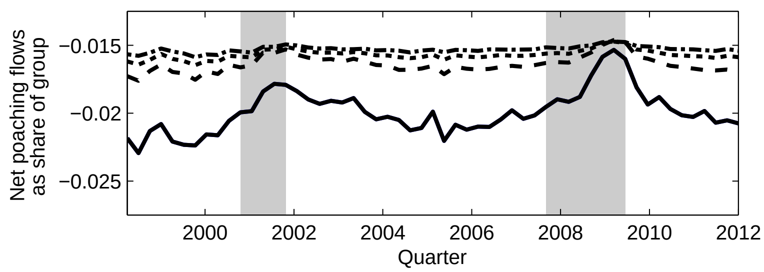

Notes:Transition rates are calculated on a quarterly basis from 1998:Q2 to 2011:Q4. Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11. "High Wage" indicates that a firm is within the top two quintiles of the firm wage distribution. "Low Wage" indicates that a firm is in the bottom quintile of the firm wage distribution.

Figure A.3: Net Poaching Flows by Firm Wage and Worker Age

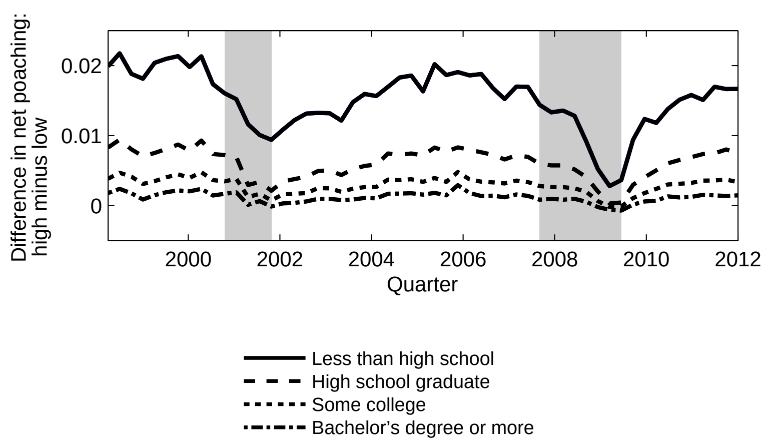
(a) High Wage




(b) Low Wage



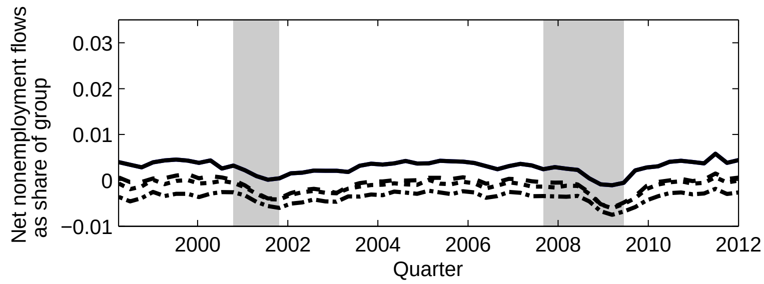

(c) Net Differential



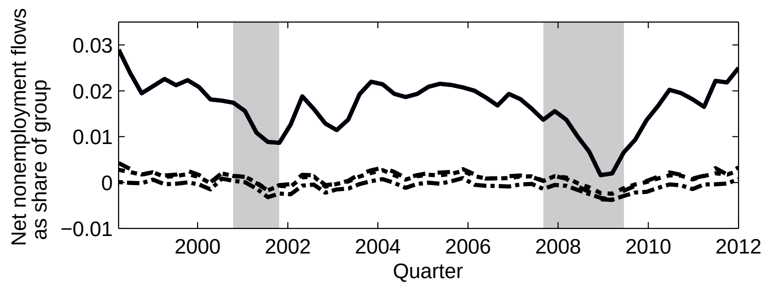

Notes: Transition rates are calculated on a quarterly basis from 1998:Q2 to 2011:Q4. Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11. "High Wage" indicates that a firm is within the top two quintiles of the firm wage distribution. "Low Wage" indicates that a firm is in the bottom quintile of the firm wage distribution.

Figure A.4: Net Nonemployment Flows by Firm Wage and Worker Age

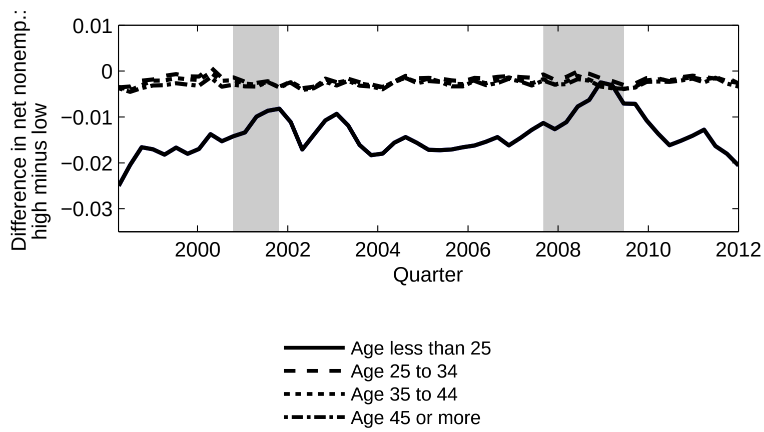
(a) High Wage




(b) Low Wage




(c) Net Differential




Notes: Transition rates are calculated on a quarterly basis from 1998:Q2 to 2011:Q4. Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11. "High Wage" indicates that a firm is within the top two quintiles of the firm wage distribution. "Low Wage" indicates that a firm is in the bottom quintile of the firm wage distribution.

Table A.1: Hiring and Separation Rates by Firm Wage

| Firm Wage Type | Poaching Rates | | Nonemp. Rates | | Net Poaching Rate | Net Nonemp. Rate | Net Emp. Rate |
|---|---|---|---|---|---|---|---|
| | Hires | Separations | Hires | Separations | | | |
| High | 0.056 | 0.049 | 0.06 | 0.041 | 0.007 | -0.005 | 0.002 |
| Low | 0.115 | 0.127 | 0.137 | 0.124 | -0.012 | 0.012 | 0.000 |

Notes: All statistics are calculated as averages across time for 1998:Q2 to 2011:Q4. "High" indicates that a firm is within the top two quintiles of the firm wage distribution. "Low" indicates that a firm is in the bottom quintile of the firm wage distribution.

Table A.2: Wage Ladder by Worker Education and Age

| Worker Category | Share of Net Poaching Flows | Share of Workforce | Ratio |
|---|---|---|---|
| | High Wage Firms | | |
| Less than high school | 0.16 | 0.13 | 1.16 |
| High school graduate | 0.28 | 0.28 | 1.01 |
| Some college | 0.32 | 0.32 | 1.03 |
| Bachelor's degree or more | 0.24 | 0.27 | 0.87 |
| | Low Wage Firms | | |
| Less than high school | 0.18 | 0.13 | 1.5 |
| High school graduate | 0.31 | 0.28 | 1.11 |
| Some college | 0.32 | 0.32 | 1.02 |
| Bachelor's degree or more | 0.19 | 0.27 | 0.70 |
| | High Wage Firms | | |
| Age less than 25 | 0.41 | 0.16 | 2.48 |
| Age 25 to 34 | 0.33 | 0.22 | 1.52 |
| Age 35 to 44 | 0.16 | 0.23 | 0.69 |
| Age 45 or above | 0.10 | 0.38 | 0.26 |
| | Low Wage Firms | | |
| Age less than 25 | 0.58 | 0.16 | 3.55 |
| Age 25 to 34 | 0.22 | 0.22 | 1.02 |
| Age 35 to 44 | 0.12 | 0.23 | 0.51 |
| Age 45 or above | 0.08 | 0.38 | 0.21 |

Notes: Shares of poaching flows and employment are calculated as the average across time for 1998:Q2 to 2011:Q4. "Ratio" divides the share of net poaching by the share of the workforce.

Table A.3: Net Difference: High Minus Low Wage, by Worker Education

| | Net Employment Differential | Poaching Differential | Nonemployment Differential |
|---|---|---|---|
| | **Less than High School** | | |
| Change in unemployment rate | $-0.191^{**}$ | $-0.485^{***}$ | $0.295^{***}$ |
| | (0.072) | (0.054) | (0.056) |
| Time trend | $0.011^{***}$ | $-0.003^{**}$ | $0.013^{***}$ |
| | (0.002) | (0.001) | (0.001) |
| $N$ | 55 | 55 | 55 |
| | **High School Graduate** | | |
| Change in unemployment rate | $-0.259^{***}$ | $-0.396^{***}$ | $0.137^{***}$ |
| | (0.064) | (0.047) | (0.042) |
| Time trend | $0.007^{***}$ | $-0.004^{***}$ | $0.010^{***}$ |
| | (0.001) | (0.001) | (0.001) |
| $N$ | 55 | 55 | 55 |
| | **Some College** | | |
| Change in unemployment rate | $-0.313^{***}$ | $-0.35^{***}$ | 0.034 |
| | (0.061) | (0.044) | (0.034) |
| Time trend | 0.001 | $-0.006^{***}$ | $0.008^{***}$ |
| | (0.001) | (0.001) | (0.001) |
| $N$ | 55 | 55 | 55 |
| | **Bachelor's Degree or More** | | |
| Change in unemployment rate | $-0.398^{***}$ | $-0.225^{***}$ | $-0.173^{***}$ |
| | (0.016) | (0.008) | (0.013) |
| Time trend | $-0.006^{**}$ | $-0.007^{***}$ | 0.001 |
| | (0.001) | (0.001) | (0.001) |
| $N$ | 55 | 55 | 55 |

Notes: Point estimates are taken from national-level regressions run separately by education and dependent variable (net employment differential, poaching differential, and nonemployment differential). All regressions use 55 quarterly observations from 1998:Q2 to 2011:Q4. Standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.4: Net Difference: High Minus Low Wage, by Worker Age

| | Net Employment Differential | Poaching Differential | Nonemployment Differential |
|---|---|---|---|
| | **Age Less than 25** | | |
| Change in unemployment rate | −0.030 | −0.947*** | 0.976*** |
| | (0.102) | (0.095) | (0.013) |
| Time trend | −0.002 | −0.008*** | 0.006** |
| | (0.002) | (0.002) | (0.002) |
| $N$ | 55 | 55 | 55 |
| | **Age 25 to 34** | | |
| Change in unemployment rate | −0.515*** | −0.481*** | −0.034 |
| | (0.079) | (0.055) | (0.037) |
| Time trend | −0.001 | −0.002 | 0.001 |
| | (0.002) | (0.001) | (0.001) |
| $N$ | 55 | 55 | 55 |
| | **Age 35 to 44** | | |
| Change in unemployment rate | −0.332*** | −0.248*** | 0.084*** |
| | (0.050) | (0.01) | (0.030) |
| Time trend | −0.000 | −0.001* | 0.001 |
| | (0.001) | (0.001) | (0.001) |
| $N$ | 55 | 55 | 55 |
| | **Age 45 or Above** | | |
| Change in unemployment rate | −0.207*** | −0.147*** | 0.060** |
| | (0.037) | (0.021) | (0.027) |
| Time trend | 0.001 | −0.001** | 0.002*** |
| | (0.001) | (0.000) | (0.001) |
| $N$ | 55 | 55 | 55 |

Notes: Point estimates are taken from national-level regressions run separately by education and dependent variable (net employment differential, poaching differential, and nonemployment differential). All regressions use 55 quarterly observations from 1998:Q2 to 2011:Q4. Standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.