Who Moves Up the Job Ladder?

John Haltiwanger, *University of Maryland, College Park*

Henry Hyatt, *Center for Economic Studies, US Census Bureau*

Erika McEntarfer, *Center for Economic Studies, US Census Bureau*

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 highly educated workers are less likely to match to low-productivity firms, they are also less likely to separate from them, with less educated workers 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 better-paying employers.

We thank Leland Crane, Emin Dinlersoz, Kristin McCue, Rasmus Lentz, Paul Oyer, and participants of the US Census Bureau Economic Research lunch seminar, the fall 2015 National Bureau of Economic Research Labor Studies meeting, the 2016 Society of Labor Economists conference, and the 2016 Southern Economic

[*Journal of Labor Economics*, 2018, vol. 36, no. S1]

Submitted March 21, 2016; Accepted August 10, 2017

I. 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 coexist 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 2016b) 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 for 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

Association meeting for helpful comments and suggestions. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the US Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. Contact the corresponding author, John Haltiwanger, at haltiwan@econ.umd.edu. Information concerning access to the data used in this paper is available as supplementary material online.

[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 2008; Hsieh and Klenow 2009; Bartelsman, Haltiwanger, and Scarpetta 2013) have investigated the hypothesis that misallocation accounts for much of the cross-country variation in GDP per capita because 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.

more productive and higher-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) relative to those of Burdett and Mortensen (1998) and, more recently, Moscarini and Postel-Vinay (2009, 2012, 2013, 2016). Mortensen and Pissarides (1994) and subsequent extensions of their framework with multiple worker firms (see, e.g., Cooper, Haltiwanger, and Willis 2007; 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 Moscarini and Postel-Vinay (2009, 2012, 2013, 2016) 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. 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. Moscarini and Postel-Vinay (2009, 2012, 2013, 2016) show that this movement up the ladder will be procyclical.

[3] These models are closely connected to canonical firm dynamics 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.

During booms, firms on average 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 Mortensen and Pissarides (1994) type models since on-the-job search is incorporated, but variants of these models that include business cycles such as Moscarini and Postel-Vinay (2009, 2012, 2013, 2016) 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, Haltiwanger et al. (2016b) 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 that is consistent with the predictions of Mortensen and Pissarides (1994) models.

Both Mortensen and Pissarides (1994) and Moscarini and Postel-Vinay (2009, 2012, 2013, 2016) assume worker homogeneity and thus are silent about what types of workers move up the job ladder. But recent search and matching papers (e.g., Bagger and Lentz 2016; Lopes de Melo 2016; Hagedorn, Law, and Manovskii 2017; Lise and Robin 2017) present model estimates that imply that worker flows will be characterized by positive assortative matching, that is, 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 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

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

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 with 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 life cycle 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 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

[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), similar to several other recent models of labor market sorting, rank workers and firms on the basis of a univariate dimension of productivity, treating the nature of the complementarity between workers and firms of different ranks as a question of interest.

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 the appendix (available online), 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 who has been moving up the job ladder in recent years. Section IV presents concluding remarks.

II. Data

We use linked employer-employee data from the Longitudinal Employer-Household Dynamics (LEHD) program at the US 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, the District of Columbia, 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% 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)

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

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 that 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 have only 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 because 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 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 nonfarm (for profit) firms. Revenue is deflated with the gross domestic product (GDP) price deflator.

[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.

[10] Haltiwanger, Hyatt, and McEntarfer (2015) compare this definition to two alternative definitions of job-to-job moves that are more restrictive: one definition including only transitions where the job end and start are in the same quarter and an alternative definition that 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 Current Population Survey (CPS)-based job-to-job flows. On the basis of the robustness analysis in our earlier paper, we are confident that 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 additional details of the link between LEHD and the Longitudinal Business Database, see Haltiwanger et al. (2014).

Our measure of productivity is gross output per worker, which is commonly used to measure productivity at the micro and macro level but is a relatively crude measure compared with 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 nonprofits, 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 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 four-digit North American Industry Classification System (NAICS) level. Specifically, we compute the employment-weighted quintiles of the (within-industry year) productivity distribution. Using these quintiles, we define high-productivity

[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 nonprofits such as religious organizations where productivity is not well defined.

[13] Another source of mismatch is that 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.

firms as those in the top quintile and low-productivity firms 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 more than 98% of workers in the LEHD data. In our analysis, we use four age categories: less than 25 years, 25–34 years, 35–44 years, and 45 years 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 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 25 years 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% of workers in the LEHD data. For the remaining 90% of workers, educational attainment at age 25 years 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 coworkers, 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]

[14] Another limitation of our firm-level productivity measure is that it reflects only 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 interindustry differences in productivity. To capture such interindustry productivity differences, Haltiwanger et al. (2016b) 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.

[15] While workers can, of course, return to school after the age of 25 years, bachelor's degree attainment drops offs sharply after age 25 years; 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 with the CPS and ACS. This

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% of employment) and to parts of the nonprofit 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 many of the largest states so that our sample accounts for 65% 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 2003–11 period, given that the productivity data are available only starting in that period on a year-to-year basis.

III. Results

A. 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 produc-

is possibly due to the Great Recession lowering returns to education for young workers. We do not think this is a substantial issue for our analysis because 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 years 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 do not report the patterns for this group.

[17] Our 28 states are California, Florida, Georgia, Hawaii, Idaho, Illinois, Indiana, Kansas, Maine, Maryland, Minnesota, Missouri, Montana, North Carolina, New Jersey, North Dakota, New Mexico, Nevada, Pennsylvania, Oregon, Rhode Island, South Carolina, South Dakota, Tennessee, Virginia, Washington, Wisconsin, and West Virginia. 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 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.

tivity 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 autoregression (AR1) specification on the annual firm-level data of log real revenue per worker yields a 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) 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 a value of 1 if the firm exits between $t-1$ and t and is 0 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 because 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. An increase of 1 standard deviation in within-industry productivity yields a 21 percentage point increase in net employment growth and a 5 percentage point decrease in the likelihood of exit. This evidence gives us confidence to proceed with our measure of revenue labor productivity because 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 pro-

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

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

Table 1
Relationship between Productivity Growth and Survival

Dependent Variable	Lagged Productivity	Lagged Log(Employment)
Net growth rate	.2643***	.0583***
	(.0002)	(.0001)
Exit	−.0739***	−.0454***
	(.0001)	(.0000)

NOTE.—Parameter estimates from two firm-level regressions. Standard errors are in parentheses. This regression is based on more than 40 million firm-year observations. Productivity is measured as log real revenue per worker deviated from six-digit North American Industry Classification System industry by year means.
*** Significant at the 1% level.

ductivity 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

Table 2
Within-Industry Firm Percentile Rank

	Parameter Estimate
Intercept	6.2024***
	(.0715)
Share of employment:	
Male	.1918***
	(.0002)
Age less than 25 years	.1994***
	(.0008)
Age 25–34 years	.0359***
	(.0005)
Age 35–44 years	.1183***
	(.0005)
High school graduate	−.3359***
	(.0010)
Some college	.4723***
	(.0010)
Bachelor's degree or more	.6642***
	(.0007)
R^2	.127

NOTE.—Parameter estimates from a firm-level regression, weighted by employment. Standard errors are in parentheses. Firm productivity ranks are calculated within a four-digit North American Industry Classification System industry.
*** Significant at the 1% level.

of a firm in the within-industry firm productivity distribution on the shares of workers in age, gender, and 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 (younger than 45 years of age), and males are more productive. For example, a 1 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% 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; 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 Abowd, Kramarz, and Margolis (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 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

[20] Barth, Davis, and Freeman (2016b) 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 5-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 appear to be high productivity only because of an aspect of worker or firm productivity that we do not measure; see Eeckhout and Kircher (2011).

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).

B. Worker Reallocation and Firm Productivity Dispersion

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

$$\text{NetJobFlows (NJF)} = H - S = \left(H_p - S_p\right) + \left(H_n - S_n\right), \qquad (1)$$

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.

To investigate productivity-enhancing reallocation, we consider the above decomposition for high- versus 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

[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 by Haltiwanger et al. (2016b), 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 one-half (within/adjacent quarter) of worker reallocation.

Table 3
Hiring and Separation Rates by Within-Industry Productivity

	Poaching Rates		Nonemployment Rates		Net Rates		
Firm Productivity Type	Hires	Separations	Hires	Separations	Poaching	Nonemployment	Employment
High	.065	.060	.057	.057	.004	.000	.005
Low	.072	.080	.077	.079	−.008	−.002	−.010

NOTE.—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 four-digit North American Industry Classification System (NAICS) industry. Low indicates that a firm is in the bottom quintile of the productivity distribution within a four-digit NAICS industry.

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% is due to job-to-job flows.

Haltiwanger et al. (2016b) show that these average patterns mask important cyclical fluctuations. The net job flow differential between high- and low-productivity firms during the boom of 2004–6 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% of workers to more productive firms each quarter but only contracted by about −0.7% 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 with high-productivity firms. Low-productivity firms not only are net losers of jobs but also are much more volatile in terms of a high pace of hires and separations. Also, as emphasized by Haltiwanger et al. (2016b), the gross poaching flows largely reflect a within-firm type flow. That 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

[24] These results are time series averages of quarterly patterns reported by Haltiwanger et al. (2016b).

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.

C. Who Moves from Low- 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:

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

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

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

$$\text{NetPoachingRate}(Y, X) = \frac{H_p(Y, X) - S_p(Y, X)}{\text{Emp}(Y)}, \tag{4}$$

$$\text{NetPoachingPropensity}(Y, X) = \frac{H_p(Y, X) - S_p(Y, X)}{\text{Emp}(X)}. \tag{5}$$

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% for high school graduates at high-productivity firms means that high-productivity firms grew by 0.05% 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% for high school graduates at high-productivity firms means that, on net, 0.05% 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 equation (5).

We begin with the poaching flows as fractions of employment by firm type Y groups (eq. [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 1 disproportionately account for the Y specific flows.

As seen in table 4, while workers with college degrees account for a sizable share (22%) of worker reallocation into high-productivity firms, this is less than their overall share of the workforce (27%). 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

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	.16	.13	1.23
High school graduate	.30	.28	1.06
Some college	.32	.32	1.01
Bachelor's degree or more	.22	.27	.81
Low-productivity firms:			
Less than high school	.17	.13	1.24
High school graduate	.31	.28	1.12
Some college	.32	.32	1.00
Bachelor's degree or more	.21	.27	.76
High-productivity firms:			
Age less than 25 years	.29	.16	1.75
Age 25–34 years	.30	.22	1.40
Age 35–44 years	.20	.23	.85
Age 45 years or older	.21	.38	.54
Low-productivity firms:			
Age less than 25 years	.37	.16	2.24
Age 25–34 years	.26	.22	1.18
Age 35–44 years	.18	.23	.79
Age 45 years or older	.19	.38	.50

Note.—For education results, workers younger than 25 years of age are dropped because 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.

that the role of life cycle dynamics in reallocating workers up the job ladder is very pronounced. Workers younger 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 years account for 29% of flows to high-productivity firms and 37% of flows from low-productivity firms, even though they account for only 16% 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 (eq. [5]). First, note that net poaching to high-productivity firms is positive for all groups in all periods (fig. 1*A*) while net poaching to low-productivity firms is negative for all groups in all periods (fig. 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, that is, 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 (fig. 2*A*, 2*B*). In contractions, net hires from nonemployment are negative but especially more so for workers with lower educational attainment at low-productivity firms (fig. 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. Figure 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 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 with other groups in expansions. This reflects

[25] The magnitudes in figure 1 are small, but it is important to remember that 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% 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% of workers at low-productivity firms get poached away to higher productivity firms and 1.6% of workers at high-productivity firms are poached from lower productivity firms.

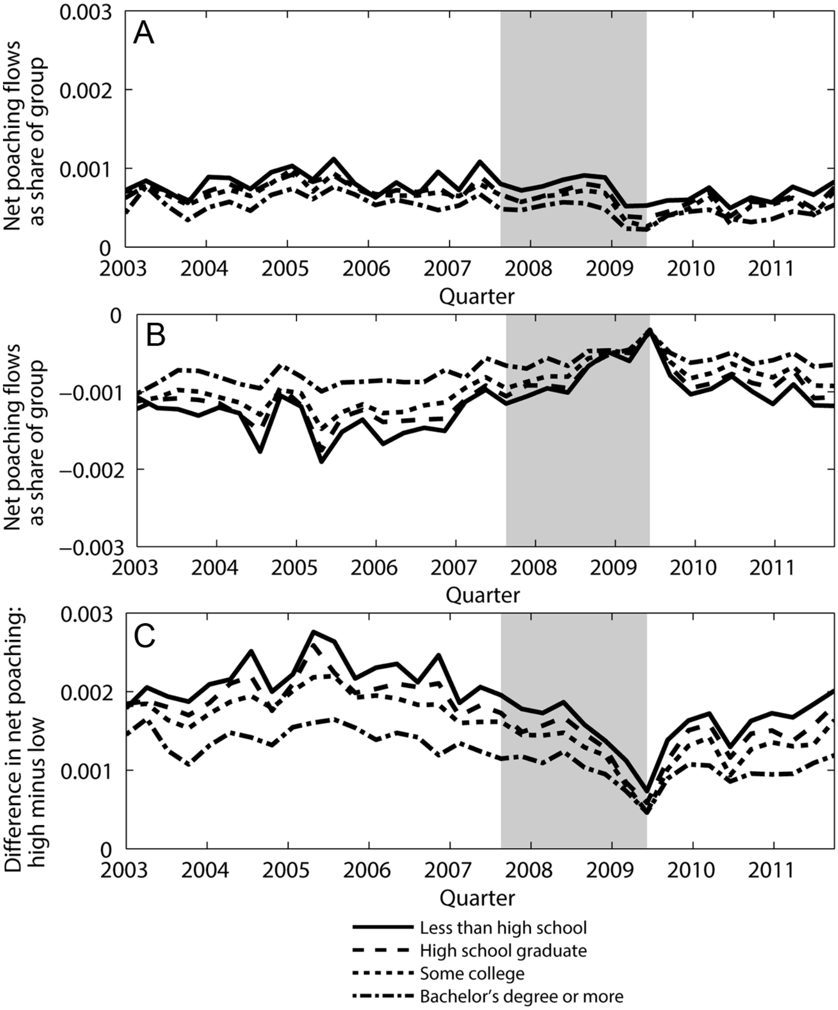

FIG. 1.—Net poaching flows by within-industry firm productivity and worker education. *A*, High productivity. *B*, Low productivity. *C*, Net differential. Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate National Bureau of Economic Research recession 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 four-digit North American Industry Classification System (NAICS) industry, and low productivity indicates that a firm is in the bottom quintile of the productivity distribution within a four-digit NAICS industry.

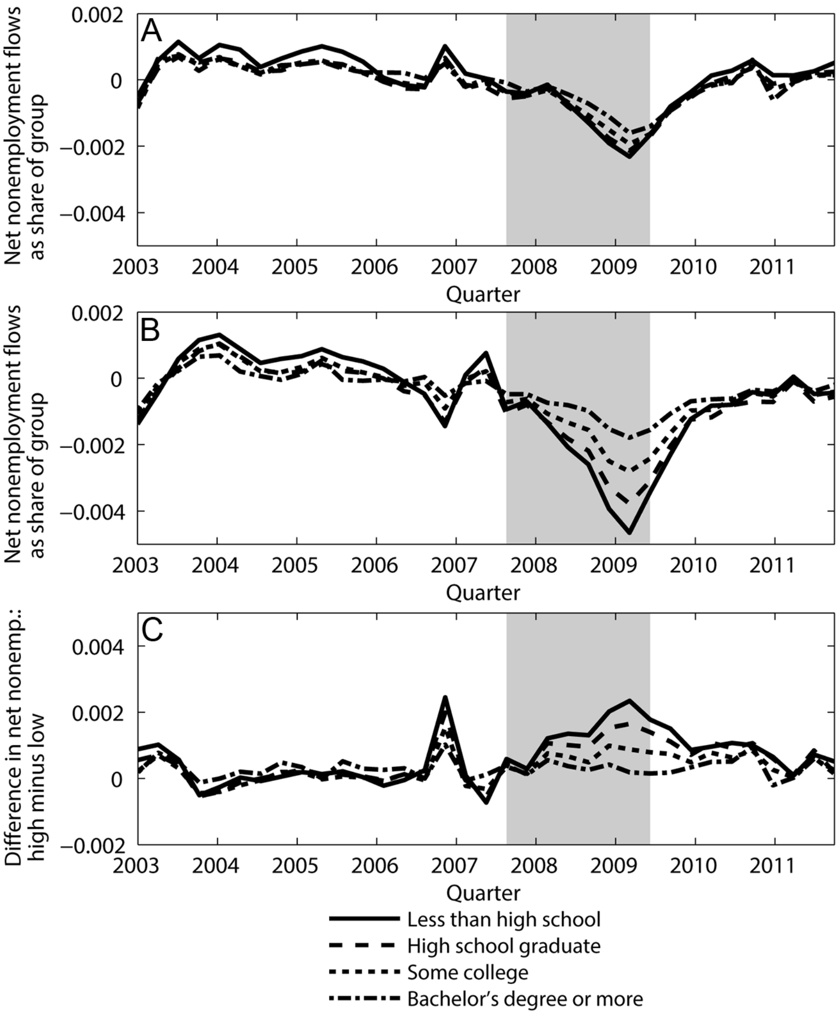

FIG. 2.—Net nonemployment (nonemp.) flows by within-industry firm productivity and worker education. *A*, High productivity. *B*, Low productivity. *C*, Net differential. Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate National Bureau of Economic Research 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 four-digit North American Industry Classification System (NAICS) industry, and low productivity indicates that a firm is in the bottom quintile of the productivity distribution within a four-digit NAICS industry.

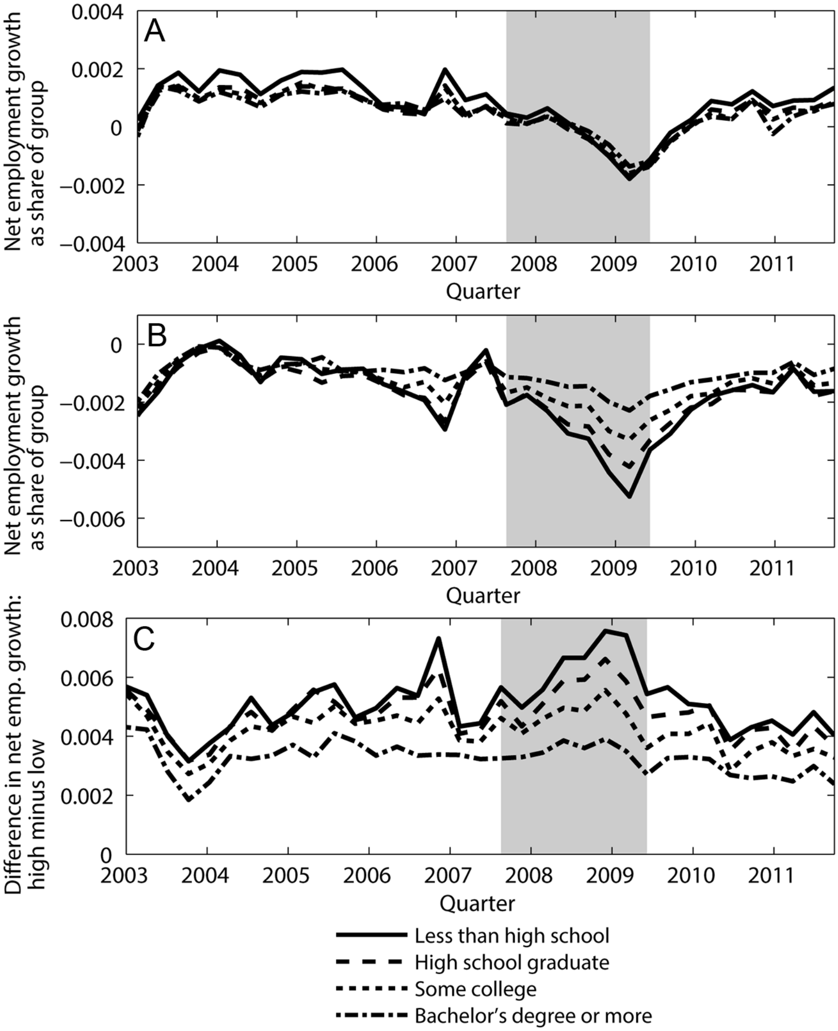

FIG. 3.—Net employment (emp.) growth (sum of net poaching and net nonemployment flows) by within-industry firm productivity and worker education. *A*, High productivity. *B*, Low productivity. *C*, Net differential. Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate National Bureau of Economic Research 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 four-digit North American Industry Classification System (NAICS) industry, and low productivity indicates that a firm is in the bottom quintile of the productivity distribution within a four-digit NAICS industry.

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. Figure 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 figures 1*B* and 2*B*, 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 figures 1*C*–3*C*, estimating the following equation:

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

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	.064**	−.059***	.124***
	(.028)	(.013)	(.024)
Time trend	.000	−.002***	.002**
	(.001)	(.000)	(.001)
N	35	35	35
High school graduate:			
Change in unemployment rate	.028	−.055***	.083***
	(.024)	(.011)	(.020)
Time trend	.000	−.002***	.002***
	(.001)	(.000)	(.001)
N	35	35	35
Some college:			
Change in unemployment rate	−.000	−.048***	.048***
	(.020)	(.010)	(.016)
Time trend	−.000	−.002***	.002***
	(.001)	(.000)	(.001)
N	35	35	35
Bachelor's degree or more:			
Change in unemployment rate	−.025	−.025***	.001
	(.016)	(.008)	(.013)
Time trend	−.001**	−.002***	.000
	(.001)	(.000)	(.000)
N	35	35	35

Note.—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 are in parentheses.
** Significant at the 5% level.
*** Significant at the 1% level.

where the left-hand side variable is the difference between worker reallocation at high- versus low-productivity firms, ΔU is the change in the unemployment rate with marginal effect β, α is a constant, and γ 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 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 figure 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 discernibly more pronounced when the unemployment rate increases.

Table 6 examines gross worker flows to see whether either the hires or the separation margin is driving the worker reallocation patterns shown

[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% level for 90% of the specifications.

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

Table 6
Hires and Separations at High- versus Low-Productivity Firms by Worker Education

	High Productivity		Low Productivity	
	Hires	Separations	Hires	Separations
Less than high school	−.126***	.048***	−.170***	.129***
	(.015)	(.012)	(.024)	(.021)
High school graduate	−.112***	.036***	−.138***	.094***
	(.016)	(.011)	(.021)	(.016)
Some college	−.103***	.028**	−.112***	.069***
	(.015)	(.012)	(.017)	(.013)
Bachelor's degree or more	−.089***	.020*	−.072***	.039***
	(.014)	(.011)	(.012)	(.011)
N	35	35	35	35

Note.—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 are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

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 life cycle 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. Figure 4*A* shows that high-productivity firms grow by disproportionately poaching younger workers away from less productive firms. Figure 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-productivity (fig. 5*A*) and low-productivity (fig. 5*B*)

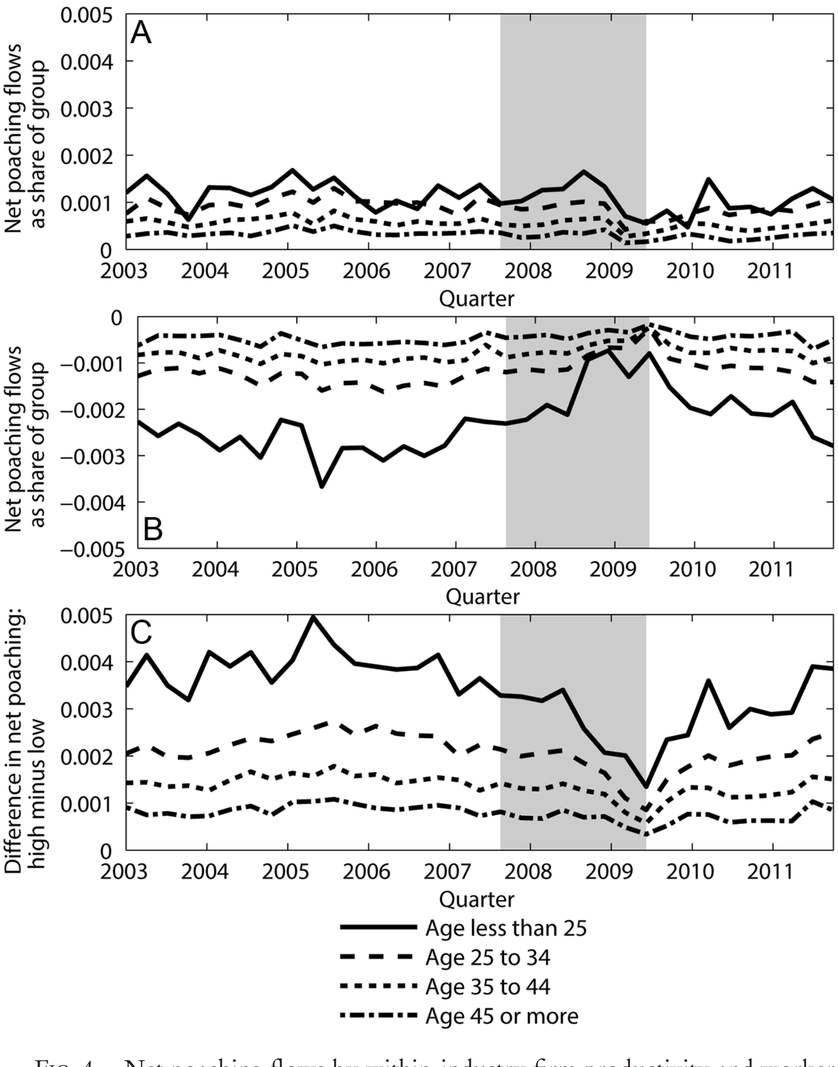

FIG. 4.—Net poaching flows by within-industry firm productivity and worker age. *A*, High productivity. *B*, Low productivity. *C*, Net differential. Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate National Bureau of Economic Research recession quarters. Data are seasonally adjusted using X-11. High productivity indicates that a firm is in the top quintile of the productivity distribution within a four-digit North American Industry Classification System (NAICS) industry, and low productivity indicates that a firm is in the bottom quintile of the productivity distribution within a four-digit NAICS industry.

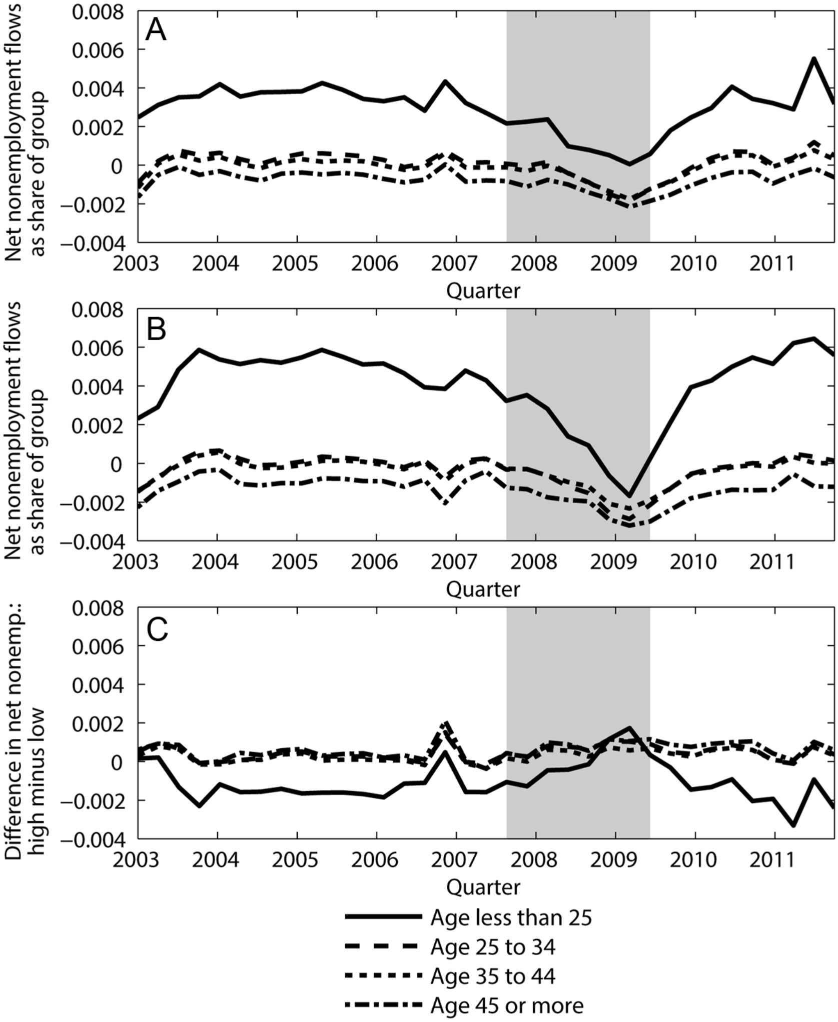

FIG. 5.—Net nonemployment (nonemp.) flows by within-industry firm productivity and worker age. *A*, High productivity. *B*, Low productivity. *C*, Net differential. Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate National Bureau of Economic Research 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 four-digit North American Industry Classification System (NAICS) industry, and low productivity indicates that a firm is in the bottom quintile of the productivity distribution within a four-digit NAICS industry.

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. Because high-productivity firms disproportionately poach and hire from nonemployment younger workers, not surprisingly they also grow by adding young workers to their firms (fig. 6*A*). Low-productivity firms, however, lose employment among all groups except the youngest workers. While low-productivity firms lose many young workers through poaching (fig. 4*B*), they also hire a great many others from nonemployment (fig. 5*B*) more than offsetting the employment losses of the youngest workers moving up the ladder (fig. 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 figures 4*C*–6*C*, 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 (col. 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 (col. 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 younger than 25 years.

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 because 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.

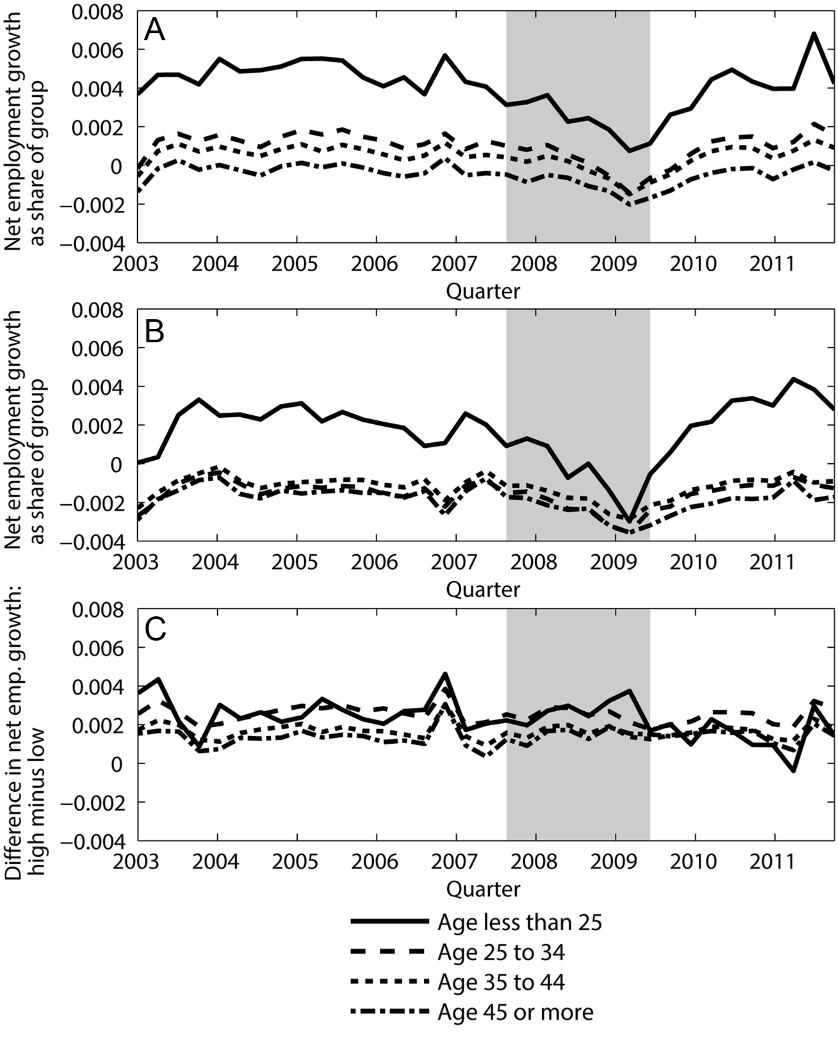

FIG. 6.—Net employment (emp.) growth (sum of net poaching and net nonemployment flows) by within-industry firm productivity and worker age. *A*, High productivity. *B*, Low productivity. *C*, Net differential. Transition rates are calculated on a quarterly basis from 2003:Q1 to 2011:Q3. Shaded regions indicate National Bureau of Economic Research 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 four-digit North American Industry Classification System (NAICS) industry, and low productivity indicates that a firm is in the bottom quintile of the productivity distribution within a four-digit NAICS industry.

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

	Net Employment Differential	Poaching Differential	Nonemployment Differential
Age less than 25 years:			
Change in unemployment rate	.118***	−.114***	.232***
	(.037)	(.023)	(.026)
Time trend	−.005***	−.003***	.002**
	(.001)	(.001)	(.001)
N	35	35	35
Age 25–34 years:			
Change in unemployment rate	−.016	−.069***	.053***
	(.021)	(.012)	(.015)
Time trend	−.001	−.001*	.000
	(.001)	(.000)	(.001)
N	35	35	35
Age 35–44 years:			
Change in unemployment rate	−.005	−.034	.030*
	(.019)	(.008)	(.016)
Time trend	−.000	−.001**	.001
	(.001)	(.000)	(.001)
N	35	35	35
Age 45 years or older:			
Change in unemployment rate	.026	−.018***	.045***
	(.022)	(.006)	(.020)
Time trend	.000	−.001**	.001
	(.001)	(.000)	(.001)
N	35	35	35

NOTE.—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 are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

D. 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 past 30 years can be attributed to increased pay dispersion across firms (Barth et al. 2016a; 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 the appendix we repeat our analysis, ranking firms instead by average pay across all industries. Our results for the job ladder are robust to ranking

Table 8
Hires and Separations at High- versus Low-Productivity Firms by Worker Age

	High Productivity		Low Productivity	
	Hires	Separations	Hires	Separations
Age less than 25 years	−.227***	.018	−.328***	.146***
	(.037)	(.021)	(.043)	(.027)
Age 25–34 years	−.115***	.035***	−.115***	.089***
	(.017)	(.013)	(.017)	(.015)
Age 35–44 years	−.089***	.040***	−.081***	.078***
	(.014)	(.012)	(.014)	(.013)
Age 45 years or older	−.074***	.030**	−.082***	.067***
	(.013)	(.011)	(.016)	(.013)
N	35	35	35	35

NOTE.—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 are in parentheses.
** Significant at the 5% level.
*** Significant at the 1% level.

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 with 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, and high-wage sectors such as 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 also they are more likely to be knocked off the 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. Last, 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 is a primary means of matching less skilled workers to higher paying employers.

IV. Concluding Remarks

Who moves up the job ladder? Using rich matched employer-employee data for the United States, 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 because 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 Mortensen and Pissarides (1994) 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 Mortensen and Pissarides (1994) 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.

References

Abowd, John, John Haltiwanger, Ron Jarmin, Julia Lane, Paul Lengermann, Kristin McCue, Kevin McKinney, and Kristin Sandusky. 2005. The relation among human capital, productivity, and market value: building up from micro evidence. In *Measuring capital in the new economy*, Studies in Income and Wealth, vol. 68, ed. Carol Corrado, John Haltiwanger, and Daniel Sichel, 153–98. Chicago: University of Chicago Press.

Abowd, John, Bryce Stephens, Lars Vilhuber, Fredrik Andersson, Kevin McKinney, Marc Roemer, and Simon Woodcock. 2009. The LEHD infrastructure files and the creation of the quarterly workforce indicators. In *Producer dynamics: New evidence from micro data*, Studies in Income and Wealth, vol. 68, ed. Timothy Dunne, J. Bradford Jensen, and Mark J. Roberts, 149–230. Chicago: University of Chicago Press.

Bagger, Jesper, and Rasmus Lentz. 2016. An equilibrium model of wage dispersion with sorting. Unpublished manuscript, University of Wisconsin.

Barlevy, Gadi. 2002. The sullying effect of recessions. *Review of Economic Studies* 69, no. 1:65–96.

Bartelsman, Eric, John Haltiwanger, and Stefano Scarpetta. 2013. Cross country differences in productivity: The role of allocative efficiency. *American Economic Review* 103, no. 1:305–34.

Barth, Earling, Alex Bryson, James Davis, and Richard Freeman. 2016a. It's where you work: Increases in the dispersion of earnings across establishments and individuals in the United States. *Journal of Labor Economics* 34, no. S2:S67–S97.

Barth, Earling, James Davis, and Richard Freeman. 2016b. Augmenting the human capital earnings equation with measures of where people work. Unpublished manuscript, Harvard University.

Burdett, Kenneth, and Dale Mortensen. 1998. Wage differentials, employer size, and unemployment. *International Economic Review* 39, no. 2:257–73.

Card, David, Ana Rute Cardoso, Jeorg Heining, and Patrick Kline. 2016. Firms and labor market inequality: Evidence and some theory. IZA Discussion Paper no. 9850.

Coles, Melvyn, and Dale Mortensen. 2016. Equilibrium labor turnover, firm growth, and unemployment. *Econometrica* 84, no. 1:347–63.

Cooper, Russell, John Haltiwanger, and Jonathan Willis. 2007. Search frictions: Matching aggregate and establishment observations. *Journal of Monetary Economics* 54:56–78.

Davis, Steven, and John Haltiwanger. 2014. Labor market fluidity and economic performance. NBER Working Paper no. 20479, National Bureau of Economic Research, Cambridge, MA.

Davis, Steven, John Haltiwanger, and Scott Schuh. 1996. *Job creation and destruction*. Cambridge, MA: MIT Press.

Eeckhout, Jan, and Philipp Kircher. 2011. Identifying sorting—In theory. *Review of Economic Studies* 78, no. 3:872–906.

Elsby, Michael, and Ryan Michaels. 2013. Marginal jobs, heterogeneous firms, and unemployment flows. *American Economic Journal: Macroeconomics* 5, no. 1:1–48.

Foster, Lucia, John Haltiwanger, and C. J. Krizan. 2001. Aggregate productivity growth: Lessons from microeconomic evidence. In *New developments in productivity analysis*, Studies in Income and Wealth, vol. 63, ed. Charles Hulten, Edwin Dean, and Michael Harper, 303–72. Chicago: University of Chicago Press.

Foster, Lucia, John Haltiwanger, and Chad Syverson. 2008. Reallocation, firm turnover, and efficiency: selection on productivity or profitability? *American Economic Review* 98, no. 1:394–425.

Hagedorn, Marcus, Tzuo Law, and Iourii Manovskii. 2017. Identifying equilibrium models of labor market sorting. *Econometrica* 85, no. 1:29–65.

Haltiwanger, John, Henry Hyatt, Lisa Kahn, and Erika McEntarfer. 2016a. Cyclical job ladders by firm size and firm wage. Unpublished manuscript, University of Maryland.

Haltiwanger, John, Henry Hyatt, Erika McEntarfer. 2015. Cyclical reallocation of workers across employers by firm size and wage. NBER Working Paper no. 21235, National Bureau of Economic Research, Cambridge, MA.

———. 2016b. Do workers move up the firm productivity ladder? Unpublished manuscript, University of Maryland.

Haltiwanger, John, Henry Hyatt, Erika McEntarfer, Liliana Sousa, and Stephen Tibbets. 2014. Firm age and size in the longitudinal employer-household dynamics data. US Census Bureau Center for Economic Studies Discussion Paper no. CES-14-16, Washington, DC.

Haltiwanger, John, Ron Jarmin, Robert Kulick, and Javier Miranda. 2017. High growth young firms: Contribution to job growth, revenue growth, and productivity. In *Measuring entrepreneurial businesses: Current knowledge and challenges*, ed. John Haltiwanger, Erik Hurst, Javier Miranda, and Antoinette Schoar, 11–62. Chicago: University of Chicago Press.

Haltiwanger, John, Ron Jarmin, and Javier Miranda. 2013. Who creates jobs? Small versus large versus young. *Review of Economics and Statistics* 95, no. 2:347–61.

Henderson, Cody, and Henry Hyatt. 2012. Estimation of job-to-job flow rates under partially missing geography. US Census Bureau Center for Economic Studies Discussion Paper no. CES-12-29, Washington, DC.
Hopenhayn, Hugo. 1992. Entry, exit, and firm dynamics in long run equilibrium. *Econometrica* 60, no. 5:1127–50.
Hopenhayn, Hugo, and Richard Rogerson. 1993. Job turnover and policy evaluation: A general equilibrium analysis. *Journal of Political Economy* 101, no. 5:915–38.
Hsieh, Chang-Tai, and Peter Klenow. 2009. Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics* 124, no. 4: 1403–48.
Hyatt, Henry, Erika McEntarfer, Kevin McKinney, Stephen Tibbets, and Douglas Walton. 2014. Job-to-job (J2J) flows: New labor market statistics from linked employer-employee data. *JSM Proceedings 2014*, Business and Economics Statistics Section, 231–45.
Lentz, Rasmus, and Dale Mortensen. 2010. Labor market models of worker and firm heterogeneity. *Annual Review of Economics* 2:577–602.
Lise, Jeremy, and Jean-Marc Robin. 2017. The macrodynamics of sorting between workers and firms. *American Economic Review* 107, no. 4:1104–35.
Lopes de Melo, Rafael. 2016. Firm wage differentials and labor market sorting: reconciling theory and evidence. *Journal of Political Economy*, forthcoming.
Mortensen, Dale, and Christopher Pissarides. 1994. Job creation and job destruction in the theory of unemployment. *Review of Economic Studies* 61, no. 3:397–415.
Moscarini, Giuseppe, and Fabien Postel-Vinay. 2009. The timing of labor market expansions: new facts and a new hypothesis. In *NBER Macroeconomics Annual 2008*, vol. 23, ed. Daron Acemoglu, Kenneth Rogoff, and Michael Woodford, 1–52. Chicago: University of Chicago Press.
———. 2012. The contribution of large and small employers to job creation in times of high and low unemployment. *American Economic Review* 102, no. 6:2509–39.
———. 2013. Stochastic search equilibrium. *Review of Economic Studies* 80, no. 4:1545–81.
———. 2016. Did the job ladder fail after the great recession? *Journal of Labor Economics* 34, no. S1:S55–S93.
Restuccia, Diego, and Richard Rogerson. 2008. Policy distortions and aggregate productivity with heterogeneous establishments." *Review of Economic Dynamics* 11, no. 4:707–20.
Schaal, Edouard. 2015. Uncertainty and unemployment. Unpublished manuscript, New York University.
Syverson, Chad. 2004. Market structure and productivity: a concrete example. *Journal of Political Economy* 112, no. 6:1181–222.
———. 2011. What determines productivity? *Journal of Economic Literature* 49, no. 2:326–65.