Do Workers Move Up the Firm Productivity Job Ladder?*

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Abstract

In this paper, we use linked employer-employee data to provide direct evidence on the role of job-to-job flows in reallocating workers from less productive to more productive firms in the U.S. economy. We present evidence that workers move up the firm productivity ladder, and that job-to-job moves of workers explain almost all of the differential employment growth rates of high and low productivity firms. Movements up the firm productivity ladder are procyclical but there has also been a downward trend in movements up the ladder. The latter suggests that job-to-job flows are contributing less to productivity growth and potentially reflects a decline in economic mobility in the U.S. Integrating these new findings with evidence on job ladders by firm size and wage, we observe that job-to-job moves reallocate workers up the firm productivity and the firm pay distribution, but not up the size distribution. This suggests to us that the tight relationship between firm productivity, wages, and size that is central to many macro-labor models does not hold in real world data. To resolve this discrepancy, we investigate the nature of the joint distribution of firm wages, firm size and firm productivity. We find evidence that firm productivity and firm wages are much more closely related than firm productivity and firm size, and that the firm productivity/size relationship varies systematically across industries. We hypothesize and present evidence that the weak relationship we observe between size and productivity in many industries is due to market segmentation in those industries.

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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.

In this paper, we investigate the role of job-to-job flows in reallocating employment across the firm productivity distribution. Specifically, we use linked employer-employee data merged with new firm productivity data to decompose net employment growth in high and low productivity firms into two components: net growth accounted for by job-to-job flows and growth accounted for by net flows through non-employment. Our findings suggest that job-to-job moves of workers play a surprisingly important role in accounting for the dispersion in growth rates across high and low productivity firms. Although job-to-job flows overall account for about 50 percent of total worker reallocation, we find that about 90 percent of the net reallocation of workers from low productivity to high productivity firms is accounted for by job-to-job flows.

Given the critical role of job-to-job flows in this productivity enhancing reallocation of workers, some of our other findings give cause for concern. We find that net employment reallocation to more productive firms via job-to-job flows is procyclical and exhibits a pronounced downward trend. This suggests that one of the costs of recessions is a slowdown in the productivity enhancing reallocation of workers across firms via job-to-job flows. The latter is consistent with a sullying effect of recessions. The downward trend suggests there are secular forces yielding

[1]New sources of producer-level data have resulted in a wealth of new 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 is not the focus of the current paper but these findings highlight the importance of understanding the connection between productivity and reallocation.

a slowdown in productivity enhancing reallocation of workers across firms via job-to-job flows. Overall, our findings emphasize that job-to-job flows play a critical role in productivity enhancing reallocation of workers and that understanding the determinants of job-to-job flows is of critical importance.

Our findings also have implications for economic mobility and inequality. Many macro-labor models posit a tight link between firm productivity and wages; all else equal, more productive firms should offer higher wages to workers. One version of these models (e.g., Mortensen and Pissarides (1994)) emphasizes that an important aspect of these frictions is that reallocating workers from one firm to another often involves a spell of unemployment. Alternatively, the on-the-job search models of Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2013) emphasize a role for job-to-job moves in worker reallocation across firms. These models have additional implications with respect to the patterns of job-to-job flows by firm size and firm wage. Specifically, these models predict that there should be a firm productivity, firm wage, firm size job ladder. In the wage posting models of on-the-job search, large, high productivity firms post high wages in order to be able to poach workers away from smaller, less productive, lower paying firms. In these models, workers moving up the firm productivity ladder are also moving up the firm wage ladder so the pace of job-to-job flows is an important indicator of economic mobility.

Recent empirical findings in Kahn and McEntarfer (2014) and Haltiwanger, Hyatt and McEntarfer (2015) (hereafter HHM (2015)) provide mixed support for the predictions of firm wage and firm size ladders.[3] Kahn and McEntarfer (2014) find that hires at high wage firms and separations at low wage firms are procyclical. In addition, they show that the components of these hires and separations that are likely to reflect job-to-job flows are procyclical. HHM (2015) jointly examine the patterns of job-to-job flows by firm size and firm wage. They find that job-to-job flows from low wage to high wage firms are positive on average and procyclical. However, they find that similar patterns don't hold for firm size. They find that job-to-job flows from small to large firms is negative on average and exhibits little cyclicality. Putting the results from these recent papers with those from the current paper indicates the patterns for firm productivity and firm wages fit the predicted patterns from job ladder models while those

[3]The early empirical evidence on cyclical job ladders by Moscarini and Postel-Vinay (2009, 2012, 2014) emphasized firm size as a criterion for determining a firm's rank in the job ladder.

for firm size do not.

Given the evidence of a firm productivity and firm wage job ladder but not a firm size ladder, in this paper we also investigate the joint distribution of firm size, firm productivity and firm wages. The motivation is multi-fold. First, many models of firm heterogeneity posit a tight relationship between firm productivity and firm size. Indeed, it is common in macro models of firm heterogeneity to calibrate the firm productivity distribution with the firm size distribution (see, e.g., Hopenhayn and Rogerson (1993) and Restuccia and Rogerson (2008)). Second, understanding the relationship between firm productivity and firm wage is important for interpreting the firm wage ladder results from the recent literature.

We find that there is a strong positive relationship between firm productivity and firm wages. We also find evidence of a positive relationship between firm wages and firm size and between firm productivity and firm size but these relationships are weaker. The latter weaker relationships help account for the very different findings regarding job ladders by firm size compared to firm wages and firm productivity. Since there is a positive relationship among all three firm characteristics, we explore these relationships further to help account for why we do not observe a firm size job ladder.

The hypothesized positive relationship between firm productivity and firm size is a prediction that holds within markets defined by industry as well as by geography if the market is segmented geographically. For example, it may be that a very productive firm in a segmented market is large within that market but not large in the national economy. This perspective leads us to examine the firm productivity/size and firm wage/size relationship within detailed 4-digit NAICS industries. For completeness, we also examine the firm productivity/wage relationship within each of those industries. We find that there are some 4-digit industries with much more positive firm productivity/size and firm wage/size relationships than others. Those 4-digit industries are concentrated in sectors like manufacturing and information, which produce goods and services for the national market. For these industries, we find that large firms are net gainers from job-to-job flows, suggesting that for such industries the predictions of the canonical models are more likely to hold. However, we also show that industries with more positive high size/productivity and size/wage relationships are also industries that are on average high wage industries. As such, we find that firms that are in these industries are net gainers from job-to-job flows whether large or small. The role of firm size in thus complicated by other factors driving the patterns of job-to-job flows.

In our main analysis, we do not explicitly control for worker heterogeneity. An attractive feature of job-to-job flows is that such transitions have a built-in control for worker quality - at least for the workers engaged in the job-to-job flow. During a transition from one firm to another within a short period of time the quality of a worker engaged in the transition presumably does not change. It may be, of course, that workers of a given quality are moving across firms with a different mix of worker quality. To the extent that the latter is occurring, it still must be the case there is some form of information friction that makes this a time intensive process. For example, it may be that workers moving up the job ladder reflects workers and firms learning about worker quality. To explore this possibility, we rank industries by worker skill intensity measured by the share of workers with a college degree. We hypothesize that the information friction version of the job ladder is likely to be more relevant in skill intensive industries. We find no evidence that worker reallocation to high-wage firms via job-to-job moves is manifestly different in industries with many high-skilled workers (hospitals, high-tech, higher education) vs. those with few (courier services, automotive dealers, drywall installation). In both industry groups, job-to-job moves reallocate workers to higher-paying employers at about the same rate.

The paper proceeds as follows. We discuss the conceptual underpinnings in more detail in section II. Section III describes the data. Section IV presents the main empirical results. Section V presents concluding remarks.

2 Conceptual Underpinnings

The motivation for our empirical analyses stems from considering the interaction of firm heterogeneity and firm dynamics in the presence of search and matching frictions in the labor market. The firm heterogeneity literature has at its core starting point the evidence of wide dispersion in profitability and productivity across firms within industries (see Syverson (2004, 2011)). There remain open questions about the sources of such heterogeneity with hypotheses including exogenous differences in entrepreneurial ability (e.g., Lucas (1978)), idiosyncratic draws of productivity (e.g., Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995)), endogenous differences due to choice of technology (e.g., Caselli (1999)) or investments in innovation through R&D (Acemoglu et. al. (2013)). Endogenous choice models still typically have an exogenous component – e.g., the outcome of an investment in R&D are stochastic and exogenous.

Beyond accounting for the source of heterogeneity, alternative hypotheses have emerged to explain how low and high productivity/profitability firms coexist in the same industry. One view is that the observed dispersion reflects adjustment frictions that prevent resources from being immediately allocated to the most productive firms. Adjustment frictions to capital and labor as well as to entry and exit can play this role. In addition, there may be sources of curvature in the profit function so the most productive firms do not take over the market. Decreasing returns to scale or span of control (e.g., Lucas (1978)) yields an equilibrium size distribution of firms. Alternatively, the curvature in the profit function may come from firms facing downward sloping demand curves. This approach has become increasingly popular in the last decade or so as empirical evidence suggests substantial price dispersion across producers within the same industry consistent with models of product differentiation (see, e.g., Melitz (2003)). With such models as a backdrop, there is a rich set of models that help us understand the observed industry and firm dynamics (e.g., Hopenhayn (1992) and Ericson and Pakes (1995)). A common feature of these models is that firms are subject to new profitability shocks in any given period. Shocks are persistent but technical efficiency, demand and cost conditions are stochastic. Firms in this environment must adjust and adapt to changing economic circumstances to grow and survive. While their past successes can help in forecasting their ability to adjust and adapt, firms are regularly required to reinvent themselves. Firms that reinvent themselves successfully survive and grow; firms that do not contract and exit.

For our purpose, the critical predictions are those that relate productivity to indicators of size in the cross section and over time. Specifically, more productive firms should be larger or becoming larger. Less productive firms should be smaller or becoming smaller. The cross sectional steady state predictions that more productive firms should be larger has led many researchers to proxy the firm productivity distribution with the firm size distribution. This brief discussion here highlights such cross sectional predictions are complicated by dynamics. It may be that more productive firms are on the way to becoming larger but are not yet large and vice versa. Also, in the background is that the underlying models are industry-level models intended to account for firm dynamics within industries where the firms within the industry are producing either identical products or close substitutes. Market segmentation that varies by industry or geography may be quite important in this context. Syverson (2004) shows that industries with greater product substitutability (e.g., industries where firms produce goods for the national market) have substantially less within industry productivity dispersion. This logic suggests that the firm dynamics relating productivity to firm size and firm growth dynamics operate within segmented markets. This is a point we return to in our empirical analysis below.

Most models of firm heterogeneity and firm dynamics are silent about the nature of the worker reallocation induced by such dynamics. However, search and matching models of the labor market are one of the potentially important sources of the adjustment frictions in observed firm dynamics. Mortensen and Pissarides (1994) develop a canonical search and matching framework that can account for many of the patterns of firm dynamics discussed above with additional implications about the nature and pace of job reallocation. In their framework, vacancy posting costs along with matching frictions imply that creation of jobs at the highest level of productivity will be limited so that high and low productivity jobs can exist in equilibrium. However, jobs that have a sufficiently adverse idiosyncratic productivity shock in their model are destroyed. Workers whose jobs are destroyed become unemployed and start searching for another job. This framework thus explains productivity dispersion in equilibrium and the prediction that high productivity jobs will be created and low productivity jobs will be destroyed. As such, the ongoing job reallocation will be productivity enhancing. This framework has the added implication that high productivity jobs will be high wage jobs since firms and workers have an incentive to share the joint surplus of jobs created by the search and matching frictions.

The Mortensen and Pissarides (1994) framework has the prediction that all of the job and worker reallocation occurs through the unemployment (or more generally the non-employment) margin. That is, firms hire from the non-employed and workers separate to non-employment. While this is a prediction, it is partly through assumption as only unemployed workers can search in that framework. This is a limitation since it has long been recognized theoretically and empirically that job and worker reallocation through job-to-job flows plays a potentially important role. Theories of on-the-job search that can accommodate such job-to-job flows enrich the role of search and matching frictions in accounting for firm heterogeneity and dynamics. Burdett and Mortensen (1978) and Moscarini and Postel-Vinay (2009, 2013, 2014) show that, with on-the-job search, high productivity, large firms will have the incentive to post higher wages to attract workers from lower productivity, smaller firms. These models thus provide another reason why large, more productive firms will pay higher wages. Taken together with the earlier discussion, there are numerous reasons why we should expect to observe a positive association between firm productivity, firm size and firm wages and workers moving up the job ladder by these firm characteristics.

There are many factors that may complicate or enrich these predictions that firm productivity, firm size and firm wages should be positively related and that we should be observing reallocation of activity towards more productive firms. We have already discussed one set of complications – specifically that segmented markets may imply that there are high productivity firms that are large within a segmented market but small relative to firms in other markets. [4]

Another set of complicating factors is the role of worker heterogeneity. One alternative way of accounting for a positive association between firm productivity and firm wages is positive assortative matching (see, e.g., Shimer and Smith (2000)). At the extreme, it may simply be that firms with higher measured productivity are simply firms with higher ability workers that work together. However, the role of sorting in this context is increasingly combined with the presence of intrinsic differences in productivity across firms along the lines of the discussion above (see, e.g., Lentz and Mortensen (2010) and Bagger and Lentz (2015)). The reason is that many aspects of the firm dynamics discussed above are difficult to account for in the absence of intrinsic differences in productivity across firms. For example, a pure sorting model is silent on which firms should grow while others contract and exit. In addition, as discussed in Lentz and Mortensen (2010), a number of empirical studies have found that observable labor quality differences account for only a small fraction of the productivity differentials across firms. This does not mean that sorting is not important but can be combined with the firm heterogeneity and firm dynamics discussed above. For example, Bagger and Lentz (2015) have a model with positive assortative matching and firm productivity/skill complementarity. They show that the sorting is important for the observed positive covariance between measured firm productivity,

[4] A related complication is that the growth dynamics of firms and size distribution of activity may be more related to demand side factors than productivity/cost factors (see, e.g., Foster et. al. (2008, 2015) and Hottman, Redding, and Weinstein (2015)). The implication is that a firm may be large or becoming large not because it is high productivity but rather its demand is high. Even though we recognize demand factors may be important, we don't think neglecting demand side factors can account for our results. If the size distribution is driven more by demand side factors, then firm size should be a more comprehensive measure of firm performance than productivity. As such, the firm size job ladder should be stronger and more evident than the firm productivity ladder. We also note that by using revenue labor productivity that our measure of productivity will reflect both differences in technical efficiency and demand factors that show up in differences in firm-level prices.

size, wages.

Even in the presence of such worker heterogeneity, exploring the patterns of job-to-job flows across firms by measured productivity, firm wages and firm size is instructive. As we have argued above, workers who are engaged in a job-to-job flow are presumably not changing quality during that transition.[5] As such, systematic patterns of job-to-job flows by firm characteristic should reflect workers moving up the firm quality ladder. We acknowledge that the underlying frictions for why it might take time for workers to move up the ladder may not be search and matching frictions but rather information frictions. That is, it may be that workers moving up the firm quality ladder are those who have been revealed to be high quality workers and are thus being attracted to the high quality firms. In the empirical analysis that follows, we think this explanation of the job ladder is more likely in skill intensive industries which we explore empirically. We also note that while this information friction version of the job ladder has some intuitive appeal it is less clear to us that it should yield workers on net moving up the firm quality ladder. Rather, if information frictions are important then workers who revealed over time to be high quality workers should be moving up the ladder while workers who are revealed to be low quality workers should be moving down the ladder.

3 Data

We use linked employer-employee data from the LEHD program at the U.S. Census Bureau to examine the flows of worker 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 (LED) federal-state partnership. LEHD data coverage is quite broad; state UI covers 95% of private sector employment, as well as state and local government.[6] The unit of observation in the UI wage data is the state-level employer

[5] In what follows, we measure the transition excluding the direct contribution of the workers engaged in the transition to the characteristics of the firm the worker is separating from and being hired by (as will become clear this is especially true for firm wages where taking into account such worker heterogeneity is potentially quite important).

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

identification number (SEIN). SEINs typically capture 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 the decomposition developed by HHM (2015) that yields 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 non-employment. 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 non-employment are classified as flows to and from non-employment.[7]

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. HHM (2015) develop three alternative measures of job-to-job flows. We use the within/adjacent measure from their approach. This includes as job-to-job flows hires or separation as part of a job-to-job flow only when the separation from a former main job and accession to a new main job occur in the same quarter pooled together with job transitions where the new main job begins in the quarter after the previous main job separation. They also consider job-to-job flows restricted to those where the transition occurs within the same quarter and those with minimum disruptions in earnings. They find results are very robust across these alternatives. Each of the different measures is highly correlated with the alternatives (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 HHM (2015), we are confident our main results are not sensitive to the specific rules we use amongst the set of rules they considered.

For firm productivity, we use a new firm-level database on productivity from Haltiwanger

[7] 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.

et al. (2014b) based on the revenue and employment data from the Census Business Register and the Longitudinal Business Database (LBD). 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 for a wide coverage of the private, non-farm (for profit) firms. Revenue is deflated with the GDP price deflator. This measure of productivity is a standard gross output per worker measure of productivity that is commonly used to measure productivity at the micro and macro level but is a relatively crude measure compared to using total factor productivity. However, in the empirical literature, this revenue labor productivity measure has been shown to be highly correlated with TFP based measures of productivity within industries. That is, within detailed industry year cells, Foster, Haltiwanger, and Krizan (2001) and Foster, Haltiwanger, and Syverson (2008) find that the correlation between TFP and gross output (revenue) per worker is about 0.6. In our analysis below, we use this revenue labor productivity measure deviated from industry by year means. We also show below this measure is highly predictive of the growth and survival of firms.

The gross output per worker data while offering much wider coverage than earlier studies has some limitations. The data only cover about 80 percent of firms in the Census LBD. The latter cover all firms with at least one paid employee in the private, non-farm sector. One reason is that the revenue data are not available for non-profits. For another, the revenue data derive from different administrative sources than the payroll tax data. Most of the matches between the payroll tax and revenue data are via Employer Identification Numbers (EINs) but firms can use different EINs for filing income taxes and filing quarterly payroll taxes.[8] For such firms, name and address matching is required. Haltiwanger et al. (2014a) also show that the missingness of revenue is only weakly related to industry, firm size, or firm age characteristics.[9] 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

[8]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.

[9]The productivity data 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.

given parent firm.

Even with these limitations, we have revenue per worker for more than 4 million firms in each calendar year which we integrate with the LEHD data infrastructure via EINs. In practice, when we merge that data to our infrastructure and have missing productivity we create a missing category. To help mitigate concerns about measurement error, in most of the analysis that follows we use robust measures of the ranking of firms by productivity. For example, in the job ladder analysis 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.[10]

A 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, we use data from the Bureau of Economic Analysis at the 4-digit NAICS level on value added per worker on an annual basis. We rank industries in each year by employment-weighted quintiles of the value added per worker at the industry level. In what follows, the high productivity industries in a given year are those in the top quintile and the low productivity industries are those in the bottom quintile.

For our analysis of firm size and firm wage we follow the approaches taken in HHM (2015) for comparability. Firm size in the LEHD data is defined at the national level using the U.S. Census Bureau's Longitudinal Business Database (LBD).[11] Firm size is the national size of the firm in March of the previous year; we use three size categories: "large" firms employ 500 or more employees, "medium" firms employ 50-499 employees, and "small" firms employ 0-50 employees.

For firm wage, we use quintiles of the firm earnings per worker distribution in each quarter. We classify firms as high wage if they are in the top two quintiles, medium wage if in the next two quintiles, and low wage if they are in the bottom quintile.[12] For the measurement of firm

[10]Given the missing category, we also track workers moving to and from the missing category. Consistent with the pattern of missingness being approximately at random there are not systematic patterns of workers to and from the missing category.

[11]Haltiwanger et al. (2014a) describes the methodology for linking the LBD firm size data with the LEHD data.

[12]We define high wage firms as the top two quintiles to be consistent with the definition we used in HHM

wages, we use in each quarter the average earnings per worker of full quarter workers at the firm. The latter are workers who are employed in the prior, current and subsequent quarter by the firm. This approach has the advantage of excluding the workers who are hired or separate in the current quarter including the workers engaged in job-to-job transitions. As such, this mitigates concerns of reverse causality.

We use the state-level SEIN unit of observation to measure firm wages.[13] Another potential concern is that our average earnings per worker is not controlling for hours per worker. This implies we have a potentially noisy proxy for the desired measure of the average wage at the firm. 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.

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) non-employment. This includes flows to and from federal employment (approximately 2% 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.[14] Our 28 states include many of the largest states so that

(2015). 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.

[13]HHM (2015) conduct a number of sensitivity analyses that suggest our results are robust to a number of alternatives that could be used in this context. They use the LBD to investigate the relationship between the state-level firm wage and the national firm wage. They find they are highly correlated. They also checked the sensitivity to using the average earnings per worker at the firm over the entire sample (or over the life of the SEIN). They find very similar results using this approach.

[14]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, 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 sample to be identified as poaching flows as data for states becomes available. For example, data for Ohio becomes available in 2000

our sample accounts for 65 percent of national private sector employment. 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.

4 Results

4.1 Productivity, Growth and Survival

We begin by exploring the relationship between dispersion in firm productivity and firm growth and survival. 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 sectors. The within industry/year standard deviation of log real revenue per worker is about 0.80. This is in the range of labor productivity dispersion indices reported by Syverson (2004). Second, 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.[15] 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.[16] 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 MA activity).

We regress these two outcomes on log productivity in t-1 and on log size in t-1 (log of firm employment in t-1). While these are simple reduced form specifications, these specifications are

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 discernable but small effect on job-to-job flow rates.

[15]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.

[16]This measure is given by $g_{it} = (E_{it} - E_{it-1})/(0.5 * (E_{it} + E_{it-1}))$. It is a second order approximation to a log first difference that accommodates entry and exit.

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. We turn to those implications now.

4.2 Do Job-to-Job Moves Reallocate Workers to More Productive Firms?

To understand how job-to-job moves reallocate workers from one set of firms to another, we use 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 non-employment and S_n is separations into non-employment.[17] 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 the X-12 procedure.

[17]We use the term poaching to describe job-to-job flows since it is consistent with the terminology of the wage posting models of job ladders 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.

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 (H_p - $S_p = 0$). Drawing from Figure 3 of HHM (2015), Figure 1 shows that for our LEHD sample, net poaching (H_p - S_p) is close to, but not quite zero, given timing issues (we allow that a worker engaged in a job-to-job flow may be separating one quarter and being hired the next). As has been shown in other papers, our job-to-job flows exhibit pronounced cyclicality and an evident downward trend.[18]

As can be seen in Figure 1, both job-to-job flows and non-employment flows are important components of overall worker reallocation. About 50 percent of total worker reallocation (hires plus separations) is due to job-to-job flows; the remainder is due to hires from non-employment and separations to non-employment.[19] Since the overall pace of worker reallocation is very large (about 30 percent 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.

Figure 2 shows our decomposition of net job flows for firms in the highest and lowest (within-industry) productivity quintiles. Although in the aggregate economy, net poaching flows (H_p - S_p) are zero, for any subset of firms in the economy, net poaching need not be zero, as some firms will be more successful poaching workers away from other employers. As discussed previously, a key prediction of search and matching models is that job-to-job moves should reallocate workers away from less productive to more productive firms. Figure 2(a) shows that this prediction from the theory holds true in the data. The most productive firms have overall positive net employment growth on average and net poaching (H_p - S_p) is strongly positive. In the 2004-2006 period, the most productive firms grew on average 0.8 percent per quarter, with job-to-job moves of workers from less-productive employers accounting for 1/2 to 3/4 of total employment growth at the most productive firms in any given quarter.

The results of the decomposition are even more striking for the least productive firms. In Figure 2(b), firms in the lowest productivity quintile lose about one percent of total employment *per quarter* from workers 'voting with their feet' and moving to firms ranked higher in firm

[18]See in particular Hyatt and McEntarfer (2012), Hyatt (2015), and Haltiwanger, Hyatt, and McEntarfer (2015).

[19]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 (2015) the alternatives are very highly correlated. Across the methods, job-to-job flows account for between 30 percent (within quarter only) to 50 percent (within/adjacent quarter) of worker reallocation.

productivity distribution. In the 2004-2006 period, the least productive firms lost about 0.7 percent employment per quarter, with the loss of workers through job-to-job moves accounting for more than 100 percent of total employment losses in a typical quarter. In other words, in a typical quarter the least productive firms lose more workers via job-to-job moves than they acquire via employment flows.

Both Figure 2(a) and 2(b) suggest that job-to-job moves play a critical role in allowing more productive firms to grow faster than less productive firms. We can quantify this by decomposing the average overall net job flow differential between high and low productivity groups into the net poaching differential and the net flows from non-employment differential. The overall net job flow differential between high and low productivity firms averages 1.5 percent per quarter. The average net poaching differential between high and low productivity firms is about 1.3 percent per quarter. This implies that about 90 percent of the average growth differential between the least productive and most productive firms is accounted for by job-to-job flows.

Figures 2(a) and 2(b) also show pronounced secular and cyclical patterns that differ across the components of the net job flows. We quantify the nature of that variation in Table 2. Each row in Table 2 represents a separate regression using the national time series. The dependent variable in each row is a differential between high and low productivity firms. For example, the first row has as the dependent variable the differential in net job flows between high and low productivity firms.

We start by focusing on the net poaching differentials (the middle row) which shows that net poaching from low to high productivity firms decreases in cyclical downturns. In addition, there is a statistically significant negative trend in this net differential. The implies that efficiency gains from job-to-job flows decline in recessions and has exhibited a declining secular trend.[20] Taken at face value, the cyclical patterns suggest there is a sullying effect (e.g., Barlevy (2002)) of recessions. The declining trend reallocation from low productivity to high productivity firms is consistent with the concerns that declining labor market fluidity may have adverse aggregate productivity consequences (Davis and Haltiwanger (2014)).

It is interesting to examine the other rows of Table 2 as well. The net flows from non-

[20] We recognize our time series is relatively short so caution needs to be used in interpreting patterns here. However, HHM (2015) exploit state-specific cycles to show that the increased pace of job-to-job flows from low wage to high wage firms is robust to using state-specific variation. Moreover, the declining trend patterns depicted here are consistent with evidence that that labor market fluidity has declined in the U.S. in the post 2000 period. See Hyatt and Spletzer (2013) and Davis and Haltiwanger (2014).

employment differentials provide an indication of the reallocation of employment from low productivity to high productivity firms that involves transitions to and from non-employment. For this type of reallocation, it may not be the same workers that lose jobs that gain jobs. In addition, even when it is the same workers making the transition, the transition inherently involves intervening spells of non-employment. In that respect, this type of reallocation is more costly than job-to-job flows since it involves the time and resource costs of non-employment. We find that reallocation that works through the non-employment margin is countercyclical. This can be thought of as a cleansing effect of recessions that is working in the opposite direction of job-to-job flows. The overall net job flow differentials (first row) show that in the case of firm productivity the cyclical effects from job-to-job flows are largely canceled out by the offsetting net flows from non-employment. The trends for the net flows from non-employment also work in the opposite direction of the job-to-job flows.

Putting the pieces together, on average job-to-job flows account for most of the productivity enhancing reallocation. Productivity enhancing job-to-job flows are procyclical and exhibit a downward trend. Net flows from non-employment are also productivity enhancing on average but account for a relatively small overall share. This component is countercyclical and exhibits a positive (albeit non-significant) trend. These results suggest that productivity enhancing reallocation changes composition over the cycle – in booms it works through job-to-job flows and through non-employment flows during recessions. The composition towards non-employment flows has also increased over time given the secular decline in job-to-job flows. In considering these compositional shifts over the cycle and over time, it is important to recognize that reallocation via non-employment flows is inherently more costly since it involves a spell of non-employment.

One of the limitations of the above analysis is that we are only exploiting relative productivity measures within industries. Our revenue per worker data are not comparable across industries given we cannot compute value added at the firm level and our coverage of industries is sufficiently broad that gross output per worker is not comparable across industries. However, from other sources we can use value added per worker data to compare firm productivity across industries. Value added data by industry is taken from the Bureau of Economic Analysis and using a crosswalk we integrate at the industry sector and subsector level. Using these data, we rank industries by value added per worker and put each industry into employment-weighted quintiles.

Using these industry rankings, we investigate the role of industry job ladders defined by quintiles of the industry productivity distribution. Results are presented in Figure 3.[21] Figure 3(a) shows that top quintile productivity industries account for most of their hires via job-to-job flows and that net poaching is positive and procyclical. The average net poaching rate for the top quintile industries is 0.4 percent. Figure 3(b) shows that the bottom quintile industry in terms of value added per worker exhibits negative net poaching. The average net poaching rate for the bottom quintile industries is -0.7 percent. The magnitude of the negative net poaching in the bottom quintile industries declines in economic contractions. Taken together with the results from Figure 2, our findings show that there is productivity job ladder that is procyclical both in terms of moving up the job ladder to firms with higher productivity within industries but also moving up to industries higher in the between industry productivity distribution.

One open issue is how to think about combining the results using within vs. between industry variation. We regard finding ways of integrating these different aspects of productivity differences across firms as an interesting area for future research but we provide a few remarks to help provide perspective. First, it is important to emphasize that we are focusing on net poaching patterns by firm type. That is, there may be poaching from a firm in a high productivity industry but low in the within industry distribution towards a firm that is high productivity in a low productivity industry. It is clear from our results that there are substantial poaching separations in the high productivity quintiles (whether based on within or between industry variation) and poaching hires in low productivity quintiles. However, in either case, the net patterns for a given firm type (comparisons in firm type by alternative productivity measures) should work in a particular direction and this is what we find. We also note that there is guidance from the literature about which type of variation is likely to be more important. Dunne et. al. (2004) find that in decomposing the variance of log gross output per hour across manufacturing establishments that within industry dispersion is much larger than between industry dispersion.[22] In what follows, we focus on the firm-level relative productivity differences in productivity since this is likely the more important source of variation.

[21] Cairó, Hyatt, and Zhao (2015) consider reallocation across industries by average worker earnings in an industry and find broadly similar results.

[22] They also find the same holds for dispersion in hourly wages across establishments.

4.3 Empirical Support for Wage Posting Models

In HHM (2015), we showed that predictions from the wage posting literature that workers would move from smaller, lower productivity, lower paying employers to larger, higher productivity, higher paying employers held true for firm wage, but not for firm size. Figure 4 integrates our new findings on job-to-job moves by firm productivity with these earlier results. Figure 4(a) shows net worker reallocation via job-to-job flows for the highest quintile of within-industry productivity, relative to high wage and large employers. The latter two lines are from HHM (2015). This figure summarizes the starkly different patterns of net poaching flows for high productivity/high wage firms relative to large employers. Job-to-job flows *do* reallocate a substantial percentage of workers each quarter to higher-paying, higher-productivity employers, but not to larger employers. This suggests to us that the relationship between firm size and productivity (and firm size and firm wage) is much weaker in data than in many theoretical models. We explore this further in the next section of the paper, looking at the joint distribution of firm size, wages, and productivity.

Figure 4(b) compares net worker reallocation for the lowest quintile of within-industry productivity, relative to low wage and small employers. Here we see parallel, although more dramatic, results for net worker reallocation via job-to-job moves out of the bottom of the wage and productivity distributions. Again, reallocation by size goes against the predictions from the theory, with small positive employment gains for small firms via job-to-job moves. Rates of worker reallocation out of the lowest rungs of the wage and productivity distribution are higher than reallocation into the top rung shown in Figure 4(a).

It is also apparent from Figure 4 that the firm wage ladder exhibits similar cyclical and trend patterns as the firm productivity ladder. To validate this, Table 3 reports the analogue of Table 2 for the decomposition of net job flow components by firm wage.[23] Net poaching from low to high wage firms is highly procyclical and exhibits a downward trend in the same manner as we found for the firm productivity ladder in Table 2. If we interpret the firm wage ladder as an indicator of economic mobility for workers, economic mobility is both procyclical and exhibits a downward trend.[24]

[23]Table 3 uses the 1998-2011 period given that the firm wage data are available for the entire time period while Table 2 uses only the 2003-2011 period. We have checked and the results for Table 3 are almost identical restricting the sample to 2003-2011.

[24]HHM (2015) also investigate the cyclicality of the wrong signed firm size job ladder. They find the net

4.4 Firm Size, Wages, and Productivity

Given the evidence we find here for a firm productivity and a firm wage job ladder but not a firm size ladder, we turn now to investigate the joint distribution of firm size, productivity, and wages. We begin by first estimating simple regressions of the form:

$$y_{jt} = \alpha + \beta_1 * x_{jt-1} + \beta_2 * x_{jt-1}^2 + \epsilon_t \qquad (2)$$

where x_{jt-1} is the national log size of firm j in March of the previous year, and y_{jt} is either the deviation of log revenue per worker from the industry (four digit NAICS) mean or the deviation of average earnings per worker from the industry mean. We use lagged size in these regressions to mitigate any problems from division bias. This is potentially a bigger problem for the productivity/size regression since the denominator for the productivity measure is from the same LBD data as the size measure. We have examined this in unreported results and found they are similar using contemporaneous size measures as the RHS variables. In a third specification, we estimate the relationship between both dependent variables, wages and productivity.[25]

Table 4 shows the results from these simple regressions. Column 1 of Table 4 shows the estimated relationship between size of the firm and its within-industry productivity. The coefficient on firm size is -0.056, on the square of firm size, 0.010. Graphing the implied size/productivity relationship from these regressions helps the interpretation considerably here, and we show this graph in Figure 5. As you can see in Figure 5, many very small firms (less than 10 employees) have relatively high productivity within their industry, higher than that of firms with 10-30 employees. Around 50 or more employees, the expected positive relationship between productivity and size appears, although we should note the R-squared for this regression (0.02) is remarkably weak. Column 2 of Table 4 shows this regression with the within-industry average wage as the dependent variable. The coefficient here, 0.173, has the expected positive sign but again the R-squared (0.07) is very weak. The relationship between wages and productivity shown in Column 3 is stronger, with an R-squared of 0.16.

These regressions suggest that while more productive firms are more likely to be larger

losses from poaching that large firms exhibit in Figure 4 diminish some in recessions.

[25] Firm productivity and firm wage are measured in the same calendar year but division bias should not be a problem since firm productivity is real revenue per employee for the national firm and firm wage are full quarter earnings per worker for the SEIN. Also, the employment measures derive from different sources so that measurement error in employment in the two measures should be uncorrelated.

and higher paying, the relationship between size and productivity (and size and wage) is fairly weak. This is also suggested by our job ladder results, where worker vote with their feet to more productive (and better paying employers) but not necessarily to larger ones. What might be driving a wedge between firm size and productivity? Firm dynamics clearly play a role, as some large firms may have once been highly productive but are now shrinking, and some small young highly productive firms may be growing. In HHM (2015), we investigated this hypothesis by controlling for firm age in examining the patterns of job-to-job flows. We did find that the positive net poaching of small firms is associated with young, small firms growing on average. However, HHM (2015) find that the net poaching differential between large/mature and small/mature firms while positive is very small and only mildly procyclical. This finding is consistent with Figure 4(a) above since the net poaching for large firms depicted in that figure is effectively the net poaching for large/mature firms (since there are few young/large firms). In Figure 4(a), net poaching of large firms is slightly negative and not highly cyclical.

In this paper we investigate an alternative candidate hypothesis: market segmentation. The hypothesized positive relationship between productivity and firm size holds within a given market defined by either industry or geography. When there is market segmentation, a highly-productive firm may be large within the market it serves, while not being large in the national economy. For example, a regional hospital may provide high quality care, but few hospital patients (or their families) are willing to travel hundreds of miles for health care services.[26]

To investigate the role of market segmentation, we explore the heterogeneity in the size/ productivity relationship across industries. A weaker relationship between size and productivity in industries characterized by market segmentation would suggest that it plays a role in explaining the weaker than expected relationship between size and productivity/wages we find in the data. To examine across-industry heterogeneity in the size and productivity relationship we estimate within-industry rank-rank regressions of the form:

$$RankProd_{jit} = \alpha + \beta_1 * RankSize_{jit-1} + \epsilon_t \tag{3}$$

where $RankProd_{jt}$ is the within four-digit NAICS rank of the productivity of firm j in industry

[26]Market segmentation may not only be geographic but also segmentation in detailed product classes. For example, it may be that in some industries, the products within the industry are not close substitutes compared to other industries.

i, and $RankSize_{jt-1}$ is the firm size rank of firm j within the same industry. We estimate this rank-rank regression for every four-digit NAICS industry group, assigning the mean rank in the case of ties.[27] The coefficient on rank size in this simple framework is essentially the correlation between firm size rank within the industry and firm productivity rank within the industry. When this coefficient is one, firms in the top percentile of the productivity distribution within the industry are also in the top percentile of the size distribution within the industry, and similarly for the bottom percentile. We again use lagged size to avoid division bias issues although they should be mitigated by the use of the rank based measures.[28] We use rank based measures in this context to make the differential within industry productivity/size relationships comparable across industries.[29]

The results of the rank-rank regressions for productivity and size are shown in Figure 6.[30] Here we summarize hundreds of detailed industry rank-rank coefficients by grouping them by industry sector in a box and whisker plot. The most immediately striking feature of Figure 6 is the enormous heterogeneity in the size-productivity relationship across industry sectors. For example, the mean coefficient on the size/productivity relationship among detailed industries in the manufacturing sector is about 0.43, and the 25th and 75th percentiles are 0.33 and 0.53, respectively. In the Health Care sector, by contrast, the mean of the distribution of detailed industry rank-rank coefficients is just under zero, and the 25th and 75th percentiles are -0.17 and 0.10, respectively. Thus in the health care industry, there appears to be little evidence of any systematic relationship between firm size and productivity. Nor is health care alone in this respect. Consistent with our hypothesis that market segmentation plays a role in driving a wedge in the size/productivity relationship, industries with national markets (in particular, manufacturing, mining, and information) have a stronger correspondence between size and productivity. Other industries largely do not show evidence of a strong relationship between rank productivity and rank size within the industry. While this is not conclusive evidence for

[27]We also estimated this rank-rank regression for every 6-digit NAICS industry and obtained similar results.

[28]As a robustness check, we estimated the rank-rank regressions using deciles rather than percentiles of the distributions which should mitigate against division bias and also transitory shocks. We find very similar results.

[29]Rank-rank regressions have recently been used in the intergenerational mobility literature to make comparisons of intergenerational mobility patterns within geographic areas comparable across geographic areas (see Chetty et. al. (2014)). Even though our setting is very different the motivation for using rank-rank regressions is similar.

[30]We don't report statistical significance for all the coefficients in Figures 6-8 since there are several hundred estimated regression coefficients. We note that almost all are statistically significant at the 0.001 level. A handful of exceptions occur when the estimated coefficient is very close to zero.

the role of market segmentation, these findings here are consistent.

For comparison purposes, we also estimate rank-rank regressions for the relationship between within industry firm productivity and wage. The coefficients for these regressions are shown in Figure 7. Compared to the results for size and productivity, the distribution of coefficients for the wage/productivity relationship is remarkably tightly clustered around 0.45, for almost all industries. Taken together, Figures 6 and 7 suggest that the relationship between firm size and productivity varies widely across industries, but the much stronger relationship between firm wages and productivity does not. Figure 8 shows coefficients of rank-rank regressions on the size/wage relationship. The coefficients here are generally more disperse across industries (and weaker) than the results for the wage/productivity relationship, but not quite as disperse across industries as the size/productivity relationship.

The substantial differences across industries in the productivity/size (and wage/size) relationships prompted us to examine whether the prediction that job-to-job moves would reallocate workers into larger firms *did* hold if we restricted our analysis to industries with a high correlation between firm size and productivity. In Figure 9 we show this decomposition for large and small firms in a group of four-digit industries with rank-rank size/productivity coefficients in either the fourth or fifth quintile. While we do see positive reallocation via job-to-job moves into large firms in this industry group (Figure 9(a)), we also see positive net poaching for small firms in this group (Figure 9(c)). Underlying this latter finding is that high productivity/size correlation industries are generally higher paying industries (the correlation is 0.34). Thus, we are finding that the role of firm size is complicated by other factors like the role of inter-industry wage differentials. More broadly, it is critical to recognize that job-to-job flows reflect both within industry and between industry flows. It may be that relative size in an industry is a reasonable proxy for productivity within national market industries but that is insufficient for capturing the firm quality ladder since it turns out those national market industries are high wage industries so that there are job-to-job flows towards all firms in such industries.

Figure 9(b) shows that large firms in low productivity/size correlation industries exhibit substantially negative net poaching rates (and even more than small firms in such industries as seen in Figure 9(d)). These findings suggest that the overall finding of large firms being net losers from net poaching is driven by such industries. As seen in Figure 6, Accomodation and Food Services is one such industry. This is a low wage industry delivering local nontradables. Large firms in this industry are likely large, national chains with many different establishments serving many different locations. Further research is needed but such firms are apparently common targets of net poaching. Figure 9(b) shows that net hiring for such firms is overwhelming from non-employment.

4.5 Worker Ability and Information Frictions

In our analysis so far, we have not explicitly controlled for worker heterogeneity. As we have noted, job-to-job flows have a built in control for worker quality at the individual worker level. But it is still possible that some of our findings on workers moving up firm productivity and wage ladders may be related to worker quality. It may be, for example, that we are capturing high quality workers moving up the firm quality ladder. The reason that high quality workers may be in low quality firms is that it may take time for worker quality to be revealed due to information frictions. A full investigation of this hypothesis is beyond the scope of the current paper but we undertake an exercise that we think sheds light on this hypothesis. We sort industries by their share of college educated workers in 2000.[31] Our working hypothesis is that the slow revelation of worker quality is more likely to be important in skill intensive industries.

Figure 10 presents the job-to-job flow patterns for high wage firms in high skill intensive industries (Figure 10(a)) and low skill intensive industries (Figure 10(b)).[32] High wage firms are, as before, firms that are in the upper two quartiles of the firm wage distribution. We find that high wage firms in both high skill and low skill intensive industries are positive net gainers from job-to-job flows. In addition, we find that the procylicality of the job-to-job flows is similar in both types of industries. Table 5 shows the top 15 4-digit industries that are high wage, high skill intensive and high wage, low skill intensive industries. The latter industries are of particular interest as they include industries like construction and parts of the manufacturing sector where it has been previously recognized in the literature that there are industry wage premiums that are not accounted for by observable worker skills (see, e.g., Krueger and Summers (1988) and Abowd et. al (2012)). From the perspective of the worker, high wage firms in these industries are at the top of the ladder. We also note that in Figure 8 we find that in the construction

[31]We chose to look at the college share in 2000 because education data in LEHD is based on the 2000 Decennial Long Form data.

[32]High skill intensive industries are in top quintile of industry skill-intensity on an employment-weighted basis. Low skill intensive industries are in bottom quintile of industry skill-intensity.

and the manufacturing sectors, there is a strong positive relationship between high productivity and high wage firms within those industries. In these industries, search and matching frictions seem a more plausible explanation than worker ability differences interacting with information frictions for positive net poaching by higher-paying firms.

5 Conclusion

Consistent with the existing literature on firm heterogeneity, we find evidence of large differences in productivity across firms within the same industry. We also find that more productive firms in the same industry are more likely to grow and less productive firms more likely to contract and exit. The dispersion of productivity across firms is large in magnitude contributing to a high pace of reallocation of jobs and workers across firms. Using a decomposition of net job flows into those accounted for by job-to-job flows and those accounted for net flows from non-employment, we find that much of the overall reallocation of employment from less productive to more productive firms is accounted for by job-to-job flows. We also find that the patterns for job-to-job flows by firm productivity are mimicked by similar patterns for firm wages. The similar patterns for firm productivity and firm wages is not surprising in light of the tight relationship between firm productivity and firm wages that we find in the data. The pace at which workers move up the job ladder by firm wage and firm productivity is procyclical and exhibits a declining downward trend. These patterns suggest economic mobility and economic efficiency gains from job-to-job flows are procyclical and have diminished over time.

The job-to-job flow patterns by firm size don't match those of firm productivity and firm wages. This is surprising since many models in the firm dynamics literature imply a tight relationship betwen firm size and firm productivity. While there are numerous empirical studies that find a positive relationship between productivity and firm size, most of the studies have been for the manufacturing sector. In our examination of data for the entire U.S. private sector, we find that firm productivity and firm size are much less strongly related than firm productivity and firm wages. Underlying the weaker relationship between firm productivity and firm size are substantial differences across industries in the covariance between productivity and size within industries. Industries with national markets like information and manufacturing exhibit strong positive covariances while non-tradable sectors like food and accommodations and retail trade exhibit weaker or even negative covariances. These patterns suggest the differences in job ladder patterns for firm size compared to firm wage and firm productivity may be driven by differences in market segmentation within industries. Returning to the patterns for job ladders, we find that large firms in the high positive productivity/size covariance industries are positive net gainers from job-to-job flows. However, even small firms in those industries are net gainers from job-to-job flows. The reason appears to be that high positive productivity/size covariance industries are also high wage industries.

We interpret our findings as being consistent with economic theories that posit that there are intrinsic differences in productivity across firms but that frictions, including those in the labor market such as search and matching frictions, imply that the reallocation of resources from less productive to more productive firms is a slow ongoing process. Job-to-job flows play an important role in the reallocation of workers from less productive to more productive firms. The finding that firm productivity and firm wages are so tightly connected is consistent with search and matching theories that imply that high productivity firms offer high wages.

We largely abstract from worker heterogeneity in our analysis which may be playing a role in our findings. One attractive feature of our focus on job ladders is that there is a built in control for worker quality in examining the patterns of workers engaged in job-to-job flows. For the workers engaged in such transitions, the quality of the worker presumably does not change during the transition. It might be, however, that workers of higher quality are moving up the firm quality ladder because of information frictions that make the revelation of worker quality a slow process. This suggests that part of our findings on workers moving up the firm quality ladder might be driven by such information frictions. It is beyond the scope of our paper to fully investigate the role of worker heterogeneity but we think that the information friction version of the job ladder is more plausible in high skill industries. We find that there are strong firm wage ladders even in low skill intensive industries like construction. These patterns suggest that higher quality workers moving up the firm quality ladder can't account for our findings.

There are many open questions that arise from our findings in the context of the related literature. It remains somewhat of a puzzle how to think about firm size in this context given our findings on job-to-job flows by firm size. We think our findings on differential patterns by industry shed some light on this puzzle. Also, as we have noted, we have only explored the role of worker heterogeneity in a limited manner in our analysis. We know that in the overall distribution of worker wages that observable worker characteristics account for a substantial share of wage dispersion. Unobservable worker characteristics undoubtedly account for an important share as well. Exactly how the observable and unobservable worker characteristics account for and how they interact with the type of firm heterogeneity we focus on is an area of active ongoing research. Our findings suggest that investigating these issues in the context of job-to-job flows is likely to be promising.

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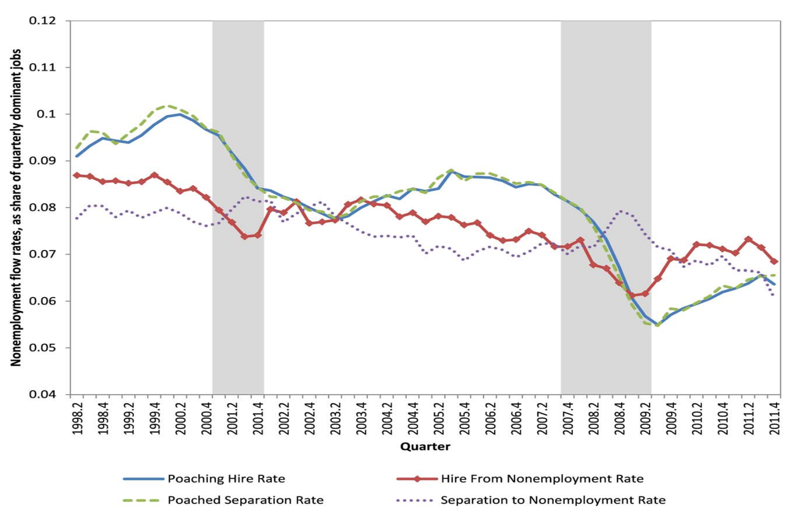
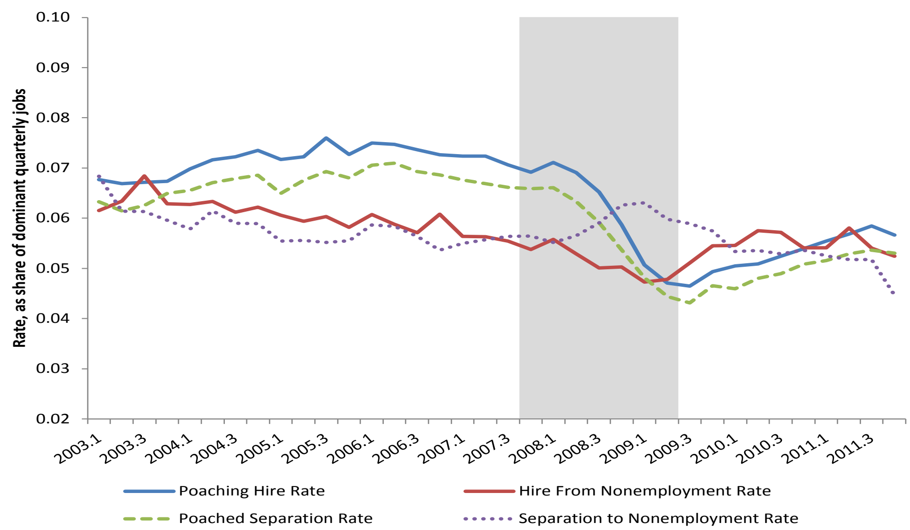
Figure 1: Hires and Separations: Poaching vs. Flows to and from Non-Employment

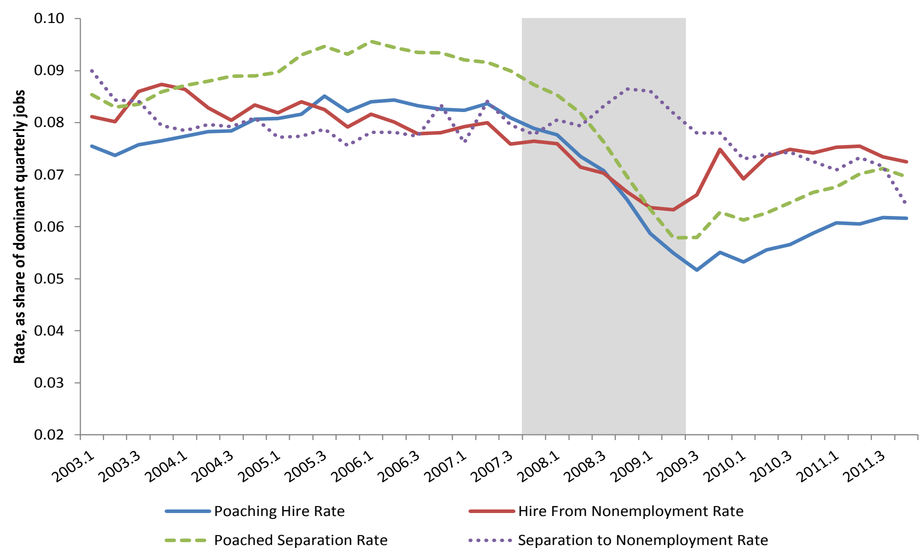


Notes: Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11.

Figure 2: Poaching Flows vs. Flows to and from Non-Employment: By Firm Productivity



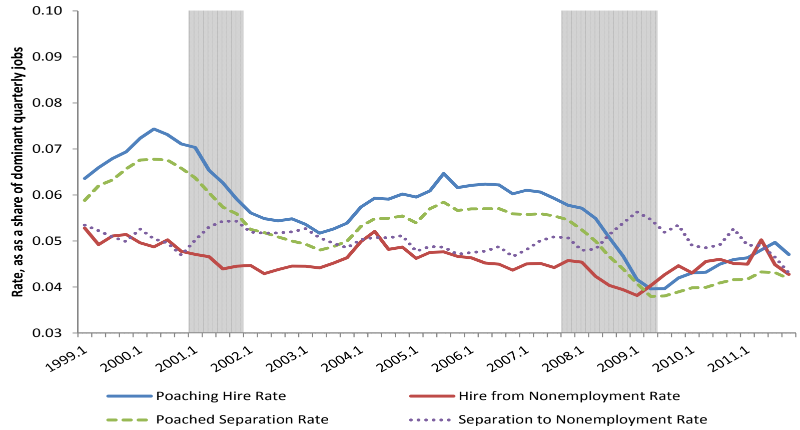
(a) Highest Quintile of Within-Industry Productivity



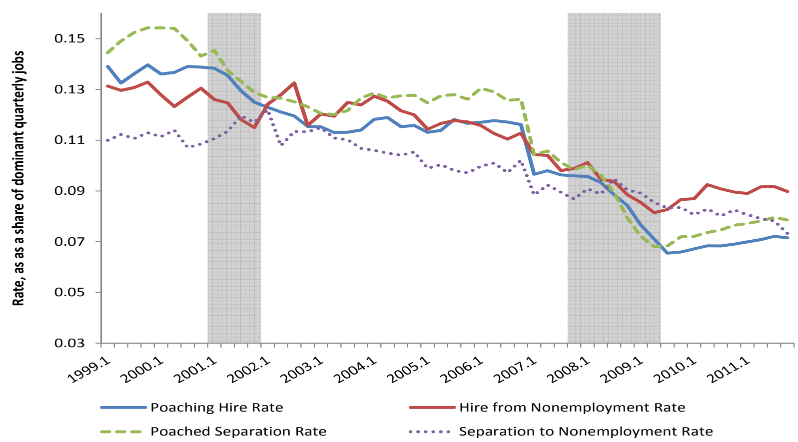
(b) Lowest Quintile of Within-Industry Productivity

Notes: High productivity indicates that the firm is in the top quintile of the employment-weighted within industry productivity distribution. Low productivity indicates the firm is the bottom quintile of the employment-weighted within industry productivity distribution. Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11.

Figure 3: Poaching Flows vs. Flows to and from Non-Employment: By Industry Productivity



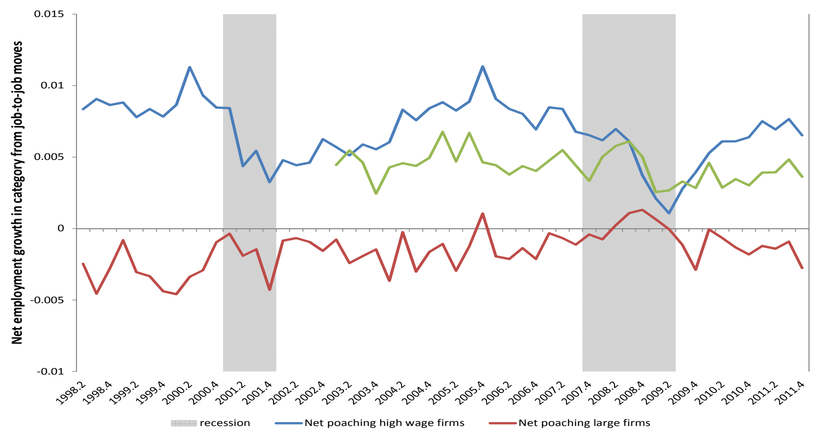
(a) Highest Quintile BEA Value Added Industries



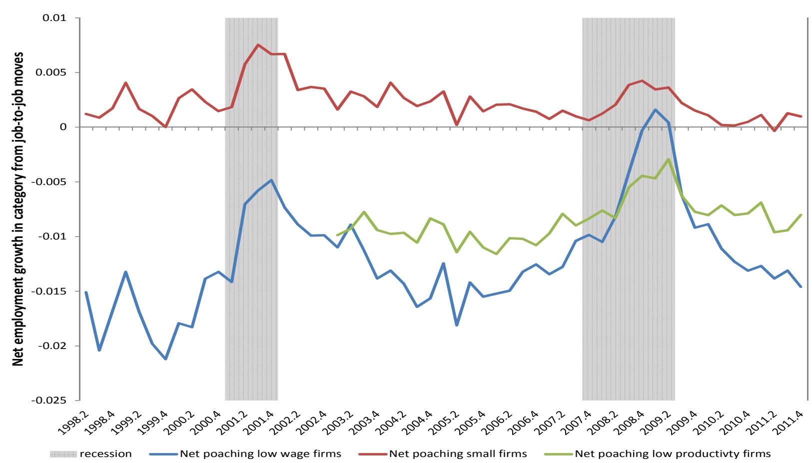
(b) Lowest Quintile BEA Value Added Industries

Notes: High productivity indicates that the firm is in the top quintile of the employment-weighted BEA industry productivity distribution. Low productivity indicates the firm is the bottom quintile of the employment-weighted BEA industry productivity distribution. Shaded areas indicate NBER recession quarters. Data are seasonally adjusted using X-11.

Figure 4: Net Poaching Flows: By Firm Productivity, Firm Wage and Firm Size



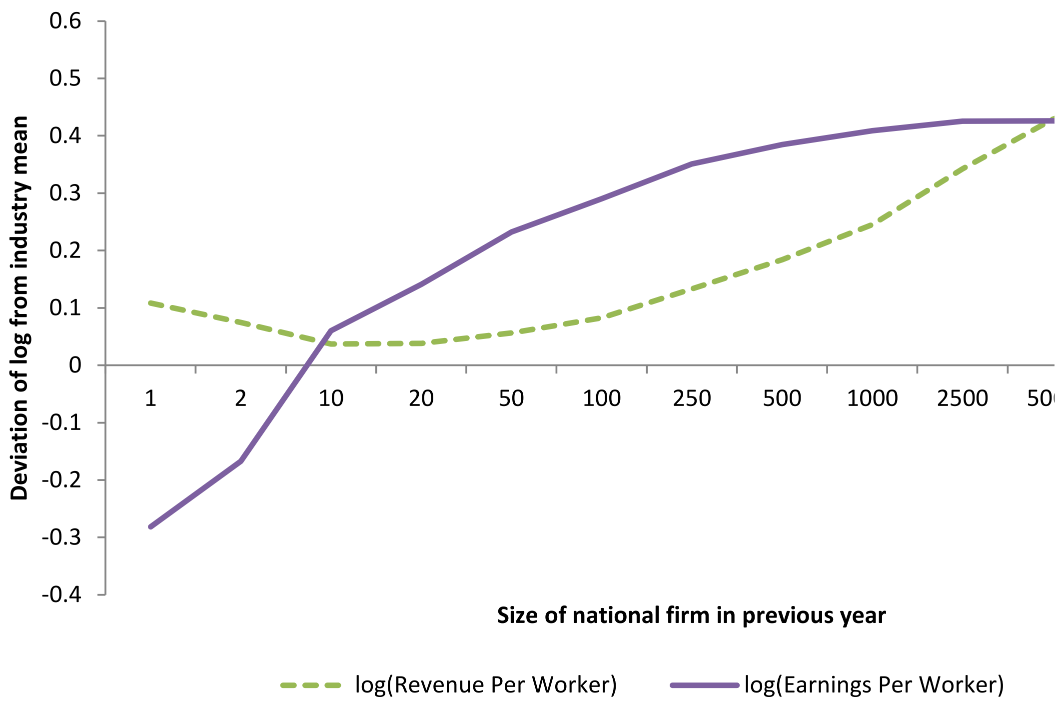
(a) High-Wage, High-Productivity, and Large firms



(b) Low-wage, Low-Productivity, and Small Firms

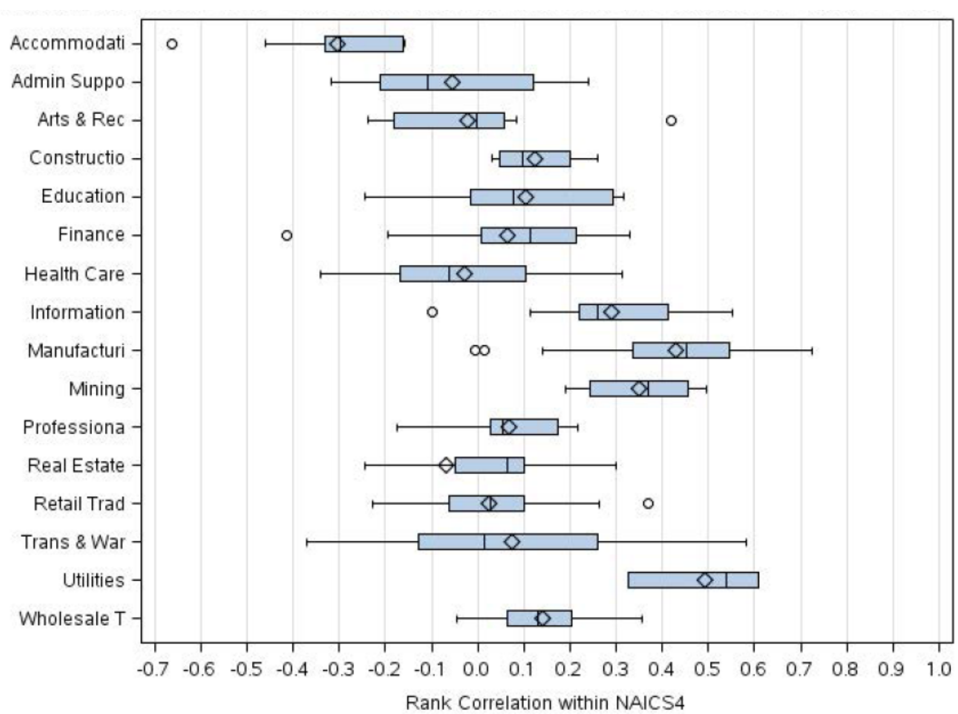
Notes: High productivity indicates that the firm is in the top quintile of the employment-weighted within industry productivity distribution. Low productivity indicates the firm is the bottom quintile of the employment-weighted within industry productivity distribution. Following HHM (2015), high wage indicates that the firm is in the top two employment-weighted quintiles of the earnings distribution, and low wage indicates that the firm is in the lowest quintile of the employment-weighted average earnings distribution, a firm is small if it has less than 50 employees, and a firm is large if it has 500 or more employees. Shaded areas indicate NBER recession quarters. Data are seasonally adjusted using X-11.

Figure 5: Relationship between National Firm Size Relative to Revenue per Worker and Earnings per Worker



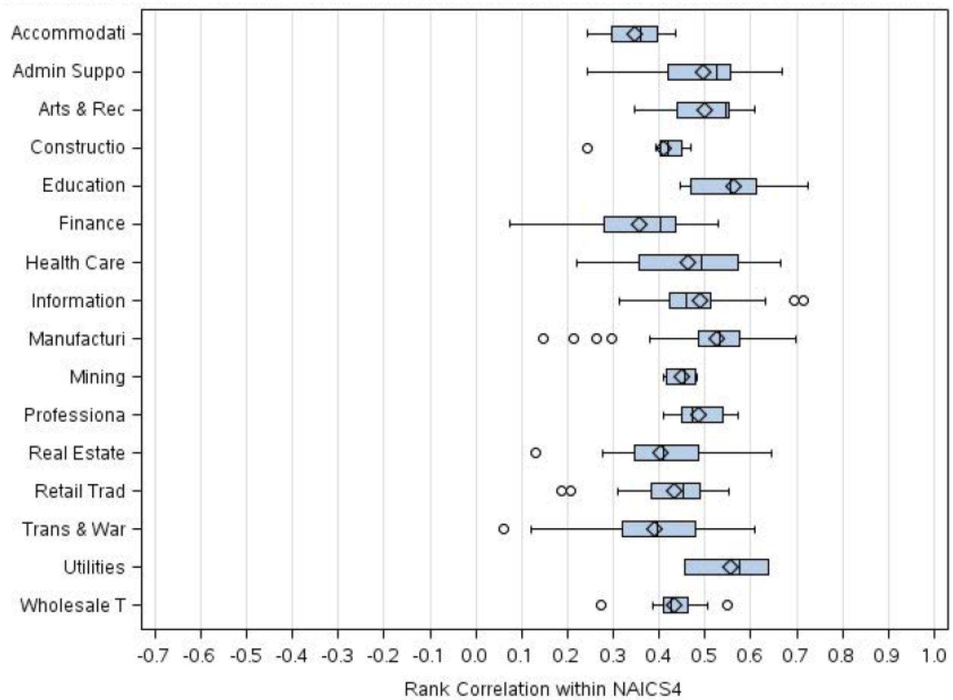
Notes: Visual representation of point estimates from Table 2.

Figure 6: Distribution of Rank Order Correlation of Productivity and Size within NAICS4, by Sector



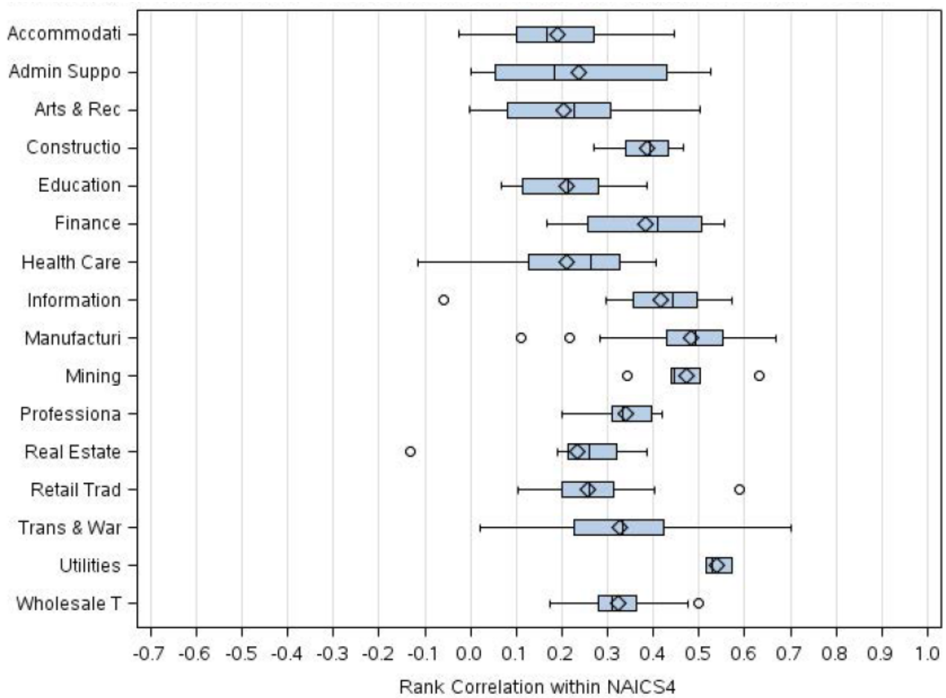
Notes: Boxes indicate 25th and 75th percentile, line inside box indicates 50th percentile, whisker lines indicate 5th and 95th percentiles, dots indicate substantial outliers.

Figure 7: Distribution of Rank Order Correlation of Productivity and Wage within NAICS4, by Sector



Notes: Boxes indicate 25th and 75th percentile, line inside box indicates 50th percentile, whisker lines indicate 5th and 95th percentiles, dots indicate substantial outliers.

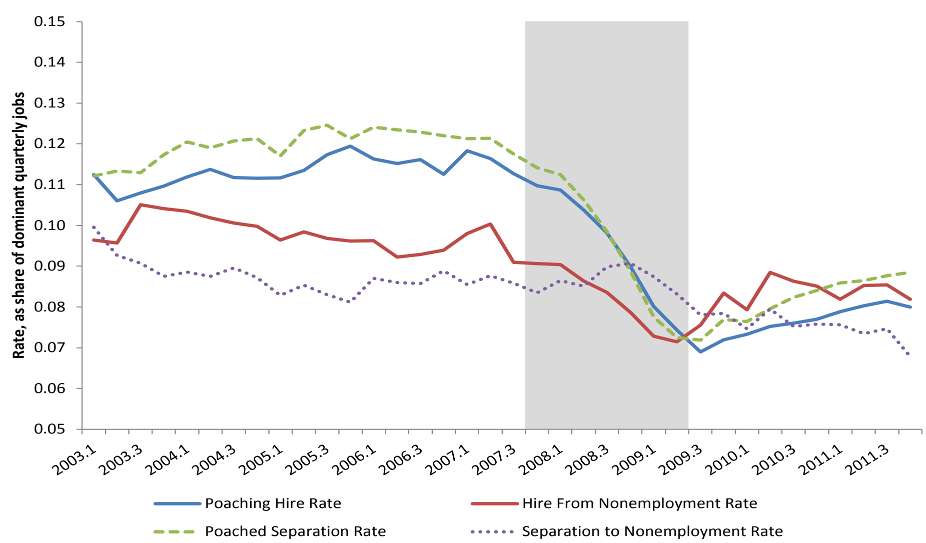
Figure 8: Distribution of Rank Order Correlation of Wage and Size within NAICS4, by Sector



Notes: Boxes indicate 25th and 75th percentile, line inside box indicates 50th percentile, whisker lines indicate 5th and 95th percentiles, dots indicate substantial outliers.

Figure 9: Poaching vs. Flows to and from Non-Employment: By Firm Size and Size-Productivity Relationship

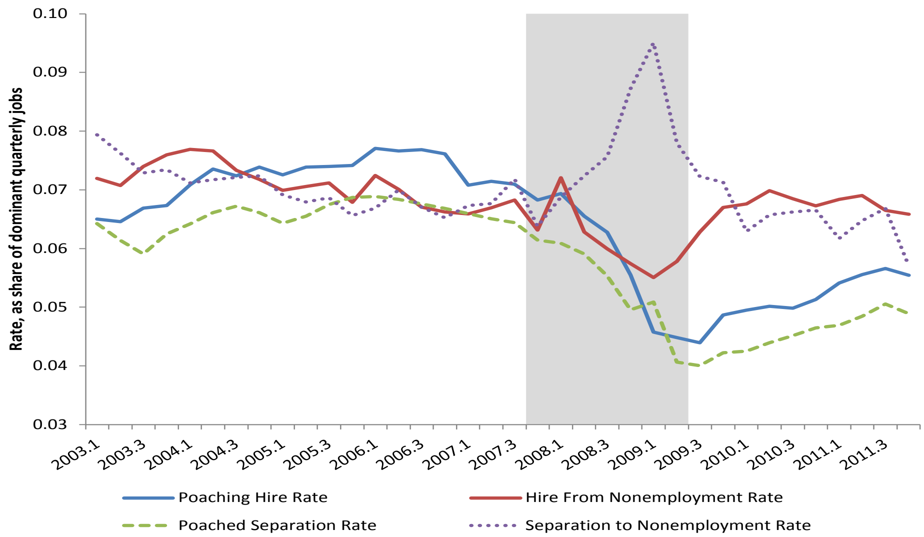
(a) Large, High Size-Productivity Relationship



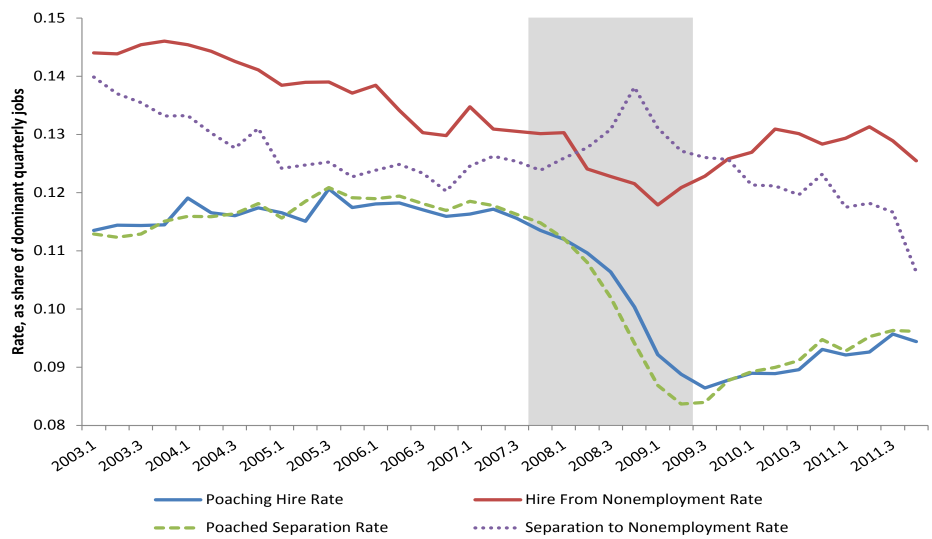
(b) Large, Low Size-Productivity Relationship

Notes: Large indicates that a firm has 500 or more employees, and small indicates that a firm has less than 50 employees. The high size-productivity relationship is defined as being in the top two quintiles of the size-productivity relationship, while low size-productivity indicates the bottom quintile. Shaded areas indicate NBER recession quarters. Data are seasonally adjusted using X-11.

Figure 9: Poaching vs. Flows to and from Non-Employment: By Firm Size and Size-Productivity Relationship



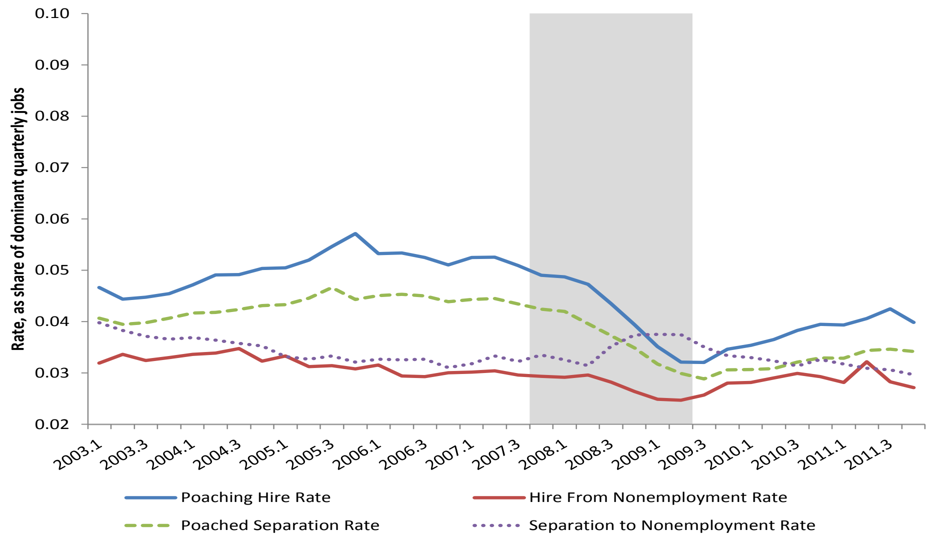
(c) Small, High Size-Productivity Relationship



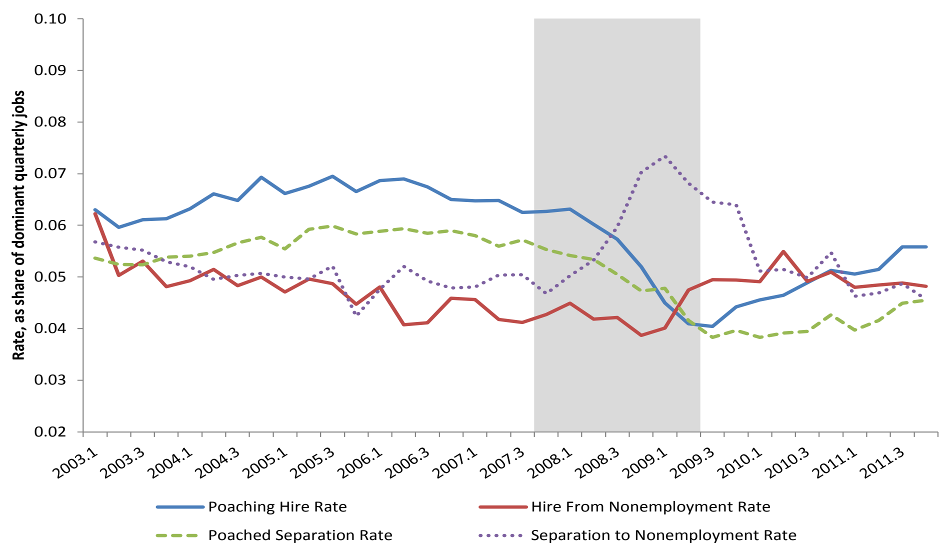
(d) Small, Low Size-Productivity Relationship

Notes: Large indicates that a firm has 500 or more employees, and small indicates that a firm has less than 50 employees. The high size-productivity relationship is defined as being in the top two quintiles of the size-productivity relationship, while low size-productivity indicates the bottom quintile. Shaded areas indicate NBER recession quarters. Data are seasonally adjusted using X-11.

Figure 10: Poaching Flows vs. Flows to and from Non-Employment: By Industry Skill Intensity among High Wage Firms



(a) High Skill Intensive Industries



(b) Low Skill Intensive Industries

Notes: Results are for high wage firms only, defined as firms in the top two employment-weighted quintiles of the earnings distribution. High skill intensive industries are in top quintile of industry skill-intensity on an employment-weighted basis. Low skill intensive industries are in bottom quintile of industry skill-intensity. Shaded areas indicate NBER recession quarters. Data are seasonally adjusted using X-11.

Table 1: The Relationship Between Productivity Growth and Survival

Dependent Variable	**Lagged Productivity**	**Lagged Log(Employment)**
	Firm-Level Regression	
Net Growth Rate	0.2643***	0.0583***
	(0.0002)	(0.0001)
Exit	−0.07389***	−0.04539***
	(0.0001)	(0.0000)

Notes: 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.

Table 2: Differential Net Flows
National Time Series, Within/Adjacent

Dependent Variable	**Change in Unemployment Rate**	**Trend**
By Productivity: High Productivity minus Low Productivity		
Net Job Flows	0.146	−0.007
	(0.167)	(0.006)
Net Poaching Flows:	−0.343***	−0.010***
	(0.074)	(0.003)
Net Non-Employment Flows	0.488***	0.003
	(0.142)	(0.005)

Notes: Standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. High productivity indicates that the firm is in the top quintile of the within industry productivity distribution. Low productivity indicates the firm is the bottom quintile of the within industry productivity distribution. Net poaching and net non-employment flows are seasonally adjusted using X-11, net job flows reports the sum of these two components. Each specification includes a linear trend.

Table 3: Differential Net Flows
National Time Series, Within/Adjacent

Dependent Variable	**Change in Unemployment Rate**	**Trend**
	By Wage: High Wage minus Low Wage	
Net Job Flows	-0.557^{***}	-0.003
	(0.198)	(0.004)
Net Poaching Flows	-1.460^{***}	-0.012^{***}
	(0.157)	(0.003)
Net Non-Employment Flows	0.903^{***}	0.009^{***}
	(0.139)	(0.003)

Notes: Standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. High wage indicates that the firm is in the top two quintiles of the wage distribution across firms. Low wage indicates that the firm is in the bottom quintile of the wage distribution across firms. Net poaching and net non-employment flows are seasonally adjusted using X-11, net job flows reports the sum of these two components. Each specification includes a linear trend.

Table 4: Size, Earnings per Worker, and Revenue per Worker

	Revenue per Worker	**Earnings per Worker**	
Size	-0.056**	0.173**	
	(0.000)	(0.000)	
Size^2	0.010**	-0.010**	
	(0.000)	(0.000)	
Revenue per Worker			0.391**
			(0.000)
$\text{Revenue per Worker}^2$			-0.573**
			(0.000)
R^2	0.02	0.07	0.16

Notes: Standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. This regression employs more than 40 million firm-year observations, so the standard errors are quite small.

Table 5: High-Paying Firms, Industries with High vs. Low Share College Graduates

High-Wage Firm Employment Rank	Industry in High College Share Quintile	Industry in Low College Share Quintile
1	Hospitals (general)	Building finishing contractors (drywall, flooring)
2	Physicians offices	Motor vehicle parts manufacturing (engines, electrical)
3	Computer systems design	Courier service and parcel delivery (e.g. FedEx, UPS)
4	Insurance carriers	Highway, street, & bridge construction
5	Management of companies	Demolition and site clearing
6	Banking	Automotive repair
7	Architectural and engineering services	Architectural metals manufacturing
8	Legal services	Cement and concrete manufacturing
9	Wired communications carriers	Rubber product manufacturing
10	Management, scientific, and technical services	Ship and boat builders
11	Professional equipment suppliers	Heating and air-conditioning manufacturing
12	Colleges and universities	Fruit and vegetable preserving
13	Insurance agencies	Automotive dealers
14	Wholesale electronics markets	Non-metalic mineral mining
15	Aerospace parts manufacturing	Glass and glass product manufacturing

Notes: Selected industries.