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. During recessions, we find that reallocation through the non-employment margin contributes to productivity enhancing reallocation. In this respect, we find evidence for both a cleansing and sully effects of recessions. Workers move up the productivity job ladder during booms but this collapses during contractions. During contractions, there is a substitution of reallocation away from job-to-job flows to flows through non-employment. We also integrate our findings with the recent evidence of a strongly procyclical firm wage ladder but little evidence of a firm size job ladder. To help reconcile our findings with this evidence, we show that 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.

We also find that net employment reallocation to more productive firms via job-to-job flows is highly 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. While job-to-job flows decline in recessions, we find that productivity enhancing reallocation via non-employment flows increases in recessions. Specifically, we find that low productivity businesses

[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.

exhibit greater declines in net hiring from non-employment during recessions. The latter is consistent with a cleansing effect of recessions.

By decomposing the reallocation of workers from low to high productivity firms into the component from job-to-job flows and the component from non-employment flows, our findings provide new perspective about alternative hypotheses about the nature of productivity enhancing reallocation. One hypothesis from models such as that from Mortensen and Pissarides (1994) is that unemployment plays a critical role in productivity enhancing reallocation. This class of models emphasizes that to move workers from low productivity to high productivity firms involves workers passing through the state of unemployment. Workers whose jobs are destroyed at low productivity firms flow into unemployment and then engage in search for a new job at a high productivity firms where new jobs are being created. In this setting, reallocation via unemployment is countercyclical. An alternative hypothesis that emerges from the models such as Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2013) emphasizes the the for job-to-job moves in worker reallocation across firms. These models predict that workers move up the productivity job ladder. Such job-to-job flows will be procyclical as firms at the top of the productivity ladder will have the greatest incentive to poach workers from the bottom of the ladder during booms. Thus, these models hypothesize that the component of reallocation via job-to-job flows should be procyclical.

Our evidence provides support for both of these hypotheses. However, this interpretation is made with caution since these alternative hypotheses derive from modeling assumptions that are quite different. The Mortensen and Pissarides (1994) model does not permit on-the-job search. In contrast, the job ladder models only permit permanent differences in productivity across firms and thus are missing the adverse idiosyncratic productivity shocks that yield endogenous job destruction in the Mortensen and Pissarides (1994) model. In this respect, interpreting our findings as providing support for both hypotheses is in part a call for developing theoretical models that incorporate simultaneously the different components of reallocation that are evidently important empirically.

Interpreting our evidence as supportive of job ladder models also requires reconciling our evidence with recent empirical evidence on the nature of firm wage and firm size job ladders. The job ladder models of Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2013) suggest a tight link between firm productivity, firm size and firm wages. In these models, high productivity firms are large and pay high wages. Such firms at the top of the firm productivity, firm size and firm wage ladder poach workers away from the bottom of the ladder. Moreover, such poaching should be procyclical for the reasons articulated above.

The recent evidence in Haltiwanger, Hyatt, Kahn and McEntarfer (2017) (hereafter HHKM (2017)) provides strong support for a strongly procylical firm wage ladder but not a firm size job ladder.[3] Somewhat surprisingly they find evidence that small firms tend to poach workers away from large firms. Part of the reason for this is that young, small firms that are fast growing poach workers away from other firms. However, they find that even controlling for firm age, there is much less support for a firm size ladder than a firm wage ladder.

The current paper adds firm productivity into the mix. We show that the firm productivity job ladder patterns that are novel to the current paper closely mimic the firm wage patterns of HHKM (2017). 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. 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.

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

[3]This paper reflects a merger of the earlier work by Kahn and McEntarfer (2014) (hereafter KM (2014) and Haltiwanger, Hyatt and McEntarfer (2015) (hereafter HHM (2015).

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.

The analysis in the current paper does not explicitly control for worker heterogeneity. A companion paper, Haltiwanger, Hyatt and McEntarfer (2017), investigates the characteristics of workers moving up the productivity job ladder. In that paper, 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 productivity job ladder. This finding holds even though we find that more educated workers are more likely to work with more productive firms. 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 both more likely to separate to a better employer in expansions and to be shaken off the ladder (separate to nonemployment) in contractions. For current purposes, the results in this companion paper highlight that the patterns we find in terms of moving workers up the productivity job ladder remain true when holding observable worker quality constant.See for example Table 4 from Haltiwanger, Hyatt and McEntarfer (2017).

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 an 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

[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.

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, 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. Still it is of interest to consider the role of worker heterogeneity explicitly. As noted in the introduction, in a companion paper, Haltiwanger, Hyatt and McEntarfer (2017), we show that the directional job ladder by firm productivity that is procyclical is present holding worker characteristics such as age, gender and education constant.

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 identification number (SEIN). SEINs typically capture the activity of a firm within a state in a specific industry.

[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).

The LEHD data allow us to decompose employment growth by worker hires and separations. We use the decomposition developed by HHM (2015) and HHKM (2017) 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 et al. (2017) based on the revenue and employment data from the Census Business Register and the Longitudinal Business Database (LBD). Since the underlying revenue and employment

[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.

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 the manufacturing sector. This finding is consistent with the implications of models with labor market adjustment frictions (which motivate our analysis).[8] 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.[9] 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.[10] 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]See for example Decker et. al. (2017). In their calibrated model of labor adjustment frictions, they obtain a correlation of TFP and revenue labor productivity of 0.90.

[9]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.

[10]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.[11]

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).[12] 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.[13] For the measurement of firm

[11]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.

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

[13]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.[14] 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, such measurement error should imply 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.[15] Our 28 states include many of the largest states so

(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.

[14]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.

[15]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

that our sample accounts for 65 percent of national private sector employment. We note that our analysis of job-to-job flows uses quarterly data from 1998-2011.

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.[16] 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.[17] 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 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

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.

[16]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.

[17]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.

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.[18]

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.[19] 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.

[18] Decker et. al. (2017) develop a simply model of firm dynamics with adjustment frictions that shows that the relationship between growth and surival from t-1 to t with realizations of labor productivity in period t is very similar as with TFP, holding firm size constant in t-1.

[19] 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.[20]

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.[21] 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. The average net employment growth of the top quintile firms is 0.8 percent per quarter with net poaching averaging 0.6 percent per quarter. In the 2004-2006 period, the most productive firms grew on average 1.1 percent per quarter, with job-to-job moves of workers from less-productive employers accounting for 60 percent of this growth.

The results of the decomposition are also striking for the least productive firms. In Figure 2(b), firms in the lowest productivity quintile lose about 1.1 percent of total employment *per quarter*. Almost ninety percent of this is accounted for by workers 'voting with their feet' and

[20]See in particular Hyatt and McEntarfer (2012), Hyatt (2015), and HHM (2015) and HHKM (2017).

[21]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.

moving to firms ranked higher in firm 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 1.9 percent per quarter. The average net poaching differential between high and low productivity firms is about 1.6 percent per quarter. This implies that about 83 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. These findings are consistent with 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)).

There is also evidence of a cleansing effect that works through flows to and from non-employment. The net flows from non-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.[22] 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 comparing and contrasting the results using within vs. between industry variation. While results are broadly similar in terms of poaching patterns, some further remarks are useful to interpret these results. First, it is important to emphasize that for the within industry variation we are focusing on relative productivity rankings within industries. This implies that workers moving from a low relative productivity firm to a high relative productivity firm may reflect workers moving from a high productivity industry to a low productivity industry. In interpreting such flows, it is helpful to recall that the literature has shown that within industry variation in productivity accounts for about 90 percent of overall between firm variation (see, e.g., Foster, Haltiwanger and Krizan (2001) and Dunne et. al. (2004)). In what follows, we focus on the firm-level relative productivity differences in productivity since this is likely the more important source of variation.

There is also a subtle but important theoretical motivation for focusing on the within industry productivity differentials. In terms of net reallocation of employment, theory predicts that within industries that employment should be reallocated to higher productivity firms.[23] However, this may not hold between industries as the allocation of employment across industries may reflect demand factors. For example, an industry with rising productivity but inelastic demand may experience a decline in employment. Note that between industry differentials should still be predictive of net poaching patterns. That is, firms that are high productivity because they are in high productivity industries should be able to do more of their hiring by

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

[23]Even here theory implies resources should be reallocated to firms with higher marginal revenue products.

poaching from others. Differential patterns of net poaching across industries need not imply patterns of overall net reallocation across industries. For example, for the results in Figure 3, we find that high productivity industries have higher net poaching rates but not net job flow rates.

4.3 Reconciling Productivity Ladder with Firm Wage and Size Job Ladders

HHKM (2017) show 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 HHKM (2017). 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. HHKM (2017) provide validation of this as they find that 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.

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:

$$y_{jt} = \alpha + \beta_1 * x_{jt-1} + \beta_2 * x^2_{jt-1} + \epsilon_t \tag{2}$$

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.[24]

Table 3 shows the results from these simple regressions. Column 1 of Table 3 shows the estimated relationship between size of the firm and its within-industry productivity. The coefficient on firm size is -0.062, on the square of firm size, 0.010. and the R-squared for this regression (0.01) is very small. Column 2 of Table 3 shows this regression with the within-industry average wage as the dependent variable. The main effect estimate, 0.173, has the expected positive sign but again the R-squared (0.07) is relatively small. The relationship between wages and productivity shown in Column 3 is much stronger as evidenced by the mangitude of the coefficients along with an R-squared of 0.13.

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

[24]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.

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. HHKM (2017 investigated this hypothesis by controlling for firm age in examining the patterns of job-to-job flows. They did find that the positive net poaching of small firms is associated with young, small firms growing on average. However, they also 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.

Taken together, the results in this paper and HHKM (2017) suggest that the weak patterns of the job ladder by firm size remain somewhat of a puzzle. To shed further light on this puzzle, we investigate a hypothesis not investigated in the prior work: 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.[25]

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

[25] 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.[26] 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.[27] We use rank based measures in this context to make the differential within industry productivity/size relationships comparable across industries.[28]

The results of the rank-rank regressions for productivity and size are shown in Figure 5.[29] 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 5 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

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

[27]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.

[28]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.

[29]We don't report statistical significance for all the coefficients in Figures 5-7 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 6. 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 5 and 6 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 7 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 8 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.[30] While we do see positive reallocation via job-to-job moves into large firms in this industry group (Figure 8(a)), we also see positive net poaching for small firms in this group (Figure 8(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 8(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 8(d)). These findings suggest that the overall finding of large firms being

[30]The versions of Figure 8 are from an earlier version of this paper that included productivity data starting in 2003. These will be updated in a future draft.

net losers from net poaching is driven by such industries. As seen in Figure 5, Accomodation and Food Services is one such industry. This is a low wage industry delivering local non-tradables. 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 8(b) shows that net hiring for such firms is overwhelming from non-employment.

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. The pace at which workers move up the productivity job ladder is highly procyclical. The collapse of the productivity job ladder is consistent with a sullying effect of recessions. In recessions, we find that the reallocation of workers away from less productive firms via non-employment flows increases. Thus, we also find evidence that this component of reallocation is conistent with a cleansing effect of recessions.

We compare and contrast our findings on the productivity job ladder with recent evidence on the job-to-job flow patterns by firm size and firm wage. The productivity and firm wage job ladders exhibit very similar patterns in terms of magnitudes and cyclicality. Firm size remains an outlier which 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.

Our findings provide support for both the job-to-job flows and non-employment flows as contributing to productivity enhancing reallocation. Since the former component is procyclical and the latter is countercyclical we provide support for both cyclical job ladder models as well as the canonical Mortensen and Pissarides (1994) that predicts reallocation via non-employment flows should be countercyclical. However, both classes of models are arguably missing important elements that are relevant empircially. The Mortensen and Pissarides (1994) model neglects on-the-job search but the critical role of job-to-job flows highlights this is problematic. The job ladder models only permit permanent differences in productivity across firms and thus are missing the adverse idiosyncratic productivity shocks that yield endogenous job destruction with flows into unemployment that are at the core of the Mortensen and Pissarides (1994) model. Our findings suggest that an important area for future research should be developing a theoretical framework that incorporates simultaneously the different components of productivity enhancing reallocation that we find are important empirically.

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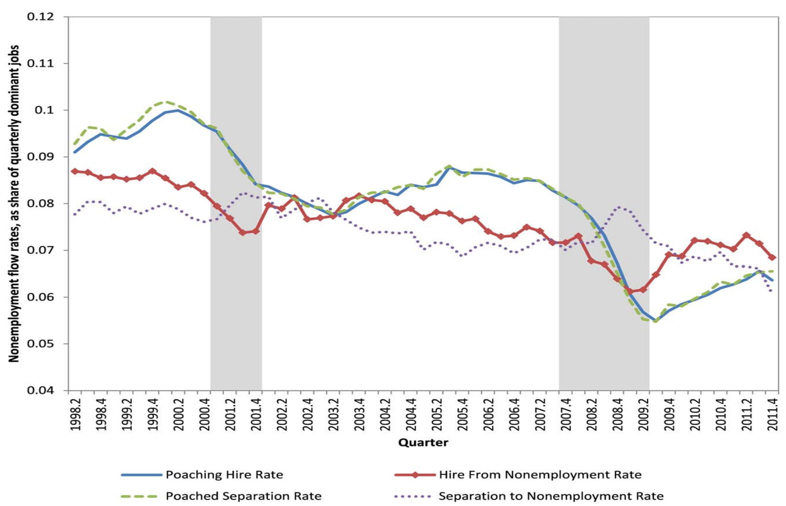
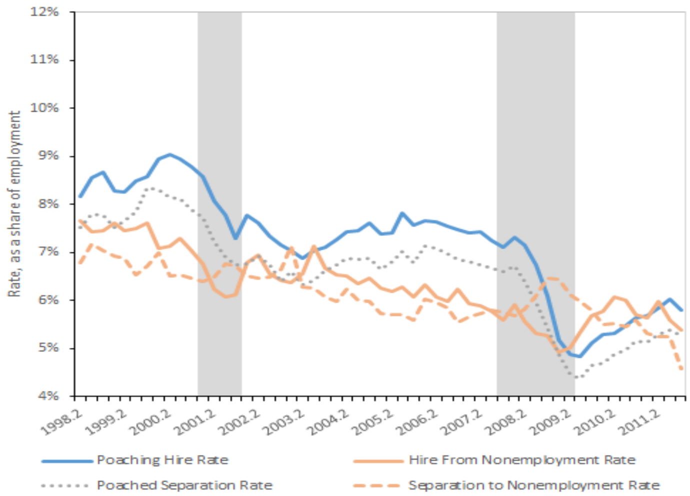
Figure 1: Hires and Separations: Poaching vs. Flows to and from Non-Employment

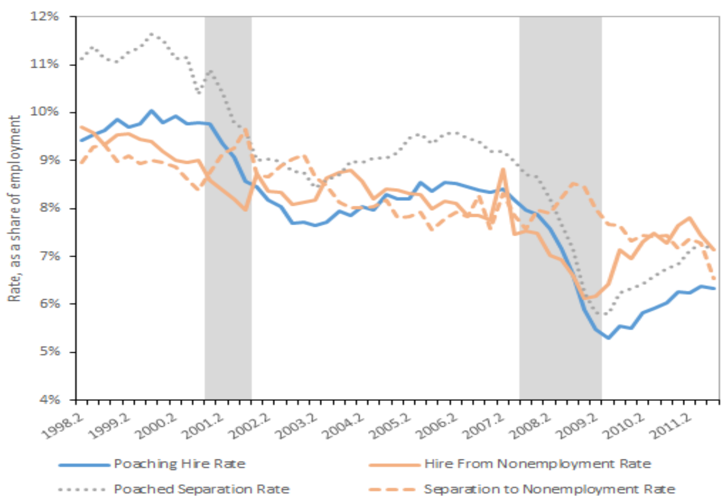


Notes: Shaded regions indicate NBER recession quarters. Data are seasonally adjusted using X-11.

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



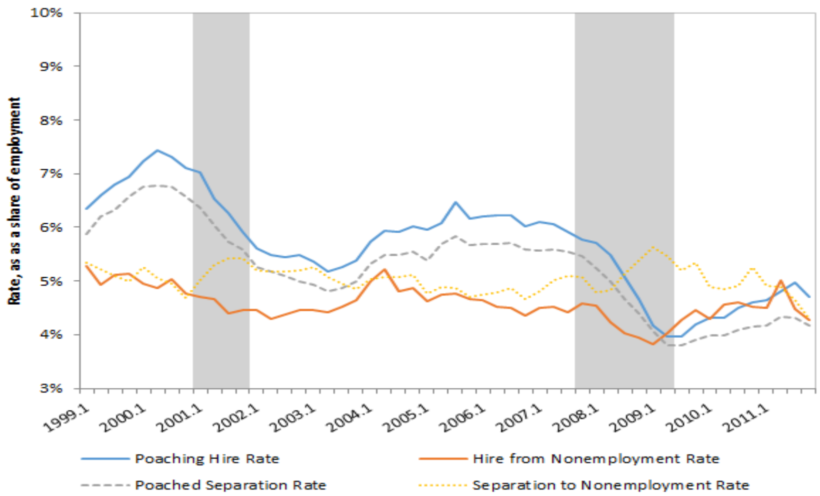
(a) Highest Quintile of Within-Industry Productivity



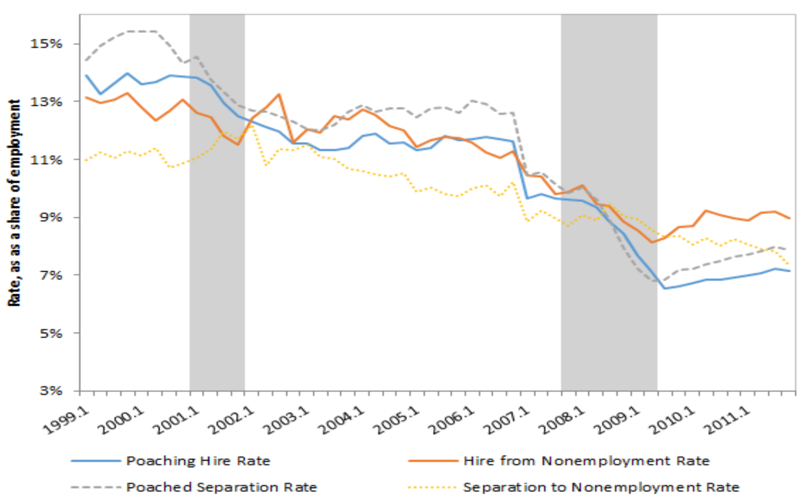
(b) Lowest Quintile of Within-Industry Productivity

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



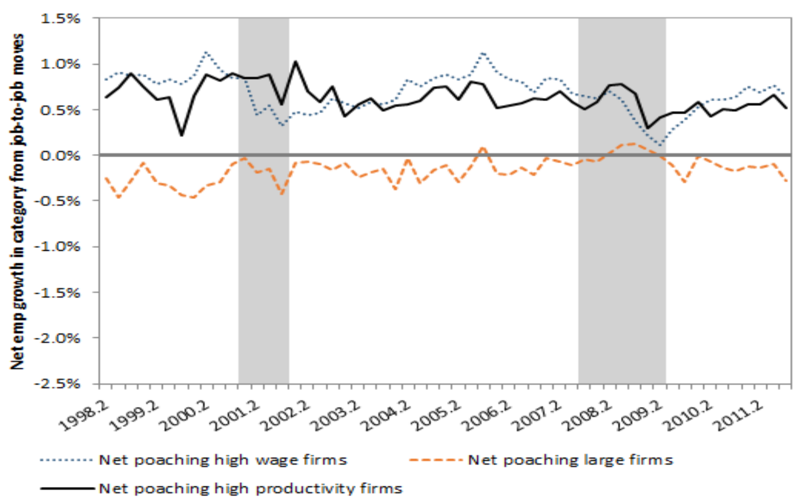
(a) Highest Quintile BEA Value Added Industries



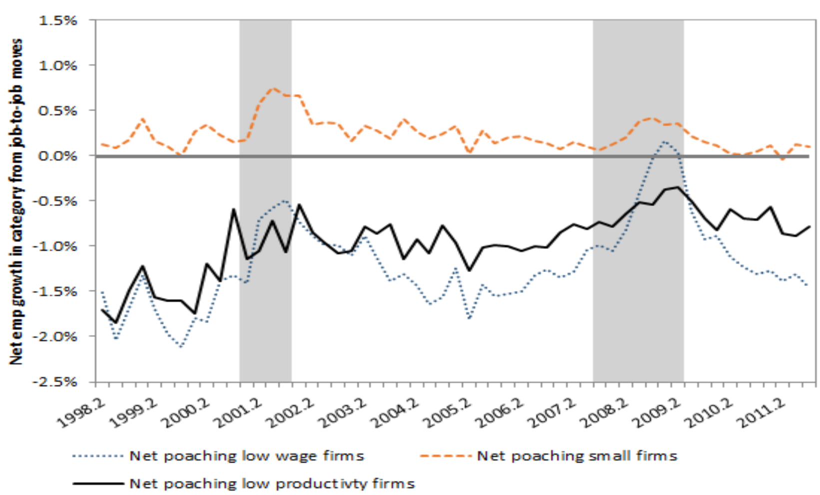
(b) Lowest Quintile BEA Value Added Industries

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



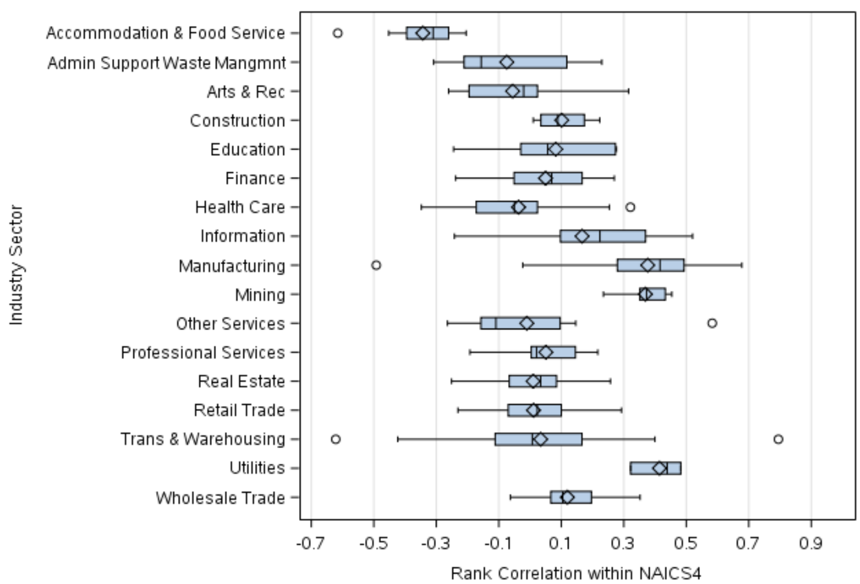
(a) High-Wage, High-Productivity, and Large firms



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

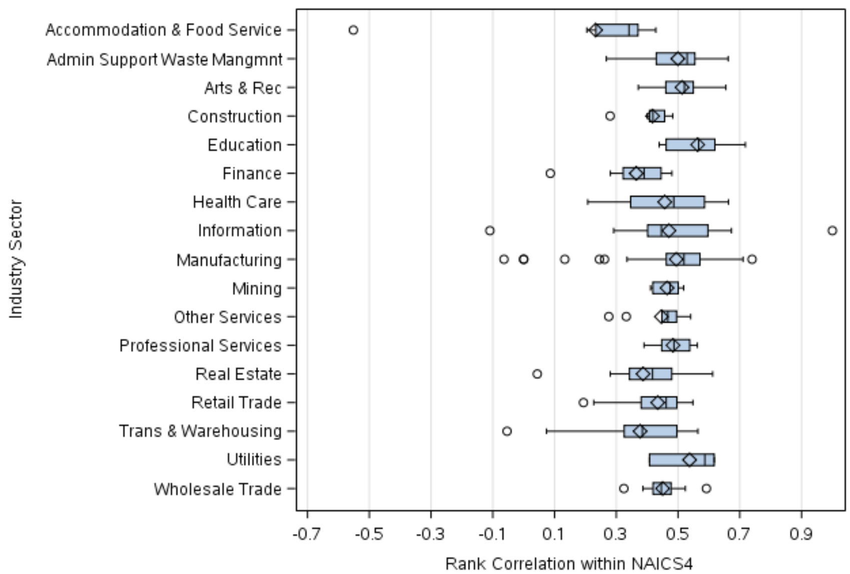
Notes: High productivity indicates that the firm is in the top quintile of the employment-weighted within industry productivity distribution. Low productivity indicates the firm is the bottom quintile of the employment-weighted within industry productivity distribution. Following HHM (2015), high wage 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: Distribution of Rank Order Correlation of Productivity and Size within NAICS4, by Sector



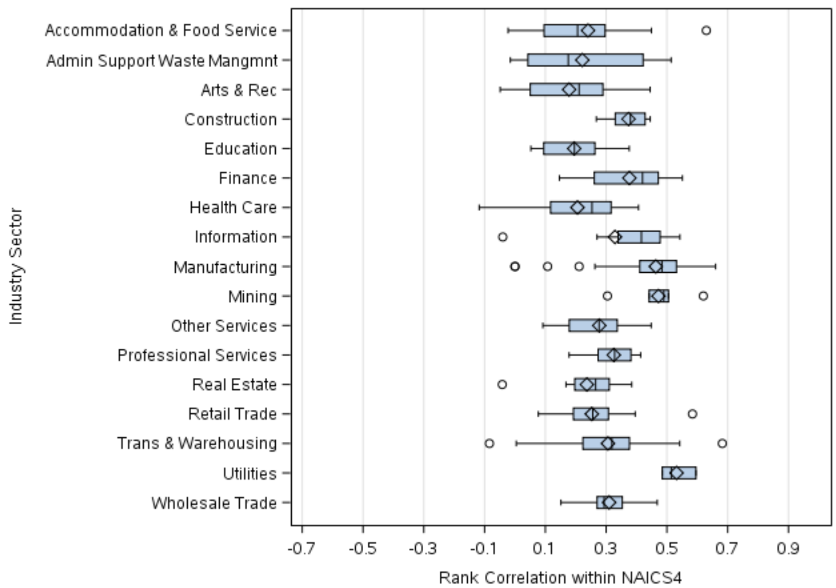
Notes: Boxes indicate 25th and 75th percentile, line inside box indicates 50th percentile, whisker lines indicate 5th and 95th percentiles, dots indicate substantial outliers.

Figure 6: 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.

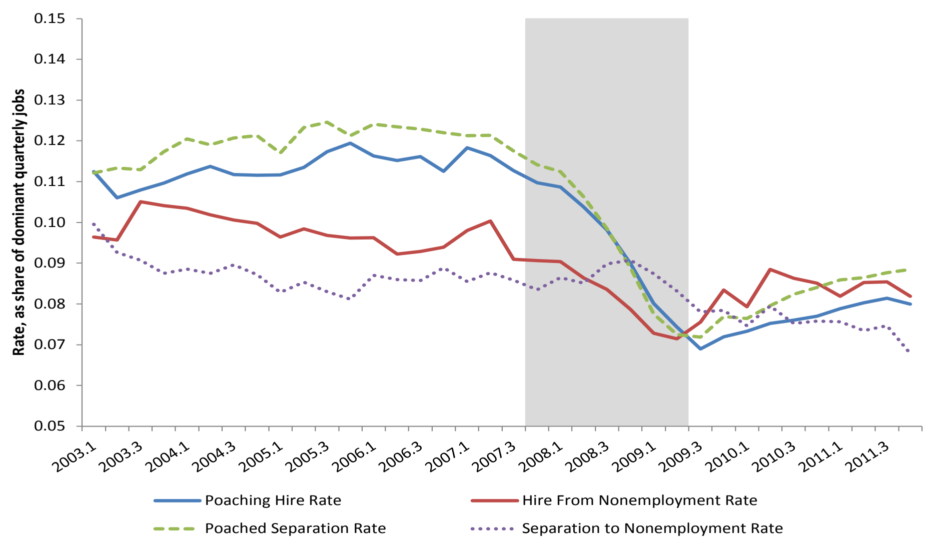
Figure 7: Distribution of Rank Order Correlation of Wage and Size within NAICS4, by Sector



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

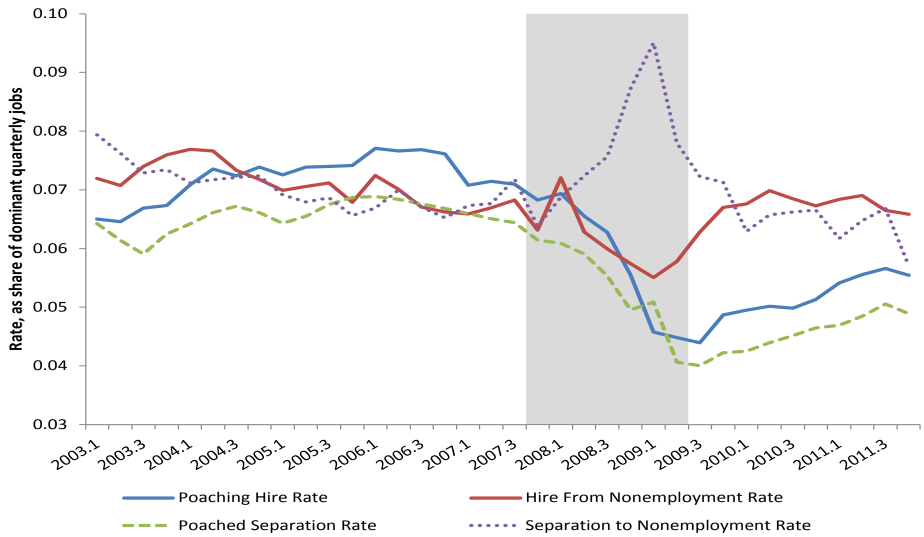
(a) Large, High Size-Productivity Relationship



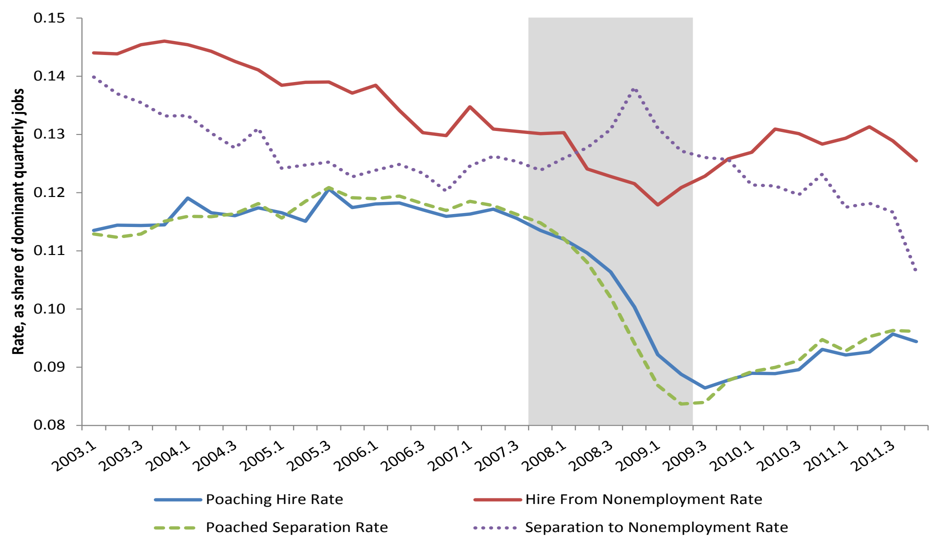
(b) Large, Low Size-Productivity Relationship

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 8: 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.

Table 1: The Relationship Between Productivity Growth and Survival

Dependent Variable	**Lagged Productivity**	**Lagged Log(Employment)**
	Firm-Level Regression	
Net Growth Rate	0.2205***	0.0574***
	(0.0001)	(0.0001)
Exit	−0.0682***	−0.0462***
	(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	0.188	−0.019
	(0.144)	(0.003)
Net Poaching Flows:	−0.332***	−0.019***
	(0.082)	(0.002)
Net Non-Employment Flows	0.520***	0.000
	(0.097)	(0.002)

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: Size, Earnings per Worker, and Revenue per Worker

	Revenue per Worker	**Earnings per Worker**	
Size	-0.062**	0.173**	
	(0.000)	(0.000)	
Size^2	0.010**	-0.010**	
	(0.000)	(0.000)	
Revenue per Worker			0.300***
			(0.000)
$\text{Revenue per Worker}^2$			0.023***
			(0.000)
R^2	0.04	0.07	0.13

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.