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Employment Reallocation over the Business Cycle: Evidence from Danish Data

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Employment Reallocation over the Business Cycle: Evidence from Danish Data

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ABSTRACT

Employment Reallocation over the Business Cycle: Evidence from Danish Data*

We present new evidence on how employment growth varies across firm types (size, productivity, and wage) and over the business cycle using Danish data covering almost 30 years. We decompose net employment growth into two recruitment margins: net hirings from/to employment (poaching) and net hirings from nonemployment. High-productivity firms are the most growing firms due to poaching. High wage firms poach almost as many workers, but shed an almost equal amount to non-employment. Large firms do not poach workers from smaller firms. In terms of employment cyclicalities, we find that low-productive and low-wage firms shed proportionally more jobs in recessions. We relate our findings to recent models of employment fluctuations that jointly analyze worker and firm dynamics.

JEL Classification: E24, E32, J63

Keywords: worker flows, firm heterogeneity, matched employer-employee data, business cycle, equilibrium search models

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1 Introduction

A key question in economics concerns the determinants of the level and cyclical nature of (un)employment. For many years labor economists have exploited microdata on worker mobility to get a better understanding of the drivers of unemployment at the aggregate level (Shimer, 2012). Recently, the predominant theoretical frameworks have started to emphasize on-the-job mobility and not just moves in and out of unemployment by connecting mobility to the large differences between firms in terms of wage, size, and productivity (Moscarini and Postel-Vinay, 2013; Gottfries and Elsby, 2019). However, few studies link the large differences in key firm characteristics to worker mobility. A better empirical understanding of the intertwining between worker mobility and firm heterogeneity is necessary to complement and evaluate recent theoretical advances. The main contribution of this paper is to exploit new matched employer-employee job spell-data, which links worker mobility and firm heterogeneity, to provide a better understanding of the aggregate level and cyclical nature of (un)employment.

This paper sheds new light on employment reallocation across firms with different sizes, average wage paid, and productivity using a novel combination of administrative Danish data sets that span an almost 30 year period from 1985 to 2013. We decompose firm-level employment changes coming from job-to-job transitions and transitions involving a period of non-employment. The idea that workers quit, i.e. are poached by another firm, to better positions has already contributed to the micro-labor literature on wage inequality (Mortensen, 2003). However, the importance of quits on the firm dynamics at both the micro and macro levels is recent (Moscarini and Postel-Vinay, 2018). Our decomposition of the evolution of firms' employment into different hiring channels and across heterogeneous firms provides novel evidence on the mechanisms underlying the labor reallocation process. Especially, we shed light on two open questions: How workers are reallocated across different firm types (wage, size, and productivity)? And how does the reallocation process vary over the business cycle?

Our main findings are summarized as follows. High-wage and high-productivity firms expand by poaching workers relative to low-wage or low-productivity firms. We also find that small firms hire more from employment (poaching) than large firms. This finding contradicts most standard search models, where large firms are more attractive than small firms. However, by excluding young firms, we observe that large and mature firms poach more than small and mature firms as theory suggests. Consequently, we conclude that firm size alone does not seem to be a relevant measure of firms' desirability in the data. In line with recent evidence that large firms are not anymore the most desirable firms (Bloom et al., 2018), we also find that poaching has been increasingly taking place

by small firms over time in our sample.

Summing the poaching margin and the non-employment margin, we show that high-productive firms have the highest employment growth rate per quarter, and 90% of this growth rate come from poaching. Ranking firms through their average wage paid paints a different picture. While those firms poach almost as much as high-productivity firms, they contract through the non-employment margin.

Recently, [Moscarini and Postel-Vinay \(2013\)](#) have argued that poaching behavior plays a leading role in determining differences in employment fluctuations across large and small firms. We add to this literature by investigating how firms adjust their employment over the business cycle. We measure how hirings and separations, by poaching and non-employment margins, react to changes in aggregate labor market conditions. We find that low-productivity compared to high-productive firms shed proportionally more jobs in recessions. Indeed, low-productive firms contract more through the non-employment margin, while high-productive firms contract more through the poaching margin. As a whole, the non-employment margin dominates, therefore low-productive firms shed proportionally more employment when unemployment goes up. Also, the reallocation patterns by productivity groups provide direct support for both the negative ("sully") and positive ("cleansing") effect of business cycle fluctuations.¹ Across the average wage paid distribution, we find very similar adjustment mechanisms as firms ranked over the productivity distribution.² As top-tier firms stop poaching in slack markets, because they can attract workers in booms, those firms are more responsive to aggregate shocks, in contrast to the least attractive firms. Flows involving a transition to non-employment counterbalance this effect, and in total we do not find any difference between high-wage and low-wage firms. Small firms shrink more in contractions, measured by a *change* in unemployment, compared to large firms. Smaller firms are more cyclically sensitive in recessions, as they stop hiring from the *non-employed* pool of workers.

This paper mainly contributes to two strands of economic literature. First, it brings new evidence on worker mobility over the business cycle, and second, it relates to the literature on firm dynamics.³ Related to the literature on worker mobility, earlier studies focused on the decomposition between the flow out of employment (separations) and

¹The sully effect refers to the idea that workers are matched to better firms at a lower rate in bad economic times. The cleansing effect posits that in recessions resources are directed to more productive firms ([Foster et al., 2016](#); [Osotimehin, 2019](#)).

²We have also tried to rank firms by the firm fixed effect from an AKM model, which gives similar results.

³It also informs various literature that put firm heterogeneity at the center of their analysis. For instance, innovation and aggregate growth ([Lentz and Mortensen, 2008](#)), aggregate fluctuations ([Di Giovanni et al., 2014](#)).

the flow into employment (hires) over the business cycle (Davis and Haltiwanger, 1990; Shimer, 2012; Elsby et al., 2013; Krusell et al., 2020).⁴ Recently, firm heterogeneity and direct employment reallocation (job-to-job) have enhanced the understanding of worker mobility.⁵ In particular, in a series of papers Moscarini and Postel-Vinay (2012, 2013, 2016) find evidence that job-to-job quits matter for the macroeconomic dynamics of unemployment, wages, and firm employment.

The closest paper to our work is Haltiwanger et al. (2018b) (hereafter HHKM18). HHKM18 analyzes net job flows by taking into account both employees poached *from* other firms and employees poached *to* other firms in the US. Our paper has two major contributions compared to HHKM18. First, US data sources have short time-series and important measurement issues. For instance, employment spells are measured at the quarterly frequency. This implies that job-to-job mobility could encompass up to 3 months of non-employment. Hence, many job-to-job transitions could include transitions with a short non-employment spell. Our daily measure of employment spells does not suffer from this important limitation and we can generate an accurate distinction between direct reallocation (*job-to-job quit*) and reallocation that involves a spell of non-employment (*non-employment*), which is not possible using most data sets.⁶ Through the lens of a job ladder model, where workers rank firms according to firm characteristics (size, productivity, wage), misclassification of non-employment spells (i.e layoffs) as job-to-job spells (i.e quits) is likely to inflate the net poaching in favor of *less* desirable firms.⁷ Second, HHKM18 do not measure the (arguably) defining feature of firm heterogeneity in macroeconomics, labor and trade models: firm-level productivity. The firm panel that we construct contains firm accounting reports (including value-added) from 1992.

The paper proceeds as follows. Section 2 and 3 present the methodology and data. In Section 4 we present our results regarding the dynamics of firm employment. Section 5 concludes.

⁴Hornstein et al. (2014), Borowczyk-Martins and Lalé (2019) and Faberman, Mueller, Şahin and Topa (2020) discuss the role of out of labor force, involuntary involuntary part time and labor market underutilization to measure labor market dynamics.

⁵Recent papers include, for instance, Menzio and Shi (2011); Kaas and Kircher (2015); Lise and Robin (2017); Coles and Mortensen (2016); Audoly (2019); Gottfries and Elsby (2019); Bilal et al. (2019).

⁶Indeed most available matched employer-employee data sets either do not track all hirings and separations of firms for a long period (e.g from 2002 for France) or do not contain accounting information of firms (e.g Germany or the US). Nakamura, Nakamura, Phong and Steinsson (2019) review limitations of the leading US data sources to measure job-to-job quits.

⁷Less desirable firms are small and low-productivity firms. Moscarini and Postel-Vinay (2018) illustrate the spurious failure of the firm size ranking when non-employment spells are misclassified as job-to-job quits.

2 Methodology

In this section, we describe how we measure firm ranking by size, average wage, and labor productivity. Then, we decompose the dynamics of firm employment into two recruitment channels: net hirings from/to employment (poaching) and net hirings from non-employment. Finally, we discuss two cyclical indicators to measure the state of the economy.

2.1 Descriptive Statistics of Firm Ranking

Measurement of Firm Quality

Firms are heterogeneous in many aspects and thus could be ranked in many dimensions. Since much of the theoretical understanding of the labor reallocation process builds on equilibrium search models, we use firm characteristics inspired by this literature as guidance, see e.g. [Carrillo-Tudela and Coles \(2016\)](#) and [Moscarini and Postel-Vinay \(2018\)](#). In particular, we use firm size, firm wage, and firm productivity.⁸ First, we use firm size (employee count) to measure firm quality. There are several reasons why we want to rank on firm size: Almost all of the search models used in the literature imply that bigger firms are higher ranked firms. Also, an important line of research documents a positive link between employer size and wage, see e.g. [Brown and Medoff \(1989\)](#).⁹ Also, firm size is less subject to measurement error relative to other rankings, and the size of firms is an important feature of the political debate. However, [Haltiwanger et al. \(2013\)](#) highlight that firm size alone can be misleading if the age of firms is not taken into account. Inspired by this and also our results, we split between young and mature firms together with age. Second, we use average hourly wage paid as an underlying measure of desirability to complement results on firm size, because wages can reflect firm quality better than size (especially for young firms).¹⁰

Finally, we propose to use productivity measured by value-added. This is a potentially better ranking of firms than wages. There are two main problems with wages. First, wages only rank the workers' part of the surplus and not the total surplus. Second, wages are potentially sluggish, and especially downward wage rigidity is possible. Firm productivity allows, in principle, to directly extract the relevant firm component to mea-

⁸ [Lentz and Mortensen \(2010\)](#) and [Van Reenen \(2018\)](#) also exploit firm heterogeneity in terms of size, productivity, and average wage paid to characterize differences between firms.

⁹ Recent research shows, after controlling for firm selection and worker selection that, on the contrary, there exists a young-firm pay premium ([Babina et al., 2019](#)).

¹⁰ However, our measure of firm wage does not allow us to separate the contributions of worker characteristics, firm characteristics and the potential interactions between the latter and the former.

sure firm quality. The trade-off is that productivity is inherently difficult to measure. We measure average productivity as value-added per hour worked from 1992 when firm-level annual accounting reports are available. We are not aware of papers that use firm-level value-added data to measure the process of labor reallocation over the business cycle. [Haltiwanger et al. \(2018a\)](#) use sales per worker as a measure for productivity. However, value-added, which is the difference between sales and the cost of intermediate inputs, is a much more precise measure.¹¹

Ranking

Each year we define - Large Firms, High-Wage Firms, and High-Productivity Firms- as being firms in the top two employment-weighted quintiles. Small Firms, Low-Wage Firms, and Low-Productivity Firms are present in the bottom two employment-weighted quintiles.¹² Weighting by employment implies that results can be interpreted as the effects on the average worker rather than the average firm. To avoid reclassification bias, we use value of size, wage, and productivity in year $t - 1$ to characterize net flows in quarters of the current year t .¹³ Also, we classify firms as “young” firms in the first five years after entry and “mature” from the sixth year after entry.

Firm Characteristics Across Types

Table 1 dissects mean firm characteristics within each category.¹⁴ 95% of firms are considered small, and 1% are considered large. The mean number of employees in the ‘Small Firms’ category is 5, while for the ‘Large Firms’ category it is 322 employees. When the average wage paid increases, firms become larger but this is not the case when firms move up the productivity distribution. Young firms and old firms are present in similar proportions across the wage and productivity ranking, but large firms are twice older than small firms (29 years on average). We further study how those characteristics comove in

¹¹This is also argued by [Moscarini and Postel-Vinay \(2018\)](#) who write "The data required to estimate firm-level revenue-based TFP have been available for some time in several European countries, but to the best of our knowledge have not been used to test for the existence of a job ladder."

¹²[Haltiwanger et al. \(2018b\)](#) categorize large firms as firms having more than 500 employees and low-paying as firms in the lowest employment-weighted quintile. As [Moscarini and Postel-Vinay \(2012\)](#) we do not use this threshold as a few firms in Denmark have more than 500 employees. We do not rank firm size within industry as there is a considerable amount of employment in large firms for each sector.

¹³For new entrants, we use the value of the current year. Reclassification bias refers to the fallacy that the growth rate of large firms is higher when the economy expands and is lower in contractions. Reclassification bias occurs when variations in economic activity shift the employment distribution, but the threshold to construct groups of firms is fixed. [Moscarini and Postel-Vinay \(2012\)](#) find that this statistical fallacy is not quantitatively important.

¹⁴Table A.1 in Appendix C reports the median characteristics of firms across groups.

each part of the distribution of size, wage, and productivity. When firms become larger, the correlation between wage and productivity increases, from 0.16 in the group of small firms to 0.35 in the group of large firms. This is also true for the correlation between firm size and productivity. For small firms, we find a negative correlation (-.10) between size and productivity, which is not the case for larger firms (.06). The negative correlation between firm productivity and firm size suggests that there exists a lot of heterogeneity in the small firm category.

Firm Characteristics Over their Life-Cycle

To investigate the role of firm dynamics over their life-cycle, Table 2 reports firms' characteristics of five equally-sized bins.¹⁵ While the average size in the last age quintile is five times larger than in the first quintile, this is not true for the average wage paid and productivity. In terms of average wage paid, older firms pay more but younger firms are more productive.

2.2 Decomposition of Firm Employment

We decompose employment creation - the job creation and job destruction of firms - into two components. The first component is job-to-job transitions, which we primarily view as voluntary choices made by the employee. Using survey data combined with administrative spell data for Denmark, [Taber and Vejlin \(2020\)](#) find that 80 percent of job-to-job transitions are voluntary.

The second component is hirings (separations) from (to) non-employment. In this paper, we do not differentiate between different types of non-employment.¹⁶

Formally, we compute net job flows for firms as,

$$\text{Net Job Creation} \equiv H_t - S_t = \underbrace{H_{tp} - S_{tp}}_{\text{Poaching}} + \underbrace{H_{tn} - S_{tn}}_{\text{Non-Employment}} . \quad (1)$$

Hirings (H_t) and separations (S_t) in month t are measured as job spells that are observed for the first time in t and the last time in t , respectively. H_p and H_n represent hirings from job-to-job (*poaching*) and non-employment, respectively. S_p and S_n represent separations to job-to-job and non-employment. A hire or separation through a job-to-job transition is defined as a transition with less than 7 days of non-employment between two

¹⁵This is in contrast to Table 1 in which the firm grouping is employment-weighted.

¹⁶Due to the means-tested nature of social assistance in Denmark, it is hard to separate active job-seekers from non-active ones using only register data. Moreover, it changes over the sample period.

employment spells at two different employers.¹⁷ We deliberately choose a short number of non-employment days to minimize misclassification of spells. As highlighted in [Moscarini and Postel-Vinay \(2018\)](#), time aggregation bias (reporting worker mobility as a job-to-job whereas, in reality, a non-employment spell occurred in between the two jobs), might overestimate net poaching flow for firms at lower rungs of the job ladder. The reason is that if workers lose their jobs and quickly find new ones, it is more likely to be jobs at lower rungs of the job ladder. To our knowledge, the only study which decomposes net job flows between job-to-job and non-employment is [HHKM18](#). They use employment spells for the US at the *quarterly* frequency. This implies that job-to-job mobility could encompass up to 3 months of non-employment.¹⁸ Non-employment transitions involve at least 7 days of non-employment.¹⁹

All time-series are seasonally adjusted and are converted to quarterly rates. We convert the monthly series by summing hirings and separations during the quarter considered. To convert it to rates, we divide the quarterly series by the average aggregate employment during the quarter. We use a weighted moving average smoother to correct for seasonal fluctuations.

2.3 The Cyclicity of Firm Employment

We will first present graphical evidence using the above series. We will complement this by statistical evidence since it can be hard to judge the business cycle effects on firm employment from just the graphs.

Statistical Model

To quantify the relationship between the business cycle and the employment cyclicity across firm groups, the key dependent variables are the differential net employment growth rates, the employment growth rates, and gross flow rates. For all dependent variables, we estimate the following model on aggregated quarterly data:

$$y_t = \beta Cycle_t + \gamma_t + \epsilon_t. \quad (2)$$

¹⁷[Moscarini and Postel-Vinay \(2018\)](#) use this threshold to define job-to-job transitions in the SIPP data.

¹⁸To reduce measurement error they also compare earnings in the transition quarter to earnings in the surrounding quarters. They define job-to-job mobility as transitions characterized by less than one month of earnings losses. However, this is potentially also problematic because the selection is now based on wage changes.

¹⁹Since we focus on worker mobility between firms, transitions from one employer to non-employment to the same employer (recalls) are not counted.

In many of our regressions the dependent variable, y_t , is the *differential net growth rate*, $\Delta g_{t,t-1}$. It is the net growth rate of "High-type" firms minus the net growth rate of "Low-type" firms, i.e. $\Delta g_{t,t-1} = g_{t,t-1}^{High-type} - g_{t,t-1}^{Low-type}$. The model includes a linear time trend and a constant (γ_t). The parameter of interest is β , which measures the effect of a one percentage point increase (ppt) of the cyclical indicator on the differential net flows. To understand the adjustment that generates the differential net flows, we estimate the same model using as dependent variables the net flows (hirings minus separations) and the gross flows (hirings and separations), through poaching and non-employment.

Cyclical indicator

As cyclical indicator, $Cycle_t$, we use two different measures: the first difference of the unemployment rate and the deviation from the HP trend of the level of the unemployment rate. These two have been used previously in the literature by [HHKM18](#) and [Moscarini and Postel-Vinay \(2012\)](#), respectively.²⁰ As we show later results differ depending on which indicator is used. Both indicators are interesting because they refer to different stages of the business cycle. This is illustrated in [Figure 1](#), which shows that a period of high level of unemployment (in deviation from its HP trend) occurs late in and right after a recession, whereas a large increase in the change in the unemployment occurs in the early part of recessions. The correlation between the change in unemployment rate and its cyclical component from the HP filter is 0.20 for Denmark, which is similar to the US.

3 Data

In this section we describe the characteristics of the Danish labor market, the features of our unique matched employer-employee data set, and document aggregate labor market transitions.

3.1 Some Features of the Danish Labor Market

The Danish labor market is known for its so-called ‘flexicurity’. Through lax employment protection and generous unemployment insurance, which has been in place since the 1970s, it is the implementation of a string of reforms in the 90s that is considered to have

²⁰Unemployment rate series is the OECD harmonized unemployment rate from 1983Q1 to 2017Q4 at the quarterly frequency. We use a smoothing parameter of 1600 to compute HP detrended unemployment rate. We choose unemployment rate as a cyclical indicator motivated by theoretical work. In labor search models, the aggregate statistics for worker turnover is the labor market tightness (ratio of unemployed over vacancy).

changed the structural level of unemployment, see [Andersen and Svarer \(2007\)](#). Figure 1 reports the unemployment rate. Unemployment reaches its peak in 1993 at 10%, before going down to 3% in 2007. After a slack labor market following the Great Recession and the European debt crisis that persisted from 2009 to 2013, unemployment went down in recent years and is hovering at about 5%. Appendix A gives details about the relevant features and macroeconomic trends of the Danish labor market.

3.2 Labor Market History and Firm Accounting Data

Here we present the data used for our analysis.

A Novel Labor Market History Data Set

Our analysis relies on a novel combination of several administrative data sets to record all job spells daily from 1985 to 2013 for all individuals living in Denmark. Details on data sources and data construction are reported in Appendix B. Each observation in the dataset contains worker, firm, and job identifiers. In the case of multiple job holdings in a given month, we select the primary job.²¹ For each job, we have information on the start and end date of the job, and earnings and hours worked at the annual frequency. This dataset is particularly rich for several reasons. First, both public and private sector jobs are recorded. Second, there is not a minimum threshold of days or hours worked for a job spell to be recorded. Third, if a worker goes back and forth from a particular employer to non-employment, distinct job spells are recorded. Fourth, earnings are not top-coded. Having access to the exact timing for each employment spell reduces measurement error, which has been a problem in previous studies as mentioned before.²² Without the exact length of the job spell, it is difficult to distinguish between job-to-job transitions and transitions involving a non-employment period.

Firm Accounting Data

We complement the job spell data with administrative panel data on workers and firms. Especially, we have access to a panel data of firms with account reporting from 1992. Since the introduction of the Danish Financial Statement Act in 1981, every company is obliged to submit an “annual report”, which for most companies consists of a statement issued by the management on the annual report, a balance sheet, and an income statement. This dataset allows us to measure value-added for firms for a long period.

²¹The primary job in a given month for a given worker is defined as employment at the firm at which the worker spends the most time working aggregated over the current and the two following months.

²²We correct for fictitious transitions that are driven by a change of employer identifiers. See appendix B.1.

The resulting dataset contains detailed information for each job (hours worked, earnings, and tenure) and firms (value-added, capital, labor cost, age, and sector).

3.3 Aggregate Labor Market Transitions

Before we move ahead and decompose employment flows by firm type, we first present aggregate flows. In particular, we decompose net job flows - the job creation and job destruction of firms - into their source. Figure 2 shows the aggregate hire and separation rates decomposed into job-to-job and non-employment transitions. Shaded areas represent recession periods. Figure 1 represents the unemployment rate using OECD data, the cyclical indicator is used to define recession periods. At the aggregate level, hire and separation rates to and from job-to-job are almost equal by definition.²³ Aggregate net employment growth is determined by hirings and separations from and to non-employment. Several empirical regularities stand out. First, we observe an increase in the level of transitions from around 1997 to 1998 in an otherwise stable labor market, see Figure 2. This was caused by a change in data sources, see Appendix B.1. Second, job-to-job transitions are quantitatively important and strongly pro-cyclical. The high share of job-to-job transition is a pervasive feature of countries with wage growth over the life cycle (Engbom, 2020).

This new evidence on the behavior of job-to-job transitions for a long period is informative on the debate about the changing stability of employment relationships in recent decades. We do not see a decline in job-to-job reallocation rates in general over the 30 years in Denmark. This is contrary to Davis and Haltiwanger (2014) who find declining mobility for the US, but in line with Fujita et al. (2020) who argue that the reason for the decline in mobility in the US is measurement error in transitions.

4 Results

In this section, we decompose the employment dynamics for firms ranked by size, mean wages, and productivity. We first decompose the net employment growth, through flows from/to employment (poaching) and flows from/to non-employment. Second, we measure the variation of employment growth to business cycle conditions across firms. We show that the poaching channel explains 90% of the employment growth of high-productive firms, and these firms are less sensitive than low productive firms to deterioration of economic conditions.

²³A separation classified as job-to-job is followed by a hire (also classified as job-to-job) within 7 days. By definition job-to-job hire and separation can overlap two months, rendering not exact hire and separation rates from job-to-job.

4.1 Net Employment Growth from/to Employment (Poaching)

Net Poaching by Firm Size, Wage, and Productivity

Figures 3 and 4 report employment growth by net poaching, i.e. the change in employment induced by workers that switch jobs without a spell of non-employment. Figure 3 reports the flows for all firms ranked by size and wage, and 4 focuses on flows for private sector firms with value-added data ranked by size, wage, and productivity. This figure starts in 1992 since this is the first year with value-added data. In Figure 3, we observe that large firms are net poachers on average from 1985 to 1995. Since the mid-90s, the net poaching rate of large firms is negative. This is also true if we focus only on private firms, where the net poaching of large firms is almost always negative. The finding that large firms are not anymore net poachers is in line with recent evidence that the firm size wage premium has declined over the last 30 years (Bloom et al., 2018).²⁴ This is at odds with wage posting models in the style of Burdett and Mortensen (1998) and more recent versions of posting models by e.g. Moscarini and Postel-Vinay (2013). In these types of models firm size becomes a relevant characteristic of the employer to determine the rung on the job ladder. The reason is simply that high-productive firms become large exactly through their ability to poach workers from other firms and retain their workers despite the competition from other firms. However, it is consistent with more recent work by Bilal et al. (2019) who find that net poaching is positively related to firm productivity, but not to the size of the firm.²⁵ Haltiwanger et al. (2018b) using US data find the same as we do, but they only use data from 1998-2013. It is interesting to note that the time from the late 90s until the Great Recession is also the period, where we find the lowest net poaching rate, whereas it becomes positive for all firms during the Great Recession, which is also consistent with Haltiwanger et al. (2018b).

In Figure 4, we clearly see that the poaching behavior of firms ranked by average wage paid and labor productivity is very similar.²⁶ On average over the 1992-2013 period, high-productivity firms grow by 0.42%, high-wage by 0.34% , and large firms by -0.20% each quarter. The difference in employment growth through poaching is important across booms and busts. The net poaching of high-wage firms fluctuates from almost 0 percent to 0.75 percent. The difference over the business cycle is less clear for firms across the size distribution. The fact that high-wage and high-productivity firms poach more than their low counter-parts is in line with standard job search models and more advanced

²⁴Bloom et al. (2018) finding, based on administrative US data, is driven by a decline of the premium (very large) firm pays to a typical worker (firm fixed effect).

²⁵See Figures 10 and 11 in Bilal et al. (2019).

²⁶The correlation between high-wage and high-productivity net poaching flows is 0.91, whereas it is only -.16 between high-productivity and large firms.

models of firm dynamics with frictions (Bilal et al., 2019).

4.1.1 Exploring the Firm Size Puzzle

In this subsection, we try to go a bit deeper into why we do not observe that large firms grow by net poaching. We will explore two routes. First, we will look into age as a possible explanation, and second, we will look into if differences in size and mobility across industries matter.

Net Poaching by Age

Why do large firms not poach workers from other firms? To explain the patterns of net poaching by size, we follow the recent empirical ((Haltiwanger et al., 2013), Criscuolo et al. (2014)) and theoretical literature (e.g., Bilal et al. (2019)) that highlight firm dynamics. Frictions on the labor market (or on the product market, see e.g. Lenoir et al. (2019)) hinder the growth of high-productivity firms. Figure 5 notably shows that small and young firms are net poachers. Especially, the growth rate of young firms is strongly procyclical. It varies from 0.75 percent to 2 percent per quarter. On average, young and small firms grow by 1.26% per quarter. Mature firms that are large contract by .02%, and small and mature firms contract by 0.17% per quarter. This evidence is in line with several recent papers (e.g. Schmieder (2013), Babina, Ma, Moser, Ouimet and Zarutskie (2019), Engbom and Moser (2020)) that uncover a significant young-firm pay premium. Theoretically, it is rationalized by recent search and matching models that jointly analyze the worker dynamics and firm dynamics.²⁷

Net Poaching by Industry

Another concern regarding the finding that large firms lose workers through job-to-job mobility is that this just masks differences in the size distributions across sectors. If each sector is a different labor market then large and small firms will be misclassified when we aggregate over all sectors. If industries with larger firms have lower job-to-job mobility then we will expect to find exactly the result above. In Table 3 we dissect employment growth for eight industries and show that the negative contribution of poaching for large firms is verified for all sectors but manufacturing. Small firms grow proportionally more in the business services sector and the information and communication sector. This evidence is in line with recent research by Berlingieri, Calligaris and Criscuolo (2018) that show

²⁷Bilal et al. (2019)'s model predicts that net poaching is most closely related to firm rank in terms of labor productivity than firm rank for age and size.

that productivity and wages increase significantly with size in the manufacturing sector, whereas the gradient is flatter in services.

4.2 Net Employment Growth from/to Non-employment and Total Employment Growth

Employment growth can also be fueled by workers that switch jobs with a spell of non-employment. This channel is important to analyze as it determines the change in the employment rate. Figure 6 reports employment growth from/to non-employment. On average, low-productive (0.25%), small (0.30%) and low-wage (0.71%) firms create respectively more jobs from non-employment per quarter. Large and high-productive firms have almost zero net employment growth through this channel (0.05%), while high-wage firms shrink by -0.31% per quarter. In recessions, high-wage firms shed more workers to non-employment than low-wage firms. The pattern is not clear for firms ranked by their labor productivity. It is only during the Great Recession that small firms destroy almost as many jobs as large firms. For the preceding two recessions, large firms destroy more jobs.²⁸ Figure A.1 in Appendix C sums net poaching and net non-employment growth rates. It is clear from this figure that small firms and high-productivity firms that contribute the most to employment creation. The difference between the net creation of jobs across high-wage and low-wage firms is not evident.

Summary of Findings and Discussion Table 4 summarizes the main findings on how employment varies across firm types. Employment growth markedly differs for firms across productivity, mean wages, and size distribution. Two recruitment channels: net hirings from/to employment (poaching) and net hirings from non-employment vary a lot across firms. High-productivity firms grow by 0.48 percent per quarter, and 90% of this growth rate come from poaching. Ranking firms through their average wage paid paints a different picture. While high wage firms poach almost as much as high-productivity firms (0.34%), high-wage firms destroy jobs through non-employment at almost the same rate (-0.31%). In total, high-wage firms barely grow (0.03), and large firms mostly destroy jobs (-0.15%), as workers leave to other firms (-0.20%). Small firms create jobs, through poaching and non-employment but 80% of their employment growth rate come from the non-employment margin. Overall, our findings illuminate the literature on the reallocation of workers across heterogeneous firms [Lentz and Mortensen \(2010\)](#). A prominent question in this literature is: Does the market reallocate resources

²⁸[Moscarini and Postel-Vinay \(2016\)](#) and [Foster et al. \(2016\)](#) also find, in the US, that the Great Recession is different compared to previous recessions.

from less to more productive employers? While some previous work used a specific sector ²⁹, we are not aware of papers that directly assess how high-productivity firms grow. Table 4 clearly shows that the poaching channel is the dominant driver of employment reallocation from low-productive firms to high-productive firms.

4.3 The Cyclicity of Firm Employment

To quantify the employment dynamics across firms over the business cycle shown in the figures above, we estimate regressions as specified by the statistical model (2). The outcome is the differential growth rate between "High-type" firms (large, high-wage, and high-productivity) and "Low-type" firms (small, low-wage, and low-productivity).

The main explanatory variable is the state of the labor market. A positive sign indicates that "High-type" firms grow relatively more than "Low-type" firms when aggregate conditions deteriorate (unemployment goes up). This exercise directly speaks to the numerous models developed in the early 1990s devised in parallel to the emergence of the job flows literature, see [Davis and Haltiwanger \(1990\)](#). In those models, through different mechanisms (e.g., credit constraints, firm's reorganization), some firm characteristics like size and productivity are predictors of employment fluctuations.

Decomposing Total Differential Growth into Poaching and Non-Employment Margins

Table 5 reports the effect on the total differential growth rate for each ranking measure and Figure 7 provides a visualization of the estimated effects. Since different firms can shed proportionally more jobs either from net poaching or non-employment, we also report the breakdown of the total differential growth rate between the two margins. Table 5 reports results for years with information on productivity such that the samples for the different rankings cover the same years.³⁰ For each component of the differential employment change (poaching, non-employment, net employment), we run separate models using the detrended level of unemployment or the first difference of unemployment to measure the aggregate state of the labor market. Note that the two cyclical indicators represent different stages of the business cycle. A positive change in the first difference occurs at

²⁹E.g, [Foster et al. \(2016\)](#) study several downturns in the US for the manufacturing sector and assess whether they are "cleansing" or not.

³⁰Table A.2 in the Appendix reports results for wage and size across the entire period for all firms (Q2-1985 to Q1-2013). In this sample, as in the sample of private sector firms with non-missing value-added data used in Table 5, small firms contract more in recessions and we do not find a difference when the level of unemployment is above its trend. However, high-wage firms are more cyclically sensitive using both cyclical indicators.

the beginning of recessions when unemployment goes up. A positive change in the level of unemployment above its HP trend occurs at the end of recessions.³¹

We start by first looking at the productivity ranking. If economic downturns are times of productivity-enhancing reallocation then the employment of less-productive firms should decline more compared to the employment of high-productive firms. To our knowledge, this paper is one of the first to provide empirical evidence on the “cleansing” effect of recessions and the margin on which it operates. A one percentage point increase in the change of the unemployment rate increases the differential employment change by 0.33 percentage point (ppt). Thus, when the economy enters a recession low-productive firms shrink more than high-productive firms and are thus more cyclically sensitive. Interestingly, the difference in net employment change by poaching and by non-employment goes in the opposite direction. Adjustment by poaching leads to a stronger employment cyclicity of high-productivity firms (-0.12 ppt). This is consistent with (Moscarini and Postel-Vinay, 2013), who stress that high-productive firms are more cyclically sensitive due to poaching. Non-employment transitions however imply a stronger adjustment of employment for low-productivity firms (0.46 ppt). This finding is consistent with equilibrium unemployment models such as Mortensen and Pissarides (1994) and Lise and Robin (2017), where low productive firms become unprofitable in recessions and thus shed workers to non-employment. When the level of unemployment is high, we do not find a statistical difference of employment growth across the productivity distribution. The two recruitment channels, by poaching and non-employment, generate opposite effects but the magnitude of the effect is similar and the difference is zero.

Ranking firms by size gives similar results on the aggregate as productivity. I.e. using the change in unemployment as a cyclical indicator, a one percentage point increase in this indicator is associated with a 0.29 ppt increase in the differential employment growth rate between large and small firms, whereas using the level of unemployment we find no difference. Decomposing the aggregate differential net growth rate into the two recruiting channels, we find for both cyclical indicators that the difference in growth rates between large and small firms increases because of the poaching margin. In the model by Moscarini and Postel-Vinay (2013) large firms are more cyclically sensitive through their ability to poach workers. Thus, our results are at odds with this model. However, given that we found that size, in general, was not a good indicator for attractiveness, it is not surprising that the predictions regarding the behavior of large vs small firms over the business cycle are not correct. Thus, we would caution against over-interpreting these results.³²

³¹See Figure 1.

³²It could be that our measure of what a firm constitutes is wrong. In the Danish data, they are separate legal entities. However, firms are more appropriately thought of as separate economic entities. As suggested in the above section a more appropriate model for firm dynamics could perhaps also solve

Finally, we repeat the exercise for firms ranked by average wage paid. High-paying firms are more cyclically sensitive than low-paying firms when the unemployment rate is high, but not during contractions. For both cyclical indicators, poaching contributes to the greater cyclical sensitivity of high-wage firms.³³ These patterns are in line with the collapse of the job ladder during downturns. In recessions, workers do not reallocate directly towards "High-type" firms, that are usually high-paying. This is perfectly in accordance with the firm dynamics model of Moscarini and Postel-Vinay (2013). In this model, high-wage firms are more cyclically sensitive, due to their ability to poach workers from other firms. It is also consistent with the model of Lise and Robin (2017).

The Role of Hiring and Separation Margins

After detecting the margin (poaching, non-employment) that drives the difference between "High-type" and "Low-type" firms in Table 5, we analyze in Tables 6 and 7 whether hirings or separations drive the results. In Table 6 we use the first difference of the unemployment rate as a cyclical indicator and in Table 7 we use the deviation from the level. The decomposition permits us to gain insights about which firm types ("High-type" vs "Low-type") and through which margins (hirings vs separations in poaching and non-employment) the labor adjustment operates.

Table 5 shows that low-productivity firms shed proportionally more jobs in recessions than in high-productivity firms (0.33 ppt). This was primarily caused by non-employment transitions (0.46 ppt) but lowered by poaching (-0.12 ppt). Looking first at the non-employment margin, Table 6 reveals that a sharp decrease in hirings (-1.28 ppt) accounts for the majority of net employment change of low-productive firms (-1.21 ppt). This is also predicted by Lise and Robin (2017), who find that low-type firms almost stop hiring from non-employment during recessions, whereas they do not really start to fire workers. On the contrary, the magnitude of employment decline for high-productive firms (-0.75 ppt) is equally caused by a reduction in hirings (-0.36 ppt) and an increase of separations (0.39 ppt). The increase of separations of high-productivity firms is in line with the findings of Mueller (2017), who shows that in recessions the pool of unemployed shifts towards workers with high wages in their previous job.³⁴ It is also consistent with

the problem.

³³The effects are qualitatively similar to HHKM18. They also find that the differential employment growth rate is led by poaching with no effect of non-employment when the HP-filtered unemployment rate is used. They also find that non-employment flows counterbalance the negative effect of poaching when the first difference of unemployment is used as a cyclical indicator.

³⁴It is possible that in Mueller (2017) high wage workers are high-ability workers or/and workers that work in high-productive firms. There are several empirical evidence pointing towards this direction. First, the pass-through literature (e.g., Card et al. (2018), Kline et al. (2019)) find evidence that the

the result in [Lise and Robin \(2017\)](#) that during recessions high productive firms shed workers to non-employment whereas low productive firms do not change their EU rate. In [Lise and Robin \(2017\)](#) this is driven by low type workers that are poorly matched with the high-type firm. Looking next at the poaching margin we find that low-productive firms in bad times separate and hire less, but that the two flows cancel out. For high-productive firms the flows are less cyclically dependent, but hirings decrease more (-0.61) than separations (-0.46), and thus the net effect by poaching is -0.14.

Table 5 shows that small firms adjust more employment in contractions. Indeed, small firms contract by -1.18 ppt while large firms contract by -0.89 ppt. Looking at non-employment, which is the main driver of differential employment change, small firms contract more (-1.05 ppt) than large firms (-0.87 ppt) as they increase separations (0.37 ppt) and reduce hirings (-0.69 ppt). Large firms only contract by reducing hirings (-0.87 ppt).

Finally, we find in Table 5 that firms across the average wage paid distribution behave similarly in contractions because the opposite effects of poaching and non-employment add up to zero. By poaching high-wage firms shed proportionally more jobs in recessions (-0.31 ppt), and by non-employment low-wage firms shed more jobs (0.30 ppt). Why do low-wage firms contract more by the non-employment channel than high-wage firms? Similarly to the productivity ranking, we find that the only channel through which low-wage firms shed workers through non-employment is by hirings (-1.30 ppt). On the contrary, we find that high-wage firms reduce hirings (-0.38 ppt) *but* increase separations (0.44 ppt).³⁵ Why do high-wage firms decrease employment by poaching compared to low-wage firms? The differential poaching effect comes from the composition of a negative employment change for high-wage firms (-0.22 ppt) and a *positive* employment change for low-wage firms (0.10 ppt). Low-wage firms *grow* by poaching in contractions because workers separate at a smaller rate to other firms (-1.03 ppt) than low-wage firms hire from other firms (-0.93 ppt).

We now turn to Table 7 which uses the deviation from the trend in unemployment as a cyclical indicator. Recall that this indicator primarily changes late in the business cycle compared to the first difference in unemployment. The main conclusions about the poaching margin hold for all firm characteristics and are surprisingly similar in magnitudes. Looking at the non-employment adjustments, we find for both productivity and size that the changes in the rates are much smaller. This suggests that the adjustment

profitability of firms transmits to workers. Second, the sorting literature ([Bagger and Lentz \(2019\)](#), [Borovičková and Shimer \(2020\)](#)) finds that high wage workers work in high-productive firms.

³⁵In total, the reduction in low-wage hirings dominates the adjustment for high-wage firms. These adjustments point towards the idea that low-wage firms “hoard” incumbent workers, but not high-wage firms because they adjust through separations.

through non-employment happens early in the cycle. For productivity, we find that more productive firms are more cyclically sensitive when using the first difference in unemployment, but not when we use the deviation from the level of unemployment. From Table 7 it is clear that this is caused by differences in non-employment flows. In particular, low productive firms stop hiring workers when unemployment starts to increase, but this effect is much smaller when we use the cyclical component of unemployment.

Summary of Findings High-wage and high-productive firms adjust employment more through poaching compared to their low counter-parties. However, in total, small and low-productive firms shed proportionally more jobs in recessions, because the non-employment margin is more responsive than the poaching margin. Across all firm categories, it is dominantly through the hiring channel that firms adjust employment over the business cycle. This finding is consistent with the literature on unemployment dynamics, that highlights the role of job finding as the main driver of unemployment fluctuations (Shimer (2012), Elsby et al. (2013)).

5 Conclusion

This paper sheds new light on the worker reallocation process using detailed Danish data covering almost 30 years. The new data sources that we exploit render it possible to explore the important underlying heterogeneity among firms and labor market flows necessary to understand the aggregate flows of workers.

We find that firms depending on their position in the size, wage, and productivity distributions contribute differently to employment reallocation. High-productivity firms create most jobs growing by 0.48 percent per quarter. 90 percent of growth comes from poaching workers. However, high-wage firms only grow by 0.03 percent per quarter. This is caused by positive net poaching flows (0.34) and negative net non-employment flows (-0.31). Contrary to most search models usually used to analyze labor market fluctuations, we find that large firms lose workers by -0.15 percent per quarter. This is caused by direct mobility across firms (poaching). We show that it is especially small and young firms that tend to expand by poaching, whereas for older firms the opposite is true. Our results highlight the importance of firm life-cycle dynamics to understand the worker reallocation process.

Across all firm categories, it is dominantly through the hiring channel that firms adjust employment over the business cycle. Moreover, we find some interesting decoupling for firms ranked by their average wage and labor productivity over the business cycle. While low-productivity firms shed proportionally more jobs in recessions than high-productivity

firms, we do not find differences for firms ranked by average wage. The discrepancy between wage and productivity, as well as the understanding of firm dynamics, are two important avenues for future research to shed further light on worker flows.

A clear extension of this paper would be to include worker heterogeneity as part of the decomposition of flows. This would further complement more theoretical papers by e.g. [Lise and Robin \(2017\)](#), who uses abstract worker and firm types to understand sorting over the business cycle, and [Carrillo-Tudela and Visschers \(2020\)](#), who uses a stochastic equilibrium model with heterogeneous agents and occupations as well as aggregate uncertainty to understand occupational mobility over the business cycle. Understanding which types of workers constitute the flows is an important path for future research.

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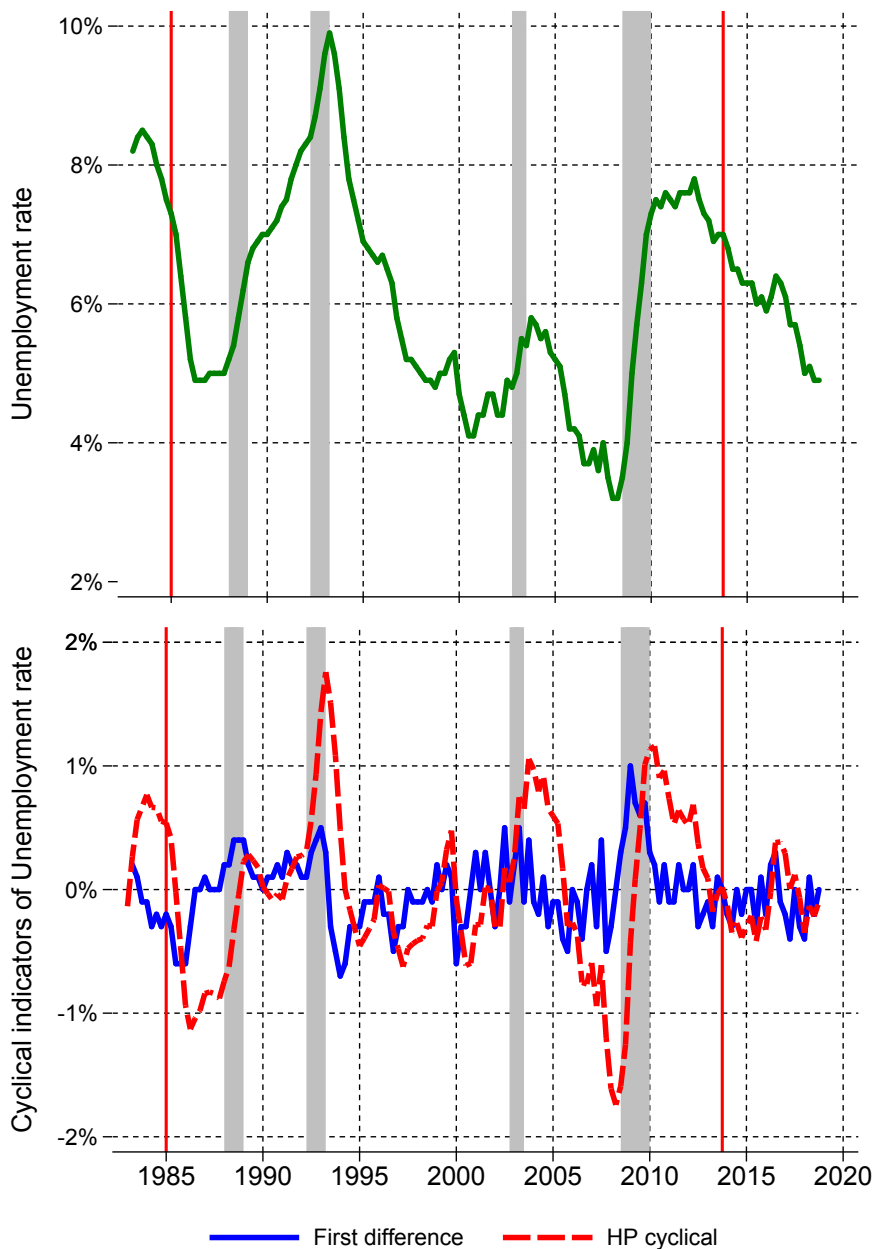
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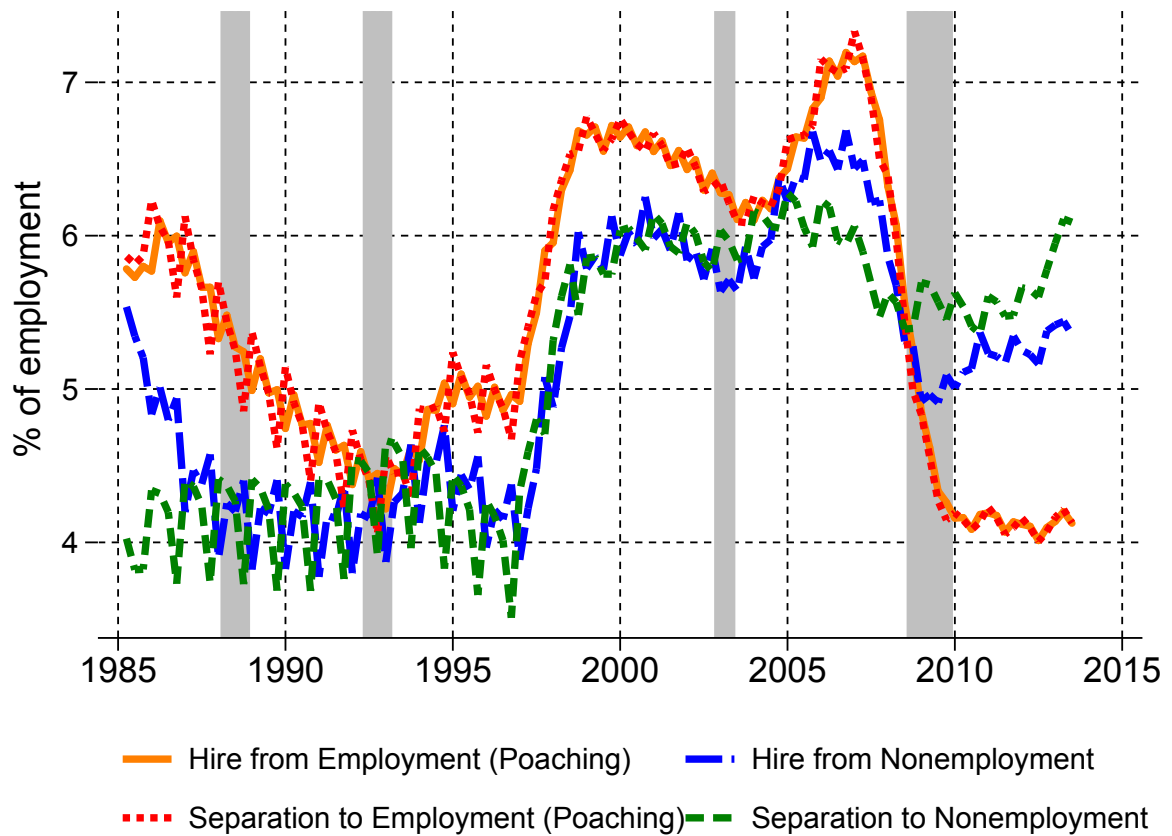
Figures

Figure 1: Cyclical Indicators



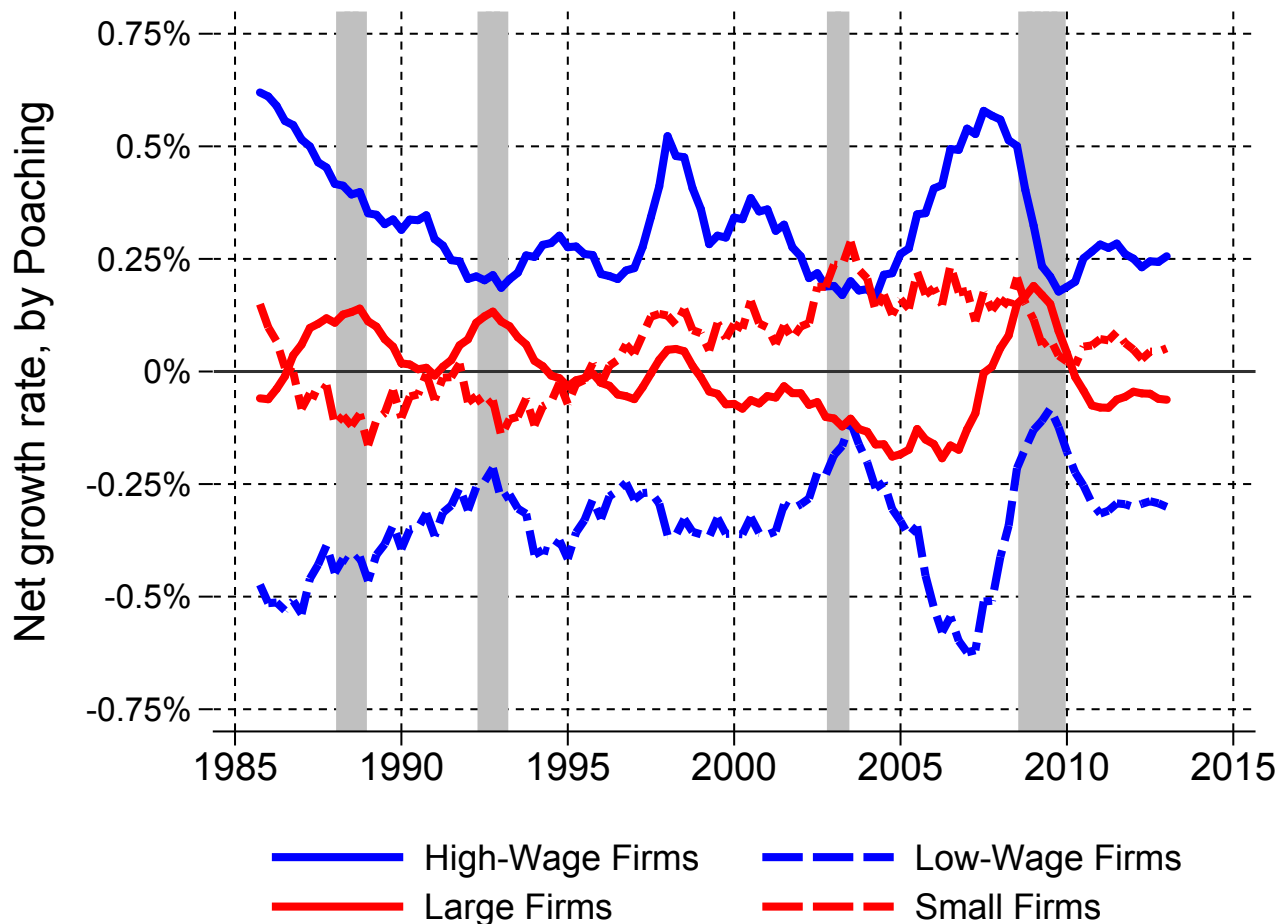
Note: The top figure plots the unemployment rate constructed from the OECD series “Quarterly Harmonized unemployment rate” (Q1-1983 to Q4-2018). The bottom figure plots cyclical indicators to measure labor market conditions. “First difference” in t is the difference between quarter $t - 1$ and t of the unemployment rate. “HP cyclical” is the cyclical component of the unemployment rate, after extracting the trend using a 1600 smoothing parameter. Grey areas denote episode recessions (1988Q2-1988Q4, 1992Q3-1993Q1, 2003Q1-2003Q2, and 2008Q4-2009Q4).

Figure 2: Hires and Separations



Note: The figure plots hirings and separations from employment (*poaching*) and non-employment. A hiring or separation through employment is defined as a transition with less than 7 days of non-employment between two employment spells at two different employers. Q2-1985 to Q1-2013. Seasonally adjusted series for all firms.

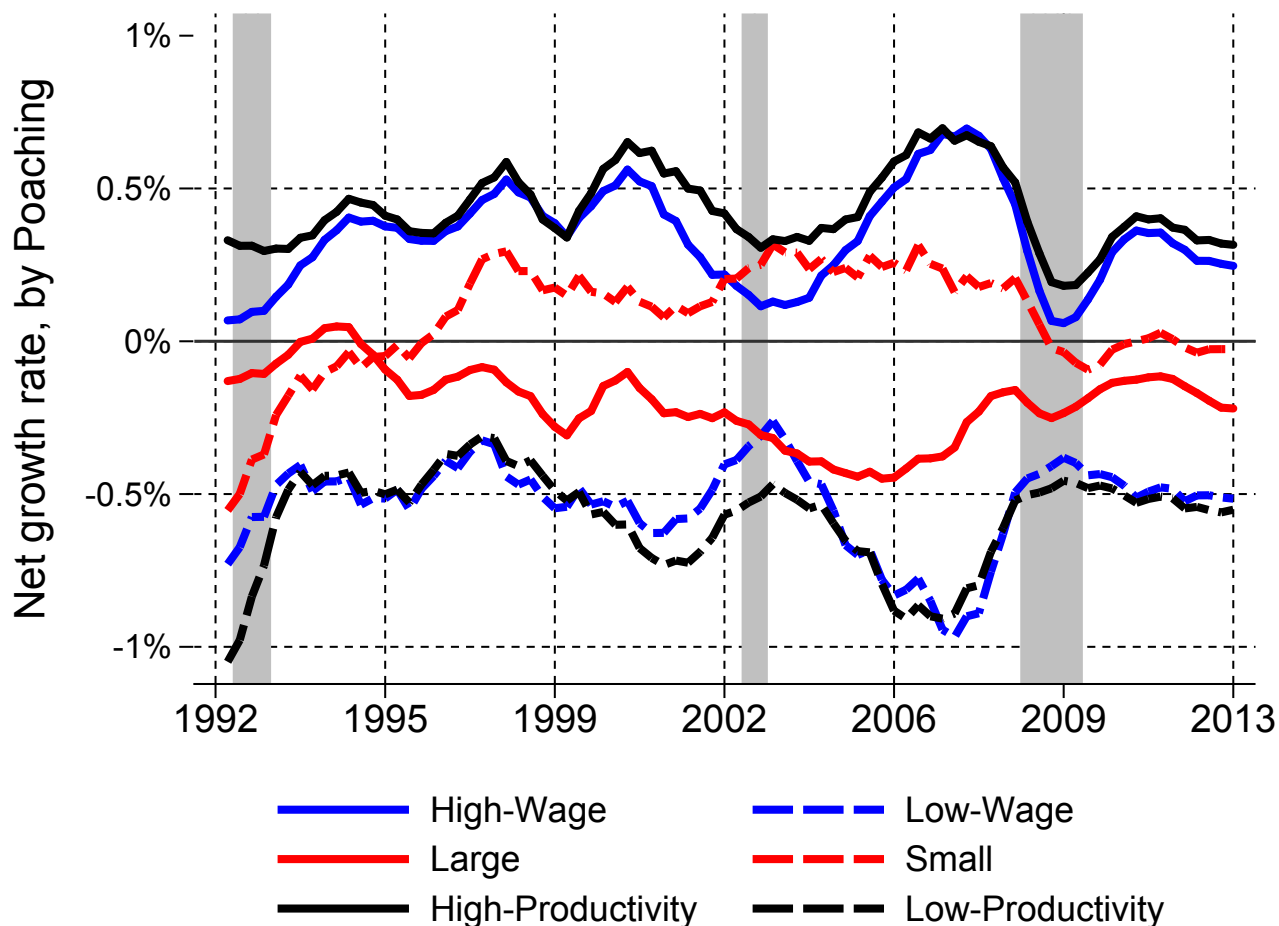
Figure 3: Net Poaching by Firm Size and Firm Wage



Note: The figure plots the net growth rate of firms coming from Net Poaching, for firms ranked by size and mean wage. Net poaching corresponds to hirings from job-to-job flows (H_{tp}) and separations to job-to-job flows (S_{tp}): $H_t - S_t = \underbrace{H_{tp} - S_{tp}}_{\text{Poaching}} + \underbrace{H_{tn} - S_{tn}}_{\text{Non-Employment}}$

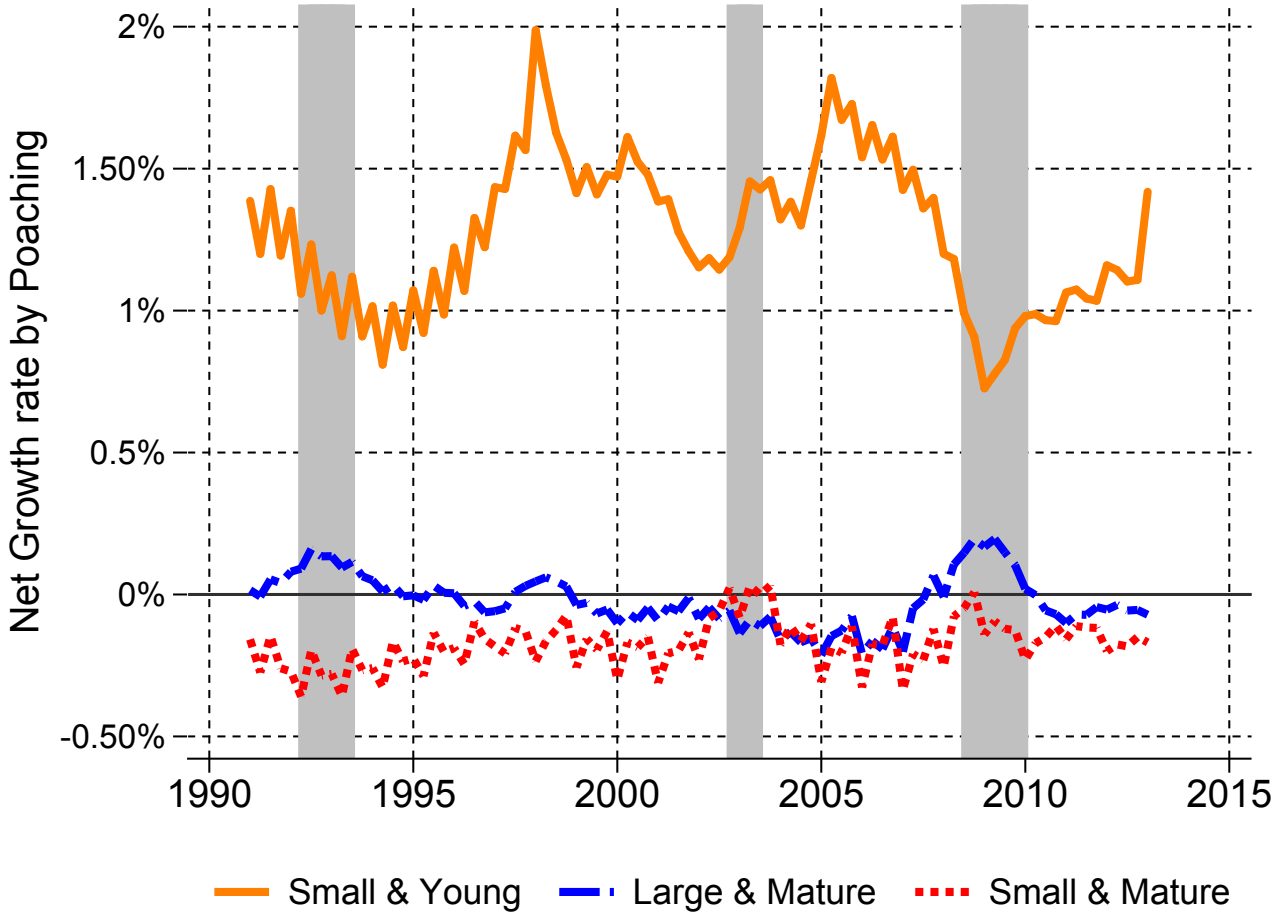
High-wage Firms and Large Firms (Low-wage and Small) are firms in the top two (bottom) employment weighted quintiles. Wage corresponds to average wage (hourly earnings). Large and Small corresponds to the average number of employees. Q2-1985 to Q1-2013. Seasonally adjusted series for all firms.

Figure 4: Net Poaching by Firm Size, Firm Wage, and Firm Productivity



Note: The figure plots the net growth rate of firms coming from Net Poaching, for firms ranked by size, wage, and productivity. Net poaching corresponds to hirings from job-to-job flows (H_{tp}) and separations to job-to-job flows (S_{tp}): $H_t - S_t = \underbrace{H_{tp} - S_{tp}}_{\text{Poaching}} + \underbrace{H_{tn} - S_{tn}}_{\text{Non-Employment}}$. High-wage Firms, High-Productivity Firms, and Large Firms (Low-wage, Low-Productivity, and Small) are firms in the top two (bottom) employment weighted quintiles. Wage corresponds to average wage (hourly earnings). Productivity corresponds to labor productivity (value-added over labor input). Large and Small correspond to the average number of employees. Q2-1992 to Q1-2013. Seasonally adjusted series for firms with value-added data.

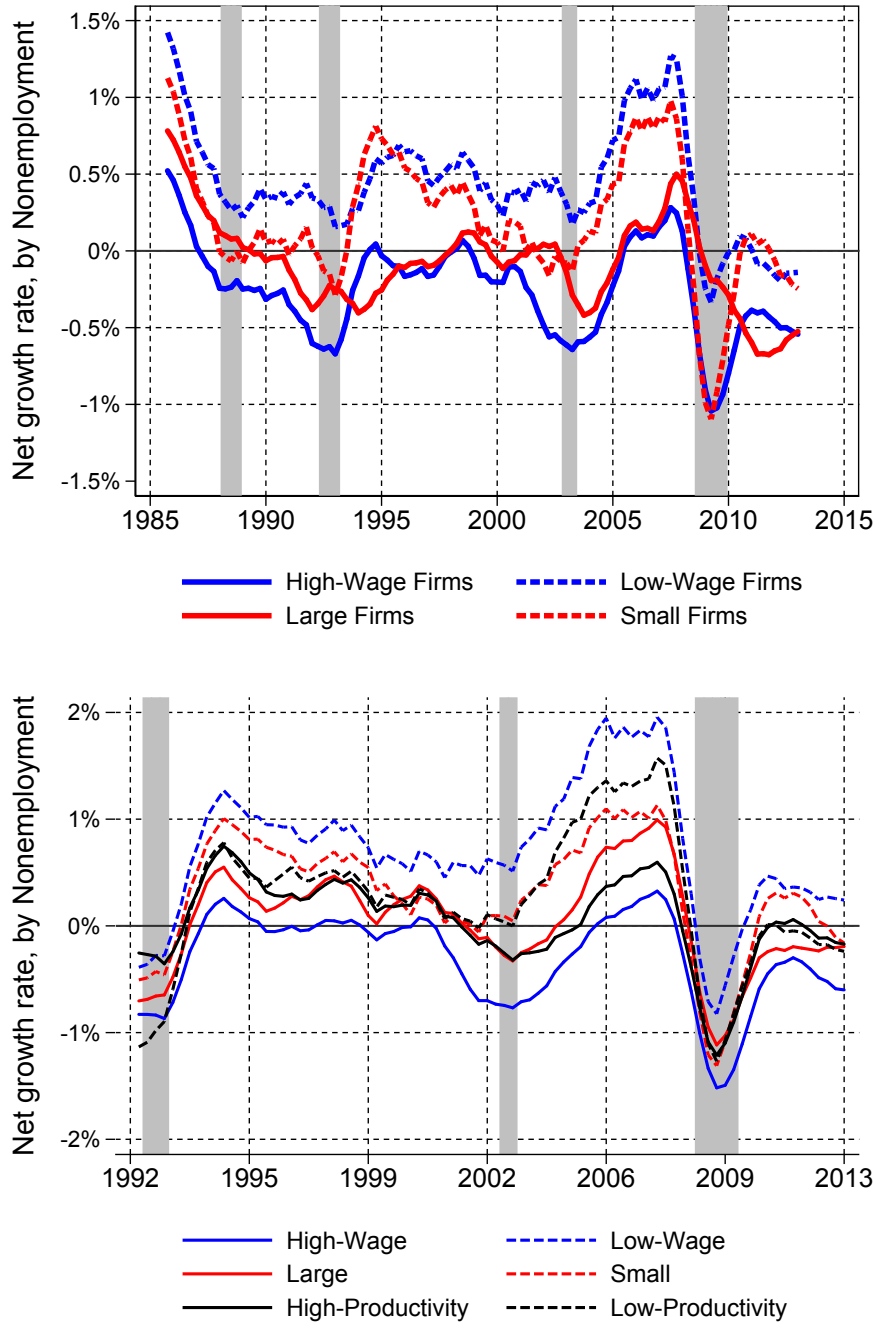
Figure 5: Net Poaching by Firm Size and Firm Age



Note: The figure plots the net growth rate of firms coming from Net Poaching, for firms ranked by size and age. Net poaching corresponds to hirings from job-to-job flows (H_{tp}) and separations to job-to-job flows (S_{tp}): $H_t - S_t = \underbrace{H_{tp} - S_{tp}}_{\text{Poaching}} + \underbrace{H_{tn} - S_{tn}}_{\text{Non-Employment}}$

Large Firms (Small) are firms in the top two (bottom) employment weighted quintiles. Large and Small correspond to the average number of employees. Q2-1992 to Q1-2013. Seasonally adjusted series for firms with value-added data. Young firms are at most 5 years old. Q1-1991 to Q1-2013, for all firms.

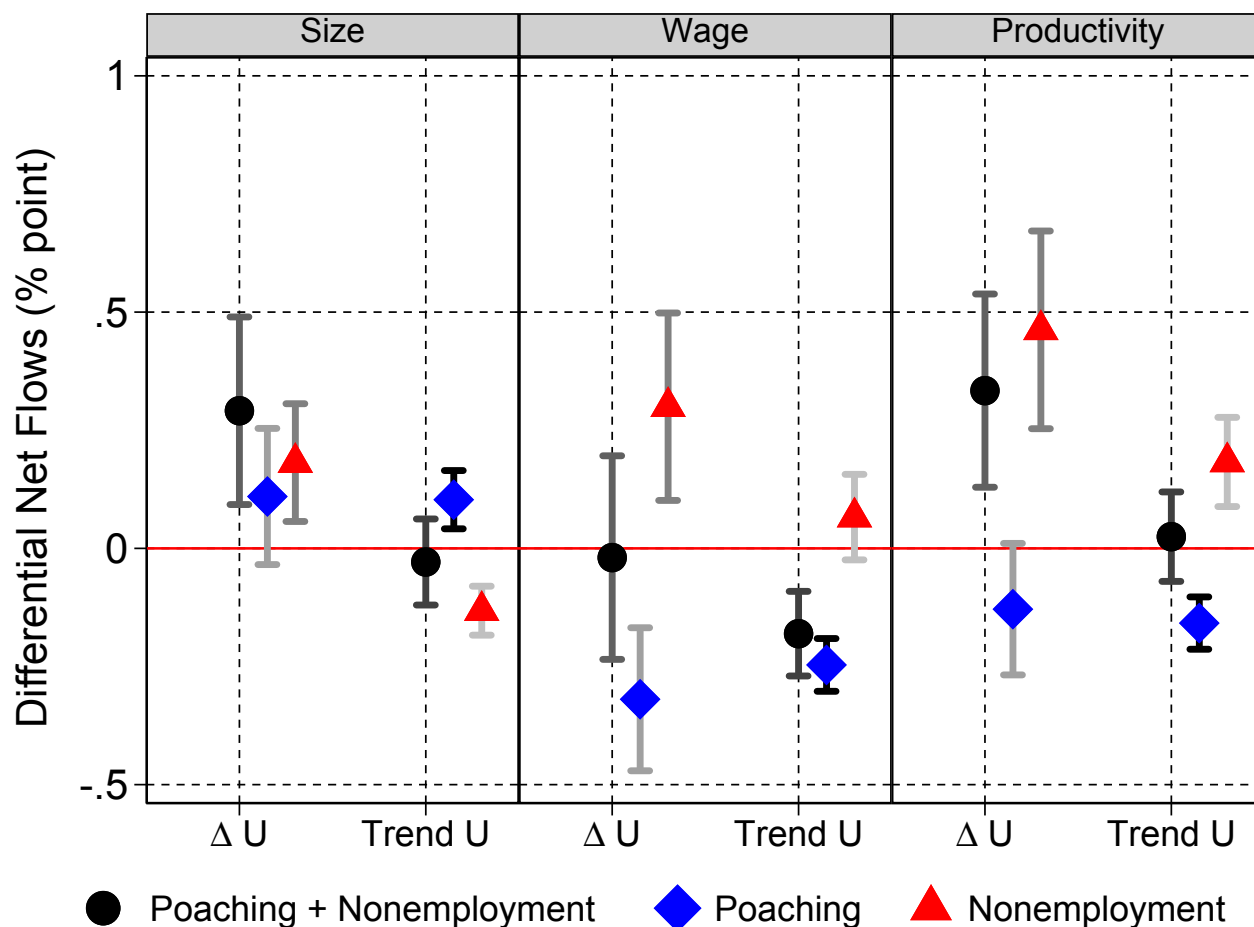
Figure 6: Non-Employment flows by Firm Size, Firm Wage, and Firm Productivity



Note: The figure plots the net growth rate of firms coming from non-employment, for firms ranked by size, wage, and productivity. The top panel shows all firms, while the bottom panel shows private sector firms.

High-wage Firms, High-Productivity Firms, and Large Firms (Low-wage, Low-Productivity, and Small firms) are firms in the top two (bottom) employment weighted quintiles. Wage corresponds to average wage (hourly earnings). Productivity corresponds to labor productivity (value-added over labor input). Large and Small correspond to the average number of employees. Seasonally adjusted series for firms with value-added data.

Figure 7: Employment Cyclicalities Across Firms: Poaching and Non-Employment



Note: The figure quantifies the role of the poaching channel and the non-employment channel for employment cyclicalities. The figure plots point estimates β of the model: $\Delta g_{t,t-1} = \beta Cycle_t + \gamma_t + \epsilon_t$. $\Delta g_{t,t-1} = g_{t,t-1}^{High-type} - g_{t,t-1}^{Low-type}$ is the differential net growth rate. Each dot corresponds to a different model: by firm types (Size, Wage, Productivity), cyclical indicators (ΔU and Trend U), and components of the employment growth rate (Poaching, Non-Employment). Confidence intervals are reported at the 90% level. Net growth rate is decomposed between Net poaching ($H_{tp} - S_{tp}$) and Non-employment ($H_{tn} - S_{tn}$). High-wage Firms, High-Productivity Firms, and Large Firms (Low-wage, Low-Productivity, and Small) are firms in the top two (bottom) employment weighted quintiles. Wage corresponds to average wage (hourly earnings). Productivity corresponds to labor productivity (value-added over labor input). Large and Small correspond to the average number of employees. $Cycle_t$ is either “ ΔU ” the first difference in unemployment or “Trend U”, the cyclical component of the detrended unemployment (see figure 1). Q2-1992 to Q1-2013. Seasonally adjusted series for firms with value-added data.

Tables

Table 1: Firm Characteristics

	Size			Wage			Productivity		
	Low	Middle	High	Low	Middle	High	Low	Middle	High
Size	5	57	322	7	16	16	11	14	9
Wage	255	282	291	180	276	433	216	249	294
Productivity	939	470	505	796	717	1310	248	417	1665
Age	13	22	29	13	16	14	13	15	13
Corr(\bar{w}, \bar{y})	.16	.29	.35	-.08	.03	.26	.01	.32	.14
Corr(\bar{w}, N)	.01	.21	.12	.09	-.02	-.06	.05	.07	.02
Corr(N, \bar{y})	-.10	.04	.06	-.03	-.03	-.04	.04	-.00	-.03
# Firm / year	99,250	4,364	1094	64,161	14,145	26,407	40,743	16,664	47,305
% Firm	95	4	1	61	14	25	39	16	45

Note: This table reports mean characteristics for firms with value-added data (1992-2013). High-Wage Firms, High-Productivity Firms, and Large Firms (Low-wage, Low-Productivity, and Small) are firms in the top two (bottom) annual employment weighted quintiles. Wage (\bar{w}) corresponds to the average wage (hourly earnings). Productivity (\bar{y}) corresponds to labor productivity (value-added over labor input). Size (N) corresponds to the average number of employees. Data is truncated at the .1st and 99.9th percentile. # Firm / year reports the mean number of firms per year. % Firm reports the share of firms in each group.

Table 2: Firm Characteristics over their life-cycle

	Firm Age				
	Q1	Q2	Q3	Q4	Q5
Size (mean)	3	6	9	13	12
Size (median)	1	2	3	4	5
Wage (mean)	262	253	251	248	269
Wage (median)	209	219	223	228	255
Productivity (mean)	1108	885	881	767	832
Productivity (median)	443	448	433	415	439
Corr(\bar{w}, \bar{y})	.19	.16	.15	.15	.15
Corr(\bar{w}, N)	-.01	.00	.01	.04	.06
Corr(N, \bar{y})	-.03	-.04	-.03	-.03	-.03
N	460,724	460,746	460,746	460,746	460,741

Notes: This table reports the mean characteristics of firms split into five age categories for firms with value-added data (1992-2013). Wage corresponds to average wage (hourly earnings). Productivity corresponds to labor productivity (value-added over labor input). Size corresponds to the average number of employees. Time span: 1992 to 2013, for firms with value-added data. Data is truncated at the 1st and 99.9th percentile.

Table 3: Differential Net Poaching (Large Firms - Small Firms) by Sector

Sector	Differential Net Poaching
Manufacturing	.14%
Business Services	-.63%
Construction	-.45%
Trade, Accommodation, catering	-.01%
Transport & Freight	-.37%
Information & Communication	-.62%
Finance & Real Estate	-.29%
Administration, Teaching, Health	-.41%

Note: The table reports the differential net growth rate for net poaching across sectors between large firms and small firms. Q2-1992 to Q1-2013. Seasonally adjusted series for all firms.

Table 4: Net Employment Growth Across Firms

	Net Employment Growth	Net Poaching	Net Non-Employment
High-Productivity	0.48	0.43	0.05
Low-Productivity	-0.32	-0.57	0.25
High-Wage	0.03	0.34	-0.31
Low-Wage	0.18	-0.53	0.71
Large Firms	-0.15	-0.20	0.05
Small Firms	0.38	0.08	0.30

Note: The table reports the net employment growth rate per quarter across firm types. “Net Employment Growth” is the sum of “Net poaching” ($H_{tp} - S_{tp}$) and “Net Non-Employment” ($H_{tn} - S_{tn}$). High-wage Firms, High-Productivity Firms, and Large Firms (Low-wage, Low-Productivity, and Small) are firms in the top two (bottom) employment weighted quintiles. Wage corresponds to average wage (hourly earnings). Productivity corresponds to labor productivity (value-added over labor input). Large and Small correspond to the average number of employees. Q2-1992 to Q1-2013. Seasonally adjusted series for firms with value-added data.

Table 5: Employment Cyclicalities Across Firms: Poaching and Non-Employment

Cyclical indicator: Unemployment rate in...		
	First Difference (1)	Deviation from HP trend (2)
Outcomes: High-Productivity minus Low-Productivity		
Poaching (1)	-.12	-.15***
Non-Employment (2)	.46***	.18**
Total (1)+(2)	.33**	.03
Outcomes: Large Firms minus Small Firms		
Poaching (1)	.11	.10**
Non-Employment (2)	.18**	-.13***
Total (1)+(2)	.29**	-.03
Outcomes: High-Wage Firms minus Low-Wage Firms		
Poaching (1)	-.31***	-.24***
Non-Employment (2)	.30**	.06
Total (1)+(2)	-.01	-.18***

Note: ***, **, and * indicate statistically significant at the 1%, 5% and 10% level. The table reports point estimates β of the model: $\Delta g_{t,t-1} = \beta Cycle_t + \gamma_t + \epsilon_t$. $\Delta g_{t,t-1}$ is the differential employment growth rate, i.e. $\Delta g_{t,t-1} = g_{t,t-1}^{\text{High-type}} - g_{t,t-1}^{\text{Low-type}}$. The model includes a time trend (γ_t). Each dot corresponds to a different model: by firm types (Size, Wage, Productivity), cyclical indicators, (ΔU and Trend U) and components of the employment changes (Poaching, Non-Employment). Employment changes are decomposed between “Poaching” ($H_{tp} - S_{tp}$) and “Non-employment” ($H_{tn} - S_{tn}$). High-wage Firms, High-Productivity Firms, and Large Firms (Low-wage, Low-Productivity, and Small) are firms in the top two (bottom) employment weighted quintiles. Wage corresponds to average wage and productivity to labor productivity (value-added over labor input). Large and Small correspond to the average number of employees. $Cycle_t$ is either “ ΔU ” the first difference in the unemployment rate or “Trend U”, the cyclical component of the unemployment rate (see figure 1). Q2-1992 to Q1-2013. Seasonally adjusted series for firms with value-added data.

Table 6: Employment Cyclicalilty Across Firms: hirings and Separations

Productivity						
	High-Productivity Firms			Low-Productivity Firms		
	Net	Poaching	Non-Employ.	Net	Poaching	Non-Employ.
Net Employ.	-0.89***	-0.14***	-0.75***	-1.23***	-0.02	-1.21***
Hire	-0.97**	-0.61**	-0.36*	-2.22**	-0.94*	-1.28**
Separations	-0.08	-0.46*	0.39**	-1.00	-0.93*	-0.07
Size						
	Large Firms			Small Firms		
	Net	Poaching	Non-Employ.	Net	Poaching	Non-Employ.
Net Employment	-0.89***	-0.02	-0.87***	-1.18***	-0.13**	-1.05***
Hire	-1.58***	-0.71**	-0.87***	-1.43*	-0.75	-0.69*
Separations	-0.70	-0.70**	0.00	-0.25	-0.62	0.37
Wage						
	High-Wage Firms			Low-Wage Firms		
	Net	Poaching	Non-Employ.	Net	Poaching	Non-Employ.
Net Employment	-1.04***	-0.22***	-0.82***	-1.02***	0.10*	-1.12***
Hire	-1.04**	-0.66**	-0.38**	-2.23*	-0.93	-1.30**
Separations	0.01	-0.44*	0.44***	-1.21	-1.03*	-0.18

Note: ***, **, and * indicate statistically significant at the 1%, 5% and 10% level. The table reports point estimates β of the model: $y_t = \beta Cycle_t + \gamma_t + \epsilon_t$. y_t corresponds to the hiring rate, separation rate, or net employment growth rate. The model includes a time trend (γ_t). Each dot corresponds to a different model: by firm types and components of the employment growth rate (Poaching, Non-Employment). High-wage Firms, High-Productivity Firms, and Large Firms (Low-wage, Low-Productivity, and Small) are firms in the top two (bottom) employment weighted quintiles. Wage corresponds to average wage (hourly earnings). Productivity corresponds to labor productivity (value-added over labor input). Large and Small correspond to the average number of employees $Cycle_t$ is “ ΔU ” the first difference in the unemployment rate. Q2-1992 to Q1-2013. Seasonally adjusted series for firms with value-added data.

Table 7: Employment Cyclicalities Across Firms: hirings and Separations

Productivity						
	High-Productivity Firms			Low-Productivity Firms		
	Net	Poaching	Non-Employ.	Net	Poaching	Non-Employ.
Net Employ.	-0.36***	-.13***	-0.24***	-0.39***	0.03	-0.42***
Hire	-0.87***	-0.73***	-0.14	-1.46***	-0.90***	-0.57**
Separations	-0.51***	-0.61***	0.10	-1.07***	-0.93***	-0.15
Size						
	Large Firms			Small Firms		
	Net	Poaching	Non-Employ.	Net	Poaching	Non-Employ.
Net Employ.	-0.39***	0.00	-0.39***	-0.36***	-0.10***	-0.26***
Hire	-1.25***	-0.75***	-0.50***	-0.96***	-0.80***	-0.16
Separations	-0.86***	-0.75***	-0.11	-0.60*	-0.70***	0.10
Wage						
	High-Wage Firms			Low-Wage Firms		
	Net	Poaching	Non-Employ.	Net	Poaching	Non-Employ.
Net Employment	-0.47***	-0.17***	-0.31***	-0.29***	0.08***	-0.37***
Hire	-0.91***	-0.76***	-0.16**	-1.47***	-0.88***	-0.60**
Separations	-0.44***	-0.59***	0.15**	-1.18**	-0.96***	-0.22

Note: ***, **, and * indicate statistically significant at the 1%, 5% and 10% level. The table reports point estimates β of the model: $y_t = \beta Cycle_t + \gamma_t + \epsilon_t$. y_t corresponds to the hiring rate, separation rate, or net employment growth rate. The model includes a time trend (γ_t). Each dot corresponds to a different model: by firm types and components of the employment growth rate (Poaching, Non-Employment). High-wage Firms, High-Productivity Firms, and Large Firms (Low-wage, Low-Productivity, and Small) are firms in the top two (bottom) employment weighted quintiles. Wage corresponds to average wage (hourly earnings). Productivity corresponds to labor productivity (value-added over labor input). Large and Small correspond to the average number of employees $Cycle_t$ is “Trend U” the cyclical component of the unemployment rate. Q2-1992 to Q1-2013. Seasonally adjusted series for firms with value-added data.

Appendix of:
Employment Reallocation over the Business Cycle: Evidence
from Danish Data

Antoine Bertheau, Henning Bunzel, and Rune Vejlin

A Institutional Setting

A full-time job in Denmark consists of 37 hours worked per week. While hours worked are low the participation rate is high around 80 percent. Furthermore, the public sector is large and social security is strong. Both are typical for a Scandinavian welfare state. Some large shocks hit the Danish labor market in the early 90s. First, the Nordic banking crisis impacted the employment of the finance and insurance industry. Second, manufacturing employment decline in some industries targeted by the Uruguay round of negotiations ending in 1994. Third, a wave of structural reforms, starting in 1994, impacted workers' rights to benefits ([Jespersen, Munch and Skipper \(2008\)](#)).

B Data Sources

We put together several administrative registers provided by Statistics Denmark and the Tax Administration. Here, we provide background on data sources and definitions of variables.

B.1 A Novel Labor Market History dataset (SPELL)

Data sources. To construct employment spells at daily frequency, we combine three different registers. The labor market history dataset that we construct covers all individuals living in Denmark.³⁶ Spells that we consider are primary employment spells. A primary job is defined as the spell with the largest amount of hours worked for the current month and the following two months. Spell data contains three key identifiers: worker, firm, and employment spell identifiers. A cell is a unique combination of worker-spell identifiers, attached to a firm identifier. The worker identifier is the *Civil Personal Registration* Number (CPR), a unique time-consistent identification number for all Danes and foreigners. The firm identifier is the identification number (the CVR number) assigned by the Central Business Register (*CVR-Det Centrale Virksomhedsregister*) for all legal entities. All firms are statutorily registered in the CVR. The Spell identifier is designed to

³⁶[Bagger, Fontaine, Galenianos and Trapeznikova \(2020\)](#) exploit this data and provide new evidence into the employment adjustment after firm-specific shocks, that are either permanent or transitory.

track the entire work history for all CPR from 1985.³⁷ Work history is based on several registers of datasets from the Central Customs and Tax Administration (SKAT), an affiliated agency of the Danish Ministry of Taxation (*Skatteministeriet*), responsible for the administration and collection of direct taxation. Before 2008, information on employment spells mainly uses the annual reports that firms sent to SKAT (the Central Information Sheet. *Oplysningssedler*, CONESR). Each record is identified at the (worker identifier, establishment identifier, year) level with information on the employment period.³⁸ For years In 2008, SKAT introduced the e-income register data (*E-indkomst*), aiming at reducing red tape costs for firms by avoiding to report the same information to different authorities. Therefore from 2008, hours worked, labor earnings, and employment spell periods are collected at the monthly frequency in a single register (*Beskæftigelse for Lønmodtagere*, BFL).

Definition of variables. The variables used are defined as follows.

Hours: Hours worked are estimated using mandatory pension fund contribution (ATP). ATP contribution varies according to the working hours at the same employer. ATP contribution rates are divided into four groups (by the number of hours per week): 1) 9: paid no ATP 2) 9-17: 1/3 of contribution 3) 18-26: 2/3 of contribution 4) 26: full contribution. From 2008, we use paid hours reported at the monthly frequency by firms.

Labor earnings: are measured from the variable *lonblb* in CONESR.

Correction for fictitious transitions. Spell data is not corrected for change of firm identifiers for fiscal reasons, mergers, or split-ups. We use an employee-flow procedure to detect transitions triggered by these events. Correcting for these events is essential to correctly measure job reallocation, growth of medium and large firms as well as patterns

³⁷Even if CON data is available from 1980, unemployment data is available from 1985. We use unemployment data to correct CON employment spells.

³⁸We use Statistics Denmark registers of data CONS, MIANPNR, and RAS from 1985 to 2007. From 2008 we use Statistics Denmark BFL. The structure of the records in CONS and RAS does not differ. The reason for using both datasets is that they cover two different periods, i.e. CONS contains employment records from 1985 to (and including) 2005 and RAS contains employment records for 2006 and 2007. Variables used to construct employment spells are: HELARKOD (full-year employment), ANSFRA (start date of employment), ANSTIL (employment until date), ANS2911K, EJANSNOV, and HELAARK (variables describing multiple employment spells within a year at the same employer). Therefore, COR does not allow observing recall within the same year since we cannot observe multiple employment periods on (worker identifier, establishment identifier, year). In this case, the SPELL dataset sets the start date equal to January first and the end date equal to December 31 of the given year. These artificial start and end date values lead to the employment being too wide in the sense that it covers the employment period but also the time when a person has not worked.

of entry and exit of firms. The employee-flow method detects changes of firm ID or firm structure by tracing large clusters of employees that appear to "move" from one firm identification number to another between two subsequent observations in time (Geurts, 2016). We apply this method by counting the number of workers that are transiting from a firm ID in year y quarter t , which start their next employment spell in the subsequent quarter at the *same* firm ID. The number of workers involved represents the size of the cluster. Table A.3 in Appendix C describes fictitious transitions by the size of the cluster. Although transitions that involve more than 10 workers are rare events (0.31%), they represent 10.53 % of firm-to-firm transitions. It does seem likely that, for cluster mobility of at least 5 workers, transitions are fictitious. Therefore, we delete these transitions and modify the job spell identifier. In particular, we extend the job spell identifier and do not take into account the job spell identifier which is created due to a fictitious transition. We repeat this procedure for subsequent fictitious transitions if detected.³⁹

B.2 Worker and Firm registers

Registers. We add firm-level information to the labor market history dataset using several firm registers . We use FIGF (*Firmastatistik regnskabsdata*) from 1992 to 1998, then the dataset FIRM (*Generel firmastatistik*) from 1999.⁴⁰ Since the introduction of the Danish Financial Statement Act (*årsregnskabsloven*) in 1981, every company is obliged to submit an "annual report", which for most companies consists of a statement by the management on the annual report, a balance sheet, and an income statement. A sole proprietorship (regardless of size) and partnerships can report an annual report voluntarily but are not obliged to do so. Basic components of the income statement and the balance sheet statement are reported in registers FIGF and FIRM.

Definition of variables. The variables used are defined as follows.

Value-added: consists of turnover minus costs (VT in FIGF and GF-VTV in FIRM) .

Firm Age: age of the oldest establishment from IDAS. Year of creation of legal units from FIRM.

³⁹ Besides of overestimating job reallocation (and mainly job-to-job mobility), fictitious transitions wrongly modify the cyclical pattern of worker flows. A spike of fictitious transitions happens in January 2007 due to an administrative reform (the *Strukturreformen*).

⁴⁰ FIGF only included companies in the taxable industries and the private sector, FIRM covers all sectors. We also use FIGT (*Gammel Firmastatistik*) to collect industry code.

Education: split educational achievement into 4 groups:⁴¹

1) Primary education, 2) High-school and Vocational, 3) Bachelor or related diploma, 4) Master and PhD.

Experience: this variable is available from 1964. As we use all workers from 1985, the experience variable is censored for older workers.

Occupation: DISCO classification to categorize workers into routine, abstract, or manual jobs. The quality of the Danish occupation data is considered to be high because they are monitored by employers and unions to form the basis of wage bargaining at the national level. DISCO is the Danish version of the ISCO-88 classification (International Standard Classification of Occupations) from 1991 to 2009. From 2010, DISCO uses ISCO-08, which is the current version of the International Standard Classification of occupations.⁴² Workers have missing DISCO codes if they are in the following groups: individuals who are out of the labor force, unemployed, self-employed, working in the workplace with fewer than 10 employees, or working in a firm directly engaged in agriculture, fishery, or forestry.

⁴¹Education variables are from education registers UDDF and UDDA. We use the following variables: UDD, (education code), HF-VFRA (date of highest completed education), HFFSP, HFAUDD (highest completed education).

⁴²We use the variable *discoalle-indk* from 1992 to 2009 and *disco08-alle-indk* from 2010. These variables are constructed from the AKM register, and follow the ISCO code values at the two digits level. To assure consistency of code values across time, we use the following procedure. Conditional on observing a worker in the same establishment from 2009 to 2010, we calculate the number of observations in each cell of the first two digits of the ISCO-08 classification and ISCO-88 classifications. For each value of ISCO-08 classification, we select the ISCO-88 classification with the highest number of observations. Our mapping closely follows the correspondence table of the International Labor Organization.

C Additional Tables and Figures

Figure A.1: Net Job Flows by Firm Size, Firm Wage, and Firm Productivity

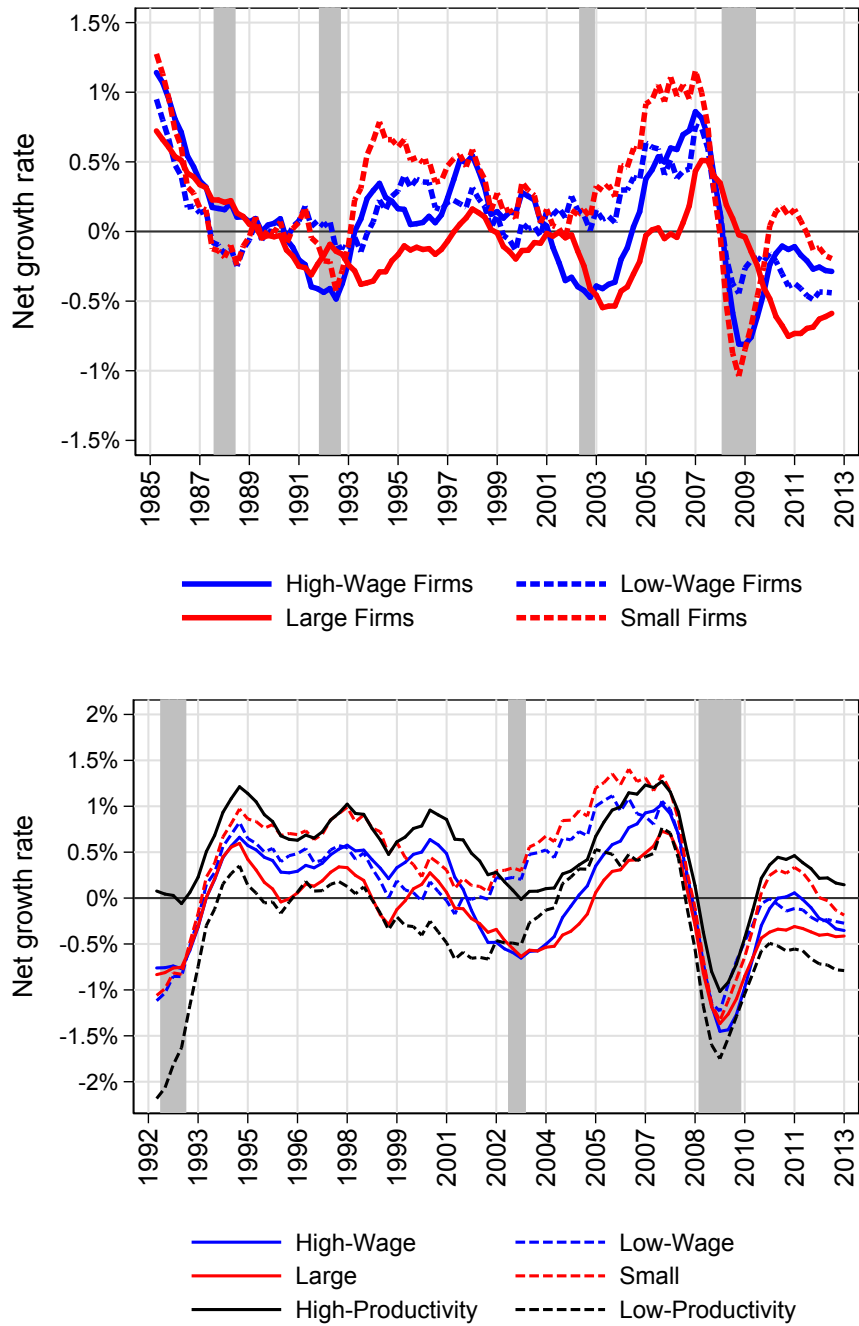


Table A.1: Firm Characteristics

	Size			Wage			Productivity		
	Small	Medium	Large	Low	Middle	High	Low	Middle	High
Size	3	49	131	3	4	3	4	4	2
Wage	226	270	278	184	286	361	206	241	252
Productivity	437	394	432	380	447	567	270	416	713
Corr(\bar{w}, \bar{y})	.16	.29	.35	-.08	.03	.26	.01	.32	.14
Corr(\bar{w}, N)	.01	.21	.12	.09	-.02	-.06	.05	.07	.02
Corr(N, \bar{y})	-.10	.04	.06	-.03	-.03	-.04	.04	-.00	-.03
Age (median)	11	19	25	11	14	11	12	13	11
# Firm / year	99,250	4,364	1094	64,161	14,145	26,407	40,743	16,664	47,305
% Firm	95	4	1	61	14	25	39	16	45

This table reports firm characteristics for firms with value-added data (1992-2013). High-Wage Firms, High-Productivity Firms, and Large Firms (Low-wage, Low-Productivity, and Small) are firms in the top two (bottom) annual employment weighted quintiles. Wage corresponds to average wage (hourly earnings). Productivity corresponds to labor productivity (value-added over labor input). Size corresponds to the average number of employees. Data is truncated at the 1st and 99.9th percentile. # Firm / year reports the mean number of firms per year. % Firm reports the share of firms in each group.

Table A.2: Employment Cyclicity, by Size and Wage

Cyclical indicator: Unemployment rate in...		
	First Difference (1)	Deviation from HP trend (2)
Outcomes: Large Firms minus Small Firms		
Net Poaching (1)	.19***	.03*
Net Non-Employment (2)	.77***	-.06
NetTotal (1)+(2)	.96***	-.025
Outcomes: High-Wage Firms minus Low-Wage Firms		
Net Poaching (1)	-.20**	-.21***
Net Non-Employment (2)	-.04	.020
NetTotal (1)+(2)	-.24**	-.19***

Note: The table reports point estimates β of the model: $\Delta g_{t,t-1} = \beta Cycle_t + \gamma_t + \epsilon_t$. $\Delta g_{t,t-1}$ is the differential net growth rate. It is the net growth rate of "High-type" firms minus the net growth rate of "Low-type" firms, i.e. $\Delta g_{t,t-1} = g_{t,t-1}^{\text{High-type}} - g_{t,t-1}^{\text{Low-type}}$. The model includes a time trend (γ_t). Each dot corresponds to a different model: by firm types (Size, Wage, Productivity), cyclical indicators (ΔU and Trend U), and components of the employment growth rate (Poaching, Non-Employment). Confidence intervals are reported at the 90% level. Net growth rate is decomposed between net poaching ($H_{tp} - S_{tp}$) and net non-employment ($H_{tn} - S_{tn}$). High-wage Firms, High-Productivity Firms, and Large Firms (Low-wage, Low-Productivity, and Small firms) are firms in the top two (bottom) employment weighted quintiles. Wage corresponds to average wage (hourly earnings). Productivity corresponds to labor productivity (value-added over labor input). Large and Small correspond to the average number of employees. $Cycle_t$ is either " ΔU " the first difference in unemployment rate or "Trend U", the cyclical component of the unemployment rate (see figure 1). Q2-1985 to Q1-2013. Seasonally adjusted series for all firms.

Table A.3: Distribution of worker cluster size

Number in cluster	Unweighted		Weighted	
	Percent	Cumulative percent	Percent	Cumulative percent
1	93.94	93.94	76.14	76.14
2	3.68	97.62	5.96	82.10
3	0.96	98.57	2.33	84.43
4	0.43	99.01	1.41	85.84
5	0.24	99.25	0.98	86.82
6	0.16	99.41	0.76	87.58
7	0.11	99.51	0.61	88.19
8	0.08	99.59	0.50	88.69
9	0.06	99.65	0.42	89.11
10	0.04	99.69	0.36	89.47
>10	0.31	100.00	10.53	100.00

Note: Number of workers that change job identifier with a firm identifier and have their subsequent job in the same firm identifier. This number gives the number of workers in the cluster. Transitions with more than 10 workers in the same cluster are rare events (0.31%) but they represent 10.53 % of all firm-to-firm transitions. Spell data, 1985-2013.