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IZA DP No. 15872

Job Ladders by Firm Wage and Productivity

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ISSN: 2365-9793

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ABSTRACT

Job Ladders by Firm Wage and Productivity*

We investigate whether workers reallocate up firm productivity and wage job ladders, and the cyclicality of this process. We document that productivity is a better measure of the job ladder than the average wage, since high productivity firms relative to low poach more workers than high wage firms relative to low. Employment cyclicality over the business cycle differs between the firm wage and productivity ladders. In recessions, employment decreases more in low than in high productivity firms. Low productivity firms fire more workers in recessions and stop hiring unemployed workers. Thus, there is a cleansing effect of recessions from the point of view of productivity reallocation. Oppositely, employment decreases more in high than in low wage firms, and the poaching channel of employment growth explains the difference. In recessions separations to other firms slow down more in low wage firms relative high wage firms and thus reallocation up the wage job ladder breaks down - a sullying effect of recessions. Thus recessions speed up productivity-enhancing reallocation but impede progression on the wage ladder.

JEL Classification: E24, E32,J63

Keywords: job creation rate, firm heterogeneity, employment fluctuations

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* We thank participants at CREST, SOLE (2018), Dale T. Mortensen Centre Conference (2017), EALE, EEA, SaM (2017), RES (2017), University of Copenhagen, briq Workshop on Firms, Jobs and Inequality (2018), and IZA Labor Statistics Workshop (2021) for helpful comments. We thank Richard Audloly, Jesper Bagger, Nikolaj Harmon, Renato Faccini, Christian Hoeck, Jeppe Druedahl, Marianna Kudlyak, Filip Rozsypal and Michael Simmons for their comments. We are especially indebted to Jason Faberman (discussant) at the IZA Labor Statistics Workshop (2021) for his comments. Mads Hejlesen and Henning Bunzel deserve special acknowledgement for their work on the data. We acknowledge referees' feedback and financial support from the Danish National Research Foundation (Niels Bohr Professorship) and the Danish Social Sciences Research Council (grant no. DFF - 6109-00037). This paper is a heavily revised version of the IZA discussion paper "*Employment Reallocation over the Business Cycle: Evidence from Danish Data*" a chapter of Bertheau's PhD dissertation.

1 Introduction

It takes time and resources for workers to find their preferred job. Consequently, many workers still look for jobs while employed and quit when a better opportunity arrives (Faberman et al., 2022). The prevalence of on-the-job-search in the economy has profoundly impacted labor market models (Burdett and Mortensen, 1998; Moscarini and Postel-Vinay, 2018). Most models define a job ladder as a common ranking by workers of available jobs. This is typically based on the average wage paid or the productivity of the employer. However, there is limited empirical work to support and guide these choices.

Is it the average wage or the productivity that best represents the firm's location on the job ladder? Relatedly, how does job creation across the ladders vary in the cross-section and over the business cycle? Do recessions slow down the reallocation process into better firms? These questions have implications for models of aggregate fluctuations in the labor market and, in general, any imperfect labor market models that assume that some jobs are more desirable than others.

We provide new evidence on these questions, which have remained open due to data challenges. The first challenge is measuring heterogeneity in firms' characteristics, which can be used to rank firms. In particular, theories of firm and wage dynamics use productivity as the underlying state that impacts a firm or worker's decision to form an employment relationship (Hopenhayn, 1992; Postel-Vinay and Robin, 2002). However, firm-level data on productivity are not yet available for the US and many European countries. The second challenge is to access data covering several expansions and recessions and at a high enough frequency to credibly measure employer-to-employer transitions. The latter is needed to separate voluntary transitions from involuntary ones, where the first embodies revealed preferences about the employer. This paper addresses these challenges by using novel matched employer-employee data that record employment spells at the daily frequency, merged with the firm's financial account data from Denmark spanning more than 20 years (1992-2013). We use this dataset to compare the magnitude and cyclicality of job creation and destruction for firms with different average wages, measured by average residualized wages, and productivity, measured by TFP using the control function approach by Olley and Pakes (1996).[1] This allows us to demonstrate which of these measures represents a desirable firm and how different types of firms react to the business cycle.

This paper offers three main results. First, we document that the firm productivity job ladder measured by TFP is better than the wage job ladder. We offer two pieces

[1]We explore several ranking methods. The main results are not affected by these specifications.

of evidence. First, the difference in growth rates between high and low productive firms is larger than between high and low wage firms. Second, the net job creation from poaching workers from/to other firms is larger using productivity as a ranking compared to wages. As poaching flows primarily reflect voluntary transitions, our results indicate that productivity is a better employer characteristic than average wages to identify job ladder rungs since firms that are high on the job ladder should be able to poach workers from other firms and also grow faster. This finding provides important evidence suggesting that a firm's productivity and not its average (spot) wage is the characteristic that workers care about. This is consistent with the on-the-job search literature (Burdett and Coles, 2003; Postel-Vinay and Robin, 2002). This finding is also consistent with high productivity firms that offer better working conditions in terms of amenities or provide better outside options in negotiations with other firms, as suggested by Postel-Vinay and Robin (2002) and shown in Caldwell and Harmon (2019). It is also consistent with the idea of compensating wage differentials, where some high wage firms pay high wages not because they are highly productive but because they are undesirable to work at due to, e.g., unpleasant work conditions or high job instability.

Our second contribution is to document that low productivity firms shed more employment in recessions than high productivity firms using both the level and change in unemployment as measures for recessions. When the unemployment rate increases by one percentage point, the difference in the job creation rate between high and low productivity firms increases by 0.30 percentage points. This corresponds to an increase of 32% compared to the average differential net job creation rate between high and low productivity firms. This cleansing effect of recessions is driven by two channels.[2] The destruction of jobs in low productivity firms through nonemployment, as hypothesized in, e.g., Mortensen and Pissarides (1994), but also a relatively lower hiring rate compared high productivity firms. This second channel is important and suggests that labor market business cycle models should encompass a mechanism which will generate this. A model with exogenous arrival rates will have a hard time fitting this pattern since when unemployment increases *more* jobs should be created from nonemployment. A model with e.g. endogenous hiring decisions seems to be an obvious choice. We also find that the difference between high and low productivity firms in terms of net poaching rates becomes smaller in recessions. This suggests that the productivity job ladder, to some extent, break down during recessions causing a sullying effect.[3] This observation is in line with models such as Audoly (2020) and Moscarini

[2]The cleansing effect posits that workers are directed to more productive firms in recessions.

[3]The sullying effect refers to the idea that workers are matched to better firms at a lower rate in bad economic times.

and Postel-Vinay (2013), which suggest that in expansions, high type firms grow more by poaching workers from low type firms.

In contrast, we find that the differential growth rate between high and low wage firms *contracts* by 0.08 percent when unemployment increases by one percentage point. This evidence suggests that high wage firms are more cyclical sensitive, in line with the findings by Mueller (2017), who shows that high wages workers are more cyclically sensitive. The difference in job creation between high and low wage firms is explained by the poaching margin, which shows that the wage job ladder collapses to some extent during recessions. Overall, we find that identifying the job ladder rungs using the average wage paid or the productivity changes the conclusion on which jobs are more affected by aggregate fluctuations in the labor market.

Our third contribution is to document that how productivity is measured matters. With less direct productivity measures, such as sales per worker, we draw different conclusions about the cyclicality of the job ladder. In particular, the matched employer-employee data for the US (the LEHD) only measures sales per worker, not total factor productivity. In our preferred specification and using the change in unemployment as a cyclical indicator, we find that a one percentage point (pp) increase in the unemployment rate increases the difference between high and low TFP firms by 0.30 pp. Using sales per worker the difference is 0.12 pp. Accordingly, using sales per worker as a measure of productivity produces an estimate around 40 percent lower than when using TFP. Interestingly, we get different signs of the effect of the business cycle using the level of unemployment as a cyclical indicator when we use sales per worker compared to TFP. Using TFP, we find that an increase in the level of unemployment increases the difference between high and low by 0.11, while it reduces it by 0.08 using sales per worker. We view this result as the first evidence showing that different productivity measures alter the extent of the measured importance of productivity-enhancing reallocation.

We show that our results are robust to different specifications. Specifically, we present results for different thresholds of high and low firm types, productivity measures (TFP, value added per worker, sales per worker). The various specifications yield the same central empirical result: productivity is a better predictor of voluntary EE transitions than average firm wages.

Our data is particularly suited to answering questions about what characteristics best define the job ladder and how firms of different types change behavior over the business cycle. The data cover several recessions, with aggregate unemployment fluctuating from 3% to 10% in our sample. In addition, we measure the start and end dates of jobs daily, which makes our data immune to the large and cyclical time aggregation bias of quarterly frequency data, as shown in Bertheau and Vejlin (2022). We can rank firms on the revenue-based TFP distribution using firm data on value added, capital stock, full-time equivalent employment, and workforce composition (educational level, gender, age, job tenure). Finally, the institutional setting in Denmark is closer to that of the US than traditional continental European countries. There are few regulations on firing and hiring, and most wages are negotiated at the firm and not at the industry level. According to the employment protection law index by Botero et al. (2004), Denmark has among the most flexible employment protection laws among advanced economies. The new data and the macroeconomic and institutional environment make the Danish labor market an ideal setting to answer our research questions.

Related studies. This paper builds mainly on a strand of papers that seek to understand employment dynamics at the firm level. The most related studies are by Haltiwanger et al. (2021, 2018a). Haltiwanger et al. (2018a) decompose job flows into employer-to-employer and non-employment margins by firm size and wage in the US. They conclude that firm wage is a better predictor of the job ladder than firm size and that high wage firms are more cyclically sensitive than low wage firms. Haltiwanger et al. (2021) report evidence on the cleansing effects of recessions, using sales per worker as a proxy for productivity. They find that whether recessions are cleansing or not depends on the cyclical indicator (change in the unemployment rate or level of the unemployment rate).

Other recent studies also focus on the differences between small and large firms. Moscarini and Postel-Vinay (2012) show that the net job creation rate of large firms shrinks more than small firms in the US and other countries when unemployment is high. Kudlyak and Sanchez (2017) show that the sales of large firms suffered more than those of small firms in the US during the 2008 financial crisis. Using Danish data, Clymo and Rozsypal (2022) find that among the youngest firms, small firms are more cyclical than large, but the reverse is true among older firms. Bachmann et al. (2021) show that worker churn is procyclical and is V-shaped in employment growth.

Audoly (2020) and Moscarini and Postel-Vinay (2013) are the studies closest to our work in terms of the theoretical framework. The role of employer-to-employer has recently been studied in richer macroeconomic models; see, for example, Faccini and Melosi (2021). They build models with firm heterogeneity, on-the-job search, and aggregate shocks. In a calibration, Audoly (2020) finds that low productivity firms destroy fewer jobs after negative aggregate shocks than high productivity firms. The reason is that low productivity firms lose fewer workers via the poaching of high productivity firms when the unemployment level is high, as the probability for workers to draw an offer from a high productivity firm is reduced as they compete with more unemployed workers. Therefore, as voluntary quits are always productivity enhancing in his model, aggregate shocks produce sullying effects (i.e., a dampening of reallocation to more productive firms). Instead, the analysis in this paper is empirical, focusing on firms ranked by average *residualized* wages and TFP to show how to best measure a good firm on the job ladder. Furthermore, we show that productivity-enhancing reallocation differs with different productivity measures.

Our paper is also related to papers that seek to identify the characteristics of good jobs (integrating offered wages and nonwage job values). Sorkin (2018) identifies good firms using EE transitions but does not provide evidence of whether good firms are highly productive firms. A more closely related paper is Lochner and Schulz (Forthcoming). They focus on sorting and show that sorting high-ability workers into high productive firms is less pronounced than sorting into high wage firms. Appendix C provides additional references related to this paper.

The paper proceeds as follows. Section 2 presents the methodology and data. In Section 3 we present our results on the dynamics of firm employment. Section 4 shows how results differ with less direct productivity measures and when we change how we rank high and low firms. Section 5 concludes.

2 Institutional Setting and Data Sources

2.1 Some Features of the Danish Labor Market

Several features make Denmark a good environment for studying employment reallocation. The labor market institutions are closer to those in the US than other countries in continental Europe. There are few regulations regarding hiring and firing. For example, advanced notice regulations for layoffs are typically short. In contrast to many European countries where firm financial data are available (such as France, Portugal, or Italy), the labor market is not segmented by contract type (permanent vs. temporary contracts). The level and cyclicality of worker mobility are also closer to the US labor market than the European ones. For example, Engbom (2021) shows that a Dane is twice as likely to make a voluntary employer-to-employer transition compared to a French or an Italian worker, while a US worker is 2.5 times as likely.

Since the mid-1990s, the unemployment rate in Denmark has been lower and more volatile than the unemployment rate in the Euro area, see Figure A.1. Unemployment peaked in 1993 at 10%, before dropping 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 has fallen in recent years and hovers around 4% in 2022. Although most workers are unionized, since the 1990s, wage and hour negotiations have been decentralized at the firm level (Dahl et al. (2013)). Again, this is in contrast to many European countries. Appendix B.1 contains more information on the Danish labor market. Overall, the combination of a flexible labor market and very rich register data provide an ideal setting to answer our research questions.

2.2 Employment Transitions and Firm Accounting Measures

We construct a unique data set from administrative records of workers and firms. The resulting data contain detailed information on each job (hours worked, earnings, daily employment dates) and firm (sales, value added, labor costs, capital stock, age, and industry).

Employment spell data. The daily employment spell data come from several administrative data sets, which we merged and processed.

The data record all employment relationships daily from 1992 to 2013. Unfortunately, the spell data do not cover the period after 2013. Each observation in the data set contains worker, firm, and job identifiers. A job is a set of successive days worked in a given firm. For each job, we have information on the start and end dates of the job, earnings, and hours worked at annual frequencies. In the case of multiple jobs in a given month, we select the primary job. The primary job is the job where the worker spends the most time working aggregated over the current and the following two months.

Due to the daily frequency of the data, we have the exact timing for each employment spell, which reduces the measurement error that causes the so-called time-aggregation bias. Time aggregation bias is a potential problem in previous studies such as Haltiwanger et al. (2018a) and Haltiwanger et al. (2021) who both use LEHD, which only records employment relationships at a quarterly frequency. Without the exact length of a job spell, it is not easy to distinguish between employer-to-employer transitions and transitions involving a non-employment period, as pointed out by Moscarini and Postel-Vinay (2018). Using Danish data, Bertheau and Vejlin (2022) shows that quarterly data overestimate the EE transition rate by approximately 30% compared to daily data. They also show that the bias is procyclical and is reduced by more than 10% in recessions.

Finally, we correct for fictitious transitions driven by a change of firm identifiers, but where the workforce does not change. Details of data construction can be found in Appendix B.2.

Accounting firm data. We link the employment spell data with administrative panel data on the firm's financial accounts reported from 1992. We use the registers FIRM from 1999 and, before that, the register FIGF ("Generel Firmastatistik"). We exploit this dataset to measure total factor productivity using value-added, capital stock, and employment in full-time equivalent units.

We conduct our analysis at the firm level as companies do not report financial data at the establishment level. The capital stock is measured as the book value of buildings, machines, inventory, patents and licenses. Value added is measured not just as sales minus purchases but also by including other into detailed accounting items.[4] Statistics Denmark gradually includes industries in the register from 1992 and only contains all industries from 1999. To have a longer panel, we select the industries present in the data from 1992. These are manufacturing, services, and trade. It is the only sample selection that we impose. Therefore, we include all workers employed in these industries. Importantly, since the job spell data are for the full population of workers, we identify employer-to-employer transitions out of and into firms that are not part of the sample. Thus, a worker moving from a firm in the sample into a firm outside the sample will be counted as an employer-to-employer transition.

2.3 Descriptive Statistics of Firm Ranking

In job ladder models, such as Burdett and Mortensen (1998), a firm's average wages and productivity are key characteristics. However, the predictions for wages in job ladder theory are not straightforward, as wages can fall after voluntary quits such as in sequential auction (Postel-Vinay and Robin, 2002) or tenure contracts (Burdett and Coles, 2003) models, where workers value the present discounted value of wages, not the spot wage alone. We rank firms based on their residualized average wage and total factor productivity (TFP). We rank firms within years and 2-digit NACE industry (industry-year cells) to control for industry heterogeneity.[5]

Measurement of productivity. To overcome the endogeneity of TFP, we follow the two-step procedure proposed by Olley and Pakes (1996). This method uses firm investment as a proxy for the unobservable productivity component of a firm. We have

[4] The definition of value added changes slightly over the years due to changes in accounting legislation, but it is, in general, defined as follows: Sales + work done within the firm + change in inventory - purchases of intermediate goods, raw materials, energy, and subcontractors - expenses for rent - expenses for operational costs, temp agencies, leasing, and other external costs.

[5] Our sample contains 68 different industries on the 2-digit level.

investment data from 1999 and forward. Thus, we use only data from 1999 and forward in the following estimation to get consistent estimates of the coefficients. Using these coefficients we can tease out TFP for the period without investment data. The implicit assumption is that the production technology did not significantly change over the data period. We assume that following production technology.

$$y_{jt} = \alpha + \mathbf{w}_{jt}\beta + \mathbf{x}_{jt}\gamma + \lambda_t + \omega_{jt} + \varepsilon_{jt} \tag{1}$$

where y_{it} is the value added of a firm j in year t. $\mathbf{w}_{jt}$ is a vector of control variables including the log the number of employees in a full-time equivalent units (FTE) and average workforce characteristics (job tenure, educational level, age, gender). $\mathbf{x}_{jt}$ is the log of capital stock, the state variable in the model. λ_t are year fixed effects. ω_{jt} is the estimated TFP value for firm j in year t. Since there are differences across industries in production technology, we estimate TFP separately by industries.[6]

We cannot estimate the revenue-based TFP using other control function methods such as Ackerberg et al. (2015); Levinsohn and Petrin (2003) as detailed information on intermediate inputs is unavailable for most firms throughout our data period.

In Appendix, we rank firms based on their value-added per full-time equivalent worker and using OLS instead of the control function approach. We find similar qualitative reallocation patterns. However, the TFP measure of productivity is a better predictor of the employment growth rate than labor productivity.

Measurement of wage. To construct a residualized average wage, we regress a firm's average hourly wages on the workforce's characteristics (job tenure, educational level, age, gender) and year fixed effects. We run separeate regressions within the 2-digit industries. An alternative would be to run the Abowd et al. (1999) statistical model (henceforth AKM) and use the firm fixed effects to rank firms. Haltiwanger et al. (2021) do not find any difference between using AKM firm fixed effect and average wages. Since our sample contains a large share of small firms, AKM firm fixed effects estimates suffer from limited mobility bias, implying that they are not precise estimates (see, e.g., Bonhomme et al. (2019)). Since we are particularly interested in how high and low type firms behave, measurement error in the classification variable is problematic; thus, we choose not to rank based on AKM firm fixed effects. Finally, we have checked that the results are similar using an unresidualized wage measure (as done in Haltiwanger et al. 2018a).

[6]TFP is a better proxy of single-factor productivity compared to e.g. labor productivity, which reflects units of output produced per unit of a particular input. Note that two firms may have different levels of labor productivity even though they have the same production technology if one uses capital more intensively (Syverson, 2011).

Measurement of high vs. low types. Following Haltiwanger et al. (2018b), we classify the firms in the low bracket as being in the bottom quintile and the high bracket in the top two quintiles. Importantly, the quintiles are employment weighted. Weighting by employment implies that results can be interpreted as effects on the average worker rather than on the average firm. To avoid reclassification bias and follow the literature, we use the average wage and TFP in year $t-1$ to characterize net flows in quarters of year t.[7] Lastly, another key characteristic is the size of the firm. However, in previous work, firm size has been shown to relate less clearly to the job ladder than wages (see Haltiwanger et al. 2018a and Bertheau et al. 2020), so we do not rank by firm size. In Section 4 we show that how we rank firms do not matter much.

Descriptive statistics. Table 1 presents the correlation between our ranking measures and size. We do not focus on size, but it is useful to show the Spearman rank correlations.

Table 1: Correlation between Characteristics Used to Rank Firms

	TFP	VA per worker	Sales per worker	Wage per worker	Size
TFP	1.00	0.62	0.48	0.32	0.04
VA per worker	0.62	1.00	0.75	0.45	-0.22
Sales per worker	0.48	0.75	1.00	0.37	-0.18
Wage per worker	0.32	0.45	0.37	1.00	0.10
Size	0.04	-0.22	-0.18	0.10	1.00

Notes: The table shows the Spearman rank correlations between revenue-based TFP, value added per worker, sales per worker, and wage per worker and firm size. "Per worker" measures are full-time equivalent. The correlations are worker-year weighted.

Table 1 provides several interesting lessons. We find that TFP and value added per worker are strongly correlated (0.62). However, TFP and sales per worker are less strongly correlated (0.48). Interestingly, residualized average wages and TFP are less correlated with a coefficient of 0.32. The low correlation indicates that employment reallocation by wages or productivity might differ. The low correlation is in line with empirical (e.g., Card et al. 2018; Maibom and Vejlin 2021) and theoretical work (e.g., Bloesch et al. (2022)). Especially, Bagger et al. (2014) study the correlation between wages and productivity and the underlying driving forces using Danish data. For example, in wage posting models such as Burdett and Mortensen (1998), wages always increase in productivity. However, this is not the case in auction models such as Postel-Vinay and Robin (2002), where part of the value of a job is that it can be used as a threat point in future negotiations with other firms. Thus, the correlation would be

[7] Results are similar when we use time-invariant ranking measures of firm types.

lower for this reason. The measure of sales per worker is more correlated with the TFP per worker than with wages. However, the correlation is 0.58, which is far from a perfect positive relationship. This correlation indicates that TFP and sales might provide different results. Wages are only weakly positively correlated with firm size (0.04), while TFP and sales are negatively correlated with firm size. Although these results are not widely documented in the literature, we are not the first to find a weak correlation between size and productivity. For example, Lentz and Mortensen (2008) also find zero correlation between firm size and productivity.

There is a concern that measurement error in small firms drives low correlations. Appendix Table A.1 reports the same correlations for firms with at least 20 employees and firms at least 10 years old. We find similar patterns in the correlations in both samples. Finally, Appendix Table A.2 shows descriptive statistics for each of our groups defined by the ranking measures.

3 Employment Reallocation Across the Wage and Productivity Ladder

This section documents the rate of job creation and destruction across firms with different average wages and productivity. We show how we decompose job flows and then analyze cross-sectional and business cycle patterns.

3.1 Decomposition of Firm Employment Changes

We decompose net employment creation, the job creation minus job destruction of firms, into two components. The first component is the employer-to-employer transitions, also called poaching flows. These transitions are viewed in the literature as primarily voluntary choices made by the worker as a result of job search on the job (Faberman et al., 2022). Combining survey data with administrative data for Denmark, Taber and Vejlin (2020) find that 80 percent of employer-to-employer transitions are voluntary. In the literature, "Employer-to-Employer (EE)" are sometimes referred to as "Job-to-Job" (J2J). This labeling is confusing, as, strictly speaking, job changes include internal moves such as promotions (see Bertheau (2021); Groes et al. (2014)). We follow Fujita et al. (2020) and use employer-to-employer to designate a direct change of employer. The second component is hiring (separation) from (to) nonemployment. We do not differentiate between different types of nonemployment. Due to the means-tested nature of social assistance in Denmark, we cannot separate active job seekers from nonactive ones using administrative data. Methodologically we follow Haltiwanger et al. (2018a) and compute net employment flows for firms as:

$$\texttt{Net Job Creation}_t = \texttt{H}_t - \texttt{S}_t = \underbrace{H_{tp} - S_{tp}}_{Net\ Poaching} + \underbrace{H_{tn} - S_{tn}}_{Net\ Non-Employment}. \quad (2)$$

The net creation of jobs in the quarter t is the difference between total hiring and separation. Hirings originate from two different pools of workers: already employed workers poached from other firms (H_{tp}) and non-employed workers (H_{tn}). Likewise, separations can occur in two different pools: to other employers (S_{tp}) and to nonemployment (S_{tn}). Direct transitions from one employer to another are defined as transitions with less than seven days of nonemployment between two jobs. We varied the threshold of seven days, and results are similar.

3.2 Cross-sectional Patterns

Figure 1 documents the net and gross flows, ranking firms by wages and productivity (measured as TFP). We decompose net employment growth into two separate channels presented in Equation (2): Net poaching and net nonemployment. *Net* poaching is the difference between poaching hires and poaching separations and also for nonemployment. These results are presented in Panel (a). In Panel (b), we further split the net flows into gross flows.

High wage vs. low wage firms. Looking first in Panel (a), we find that high wage firms grow faster than low wage firms (0.26% vs. 0.22%), and they do so through different channels. High wage firms grow predominantly by net poaching (0.21%) and a little from net nonemployment flows (0.06%). In contrast, low wage firms shrink because workers leave for other firms (-0.40%) but grow by net flows from the pool of previously nonemployed workers (0.62%). This pattern indicates that poaching is important to understand how firms with different wages grow and contract.

We divide net poaching and net nonemployment into gross flows in Panel (b) and find that there is a lot of churn in all firms. However, low wage firms have more churn than high wage firms, i.e. they have higher hiring and separation rates for both poaching and non-employment channels.

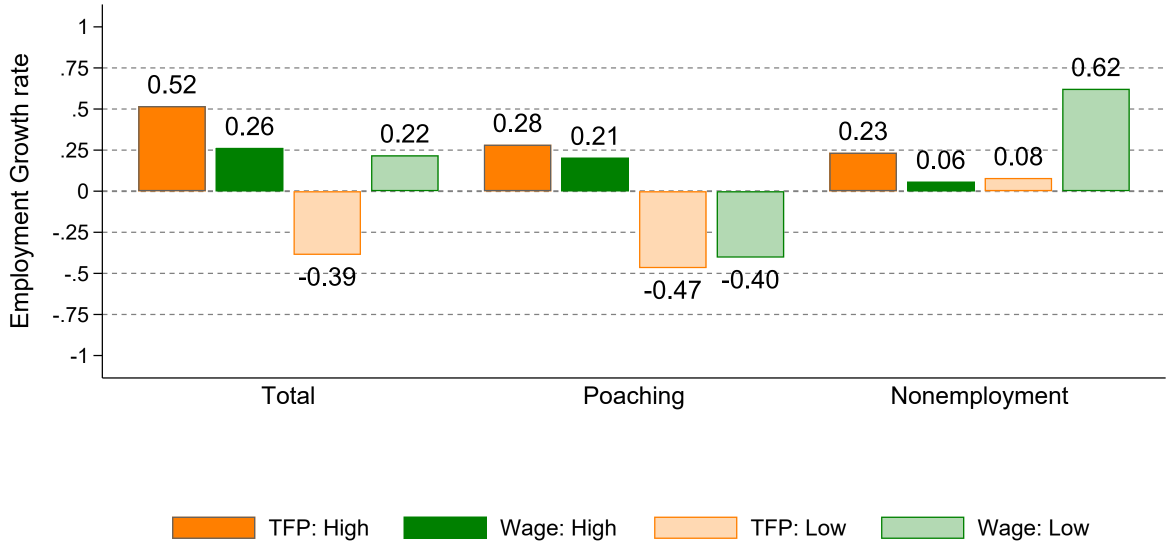
High vs. low productivity firms. Looking at Panel (a) first, the difference in job creation is much more pronounced between high vs. low productivity firms than between high vs. low wage firms (0.52% vs. -0.39% compared to 0.26% vs. 0.22% for the wage ranking). We find that the nonemployment channel explains the lion's share of the difference between the two classifications. Low productivity firms, like low wage firms, shrink through poaching (-0.47% and -0.40%). However, they grow much less (0.08% vs. 0.62%) than low wage firms by the nonemployment channel. As a result, low productivity firms are shrinking while low wage firms are growing (-0.39% vs. 0.22%).

A key question is which observable variables best capture the job ladder. Many recent papers such as Bagger and Lentz (2019) and Taber and Vejlin (2020) argue that employment-to-employment transitions are largely voluntary and thus help to identify the job ladder. In this light, it is important to note that the difference in net poaching flows between high and low type firms is larger for productivity than for wages (0.75% vs. 0.61%). Accordingly, we argue that productivity is a better proxy for the job ladder than wages, since workers voluntarily move from low to high productivity firms and they do that at a faster pace than they move from low to high wage firms. This finding supports models such as Postel-Vinay and Robin (2002), which make the point that there is not a one-to-one mapping between wages and productivity and that the job ladder is based on productivity and not wages.

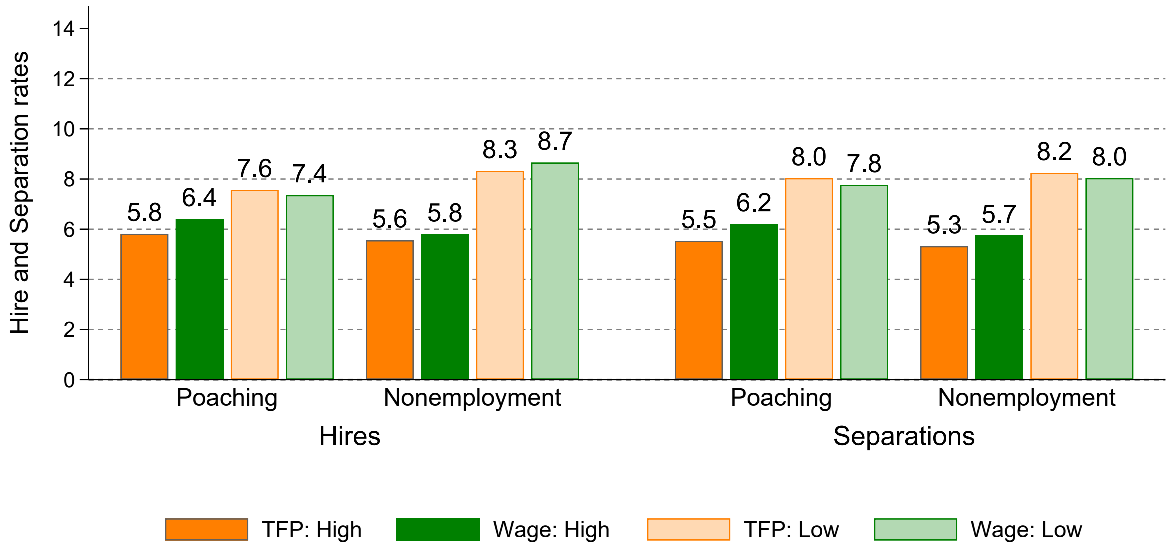
Turning to Panel (b), we find that high productivity firms have less hiring and separation than low productivity firms which echos the results for wages.

Figure 1: Job Creation, Hires and Separations by Firm Wage and Productivity

(a) Net Flows: Hires minus Separations



(b) Gross Flows: Hires and Separations



Notes: The figure shows the quarterly job creation rate (Panel (a)), hires and separation rates (Panel (b)) for firms ranked based on their average wage (residualized earnings per full-time equivalent worker) and productivity (Total Factor Productivity). "High" indicates that the firm is in the top two quintiles of the wage/TFP distribution. "Low" indicates that the firm is in the bottom quintile of the wage/TFP distribution. Poaching in Panel (a) refers to *net poaching*, the difference between the hiring into and separations from a given firm type that only involves employer-to-employer transitions.

3.3 Business Cycle Patterns

Next, we analyze how labor flows vary over the business cycle. First, we present the cyclical indicators, then visual evidence, and finally the regression results.

Cyclical indicators. We use both the level and the change in the unemployment rate to measure the business cycle. The change in unemployment is motivated by studies showing that the inflow into unemployment is the primary driver of aggregate unemployment dynamics (Elsby et al., 2013; Fujita and Ramey, 2009). In particular, Lydon and Simmons (2020) show that the inflow into unemployment explains 61% of the unemployment variation in Denmark. The level of unemployment is used as it corresponds more closely to models trying to understand labor flows. In both DMP-type models and business cycle variants of Burdett and Mortensen (1998), such as Moscarini and Postel-Vinay (2013), and bargaining models, such as Lise and Robin (2017), the level of unemployment is the relevant factor describing the state of the labor market.

Empirically, the two measures capture different parts of the cycle. The unemployment level naturally lags behind the change in unemployment. It thus captures times in the middle of a recession (expansion). In contrast, the change in unemployment captures the periods going from recessions to expansions, where unemployment decreases, and vice versa. The level of unemployment is measured as the deviation from the HP-filtered trend, whereas the change in unemployment is just the first difference in the unemployment rate (not HP-filtered).

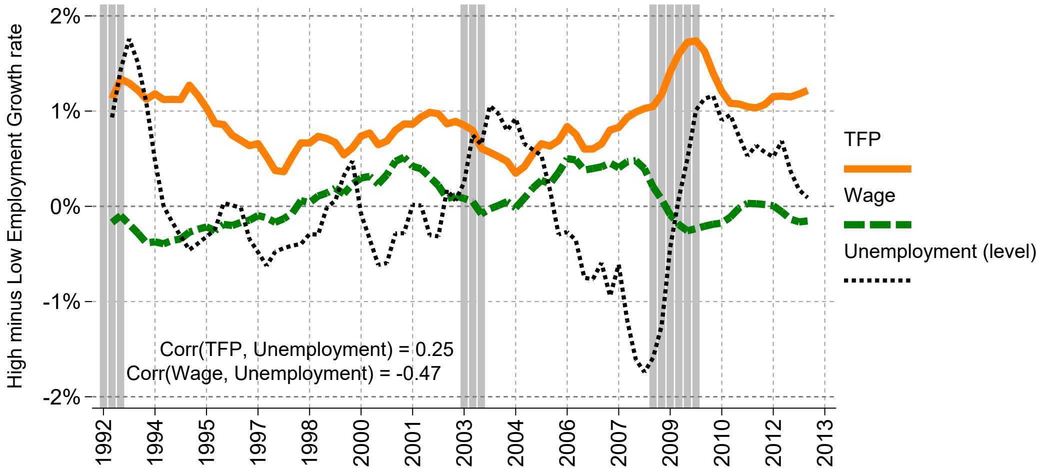
3.3.1 Graphical Evidence

Figure 2 shows the differential net employment growth rates, where the differential is high minus low types together with the level of unemployment. We only show the visual evidence using the level of unemployment, while we use both cyclical indicators when we present the regression results. Again, following Haltiwanger et al. (2018a), the differential net growth rates are given by $(H_{t,high} - S_{t,high}) - (H_{t,low} - S_{t,low})$ in Equation (2) and the detrended unemployment level is represented by the black dotted line. We present visual evidence and not just the correlations, since it is easier to detect which years are driving the correlation.

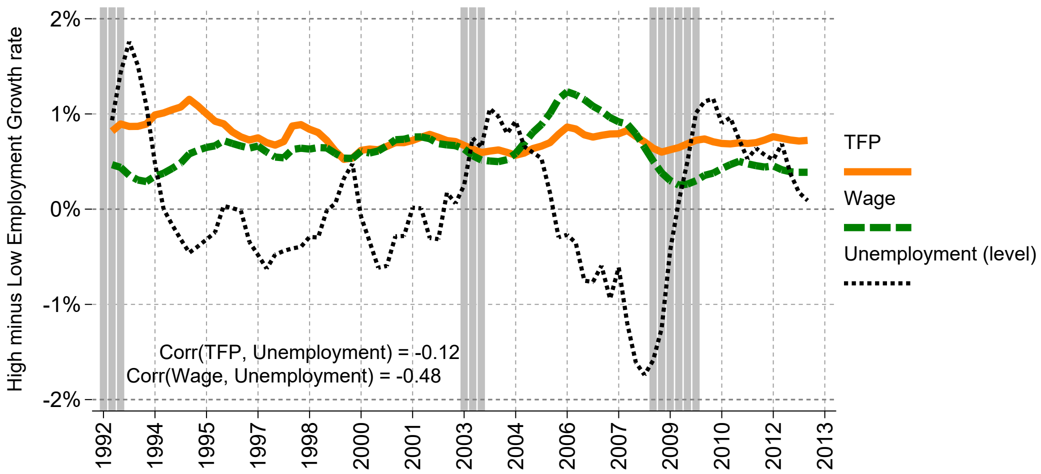
Differential employment growth rates. We find a negative correlation (-0.47) between the differential employment growth rate and the level of unemployment of the wage distribution (Panel (a)). The correlation implies that high wage firms grow rel-

Figure 2: Differential Job Creation Rates Over the Business Cycle

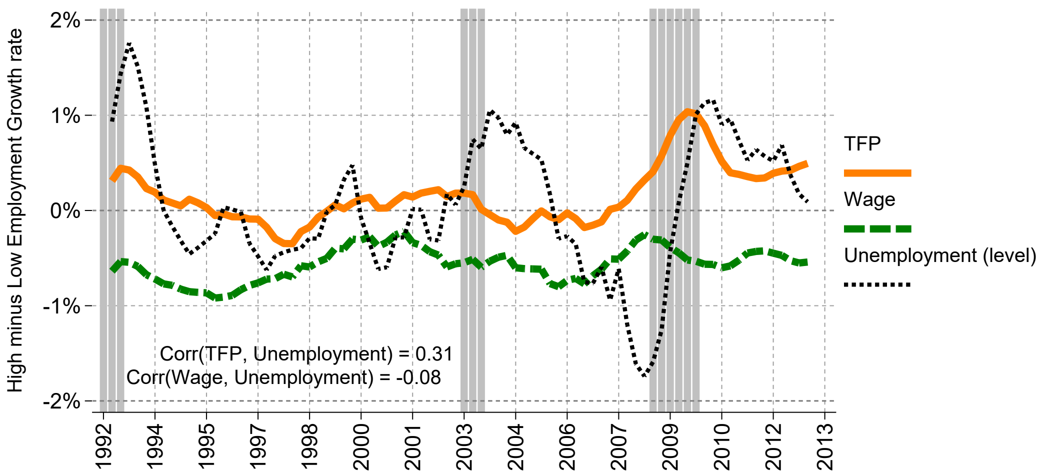
(a) Total: Poaching and Nonemployment



(b) Net Poaching



(c) Net Nonemployment



Notes: The figure shows the differential net growth rates (total, poaching, nonemployment) based on within industry-yearly rankings of firms by either wages or productivity.

atively more than low wage firms in expansions when unemployment is low, while they shrink relatively more in recessions. This pattern is especially pronounced in recessions after the dot-com bubble crash in 2003-04 and before the Great Recession in 2006-08. Interestingly, the results differ for the productivity ranking. Here, the differential net growth rate is positively correlated (0.25) with the level of unemployment. Most of the difference is driven by the mid-1990s and the period after the Great Recession. In both periods, unemployment was high and differential employment growth based on wages was small, but based on productivity, it was high. This suggests that the Great Recession had a cleansing effect in the sense that high productive firms outgrew low productive firms.

The role of poaching and nonemployment channels. The differential net growth rate can be decomposed into differential net poaching and nonemployment channels. First, we examine the poaching rate in Panel (b). It should be noted that the cross-sectional patterns found in Figure 1 are not driven by particular phases of the business cycle. Indeed, high type firms grow more through poaching than low type firms throughout the business cycle for both rankings. Using the wage, the correlation is negative (-0.48), indicating that difference in terms of net poaching flows between high and low wage firms decrease when the unemployment level is high. The correlation is also negative for the productivity ranking (-0.12). Thus, both the wage and the productivity job ladder break down in recessions, where workers do not climb them as fast as before. This result implies a sullying effect of recessions (Barlevy, 2002) since workers tend to be stuck in low wage/productivity firms in these periods of the business cycle. Most of the differences between the wage and productivity series are driven by differences in the early 1990s, when the wage job ladder is weaker. We will return to this point later when we discuss the regression evidence.

The results for nonemployment are quite different from those for poaching (Panel (c)). The difference between high and low productivity firms in net nonemployment rates is positively correlated with unemployment (0.31), while it is negative using wages (-0.08). So during recessions, when unemployment is high, high productivity firms tend to grow more compared low productivity firms through nonemployment flows. This was the opposite for poaching flows.

We found earlier that the net differential growth rates (high minus low) from nonemployment were negative for wages, while they were slightly positive for productivity. We note that the negative net different growth using wages is not driven by any particular data period, but is present throughout the period 1992-2013, while the slightly positive net differential growth rate using productivity is driven by the time around and following the Great Recession. This suggests that productive reallocation through unemployment has improved in recent years.

3.3.2 Regression Estimates

We estimate the following model to quantify the effect of the business cycle on employment cyclicality across firm types. Using regressions in additional to presenting correlations allows more interpretable results and controls for other covariates, such as time trends.

$$y_{t,t-1} = \beta Cycle_t + \gamma_{qt} + \epsilon_t. \tag{3}$$

$y_{t,t-1}$ is the flow rate measured in percentage points. The model includes seasonal dummies and a time trend (γ_{qt}). $Cycle_t$ is the cyclical indicator, but multiplied by 100 so we measure them as percentages.

The parameter of interest, β, quantifies the effect of the deterioration of the labor market conditions on the relative growth rate of high to low type firms. Specifically, it measures the effect of a one percentage point increase in the cyclical indicator on the differential net flows, which is also measured as a percentage. Recall that the cyclical indicator is either the change or the level of unemployment measured as the deviation from the unemployment rate trend. Table 3 reports the total differential net growth rate estimates using both cyclical indicators and decomposed rates. Each cell presents results of a separate regression estimated on quarterly data. In Section 4 we show how our estimated effects change when we change the way we rank firms.

Table 2: Cyclicality of Differential Job Creation Rates: Productivity vs. Wages

	Productivity (TFP)			**Wage**		
	Total	Poaching	Nonemployment	Total	Poaching	Nonemployment
Change in Unemp.	0.30***	-0.08*	0.38***	-0.08	-0.21***	0.13**
	(0.10)	(0.04)	(0.09)	(0.09)	(0.08)	(0.06)
Level of Unemp.	0.11**	-0.02	0.13***	-0.17***	-0.15***	-0.02
	(0.05)	(0.02)	(0.04)	(0.03)	(0.03)	(0.02)
Obs.	82	82	82	82	82	82
Mean of dep. var	0.91	0.75	0.15	0.05	0.61	-0.56

Notes: The table shows regression estimates of the effects of an increase in either the level or the change in the unemployment rate on the net differential employment growth rates (see Equation (3.3.2)). Each cell presents results from a separate regression estimated on quarterly data. The total differential employment growth rate is the sum of the poaching and the nonemployment channels. Both cyclical indicators are measured in percentage points of the change in the unemployment rate and as the level of the unemployment rate, HP-filtered. Flows are also measured in percentage points. Standard errors are presented in parentheses. Asterisks report statistical significance at the 1, 5, and 10% (***,**,* respectively).

High vs. low productivity firms. A one percentage point increase in the change in the unemployment rate *increases* the differential job creation rate by 0.30 pp. Thus, when the economy enters a recession, low productivity firms shrink more than high productivity firms, and the difference between them becomes larger. To get a sense of the magnitudes during our sample period, the unemployment rate in Denmark varied from 3 percent to 10 percent. According to the estimate, when the unemployment rate increases by two percentage points (not untypical in a recession as shown in Appendix Figure A.1), the differential job creation rate grows by 66 percent (2*0.30/0.91) relative to the average differential job creation rate. Therefore, there are pronounced differences across the business cycle. When we use the level of unemployment (second row), the sign is similar, but the estimated coefficient is smaller (0.11 pp). The overall effect is driven entirely by the nonemployment channel, as the point estimates are 0.38 and 0.13 pp for the change and level, respectively. In both specifications, the poaching channel pushes in the opposite direction. That is, in recessions, the difference in net poaching rates between high and low productivity firms becomes smaller. Vice versa, in expansions the difference increases between low and high. Originally in Moscarini and Postel-Vinay (2013) and later in Audoly (2020) it is highlighted that "better" firms, which are both high productivity and high wage firms, are more cyclically sensitive due to their ability to poach workers in expansions, where the number of workers in the unemployment pool is small. In booms, better firms poach workers from other firms to a greater extent than in recessions, with a larger pool of unemployed workers. We find support for this margin using TFP of the employer to identify job ladder rungs.

The finding that the difference in growth between high and low productivity firms becomes larger in recessions due to differences in net nonemployment indicates that recessions have a cleansing effect (Foster et al. 2016; Haltiwanger et al. 2021). A popular explanation is that recessions are driven by economy-wide negative TFP shocks affecting all firms. In this case low productivity firms shrink since they become unprofitable after the negative TFP shock suggesting that the difference in net nonemployment growth should come from higher separations in the low productivity firms. The next subsection will investigate whether this happens due to higher separations or lower hiring rates.

We will relate our productivity results more to the results in Haltiwanger et al. (2021), who uses sales and not TFP as the productivity measure, in Section 4, where we compare sales and TFP using the Danish data.

High vs. low wage firms. In contrast, on the wage job ladder, an increase in the change in unemployment *decreases* the differential job creation rate. Like high productivity firms, high wage firms are more sensitive to the cycle because they stop poaching (-0.21 and -0.15) in recessions. However, while the sign of effect on net differential nonemployment flows is similar using wages the effect is much smaller and thus the total effect becomes negative.

Our results for the wage classification are qualitatively similar to Haltiwanger et al. (2021). The coefficients reported for the regressions using the wage ranking have signs similar to those reported by Haltiwanger et al. (2021).[8]

Decomposition into hiring and separation margins. The previous results showed differences in cyclicality for net flows and closely followed the method in Haltiwanger et al. (2021). However, it is impossible to see whether changes in hiring or separations drive the results. This is something that Haltiwanger et al. (2021) do not do and it provides clear insights into which margins are driving the results on the net flows. Table 3 shows the estimated coefficients (β) for hiring and separation rates, using the same specification as for the net flows (see Equation (3.3.2)) and using the change in the unemployment rate.

[8] Table 2, column (2).

Table 3: The Adjustment of Hirings and Separations among Heterogeneous Firms

	High Productivity			**Low Productivity**		
	Total	Poaching	Nonemployment	Total	Poaching	Nonemployment
Net	-0.71***	-0.05*	-0.67***	-1.02***	0.03	-1.05***
	(0.13)	(0.03)	(0.11)	(0.19)	(0.03)	(0.18)
Mean of dep. var	0.52	0.28	0.23	-0.39	-0.47	0.08
Hire	-1.34**	-0.66*	-0.68***	-1.53**	-0.68	-0.85**
	(0.56)	(0.33)	(0.24)	(0.75)	(0.41)	(0.36)
Mean of dep. var	11.38	5.82	5.56	15.89	7.57	8.32
Separation	-0.62	-0.61*	-0.01	-0.52	-0.71*	0.19
	(0.50)	(0.33)	(0.20)	(0.63)	(0.40)	(0.27)
Mean of dep. var	10.86	5.53	5.33	16.28	8.04	8.24
	High Wage			**Low Wage**		
	Total	Poaching	Nonemployment	Total	Poaching	Nonemployment
Net	-0.98***	-0.13***	-0.85***	-0.89***	0.08	-0.97***
	(0.17)	(0.04)	(0.14)	(0.13)	(0.06)	(0.15)
Mean of dep. var	0.26	0.21	0.06	0.22	-0.40	0.62
Hire	-1.24*	-0.66*	-0.58*	-1.62**	-0.69*	-0.94***
	(0.67)	(0.39)	(0.30)	(0.69)	(0.37)	(0.33)
Mean of dep. var	12.21	6.41	5.80	16.02	7.36	8.66
Separation	-0.27	-0.53	0.26	-0.73	-0.77*	0.04
	(0.58)	(0.37)	(0.25)	(0.66)	(0.41)	(0.29)
Mean of dep. var	11.95	6.20	5.74	15.80	7.76	8.04

Notes: The table shows regression estimates of an increase in the change in unemployment on the employment growth rate of different firms (see Equation (3.3.2)). The total differential employment growth rate is the sum of the poaching and the nonemployment channels. Standard errors are presented in parentheses. Asterisks report statistical significance at the 1%, 5% and 10% (***,**;* respectively). Each entry in the table reports a different regression.

Table 2 reports that the gap between high and low productivity firms increases by 0.30 pp when the change in the unemployment rate increases by 1 pp. The first row in Table 3 shows that when unemployment increases, both high and low productivity firms contract, but low productivity firms contract more (-1.02 pp) than high productive firms (-0.71 pp). This difference is driven by differences in contraction through the nonemployment channel (-0.67 pp vs. -1.05 pp), while the net poaching flows in both types are much less impacted by the change in unemployment, but still the difference is pulling in the opposite direction. High-productivity firms contract a little in recessions through the poaching channel (-0.05 pp). However, low productivity firms are somewhat positively affected (0.03). Turning to rows (2) and (3) and focusing on the total net flows in columns (1) and (4), we find that hiring is generally more cyclically sensitive. This result is consistent with the results by Shimer (2012), who finds that unemployment fluctuations are driven primarily by a change in the job-finding rate. For high and low productivity firms, the decrease in the net job creation rate is driven by a hiring reduction (-1.34 pp for high vs. -1.53 pp for low productivity firms), but only a small effect on separations (-0.62 for high vs. -0.52 for low productivity).

Finally, we split the total flows for hiring and separation into poaching and nonemployment in columns (2)-(3) and (5)-(6). The main driver of differences in responses to change in unemployment between high and low productivity firms is the difference in hiring from nonemployment. When unemployment increases, low productivity firms stop hiring workers from nonemployment and start to separate workers to nonemployment to a larger extent than high productive firms. Thus, the cleansing effect of recessions previously found is only partly driven by the classical channel in the sense that low productivity firms fire workers when they become non-profitable during recessions. However, to the same extent they stop hiring new workers. There could be several explanations for this. It could be that current workers have accumulated firm-specific human capital, so they are still productive, but training new workers is not profitable in recessions and thus firms stop to hire. Or it could be that there are frictional search costs, and if firms want to reduce the number of workers employed, it is cheaper to save on hiring costs.[9] The model proposed by Lise and Robin (2017) has exactly this feature. A low aggregate shocks cause the vacancy distribution for shift to higher firm types, because low types don't find it as attractive to post jobs anymore.In their model this is partly driven by the aggregate shock and partly driven by higher values of home production in low aggregate states.

The poaching channel works in the opposite direction. During recessions, high productivity firms slow down their net poaching, while low productive firms actually increase their net poaching, but both only marginally. The main difference between high and low productivity firms comes from separations. During recessions, high productive firms separate fewer workers to other firms (-0.61 pp). However, the effect is smaller than for low productivity firms (-0.71 pp).

Next, we turn to explain why firms ranked by wage behave differently. As noted previously, Table 2 reports that we find a negative difference in total net flows using the change in the unemployment rate (-0.08 pp). Table 3 shows that when unemployment increases both high and low wage firms contract, but high wage firms contract relatively more (-0.98 pp vs -0.89 pp). As for productivity, the main channel is nonemployment flows. This negative effect is driven by a hiring reduction from the pool of nonemployment (-0.94 pp). In contrast, separations to nonemployment are less af-

[9]Both explanations are consistent with survey evidence showing that employers retain workers despite a reduction in demand to preserve firm-specific skills (Bertheau et al., 2022b).

fected (0.04 pp). Thus, during recessions low wage firms stop hiring from nonemployment, but they do not start to separate workers to nonemployment as we saw for low productivity firms. Turning to the poaching channel we see that during recessions low wage firms actually on net gain through the poaching channel (0.08 pp). The reason is that although poaching hiring slows down poaching separations slow down even more (-0.69 pp vs. -0.77 pp).

The adjustment for high wage firms is more complex as they experience a reduction in their growth rate from the poaching (-0.13 pp) and the nonemployment channels (-0.85 pp). Focusing on nonemployment, both hiring and separation matter. Interestingly, separation increases sharply (0.26 pp vs. 0.04 pp for low wage firms). This pattern is consistent with the evidence from Mueller (2017) and Züllig (2022). They find that high residual wage workers are more cyclically sensitive in the US and Denmark. It is also consistent with studies documenting the role of high wage firms in understanding the earnings losses of displaced workers over the business cycle (see, e.g., Bertheau et al. (2022a)). In Table 2 we found that the poaching channel was the driving force explaining the difference between high and low wage firms. We can now extend these results. In recessions high wage firms poach less. This result is driven by a large decrease in poaching-related hires and a smaller decrease in separations to other firms. The predictions of low and high wage firms are consistent with theoretical models such as Moscarini and Postel-Vinay (2013).

Summary. Ranking firms based on their rung on the wage or productivity ladder yields different results regarding the magnitude, the sources, and the cyclicality of employment growth. We find that the difference in growth rates between high and low productivity firms becomes larger in recessions. Most unemployment models, such as Mortensen and Pissarides (1994) and Lise and Robin (2017), would lead to different predictions. In those models, low productivity firms become unprofitable in recessions and thus lay off workers, causing the net nonemployment flow rate to increase. We confirm this for low productivity firms, but not for low wage firms. Instead, for both low wage and productivity firms, the hiring rate from nonemployment is much more cyclical sensitive than the separation rate. This suggests that models should emphasize endogenous hiring rates, which potentially shuts down new hiring during recessions since this is cheaper than firing existing workers. Also, the difference between high and low wage firms becomes smaller in recessions. Differences in the poaching channel drive this, confirming the important role of distinguishing between poaching and nonemployment channels to understand employment reallocation.

4 Are Reallocation Patterns Similar with less direct measures of Productivity?

Productivity is measured as the total factor productivity in this paper and estimated through a production function, see Section 2.3. However, other measures have been used in the literature. For example, sales per worker have been used in previous studies, such as Haltiwanger et al. (2021) for the US. In addition, there are different ways to categorize firms. In our baseline results, we follow Haltiwanger et al. (2018b) and classify low types as being in the bottom quintile and high types as being in the top two quintiles. However, other studies use different definitions.

This section shows how our main results change when we use a less direct productivity measure and how they differ across different definitions of low and high types. Our conclusion of the cyclicality of the job productivity ladder is altered.

Cross-section results. Figure 3 shows the growth of employment for the TFP and sales per worker rankings. Panels (a), (b), and (c) use different rankings of high and low firm types corresponding to our baseline in Panel (a), Haltiwanger et al. (2021) in Panel (b), who defines high as the top two and low as bottom three quintiles, and Haltiwanger et al. (2015) in Panel (c), who defines low as the first quintile and high as the top quintile.

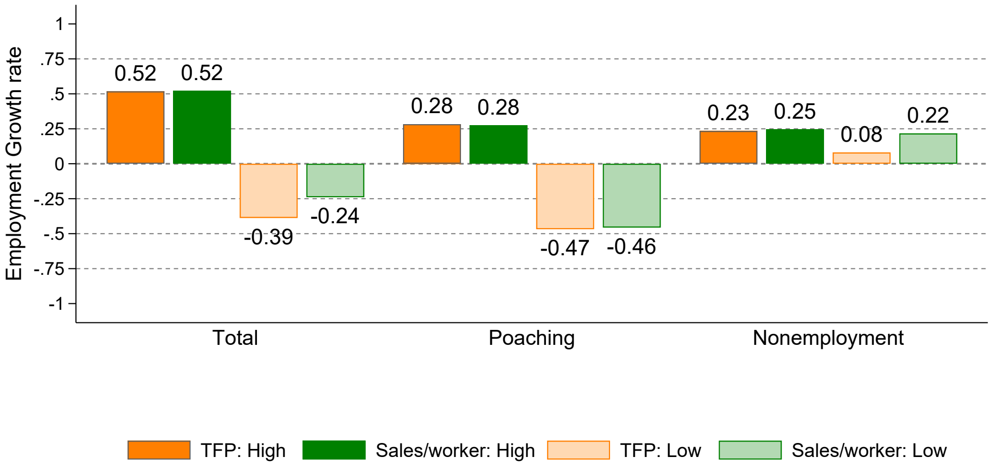
Turning first to Panel (a), we see that we get fairly similar results for TFP and sales. The main difference is that low TFP shrink more than low sales firms. This is caused by differences in the non-employment margin, where low TFP firm only grow marginally (0.08 pp), while low sales firms grow much more (0.22 pp).

Panel (b)-(c) report the results for TFP and sales using the definition of low and high types from Haltiwanger et al. (2021) and Haltiwanger et al. (2015), respectively. Panel (b) has the most extreme ranking as we only use the bottom and top quintiles. Compared to Panel (a), we see a larger difference between low and high types. This is only natural as we use firms that are more different. However, even though the differences are larger between TFP and sales than in Panel (a), the differences are not large. In Panel (c) we again find very small differences between TFP sales.

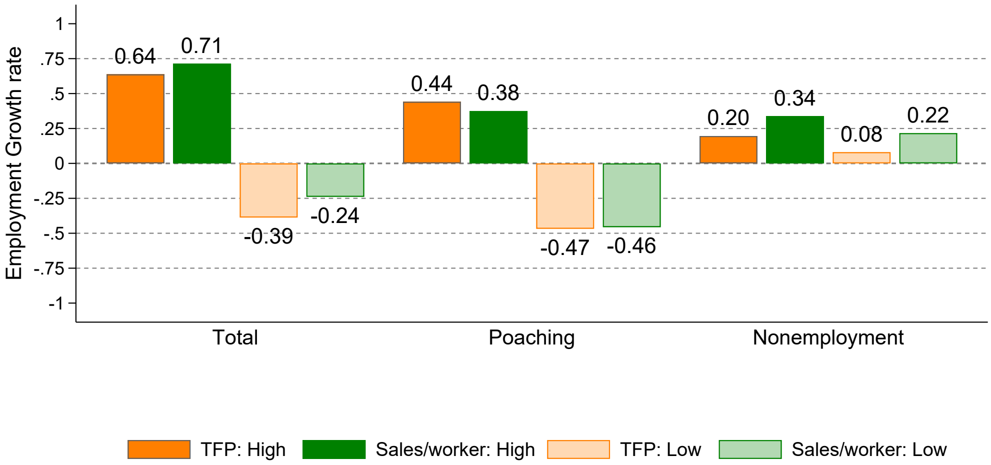
Our conclusion is that the cross-sectional results are rather similar across measures. However, based on larger net poaching flows using TFP in all three rankings, we argue that TFP is superior to sales per worker but that the difference in terms of cross-sectional flows is only minor.

Figure 3: Comparing Sales per Worker to TFP to Measure the Productivity Ladder

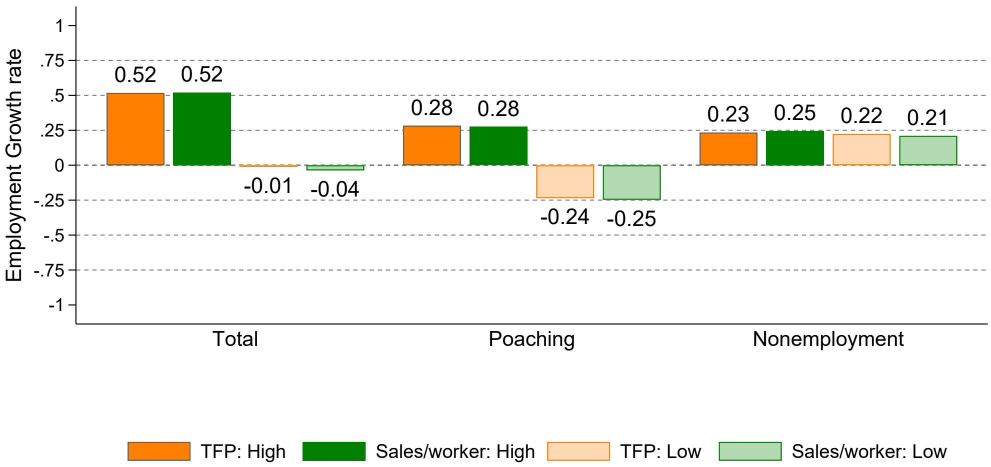
Panel (a): Baseline ranking



Panel (b): Alternative ranking: low-type (bottom quintile) and high-type (top quintile)



Panel (c): Alternative ranking: low-type (bottom 3 quintiles) and high-type (top 2 quintiles)



Notes: The figure shows the net job creation rates for two productivity measures-TFP and sales per worker- for different definitions of high and low types.

Business cycle results. Table 4 presents results on how business cycle results differ between TFP and sales and across the different definitions of low and high types.

Panel (a) shows our baseline results for TFP - these are the same as reported in Table 3 - and sales per worker. Looking first at the results when using the change in unemployment as a cyclical indicator, we find that sales per worker underestimate the cyclicality of differential growth compared to TFP. A 1 pp increase in the change in unemployment increases the differential growth rate by 0.30 pp using TFP, while the effect is only 0.12 pp using sales per worker. We confirm this finding in panels (b) and (c), which describe the other ways to classify firms. In all panels, this is driven by lower responses on the nonemployment margin. Thus, as recessions begin and unemployment increases, the difference between low and high TFP firms increases more through the nonemployment margin compared to the difference between low and high sales firms.

Turning to the level of unemployment as a cyclical indicator, we find that the sign of the estimate on the total differential growth flips. Using our baseline ranking in Panel (a), the point estimate is 0.11 pp, while using sales per worker, the estimate is -0.08. This result is an important finding, as the signs on our estimates which use sales per worker are the same as those reported by Haltiwanger et al. (2021),[10] who use sales per worker on US data. Our estimates thus suggest that we get different results for TFP using Danish data, not because Denmark is different from the US, but because sales per worker measures something other than TFP.

[10]Column 1, Table 2 in Haltiwanger et al. (2021).

Table 4: Comparing TFP vs. Sales per Worker and The Cyclicality of Job Creation Rates

	Productivity (TFP)			**Sales per FTE Worker**		
	Total	Poaching	Nonemploy.	Total	Poaching	Nonemploy.
			Panel (a): Baseline			
Change in Unemp.	0.30***	-0.08*	0.38***	0.12*	-0.09	0.21***
	(0.10)	(0.04)	(0.09)	(0.07)	(0.08)	(0.06)
Level of Unemp.	0.11**	-0.02	0.13***	-0.08***	-0.15***	0.07***
	(0.05)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)
Obs.	82	82	82	82	82	82
Mean of dep. var	0.91	0.75	0.15	0.76	0.73	0.03
		Panel (b): low (1st) and high types (5th)				
Change in Unemp.	0.34***	-0.12**	0.46***	0.18**	-0.08	0.26***
	(0.12)	(0.05)	(0.11)	(0.08)	(0.08)	(0.08)
Level of Unemp.	0.16***	-0.05**	0.21***	-0.12***	-0.16***	0.04
	(0.05)	(0.02)	(0.05)	(0.03)	(0.03)	(0.04)
Obs.	82	82	82	82	82	82
Mean of dep. var	1.03	0.91	0.12	0.95	0.83	0.12
		Panel (c): low (up to 3rd) and high types (from 4th)				
Change in Unemp.	0.32***	-0.04	0.36***	0.19***	-0.04	0.23***
	(0.07)	(0.03)	(0.06)	(0.04)	(0.05)	(0.05)
Level of Unemp.	0.00	-0.07***	0.07**	-0.02	-0.09***	0.07***
	(0.03)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
Obs.	82	82	82	82	82	82
Mean of dep. var	0.53	0.52	0.01	0.56	0.52	0.03

Notes: The table shows regression estimates of an increase in either the level or the change in unemployment on differential employment growth rates (see Equation (3.3.2)). Each cell presents results from a separate regression estimated on quarterly data. The total differential employment growth rate is the sum of the poaching and the nonemployment channels. Both cyclical indicators are measured in percentage points of the change in the unemployment rate and as the level of the unemployment rate, HP-filtered. Flows are also measured in percentage points. Standard errors are presented in parentheses. Asterisks report statistical significance at the 1%,5% and 10% (***,**,* respectively).

Value added and alternative TFP measures. In Appendix Figure A.2 we report the main cross-sectional and business-cycle results using value added per worker and a simple regression based alternative TFP measure as ranking variables.[11]

For the cross-sectional results, we find that value added per worker leads to results close to TFP, but potentially slightly better in the sense that both the differential growth and poaching rates are slightly higher for value added. Using the alternative TFP

[11] In non-reported results we have also tried to rank based on profits and employment growth. We find qualitatively similar results as for TFP.

measure, we find pretty similar, but slightly worse results than for our baseline TFP measure.

Table A.3 reports the business cycle results and compares them to our baseline results. Both value added per worker and the alternative TFP measure give similar results as our baseline TFP measure. Importantly, we do not observe the sign switch using the level of unemployment as we saw for sales per worker in Table 4.

5 Conclusion

It remains an open question how to best define the job ladder empirically (Moscarini and Postel-Vinay, 2018). The two most prominent theoretically motivated possible rankings of firms are based on the firms' rank in productivity and wage distributions. It is important to distinguish between these rankings, as it can help our understanding of aggregate productivity dynamics, workers' earnings dynamics, and the determinants of good jobs. This paper provides novel evidence on this question by combining matched employer-employee data with financial data on firms to measure TFP.

Based on TFP estimated by the control function approach in Olley and Pakes (1996), we find that high productivity firms grow more relative to low productivity firms. In particular they do so through hiring (poaching) from other firms. We argue that both results suggest that the productivity ladder is a better measure of the true job ladder than the wage ladder. The cyclicality of the net job creation rate also differs between the two measures. In recessions, firms high up the wage ladder shrink more than firms at the bottom because they stop poaching workers from other firms. In this sense, the wage ladder breaks down in recessions, since reallocation up the ladder occurs less frequently. Thus, there is a sullying effect of recessions from the point of view of the wage ladder. The same is true for the productivity ladder, but to a smaller extent. The main difference between the wage and productivity ladders over the business cycle is related to non-employment flows. Both high and low productivity firms shed workers through the nonemployment channel. However, low productivity firms stop hiring from nonemployment to a greater extent in recessions than high productivity firms. They also separate more workers to nonemployment. Both factors lead to a cleansing effect of recessions in terms of less reallocation through unemployment to low productivity firms.

Importantly, we show that the cleansing effect of recessions would not emerge, at least not as strongly as we find, using less direct productivity measures, such as sales per worker.

References

Abowd, John, Francis Kramarz, and David Margolis, "High wage workers and high wage firms," *Econometrica*, 1999, *67* (2), 251–333.

Ackerberg, Daniel, Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Audoly, Richard, "Firm Dynamics and Random Search over the Business Cycle," Technical Report, Discussion paper, University College London 2020.

Bachmann, Rüdiger, Christian Bayer, Christian Merkl, Stefan Seth, Heiko Stüber, and Felix Wellschmied, "Worker churn in the cross section and over time: New evidence from Germany," *Journal of Monetary Economics*, 2021, *117*, 781–797.

Bagger, Jesper and Rasmus Lentz, "An empirical model of wage dispersion with sorting," *The Review of Economic Studies*, 2019, *86* (1), 153–190.

_ , Bent Jesper Christensen, and Dale Mortensen, "Productivity and Wage Dispersion: Heterogeneity or Misallocation?," *Working Paper*, 2014.

Barlevy, Gadi, "The sullying effect of recessions," *The Review of Economic Studies*, 2002, *69* (1), 65–96.

Bertheau, Antoine, "Employer Search Behavior: Reasons for Internal Hiring," *Labour Economics*, 2021, *73*, 102064.

_ and Rune Vejlin, "Employer-to-Employer Transitions and Time Aggregation Bias," *Labour Economics*, 2022, *75*, 102130.

_ , Edoardo Acabbi, Cristina Barcelo, Andreas Gulyas, Stefano Lombardi, and Raffaele Saggio, "The Unequal Consequences of Job Loss Across Countries," *American Economic Review: Insights*, Accepted 2022.

_ , Henning Bunzel, and Rune Vejlin, "Employment Reallocation Over the Business Cycle: evidence from Danish Data," *IZA Discussion Paper No. 13681*, 2020.

_ , Marianna Kudlyak, Birthe Larsen, and Morten Bennedsen, "Why Firms Lay Off Workers instead of Cutting Wages : Evidence from Matched Survey-Administrative Data," *Working Paper, available at SSRN with this link*, 2022.

Bloesch, Justin, Birthe Larsen, and Bledi Taska, "Which Workers Earn More at Productive Firms? Position Specific Skills and Individual Worker Hold-up Power," *Available on Bloesch's website*, 2022.

Bonhomme, Stéphane, Thibaut Lamadon, and Elena Manresa, "A distributional framework for matched employer employee data," *Econometrica*, 2019, *87* (3), 699–739.

Botero, Juan, Simeon Djankov, Rafael La Porta, Florencio Lopez de Silanes, and Andrei Shleifer, "The regulation of labor," *The Quarterly Journal of Economics*, 2004, *119* (4), 1339–1382.

Burdett, Ken and Melvyn Coles, "Equilibrium Wage-Tenure Contracts," *Econometrica*, 2003, *71* (5), 1377–1404.

Burdett, Kenneth and Dale Mortensen, "Wage differentials, employer size, and unemployment," *International Economic Review*, 1998, pp. 257–273.

Caldwell, Sydnee and Nikolaj Harmon, "Outside options, bargaining, and wages: Evidence from coworker networks," 2019.

Card, David, Ana Rute Cardoso, Jörg Heining, and Patrick Kline, "Firms and labor market inequality: Evidence and some theory," *Journal of Labor Economics*, 2018, *36* (S1), S13–S70.

Clymo, Alex and Filip Rozsypal, "Firm Cyclicality and Financial Frictions," 2022.

Dahl, Christian, Daniel Le Maire, and Jakob Munch, "Wage Dispersion and Decentralization of Wage Bargaining," *Journal of Labor Economics*, 2013, *31* (3), 501–533.

Elsby, Michael, Bart Hobijn, and Ayşegül Şahin, "Unemployment dynamics in the OECD," *Review of Economics and Statistics*, 2013, *95* (2), 530–548.

Engbom, Niklas, "Labor Market Fluidity and Human Capital Accumulation," *Mimeo*, 2021.

Faberman, Jason, Andreas Mueller, Ayşegül Sahin, and Giorgio Topa, "Job Search Behavior among the Employed and Non-Employed," *Econometrica*, 2022, *90* (4), 1743–1779.

Faccini, Renato and Leonardo Melosi, "Bad jobs and low inflation," 2021.

Foster, Lucia, Cheryl Grim, and John Haltiwanger, "Reallocation in the Great Recession: Cleansing or Not?," *Journal of Labor Economics*, 2016, *34* (S1 Part 2), S293–S331.

Fujita, Shigeru and Garey Ramey, "The cyclicality of separation and job finding rates," *International Economic Review*, 2009, *50* (2), 415–430.

—, Giuseppe Moscarini, and Fabien Postel-Vinay, "Measuring Employer-to-Employer Reallocation," *NBER Working Paper*, July 2020, (27525).

Groes, Fane, Philipp Kircher, and Iourii Manovskii, "The U-shapes of occupational mobility," *The Review of Economic Studies*, 2014, *82* (2), 659–692.

Haltiwanger, John C, Henry R Hyatt, Erika McEntarfer, and Matthew Staiger, "Cyclical Worker Flows: Cleansing vs. Sullying," Working Paper 28802, National Bureau of Economic Research May 2021.

Haltiwanger, John, Henry Hyatt, and Erika McEntarfer, "Do Workers Move Up the Firm Productivity Job Ladder?," in "Firms and the Distribution of Income: The Roles of Productivity and Luck" 2015.

—, —, Lisa Kahn, and Erika McEntarfer, "Cyclical job ladders by firm size and firm wage," *American Economic Journal: Macroeconomics*, 2018, *10* (2), 52–85.

—, —, —, and —, "Cyclical job ladders by firm size and firm wage," *American Economic Journal: Macroeconomics*, 2018, *10* (2), 52–85.

Hopenhayn, Hugo, "Entry, exit, and firm dynamics in long run equilibrium," *Econometrica*, 1992, pp. 1127–1150.

Kudlyak, Marianna and Juan M Sanchez, "Revisiting the behavior of small and large firms during the 2008 financial crisis," *Journal of Economic Dynamics and Control*, 2017, *77*, 48–69.

Lentz, Rasmus and Dale Mortensen, "An empirical model of growth through product innovation," *Econometrica*, 2008, *76* (6), 1317–1373.

Levinsohn, James and Amil Petrin, "Estimating production functions using inputs to control for unobservables," *The Review of Economic Studies*, 2003, *70* (2), 317–341.

Lise, Jérémy and Jean Marc Robin, "The Macro-dynamics of Sorting between Workers and Firm," *The American Economic Review*, 2017, *107* (4), 1104–1135.

Lochner, Benjamin and Bastian Schulz, "Firm Productivity, Wages, and Sorting," *Journal of Labor Economics*, Forthcoming.

Lydon, Reamonn and Michael Simmons, "The ins and outs of the gender unemployment gap in the OECD," *Working paper. Central Bank of Ireland (No.10).*, 2020.

Maibom, Jonas and Rune Vejlin, "Passthrough of firm performance to income and employment stability," 2021.

Mortensen, Dale and Christopher Pissarides, "Job creation and job destruction in the theory of unemployment," *The review of economic studies*, 1994, *61* (3), 397–415.

Moscarini, Giuseppe and Fabien Postel-Vinay, "The contribution of large and small employers to job creation in times of high and low unemployment," *The American Economic Review*, 2012, *102* (6), 2509–2539.

— and —, "Stochastic search equilibrium," *Review of Economic Studies*, 2013, *80* (4), 1545–1581.

— and —, "The Cyclical Job Ladder," *Annual Review of Economics*, 2018, *10* (1), 165–188.

Mueller, Andreas, "Separations, Sorting, and Cyclical Unemployment," *American Economic Review*, 2017, *107* (7), 2081–2107.

Olley, Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 1996, *64* (6), 1263–1297.

Postel-Vinay, Fabien and Jean-Marc Robin, "Equilibrium wage dispersion with worker and employer heterogeneity," *Econometrica*, 2002, *70* (6), 2295–2350.

Shimer, Robert, "Reassessing the ins and outs of unemployment," *Review of Economic Dynamics*, 2012, *15* (2), 127–148.

Sorkin, Isaac, "Ranking Firms Using Revealed Preference," *The Quarterly Journal of Economics*, 2018, *133* (3), 1331–1393.

Syverson, Chad, "What Determines Productivity?," *Journal of Economic Literature*, 2011, *49* (2), 326–365.

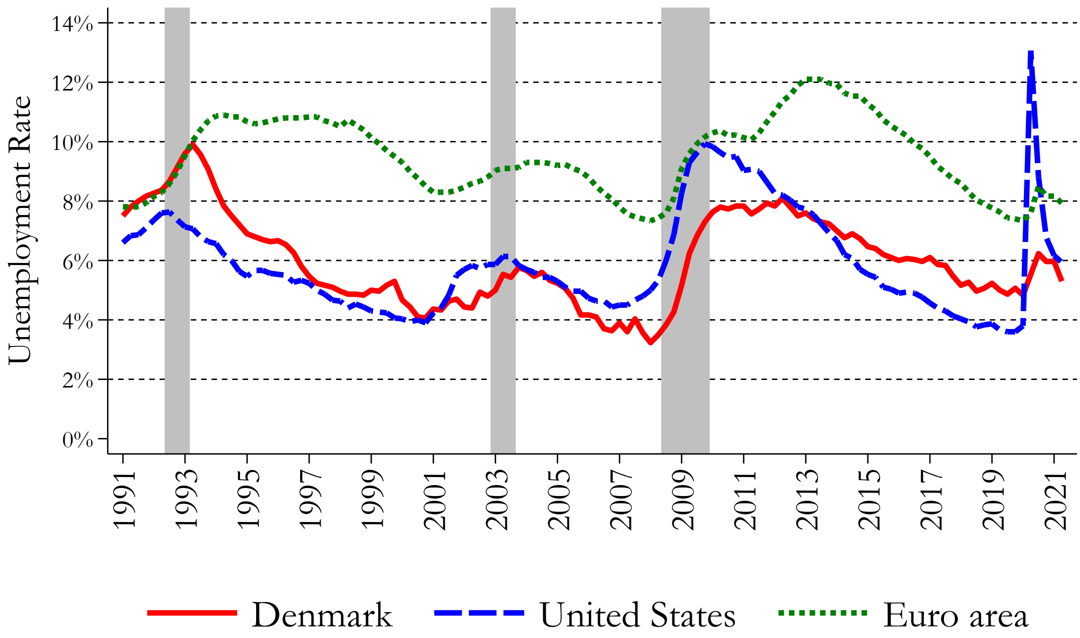
Taber, Christopher and Rune Vejlin, "Estimation of a Roy/Search/Compensating Differential Model of the Labor Market," *Econometrica*, 2020, *88* (3), 1031–1069.

Züllig, Gabriel, "Heterogeneous Employment Effects of Firms' Financial Constraints and Wageless Recoveries," *Available on Zullig's website*, 2022.

A Additional Tables and Figures

A.1 Figures

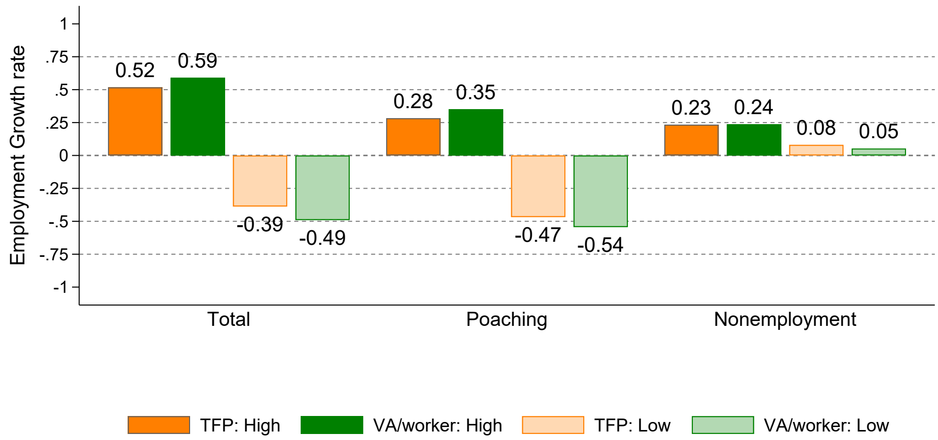
Figure A.1: Unemployment in Denmark, in the US, and in the Euro area



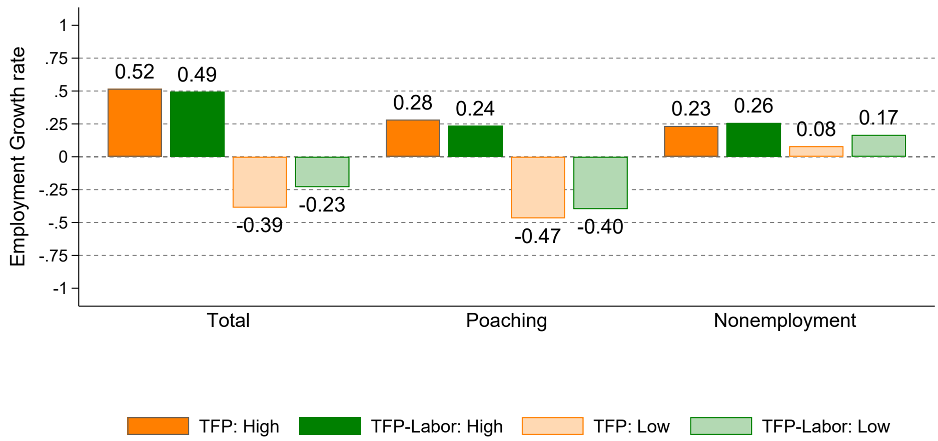
Notes: The figure shows the unemployment rate for Denmark, the US and the Euro area constructed from the OECD series "Quarterly Harmonized unemployment rate". Grey areas denote episode recessions (1992Q3-1993Q1, 2003Q1-2003Q3, and 2008Q3-2009Q4).

Figure A.2: Alternative Classification of Firm Types and Job Creation rate: Value Added per Worker and Alternative TFP Measure

(a) Value added per worker



(b) Alternative TFP Masure



Notes: Panel (a) shows the quarterly job creation rates when ranking using value added per worker. Panel (b) measures TFP using an OLS regression. High type are defined as firms in the top two quintiles, and low type are firms in the bottom quintile. Quintiles are employment-weighted.

A.2 Tables

Table A.1: Correlation Between Firm Characteristics: Firms with at least 20 employees

Panel (a): Firms with at least 20 employees					
	TFP	VA per worker	Sales per worker	Wage per worker	Size
TFP	1.00	0.60	0.44	0.43	0.20
VA per worker	0.60	1.00	0.67	0.51	0.01
Sales per worker	0.44	0.67	1.00	0.41	0.03
Wage per worker	0.43	0.51	0.41	1.00	0.14
Size	0.20	0.01	0.03	0.14	1.00
Panel (B): Firms which are at least 10 years old					
	TFP	VA per worker	Sales per worker	Wage per worker	Size
TFP	1.00	0.60	0.47	0.32	0.06
VA per worker	0.60	1.00	0.74	0.44	-0.22
Sales per worker	0.47	0.74	1.00	0.36	-0.14
Wage per worker	0.32	0.44	0.36	1.00	0.12
Size	0.06	-0.22	-0.14	0.12	1.00

Notes: The table shows the Spearman rank correlations between TFP, value added per worker, sales per worker, and wage per worker and firm size. "Per worker" measures are full-time equivalent. The correlations are worker-year weighted. Table 1 shows Spearman correlation for all firms.

Table A.2: Key Firm Characteristics Across Groups

		Wages		**TFP**		**Value Added**	
	All	Low	High	Low	High	Low	High
Size	14	11	16	10	21	14	11
Sales per worker	299	226	462	223	532	182	444
Wage	48	39	67	45	57	42	55
Value added per worker	97	75	147	71	176	55	149
Age	15	15	15	15	14	15	15
Manufacturing	16	17	15	17	15	19	13
Services	21	21	23	21	24	20	24
Other services	21	21	23	21	24	20	24
Observations	1546376	1063530	472700	1155866	377138	848665	684719

Notes: The table shows descriptive statistics for the full sample as well as for groups of firms defined by average hourly wages, sales per worker, or value added per worker. Firms are ranked based on within-industry comparisons.

Table A.3: Cyclicality of Net Differential Growth Rates: Value Added per Worker and Alternative TFP measure

Panel (a): Value Added per Worker						
	Productivity (TFP)			**Value added per worker**		
	Total	Poaching	Nonemployment	Total	Poaching	Nonemployment
Change in Unemp.	0.30***	-0.08*	0.38***	0.26**	-0.08	0.34***
	(0.10)	(0.04)	(0.09)	(0.10)	(0.08)	(0.07)
Level of Unemp.	0.11**	-0.02	0.13***	0.02	-0.12***	0.14***
	(0.05)	(0.02)	(0.04)	(0.05)	(0.03)	(0.03)
Obs.	82	82	82	82	82	82
Mean of dep. var	0.91	0.75	0.15	1.08	0.90	0.18

Panel (b): Alternative TFP Measure						
	Productivity (TFP)			**Alternative TFP measure**		
	Total	Poaching	Nonemployment	Total	Poaching	Nonemployment
Change in Unemp.	0.30***	-0.08*	0.38***	0.21***	-0.06	0.27***
	(0.10)	(0.04)	(0.09)	(0.07)	(0.04)	(0.07)
Level of Unemp.	0.11**	-0.02	0.13***	0.03	-0.06***	0.09***
	(0.05)	(0.02)	(0.04)	(0.03)	(0.02)	(0.03)
Obs.	82	82	82	82	82	82
Mean of dep. var	0.91	0.75	0.15	0.73	0.64	0.09

Notes: The table shows regression estimates of an increase in either the level or the change in the unemployment rate on the differential employment growth rates (see Equation (3.3.2)). The total differential employment growth rate is the sum of the poaching and the nonemployment channels. Both cyclical indicators are measured in percentage points of the change in the unemployment rate and as the level of the unemployment rate, HP-filtered. Asterisks report statistical significance at the 1,5 and 10% (***,**,* respectively). Panel (a) report estimates using value added per worker as a ranking measure, while Panel (b) use an alternative TFP measure, which is the residual from an OLS regression.

B Institutional Setting and Data Sources

B.1 Institutional Setting

A full-time job in Denmark consists of 37 hours worked per week and around 1800 per year. Although hours worked are low, the participation rate is around 84 percent in 2021, which is higher than the European Union or the United States average. Furthermore, the public sector is large, employing around 30% of all workers, and social security is strong. Both are typical of a Scandinavian welfare state. Some large shocks hit the Danish labor market in the early 1990s. First, the Nordic banking crisis impacted the employment of the finance and insurance industry; see Bennett and Ouazad (2019). Second, manufacturing employment declined in some industries targeted by the Uruguay round of negotiations that ended in 1994. Third, a wave of structural reforms, starting in 1994, impacted workers' rights to benefits (Jespersen et al. (2008)).

The Danish labor market is known for its so-called flexicurity, which consists of low employment protection, a strong social safety net, and workfare requirements. Although lax employment protection and generous unemployment insurance have been in place since the 1970s, the implementation of a string of workfare reforms in the 1990s is considered to have changed the structural level of unemployment (Andersen and Svarer, 2007).

B.2 Construction of Employment spell data

The labor market history dataset ("the job spell" data) that we use covers all individuals living in Denmark. Henning Bunzel built the spell data jointly with Mads Hejlesen. To construct employment spells at daily frequency, we combine different registers. 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 identification number 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.

Work history is based on several registers containing employment spells reported by employers. Employers must report employment spells to 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 used firms' annual reports for each individual to SKAT (the Central Information Sheet, *Oplysningssedler*, `CONESR`). Each employment spell is identified at the (worker identifier, establishment identifier, year) level with information on the employment period. Employers do not have to fill out days of start and end of employment spells for workers with several different employment spells. We use Statistics Denmark registers of data `CONS`, `MIANPNR`, and `RAS` from 1985 to 2007. From 2008 we use the dataset `BFL` provided by Denmark Statistics. 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 2005, and RAS contains employment records for 2006 and 2007. When employers do not have to fill out days of start and end of employment spells, the SPELL data set the start date equal to January 1 and the end date equal to December 31 of the given year. These artificial start and end date values lead to employment being too wide in that it covers the employment period and the time when a person has not worked.

To reduce measurement errors, we used an additional data source (`MIAPNR`) with employment information at the monthly level, but without exact dates, earnings, and hours worked information. This additional dataset is considered reliable because it is used to construct National Accounts. Denmark Statistics gets monthly information from all establishments about persons working there in a given month.

In 2008, SKAT introduced the e-income register data (*E-indkomst*), to reduce the red-tape costs for firms by avoiding reporting the same information to different authorities. E-indkomst is registered in the BFL dataset. Therefore, from 2008, hours worked, labor earnings, and employment spell periods are collected at the monthly frequency in a single dataset (*Beskæftigelse for Lønmodtagere*, `BFL`). This work contrasts with most papers using Danish data that use IDA, which is a yearly cross-sectional data set, to build employer-to-employer transitions (Jinkins and Morin, 2018).

B.3 Worker and Firm registers

We use the dataset `FIGF` (*Firmastatistik regnskabsdata*) from 1992 to 1998, and the dataset `FIRM` (*Generel firmastatistik*) from 1999. `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. 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.Andersen and Sőresen (2012) provides an introduction to the legislative framework. The basic components of the income and balance sheet statements are reported in the registers FIGF and FIRM. The variable used to define value added consists of revenue minus costs (the names of the variables are VT in FIGF and GF-VTV in FIRM).

C Related Studies

Worker flows. The literature on worker mobility is mature and has mainly used household surveys on the worker side (Akerlof et al., 1988; Fallick and Fleischman, 2004) and employer surveys on the employer side (Davis, Faberman and Haltiwanger, 2006). This literature is descriptive and serves several purposes. First, it sheds light on the unemployment dynamics, e.g., Davis and Haltiwanger (1990); Elsby et al. (2013); Lydon and Simmons (2020); Shimer (2012). Household surveys allow us to study participation margin (Faberman et al., 2020), involuntary part-time (Borowczyk-Martins and Lalé, 2019), and labor market underutilization (Hornstein, Kudlyak and Lange, 2014). Firm-level data shed light on the link between worker flows and job flows.

Job flows and worker flows. A series of papers links job flows to worker flows in the US (e.g. Burgess et al. (2000); Davis et al. (2006, 2012)). A notable feature of the data is that hiring and separation rates are plotted as functions of establishment-level growth rates, exhibiting nonlinear "hockey-stick" shapes. Bachmann et al. (2021), after documenting the extent and the procyclicality of churn, they show that churn does not seem to be related to reorganization, as churn is mainly driven by workers occupying jobs with similar characteristics. Tanaka et al. (Forthcoming) show that workers' earnings increase as a function of firm growth rates, particularly when workers move to a faster-growing firm.

The cleansing vs. sullying effects of recessions. Haltiwanger et al. (2015) uses sales per worker as a proxy for productivity and study transition rates in the Great Recession.[12] Haltiwanger et al. (2018a) find that workers of all educational levels move from low productivity to high productivity firms and do so more frequently during expansions. In the same vein, Foster et al. (2016) document a cleansing effect of recessions in the manufacturing sector in the United States and note that reallocation in the Great Recession differs markedly from that of earlier recessions. They conjecture the role of credit frictions in Barlevy (2002); Osotimehin and Pappadà (2017).

[12] An earlier literature use household data to study cleansing effects of recessions. Given the lack of firm-level productivity data, the duration of the job is taken as a proxy of the quality of the match, as in Bowlus (1995). She finds that jobs that start during a recession have shorter durations, implying procyclical match quality. This result has been taken as empirical evidence for the sullying effect (as opposed to the cleansing effect) of recessions in the literature. See also Baydur and Mukoyama (2020).

Theoretical framework linking firm dynamics and employer-to-employer mobility. In Moscarini and Postel-Vinay (2013), the firm's size is entirely determined by the ability of the firm to attract and retain workers. Shimer (2009) discuss other limitations of firm size, such as credit constraint, the availability of workers with appropriate human capital, technology, and span of control. Large firms should be able to poach more than small firms. This is not what Haltiwanger et al. (2018b) and Bertheau et al. (2020) find in the US and Danish data, respectively. Coles and Mortensen (2016) build a model in which firms' strategies are independent of the firm size. The trick is to use constant returns to scale recruitment cost technology to establish size independence in the firm's policies. In Moscarini and Postel-Vinay (2013), the hiring cost function is: $C(H, n) = AH^{\gamma}$ with $\gamma > 1$. Therefore, large firms, which have a higher turnover of workers and, therefore, on average, hire more, face higher marginal costs of hiring (Carrillo-Tudela and Coles, 2016). Audoly (2020) is the theoretical framework closest to this paper. He builds on the framework in Coles and Mortensen (2016), but allows endogenous firm entry and exit and search efforts to differ between employed and unemployed workers. In an empirical application, Audoly (2020) uses the Business Structure Database, which is a snapshot of the registry of all British companies, but this data set does not contain value-added or labor costs at the firm level. Two related theoretical models have predictions on net poaching by firm types. In Gottfries and Elsby (2019), the firm problem is normalized to a single variable: the marginal product of labor. Vacancy costs are linear, and there are no entry and exit decisions. In Bilal et al. (2022), the relevant variable is the marginal joint value of a firm and its workers. This includes current and future marginal products of labor, worker mobility, exit, market tightness, the composition of vacancies and workers across firms, and unemployment. If firms are endowed with CRS technology, the firm's exogenous productivity fully determines its position on the job ladder. Figure 10 (Panel C) shows that the net poaching rate should increase with labor productivity and employment growth.

References

Akerlof, George, Andrew Rose, and Janet Yellen, "Job switching and job satisfaction in the US labor market," *Brookings papers on economic activity*, 1988, *1988* (2), 495–594.

Andersen, Paul Krüger and Evelyne J.B Sôresen, "The Danish Companies Act: A modern and competitive European Law," 2012.

Andersen, Torben and Michael Svarer, "Flexicurity: labour market performance in Denmark," *CESifo Economic Studies*, 2007, *53* (3), 389–429.

Audoly, Richard, "Firm Dynamics and Random Search over the Business Cycle," Technical Report, Discussion paper, University College London 2020.

Bachmann, Rüdiger, Christian Bayer, Christian Merkl, Stefan Seth, Heiko Stüber, and Felix Wellschmied, "Worker churn in the cross section and over time: New evidence from Germany," *Journal of Monetary Economics*, 2021, *117*, 781–797.

Barlevy, Gadi, "The sullying effect of recessions," *The Review of Economic Studies*, 2002, *69* (1), 65–96.

Baydur, Ismail and Toshihiko Mukoyama, "Job duration and match characteristics over the business cycle," *Review of Economic Dynamics*, 2020, *37*, 33–53.

Bennett, Patrick and Amine Ouazad, "Job displacement, unemployment, and crime: Evidence from danish microdata and reforms," *Journal of the European Economic Association*, 2019.

Bertheau, Antoine, Henning Bunzel, and Rune Vejlin, "Employment Reallocation Over the Business Cycle: evidence from Danish Data," *IZA Discussion Paper No. 13681*, 2020.

Bilal, Adrien, Niklas Engbom, Simon Mongey, and Giovanni Violante, "Firm and worker dynamics in a frictional labor market," *Econometrica*, 2022, *90* (4), 1425–1462.

Borowczyk-Martins, Daniel and Etienne Lalé, "Employment adjustment and part-time work: Lessons from the United States and the United Kingdom," *American Economic Journal: Macroeconomics*, 2019, *11* (1), 389–435.

Bowlus, Audra, "Matching workers and jobs: Cyclical fluctuations in match quality," *Journal of Labor Economics*, 1995, *13* (2), 335–350.

Burgess, Simon, Julia Lane, and David Stevens, "Job flows, worker flows, and churning," *Journal of labor economics*, 2000, *18* (3), 473–502.

Carrillo-Tudela, Carlos and Melvyn Coles, "13. Quit turnover and the business cycle: a survey," *Research Handbook on Employee Turnover*, 2016, p. 247.

Coles, Melvyn and Dale Mortensen, "Equilibrium Labor Turnover, Firm Growth, and Unemployment," *Econometrica*, 2016, *84* (1), 347–363.

Davis, Steven and John Haltiwanger, "Gross job creation and destruction: Microeconomic evidence and macroeconomic implications," in "NBER Macroeconomics Annual 1990, Volume 5," MIT Press, 1990, pp. 123–186.

_ , Jason Faberman, and John Haltiwanger, "The Flow Approach to Labor Markets: New Data Sources and Micro-Macro Links," *The Journal of Economic Perspectives*, 2006, pp. 3–26.

_ , _ , and _ , "Labor market flows in the cross section and over time," *Journal of Monetary Economics*, 2012, *59* (1), 1–18.

Elsby, Michael, Bart Hobijn, and Ayşegül Şahin, "Unemployment dynamics in the OECD," *Review of Economics and Statistics*, 2013, *95* (2), 530–548.

Faberman, R Jason, Andreas I Mueller, Ayşegül Şahin, and Giorgio Topa, "The Shadow Margins of Labor Market Slack," *Journal of Money Credit and Banking*, 2020.

Fallick, Bruce and Charles Fleischman, "Employer-to-employer flows in the US labor market: The complete picture of gross worker flows," *Available at SSRN 594824*, 2004.

Foster, Lucia, Cheryl Grim, and John Haltiwanger, "Reallocation in the Great Recession: Cleansing or Not?," *Journal of Labor Economics*, 2016, *34* (S1 Part 2), S293–S331.

Gottfries, Axel and Mike Elsby, "Firm Dynamics, On-the-Job Search and Labor Market Fluctuations," *Working Paper*, 2019.

Haltiwanger, John, Henry Hyatt, and Erika McEntarfer, "Do Workers Move Up the Firm Productivity Job Ladder?," in "Firms and the Distribution of Income: The Roles of Productivity and Luck" 2015.

_, _, and _, "Who moves up the job ladder?," *Journal of Labor Economics*, 2018, *36* (S1), S301–S336.

_, _, Lisa Kahn, and Erika McEntarfer, "Cyclical job ladders by firm size and firm wage," *American Economic Journal: Macroeconomics*, 2018, *10* (2), 52–85.

Hornstein, Andreas, Marianna Kudlyak, and Fabian Lange, "Measuring resource utilization in the labor market," *FRB Economic Quarterly*, 2014, *100* (1), 1–21.

Jespersen, Svend, Jakob Munch, and Lars Skipper, "Costs and benefits of Danish active labour market programmes," *Labour economics*, 2008, *15* (5), 859–884.

Jinkins, David and Annaïg Morin, "Job-to-job transitions, sorting, and wage growth," *Labour Economics*, 2018, *55*, 300–327.

Lydon, Reamonn and Michael Simmons, "The ins and outs of the gender unemployment gap in the OECD," *Working paper. Central Bank of Ireland (No.10).*, 2020.

Moscarini, Giuseppe and Fabien Postel-Vinay, "Stochastic search equilibrium," *Review of Economic Studies*, 2013, *80* (4), 1545–1581.

Osotimehin, Sophie and Francesco Pappadà, "Credit frictions and the cleansing effect of recessions," *The Economic Journal*, 2017, *127* (602), 1153–1187.

Shimer, Robert, "Comment on " The Timing of Labor Market Expansions: New Facts and a New Hypothesis"," *NBER Chapters*, 2009.

_, "Reassessing the ins and outs of unemployment," *Review of Economic Dynamics*, 2012, *15* (2), 127–148.

Tanaka, Satoshi, Lawrence Warren, and David Wiczer, "Earnings growth, job flows and churn," *Journal of Monetary Economics*, Forthcoming.