Job Ladders by Firm Wage and Productivity *

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Using a unique dataset that combines daily employment spell information with firm-level accounting data from Denmark, we explore workers' progression up firm wage and productivity ladders. We find that: (1) Total Factor Productivity (TFP) emerges as a more effective indicator of the job ladder than the average wage paid, with more workers experiencing employer-to-employer transitions from lower to upper tiers of the productivity ladder compared to the wage ladder. (2) Recessions have a cleansing effect when using the productivity job ladder: Lower productivity firms experience a steeper decline in employment growth compared to their higher-tier counterparts. In contrast, due to decreased poaching, high wage firms exhibit greater employment reductions, leading to a sullying effect when using the wage job ladder. High productivity firms also experience greater employment cyclicality due to decreased poaching during recessions. However, firms at the lower end of the productivity spectrum face a more pronounced employment reduction during recessions as they intensify layoffs and reduce hiring from the unemployment pool. (3) Indirect productivity measures, such as sales per worker, can hide or even reverse the cleansing effect of recessions.

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1 Introduction

It takes time and resources for workers to find their preferred jobs. Consequently, many workers continue to look for jobs while in employment and quit when a better opportunity arises (Faberman et al., 2022). The prevalence of on-the-job search in the economy has had a profound impact on 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.

How does job creation by firm type vary in the cross-section and over the business cycle? Do recessions slow down the reallocation process into better firms? The answers have implications for assessing the cost of recession and for models of aggregate fluctuations in the labor market in general.

We provide new evidence on these questions, which have primarily remained open due to two main data challenges. The first challenge is measuring heterogeneity in firms' characteristics, which can be used to rank the firms. In particular, theories of firm and wage dynamics often use productivity as the underlying state that impacts a firm's 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 access to 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 different productivity, measured by total factor productivity (TFP).[1]

This paper offers three main results. First, we argue that the firm productivity job ladder measured by TFP is better than the wage job ladder. We offer two pieces of evidence. First, the difference in growth rates between high and low productivity 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 com-

[1]We use the control function approach by Olley and Pakes (1996) and explore several ranking methods. The main results are not affected by these specifications.

pared 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.[2]

Our second contribution is to document a cleansing effect of recessions: Low productivity firms shed more employment during recessions than high productivity firms when using both the level and change in unemployment as measures for recessions.[3] When the unemployment rate increases by one percentage point, the difference in the job creation rate between high and low productivity firms increases by 0.29 percentage points. This corresponds to an increase of 32% compared to the average differential net job creation rate between high and low productivity firms. Two channels drive this cleansing effect of recessions: the destruction of jobs in low productivity firms through nonemployment, as hypothesized in, e.g., Mortensen and Pissarides (1994), and a lower hiring rate than high productivity firms. This second channel is quantitatively important and suggests that labor market business cycle models should encompass a mechanism to generate this observation. A model with exogenous arrival rates will have difficulty 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' net poaching rates becomes smaller during recessions. This suggests that the productivity job ladder, to some extent, breaks down during recessions causing a sullying effect.[4] This observation is in line with models such as Audoly (2023) and Moscarini and Postel-Vinay (2013), which suggest that during 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 0.11 percent when unemployment increases by one percentage point. This evidence suggests that high wage firms are more cyclically sensitive, in line with findings by Mueller (2017) showing 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 using average wage paid and productivity as measures to identify the job ladder rungs provide different conclusions as to which jobs are more

[2]This assertion rests on the common assumption that poaching flows (employer-to-employer transitions) reflect voluntary transition and can thus be used as a revealed preference of the job ladder. Section 3.2 discusses the evidence supporting this assumption.

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

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

affected by aggregate fluctuations in the labor market.

Our third contribution is to document that the way in which we measure productivity matters. With less direct productivity measures, such as sales per worker, we draw different conclusions about the cyclicality of the productivity 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 0.29 pp. Using sales per worker, the difference is 0.12 pp. Accordingly, using sales per worker as a measure of productivity produces an estimate that is significantly lower than when using TFP. Interestingly, we get different signs for 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 0.07 pp, while using sales per worker reduces it by 0.08. We consider this result to be the first evidence that different productivity measures alter the extent of the measured importance of productivity-enhancing reallocation.[5]

Our data is particularly suited to answering questions about what characteristics best define the job ladder and how different types of firms 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, and age). 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 rather than at the industry level. Overall, the data availability and the macroeconomic and institutional environment make the Danish labor market an ideal setting in which to answer our research questions.

Related studies. This paper contributes to a growing body of literature that utilizes microdata to unravel employment dynamics, and builds on studies by, e.g., Haltiwanger et al. (2021, 2018). Haltiwanger et al. (2018) decompose job flows into employer-

[5]We show that our results are robust to different specifications. Specifically, we present results for different thresholds of high and low firm types, and productivity measures.

to-employer and nonemployment margins by firm size and wage. They conclude that firm wage is a better predictor of the job ladder than firm size. Haltiwanger et al. (2021) use an accounting decomposition to investigate the sources of aggregate productivity growth. They find evidence of both sullying and cleansing effects of recessions, using sales per worker as a proxy for productivity.[6]

Audoly (2023) and Moscarini and Postel-Vinay (2013) are the studies closest to ours in terms of the theoretical framework.[7] In a calibration, Audoly (2023) 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 rate is high, as the probability of workers obtaining an offer from a high productivity firm is reduced as they compete with more unemployed workers. Since quits are always productivity enhancing in this model, aggregate shocks will produce sullying effects (i.e., a dampening of reallocation to more productive firms).

Our paper is also related to studies that seek to identify the characteristics of good jobs (integrating offered wages and nonwage job values). Sorkin (2018) and Taber and Vejlin (2020) identify good firms using employer-to-employer transitions, but do not provide evidence of whether better firms are highly productive firms, while Lochner and Schulz (2023) focus on sorting and show that sorting high-ability workers into high productivity firms is less pronounced than sorting into high wage firms.

Overall, this paper complements the literature by studying workers' progression up firm wage and productivity ladders using a unique dataset that combines daily employment spell information with firm-level accounting data from a European country. To our knowledge, this is the first study to provide such evidence.

The paper proceeds as follows. Section 2 presents the institutional setting, methodology and data. Section 3 presents results on the pace and cyclicality of job creation rates across firms. Section 4 shows how results differ with less direct productivity measures, and Section 5 concludes.

[6]Other studies in this literature focus on the differences between small and large firms. Moscarini and Postel-Vinay (2012) show that the job creation rate of large firms shrinks more than small firms 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 crisis. Using Danish data, Clymo and Rozsypal (2023) find that among the youngest firms, small firms are more cyclical than large, while the reverse is true among older firms. Other literature links job flows to worker flows, see, e.g, Bachmann et al. (2021).

[7]See also Acabbi et al. (2023) for a model in a directed search framework. The role of employer-to-employer has recently been studied in richer macroeconomic models; see, for example, Faccini and Melosi (2023). Appendix C provides additional references related to this paper.

2 Institutional Setting, Data, and Measures of Wages and Productivity

This section presents the relevant institutional setting of the Danish labor market, the features of the financial account data and employment spell data, and how we define firm wage and productivity.

2.1 Some Features of the Danish Labor Market

Several features make Denmark a good environment in which to study employment reallocation. The labor market institutions resemble the US institutions more than other countries in continental Europe and there are few regulations regarding hiring and firing. For example, advanced notice regulations for layoffs are typically short.[8] The level of worker mobility is also closer to the US labor market than other European labor market.[9]

Since the mid-1990s, the unemployment rate in Denmark has been lower and more volatile than the unemployment rate in the Euro area, as seen in Figure A.1. Although most workers are unionized, wage negotiations have been decentralized at the firm level since the 1990s (Dahl et al. (2013)). Overall, the combination of a flexible labor market and rich register data provide an ideal setting in which to answer our research questions. Appendix B.1 contains more information about the Danish labor market and institutions.

2.2 Data: Linked Financial Accounts and Employment Spell Data

We construct a unique dataset from administrative records of workers and firms. The resulting data contain detailed information on each job (hours worked, earnings, daily employment dates) and details about the employing firm (sales, value added, labor costs, capital stock, age, and industry). Appendix B.2 contains details about the data construction, but we will briefly describe the sources and sample selection in the following.

Employment spell data. The daily employment spell data come from several administrative datasets, which we merged and processed. The data record all employment relationships on a daily basis from 1992 to 2013. Unfortunately, the employment

[8] In contrast to European countries where firm financial data are available (such as France or Italy), the Danish labor market is not segmented by contract type (permanent vs. temporary contracts).

[9] Engbom (2022) shows that a Dane is much more likely to make a voluntary employer-to-employer transition compared to a French or an Italian worker.

spell data do not cover the period after 2013. Each observation in the dataset 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.[10] Due to the daily frequency of the data, we have the exact timing of each employment spell, which reduces the measurement error causing what is known as time-aggregation bias. This feature of the data eases the distinction between employer-to-employer transitions and transitions involving a nonemployment period.

Accounting firm data. We link the employment spell data with annual administrative panel data on firms' financial accounts reported from 1992. We use the registers FIRM from 1999 and, for earlier years, 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 defined as revenue net of intermediate input costs.[11]

Sample selection. Statistics Denmark gradually started to include industries in the register from 1992 and only contains all industries from 1999 onward. To extend the panel, we select the industries present in the data from 1992. These are manufacturing, services, and trade. This is the only sample selection that we impose and we include all workers employed in these industries. Importantly, since the employment 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.

[10] The primary job is the job where the worker spends the most time working aggregated over the current and the subsequent two months. We correct for fictitious transitions driven by a change of firm identifiers.

[11] The definition of value added changes slightly over the years due to changes in accounting legislation, but it is, in general, defined as revenue (sales, work done within the firm, and change in inventory) minus intermediate input costs (e.g., purchases of intermediate goods, raw materials, energy, and diverse expenses).

2.3 Measures of Firm Wage and Productivity

In job ladder models such as Burdett and Mortensen (1998) and Postel-Vinay and Robin (2002), a firm's average wage and productivity are key characteristics. We now explain how these are measured in our data.

Measurement of productivity. We assume a Cobb-Douglas 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 log of the value added of a firm j in year t. $\mathbf{w}_{jt}$ is a vector of control variables for labor input including the log of the number of employees measured in 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} and ε_{jt} are both unobserved effects for the econometrician, but the firm observes ω_{jt}. Thus, ω_{jt} is correlated with the choices of input variables (labor and capital). This is a key endogeneity issue arising in production function estimation.

Notice, that Equation 1 allows for worker heterogeneity in the sense that $\mathbf{w}_{jt}$ contains information about it. Thus, the estimation of TFP via the production technology takes into account that workers differ in productivity, but workers within observable groups (job tenure, age, education, gender) are perfectly substitutable.

To overcome the endogeneity issue, we follow the two-step procedure proposed by Olley and Pakes (1996).[12] This method uses firm investment as a proxy for the unobservable productivity component of a firm, ω_{jt}. Olley and Pakes (1996) solve a firm's optimal investment decision given a set of assumptions, and show that the investment decision can be inverted to obtain information about ω_{jt}. Given a set of assumptions,[13] we obtain consistent estimates of β and γ, after which we can find the value of $\omega_{jt} + \varepsilon_{jt}$, which is the TFP estimate.

Since there are differences across production technology industries, we estimate TFP separately by industry, thereby allowing β and γ to differ across the industries.[14]

[12] We cannot use other control function methods (e.g. Ackerberg et al. (2015)) as they require intermediate input data, which is unavailable for most firms throughout our period.

[13] The key assumptions are as follows: 1) ω_{jt} follows a first-order Markov, 2) labor input is perfectly variable and only affects current period profits (no dynamics), so there are no adjustment costs, 3) capital is accumulated in a dynamic process (standard capital accumulation), 4) strict monotonicity, which implies that investments are always increasing in ω_{jt}, and 5) ω_{jt} is the only thing that is unobservable in the investment equation. We estimate auto-regressive models for TFP for a balanced panel of firms (over a 5-year window) weighted by employment. We find that the coefficient of the twice lagged TFP is much smaller than that of the one lagged TFP, see A.3

[14] Investment data are available from 1999 and onward. Thus, we only use data from 1999 in the following estimation to achieve consistent estimates of the coefficients β and γ. We can tease out TFP

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 separate regressions by industry in the same way as for the TFP estimation. 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. We therefore choose not to rank based on AKM firm fixed effects. Finally, we have checked that the results are similar when using an unresidualized wage measure.[15]

Measurement of high vs. low types. We classify the firms in the low bracket as being in the bottom quintile and the high bracket in the top two quintiles *within* 2-digit industries (68 industries). 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 in line with the literature, we use the average wage and TFP in year $t-1$ to characterize net flows in quarters of year t. The results are similar when we use time-invariant ranking measures of firm types, as we will come back to later. Lastly, another key characteristic is the size of the firm. In previous work, however, firm size has been shown to relate less clearly to the job ladder than wages (Haltiwanger et al., 2018), so we do not rank by firm size.

2.4 Correlation between Firm Characteristics

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.

for the period without investment data using these coefficients. The implicit assumption is that the production technology did not significantly change over the data period. Also note, that while the method do allow for separation of ω_{jt} and ε_{jt} we can only do this for the part of the panel, where we have investment data and thus we use $\omega_{jt} + \varepsilon_{jt}$ as our TFP measure.

[15]Tenure is potentially endogenous to the position on the job ladder, so in unreported results, we additionally estimate TFP and residualized wages without including workers' tenure. We find the same results.

Table 1: Correlation between Firm Characteristics

	TFP	VA per worker	Sales per worker	Wage per worker	Size
TFP	1.00				
VA per worker	0.61	1.00			
Sales per worker	0.47	0.75	1.00		
Wage	0.32	0.45	0.37	1.00	
Size	0.05	-0.22	-0.18	0.10	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 provides several interesting findings. We find that TFP and value added per worker are strongly correlated (0.61), while TFP and sales per worker are less strongly correlated (0.47).[16] 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 2023) and theoretical work (e.g., Bloesch et al. (2022)).[17] For example, in wage posting models such as Burdett and Mortensen (1998), wages always increase in productivity, while this is not the case in auction models such as Postel-Vinay and Robin (2002). The measure of sales per worker is more correlated with TFP per worker than with wages. However, the correlation is 0.47, which is far from a perfect relationship. This correlation indicates that TFP and sales might provide different results. Wages are only weakly positively correlated with firm size (0.05), 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, with Lentz and Mortensen (2008) in fact finding zero correlation between firm size and productivity.

Additional analysis. There is a concern that measurement error in small firms drives the low correlations. Table A.1 reports the same correlations for firms with at least 20 employees and firms that are at least 10 years old. We find similar patterns in the correlations in both samples. Table A.2 shows descriptive statistics for each of our groups defined by the ranking measures. Table A.3 shows that firm TFP is more persistent than firm average residualized wages.[18]

[16] The magnitude is similar to previous estimates in the US. Foster et al. (2008) report a correlation between TFP and revenue per worker of 0.6 in industries in the manufacturing sector.

[17] Bagger et al. (2014), Card et al. (2018), and Lochner and Schulz (2023) study the correlation between wages and productivity.

[18] We estimate auto-regressive models for a balanced panel of firms (over a 5-year window) weighted by employment. Results of estimates using an unbalanced panel, with and without employment

3 The Pace and Cyclicality of Job Creation Rates Across the Job Ladder

This section documents the rate of job creation and destruction across firms with different average wages and productivity. We show the process of decomposing job flows before analyzing cross-sectional and business cycle patterns.

3.1 Decomposition of Firms' Employment Changes

We decompose net employment creation, i.e. the job creation minus job destruction of firms, into two components. The first component is 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 on-the-job search (Faberman et al., 2022).[19] The second component is hiring (separation) from (to) nonemployment. We do not differentiate between different types of nonemployment, and nonemployed individuals could therefore either be seeking a job or not. It is difficult to separate active job seekers from nonactive ones using administrative data due to the means-tested nature of social assistance in Denmark.

Methodologically we follow Haltiwanger et al. (2018) 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 nonemployed workers (H_{tn}). Likewise, separations can occur in two different pools: to other employers (S_{tp}) and to nonemployment (S_{tn}).[20]

weights, are fairly similar. The magnitude of the persistence is in line with evidence in Lochner and Schulz (2023).

[19] Employer-to-Employer (EE) transitions are sometimes referred to as Job-to-Job (J2J) transitions. 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. (2023) and use employer-to-employer to designate a direct change of employer.

[20] 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 the results are similar.

3.2 Interpreting Job Flows in Relation to Theories

Job flows and job ladder models are intrinsically linked, and part of the motivation for creating job ladder models is to obtain a theoretical understanding of how job flows arise.

All job ladder models share the feature that when workers make job-to-job moves voluntarily, they move up the job ladder. Workers who move voluntarily between jobs do so based on the jobs' net-present values (NPVs). The ingredients of the net-present values depend on the specific model (e.g., wages, amenities, improved bargaining position, learning environment). The empirical challenge is determining which firm characteristic correlates the most with the firms' NPVs. Two prominent firm characteristics are firm average wage paid and firm productivity. However, it is important to note that the average wage paid is, at best, a noisy measure of the job ladder rung for several reasons. The main reason is that the wage-setting protocol matters. In Burdett and Mortensen (1998), which employs an (exogenous) firm productivity distribution, shows a one-to-one mapping between wages and productivity. Hence the model predicts a perfect rank correlation between average wage paid and productivity. When firms can retain workers that receive a job offer, as in Postel-Vinay and Robin (2002), firm productivity is perfectly (rank) correlated with NPVs while wages are not. This is also the case with tenure contracts in the spirit of Burdett and Coles (2010).[21] Common to both Burdett and Mortensen-type models and Postel-Vinay and Robin-type models is that the workers have a common ranking. This is the ranking that we measure by either average wages or TFP. Finally, models with amenities such as Sorkin (2018) and Taber and Vejlin (2020) argue that neither wages nor productivity correlate perfectly with NPVs. Thus, they use employer-to-employer transitions (revealed preferences) as a measure of the job ladder since they do not have data on non-pecuniary aspects of the job (amenities). The question of how to best define the job ladder in practice therefore remains open. Lentz (2023) provides a more thorough discussion of this matter. Another potential issue with the average wage paid or productivity as measured by value added is that it is hard to separate worker characteristics, firm characteristics, and the complementarity of workers and firms (e.g., high wages may be due to having highly productive workers). A key advantage of the firm productivity ranking as measured by TFP is that it isolates the firm component that, arguably, is the most direct measure of the job ladder rung, as proposed in (Moscarini and Postel-Vinay, 2018).

In the above, we have discussed several aspects of direct measures of a job ladder rung, such as the average wage paid and productivity. Net poaching flows ($H_{tp} - S_{tp}$)

[21] Recent empirical studies (e.g., Caldwell and Harmon (2019) and Di Addario et al. (2023)) provide insight into the relevance of different wage-setting protocols.

can be used to provide suggestive evidence of whether a firm's productivity or average (spot) wage is, to a higher degree, correlated with the job ladder.

Measurement of employer-to-employer transitions. Before proceeding, it is useful to remind the reader of measurement issues related to employer-to-employer transitions. There are two main issues. First, time aggregation plausibly impacts the pace and direction of employer-to-employer transitions. Time aggregation refers to the fact that nonemployed people can find a job quickly after their previous job has ended and with low frequency observations, this could resemble an employment-to-employment transition in the data. Bertheau and Vejlin (2023) and Moscarini and Postel-Vinay (2018) provide evidence on this matter. Note that our data are not subject to this concern as we measure the start and end of each employment relationship at a daily frequency. Further, the above-mentioned models imply that voluntary employer-to-employer (EE) transitions provide an indication of the job ladder. A second concern is that employer-to-employer transitions are plausibly involuntary. Taber and Vejlin (2020) use survey data and find that 80 percent of employer-to-employer transitions in Denmark are voluntary. With this caveat in mind, we proceed by interpreting poaching flows (employer-to-employer transitions) as a means of capturing voluntary transitions to more desirable firms.[22]

3.3 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, as presented in Equation (2): Net poaching and net nonemployment. *Net* poaching is the difference between poaching hires and poaching separations, including 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 at Panel (a), we find that high wage firms grow a little faster than low wage firms (0.26% vs. 0.17%), but that growth happens through different channels. High wage firms grow predominantly by net poaching (0.19%) and somewhat from net nonemployment flows (0.07%). In contrast, low

[22]Nagypál (2008) and Simmons (2023) present evidence using US data on reasons for job separations and employer-to-employer transitions. Note that randomly assigned involuntary employer-to-employer transitions are not a problem since this would affect the wage and productivity rankings in the same way. The problem arises if the reason for the involuntary move is more or less correlated with one of the rankings than the other. Administrative data in some European countries (e.g., France, Italy, and Norway) registers the reason for job separation. To our knowledge, this feature has not been exploited to link employer-to-employer transitions and involuntary separations.

wage firms shrink because workers leave for other firms (-0.43%) but grow by net flows from the pool of previously nonemployed workers (0.60%). This pattern indicates that poaching is important to understanding how firms with different wages grow and shrink.

We divide net poaching and net nonemployment into gross flows in Panel (b) and find high hire and separation rates. Low wage firms have more churn in general than high wage firms, i.e., they have higher hiring and separation rates for both poaching and nonemployment channels. In any search models, low type firms should rely more on hiring from nonemployment. Low type firms should also be more prone to becoming unprofitable and thus laying off workers to nonemployment. Likewise, their workers should be poached by other firms to a greater extent. Surprisingly, though, we also find that low wage firms have higher hiring poaching rates than high wage firms. We also find the same for productivity, meaning that it is a general pattern. Notice that as we rank firms within industry-year cells, industry differences do not explain this pattern. Interestingly, based on our calculations using Haltiwanger et al. (2018)'s replication package, we find a similar pattern in US data.[23] Thus, it appears to be a general finding that low type firms (wage and productivity) are high churn firms.

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 (0.49% vs. -0.41% compared to 0.26% vs. 0.17% for the wage ranking). 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 (-0.48% and -0.43%). However, they grow much less (0.08% vs. 0.60%) than low wage firms through the nonemployment channel. As a result, low productivity firms are shrinking while low wage firms are growing (-0.41% vs. 0.17%).

A key question reflecting the discussion in Section 3.2 is which observable firm characteristics are best at capturing the job ladder. Recent papers such as Bagger and Lentz (2019) and Taber and Vejlin (2020) argue that employment-to-employment transitions are largely voluntary and therefore help to identify the job ladder. As such, 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 (0.74% vs. 0.62%).

Accordingly, productivity is a better proxy for the job ladder than wages, since workers voluntarily move from low to high productivity firms at a faster pace than

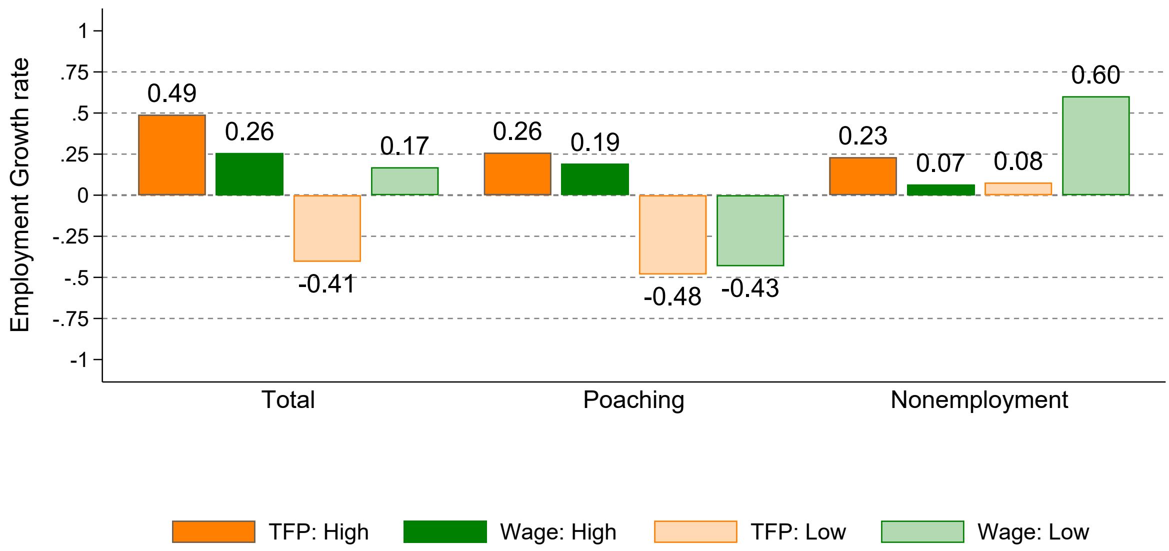
[23]The quarterly poaching hiring rate by high type firms is 5.59%, and 11.55% by low type firms. The nonemployment hiring rate by high type firms is 3.61%, and 13.66% by low type firms. The magnitude is similar for separation rates. Bachmann et al. (2021) reports a mean quarterly hiring rate of 7.02% in Germany and 11.82% in the US.

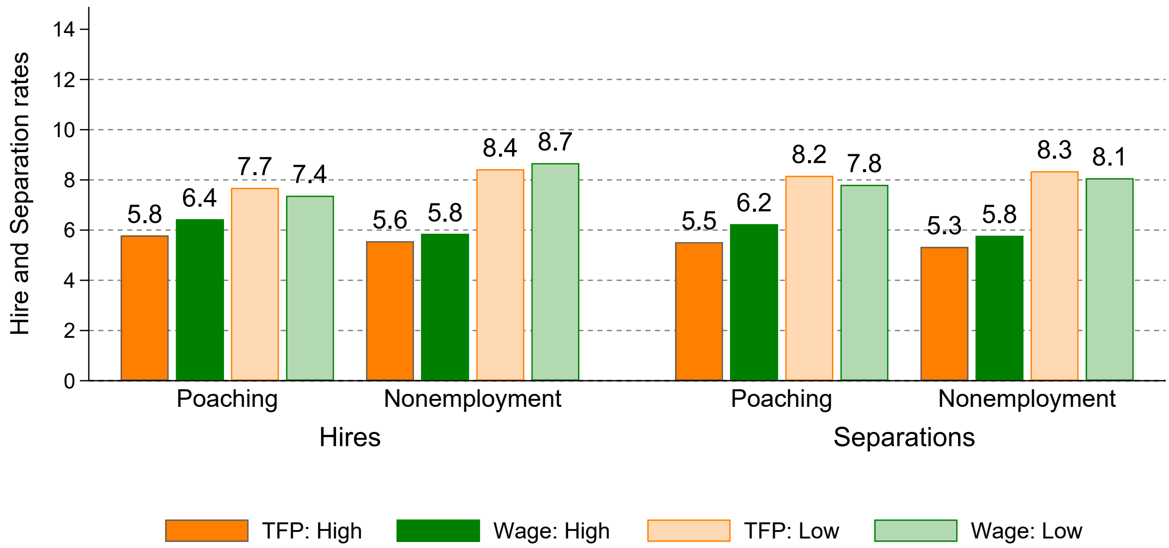
they move from low to high wage firms. This is consistent with wage protocols in the on-the-job search literature (Burdett and Coles, 2003; Postel-Vinay and Robin, 2002), where productivity is perfectly correlated with workers' ranking of jobs while wages are not. This finding is also consistent with 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 compensating wage differential models, where high wage firms pay high wages because they are undesirable workplaces due to, e.g., unpleasant work conditions.

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





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) 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*, i.e. the difference between hiring into and separations from a given firm type that only involves employer-to-employer transitions.

3.4 Business Cycle Patterns

Next, we analyze how labor flows vary over the business cycle. We first present the cyclical indicators, followed by visual evidence, and finally the regression results.

Cyclical indicators. We use the level and the change in the unemployment rate to measure the business cycle.[24] Empirically, the two measures capture different parts of the cycle. The unemployment level naturally lags behind the change in unemployment and thereby captures periods in the middle of a recession (expansion). In contrast, the change in unemployment captures the periods 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 the first difference in the unemployment rate (not HP-filtered).

3.4.1 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 presenting the regression results.[25]

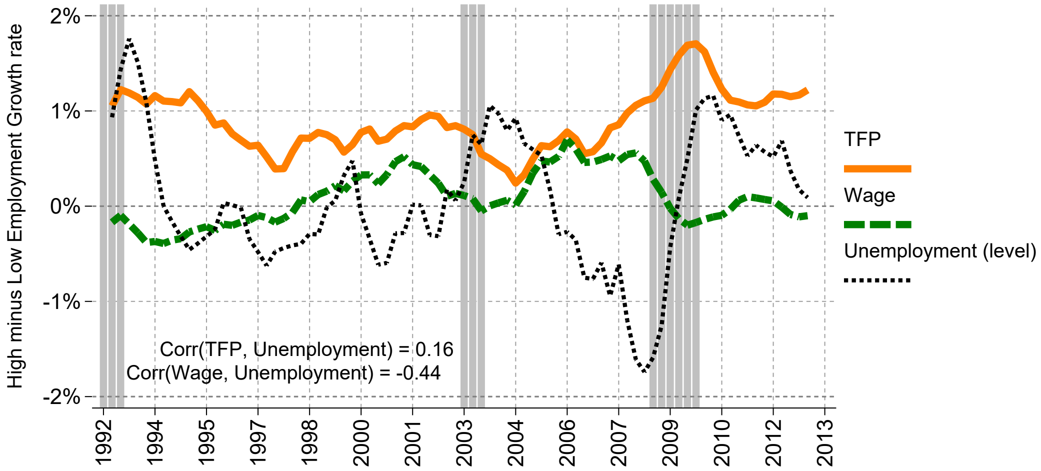
Differential employment growth rates. We find a negative correlation (-0.44) between the differential employment growth rate and the level of unemployment of the wage distribution (Panel (a)). The correlation implies that high wage firms grow relatively more than low wage firms during expansions when unemployment is low, while they shrink relatively more during recessions. This pattern is especially pronounced during the recession 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 (0.16) with the level of unemployment. Most of the difference is driven by two periods: the mid-1990s and the period after the Great Recession. During both periods, unemployment was high and differential employment growth based on wages was small, while the employment growth based on productivity was high. This suggests that the Great Recession had

[24]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). 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 attempting to understand labor flows.

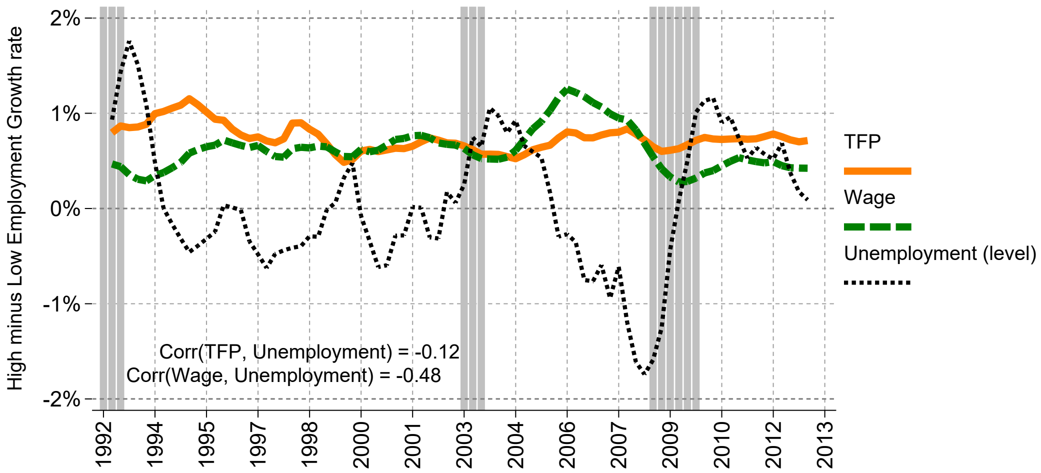
[25]The differential net growth rates are given by $(H_{t,high} - S_{t,high}) - (H_{t,low} - S_{t,low})$ in Equation (2) and the detrended unemployment level is represented by the black dotted line.

Figure 2: Differential Job Creation Rates over the Business Cycle

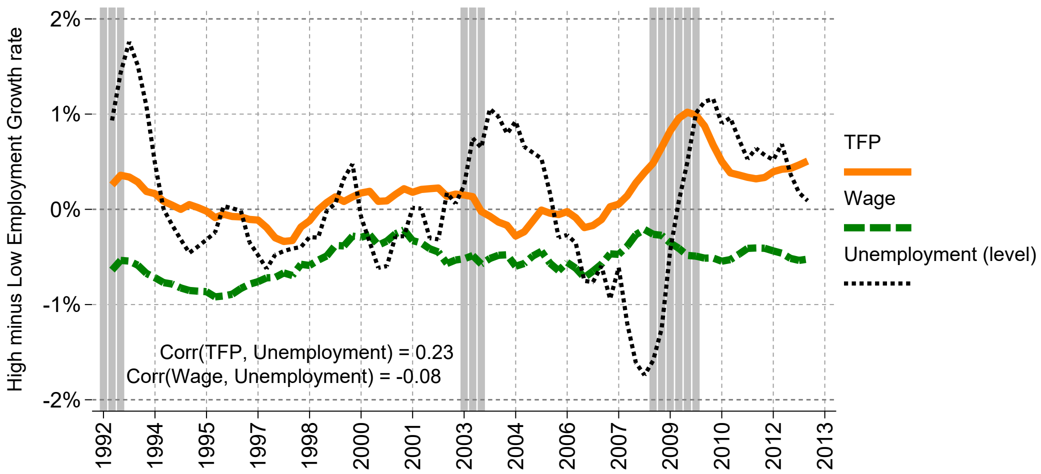
(a) Total: Poaching and Nonemployment



(b) Net Poaching



(c) Net Nonemployment



Notes: The figure shows the differential net growth rates (total, poaching, nonemployment) based on rankings of firms by either wages or productivity. "High" indicates that the firm is in the top two quintiles, while "Low" indicates that the firm is in the bottom quintile.

a cleansing effect in the sense that high productivity firms outgrew low productivity 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. For firms ranked by wages, the estimate is negative (-0.48), indicating that the 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 during recessions. This result implies a sullying effect of recessions (Barlevy, 2002) since workers tend to be stuck in low wage/productivity firms.

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 (0.23), while it is negative for wages (-0.08). During recessions when unemployment is high, high productivity firms therefore tend to grow more compared to low productivity firms through nonemployment flows. This was the opposite for poaching flows. Note that the negative net differential growth using wages is not driven by any particular data period, but is present throughout the period 1992–2013. Interestingly, the slightly positive net differential growth rate when using productivity is driven by the time around and following the Great Recession.

3.5 Business Cycle Patterns: Regression Estimates

We estimate the following model to quantify the effect of the business cycle on employment cyclicality across firm types. Using regressions in addition to presenting correlations allows more interpretable results and controls for other 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 they are measured 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 differential net flows, which is also measured as a percentage. Recall that the cyclical indicator is either the change in or the level of unemployment measured as the deviation from the unemployment rate trend. Table 3 shows the total differential net growth rate estimates using both cyclical indicators and decomposed rates. Each cell presents the estimate of a separate regression based on quarterly data.

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

	Productivity (TFP)			**Wage**		
	Total	Poaching	Nonemploy.	Total	Poaching	Nonemploy.
Change in Unemp.	0.29***	-0.09**	0.38***	-0.11	-0.21***	0.11**
	(0.11)	(0.04)	(0.08)	(0.09)	(0.08)	(0.05)
Level of Unemp.	0.07	-0.02	0.10**	-0.17***	-0.15***	-0.02
	(0.05)	(0.02)	(0.04)	(0.04)	(0.03)	(0.02)
Obs.	82	82	82	82	82	82
Mean of dep. var	0.90	0.74	0.15	0.09	0.62	-0.54

Notes: The table shows regression estimates of the effects of an increase in either the level of or the change in the unemployment rate on the net differential employment growth rates (see Equation (3.5)). 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 as 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% level (***,**,* 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 0.29 pp. Thus, when the economy enters a recession, low productivity firms shrink more than high productivity firms, and the difference between them increases. 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 during a recession as shown in Appendix Figure A.1), the differential job creation rate grows by 64 percent (2*0.29/0.90) relative to the average differential job creation rate. There are therefore 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 (0.07 pp). The overall effect is driven entirely by the nonemployment channel, as the point estimates are 0.38 and 0.10 pp for the change and level, respectively.

In line with cyclical job ladder models, the poaching channel pushes in the opposite direction. During a recession, the difference in net poaching rates between high and low productivity firms becomes smaller. Moscarini and Postel-Vinay (2013) and Audoly (2023), among others, find that "better" firms, meaning both high productivity and high wage firms, are more cyclically sensitive due to their ability to poach workers during expansions, where the number of workers in the unemployment pool is small. We find support for this margin at the onset of a recession. However, in the middle of a recession when unemployment levels are high, we do not find that the poaching margin plays a role in explaining differences in job creation rates between high and low productivity firms. Thus, the difference is largest at the beginning and ending of a recession.

Overall, our data indicates that the cleansing effect of a recession dominates the sullying effect when we rank firms by their productivity. Next, we investigate whether this is also the case when ranking firms by wages.

High vs. low wage firms. We reach a different conclusion about the cyclicality of high vs. low type firms when using wages to define the job ladder. While the poaching and the nonemployment margins impact the differential job creation rate in a similar way to our analysis on the productivity ladder, the relative importance of both forces differs, leading us to a different conclusion for the total rate.

Specifically, an increase in the change in unemployment does not increase the differential job creation rate at the onset of a recession, and we in fact find a small decrease (-0.11 pp). In the middle of recession when unemployment peaks, we find a larger negative difference. In particular, we find that an increase in the unemployment rate of 1 pp affects the differential job creation rates negatively (-0.17 pp). The role of the poaching margin is larger both at the onset and in the middle of a recession (-0.21 pp and -0.15 pp).[26] However, the role of the nonemployment channel is also smaller both at the onset and in the middle of a recession (0.11 pp and -0.02 pp).[27]

3.6 The Cyclicality of Hiring and Separation Rates

The previous results showed differences in cyclicality for net job flows. The finding that the difference in growth between high and low productivity firms becomes larger during recessions indicates that recessions have a cleansing effect (Foster et al. 2016). A popular explanation is that recessions are driven by economy-wide negative TFP

[26] Recall that on the productivity ladder, the poaching margin is less strong at the start of a recession and does not play a role during later stages.

[27] It is unlikely that our results are specific to Denmark as Haltiwanger et al. (2018) also find that a recession decreases the differential job creation rates between high and low-paying firms, and the poaching margin drives this effect.

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. Below, we investigate whether this occurs due to higher separations or lower hiring rates.

Table 3 shows the estimated coefficients (β) for hiring and separation rates, using the same specification as for the net flows (see Equation (3.5)) and using the change in the unemployment rate.

High vs. low productivity firms. Table 2 shows that the gap between high and low productivity firms increases by 0.29 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 (-1.00 pp) than high productive firms (-0.71 pp). This difference is driven by differences in contraction through the nonemployment channel (-0.66 pp vs. -1.04 pp). At the same time, the net poaching flows in both types are much less impacted by the change in unemployment, but the difference still pulls in the opposite direction. High-productivity firms contract to some degree during recessions through the poaching channel (-0.05 pp), while low productivity firms are somewhat positively affected (0.04 pp).

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 of 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 (-1.32 pp for high vs. -1.53 pp for low productivity firms), but only has a small effect on separations (-0.61 for high vs. -0.53 for low productivity). Note that some of the difference between high and low productivity firms in terms of the estimates could be driven by the fact that low productivity firms have more churn in general. The total reduction in hiring for high and low productivity firms is -1.32 and -1.53, respectively. However, the means of hiring rates are also different (11.34 and 16.11), so the *relative* decrease in hiring for low productive firms is actually just 9.4 percent, while it is 11.6 percent for high productivity firms.[28] This highlights the fact that low type firms are more cyclical in absolute terms, but not in relative terms, because they generally have a higher churn rate.

[28] The relative effects are calculated as 1.32/11.34 = 0.116 and 1.53/16.11 = 9.4.

Table 3: The Cyclicality of Hirings and Separations by Firm Productivity

	High Productivity			**Low Productivity**		
	Total	Poaching	Nonemploy.	Total	Poaching	Nonemploy.
Net	-0.71***	-0.05	-0.66***	-1.00***	0.04	-1.04***
	(0.13)	(0.03)	(0.11)	(0.18)	(0.03)	(0.17)
Mean of dep. var	0.49	0.26	0.23	-0.41	-0.48	0.08
Hire	-1.32**	-0.66**	-0.66***	-1.53*	-0.68	-0.85**
	(0.54)	(0.32)	(0.24)	(0.77)	(0.42)	(0.36)
Mean of dep. var	11.34	5.78	5.56	16.11	7.68	8.42
Separation	-0.61	-0.61*	0.01	-0.53	-0.72*	0.19
	(0.49)	(0.33)	(0.19)	(0.66)	(0.42)	(0.29)
Mean of dep. var	10.85	5.52	5.33	16.51	8.16	8.35

Notes: The table shows regression estimates of an increase in the change in unemployment on the employment growth rate of different firms (see Equation (3.5)). 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% level (***,**;* respectively). Each entry in the table reports a different regression.

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 the differences in response to change in unemployment between high and low productivity firms is the difference in hiring from the nonemployment pool. When unemployment increases, low productivity firms stop hiring workers from nonemployment and start to separate workers to nonemployment to a larger extent than high productivity 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, they also stop hiring new workers to the same extent. There could be several explanations for this. For instance, incumbent workers could have accumulated firm-specific human capital, and thereby remain productive. However, training new workers is not profitable during recessions and firms therefore stop hiring. Alternatively, there could be frictional search costs. If firms want to reduce the number of workers they employ, it is optimal to save on hiring costs.[29] The model proposed by Lise and Robin (2017) has precisely this feature. A negative aggregate shock causes the vacancy distribution to shift to higher firm types, because low types no longer find it as attractive to post jobs.[30]

The poaching channel works in the opposite direction. During recessions, high

[29]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., 2023b).

[30]In their model, this is partly driven by an aggregate shock and partly by higher values of home production in low aggregate states.

productivity firms slow down their net poaching, while low productivity 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 productivity firms separate fewer workers to other firms (-0.61 pp), but the effect is smaller than for low productivity firms (-0.72 pp).

High vs. low wage firms. We now move on to explain why firms ranked by wage behave differently. As previously noted, Table 2 shows that we find a close to zero but negative difference in total net flows using the change in the unemployment rate (-0.11 pp). Table 4 shows that when unemployment increases, both high and low wage firms contract, but high wage firms contract relatively more (-0.99 pp vs. -0.88 pp). As with productivity, the main driving channel for the total net flow is the nonemployment flow. The contraction is driven by a reduction in hiring from the nonemployment pool (-0.94 pp). In contrast, separations to nonemployment are less affected (0.04 pp). Thus, during recessions, low wage firms stop hiring from nonemployment, but they do not start to separate workers to nonemployment as was the case for low productivity firms (0.04 pp for low wage firms vs. 0.19 pp for low productivity firms). Turning to the poaching channel, we see that during recessions, low wage firms actually grow through the poaching channel (0.09 pp). The reason is that although poaching hiring slows down poaching separations slow down even more (-0.70 pp vs. -0.79 pp).

The adjustment for high wage firms is more complex as they experience a reduction in their growth rate from the poaching (-0.12 pp) and the nonemployment channels (-0.87 pp). Focusing on nonemployment, both hiring and separation matter. Interestingly, separation increases sharply (0.24 pp vs. 0.04 pp for low wage firms). This pattern is consistent with evidence of labor market transitions from other literature. For instance, Mueller (2017) and Züllig (2022) find that high residual wage workers are more cyclically sensitive in the US and Denmark. This is also consistent with the job displacement literature. Recent studies document the role of high wage firms in understanding the earnings losses of displaced workers over the business cycle (see, e.g., Schmieder et al. (2023) and Bertheau et al. (2023a)).

Table 4: The Cyclicality of Hirings and Separations by Firm Wage

	High Wage			**Low Wage**		
	Total	Poaching	Nonemploy.	Total	Poaching	Nonemploy.
Net	-0.99***	-0.12***	-0.87***	-0.88***	0.09	-0.97***
	(0.17)	(0.04)	(0.14)	(0.13)	(0.06)	(0.15)
Mean of dep. var	0.26	0.19	0.07	0.17	-0.43	0.60
Hire	-1.28*	-0.65*	-0.63**	-1.63**	-0.70*	-0.94***
	(0.68)	(0.39)	(0.31)	(0.69)	(0.37)	(0.33)
Mean of dep. var	12.28	6.43	5.84	16.04	7.37	8.67
Separation	-0.30	-0.53	0.24	-0.75	-0.79*	0.04
	(0.59)	(0.38)	(0.25)	(0.67)	(0.42)	(0.29)
Mean of dep. var	12.02	6.24	5.78	15.87	7.80	8.07

Notes: The table shows regression estimates of an increase in the change in unemployment on the employment growth rate of different firms (see Equation (3.5)). 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% level (***,**;* respectively). Each entry in the table reports a different regression.

In Table 2, we found that the poaching channel was the driving force behind the difference between high and low wage firms. We can now extend these results. During 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).

3.7 Additional Results: Alternative Firm Types and Continuing Firms

We present further findings on the cyclicality of job creation rates derived from two modifications to our principal methodology. Our analysis reveals consistent conclusions even when we alter the classification criteria for distinguishing high and low firm types. When we concentrate on continuing firms, i.e., those not experiencing entry or exit, we observe a divergence in cyclicality by firm TFP, in contrast to the results with wages.

In Table 2, we base our estimations on data from the previous year to characterize net jobs, thereby minimizing reclassification bias. This approach aligns with our analysis (see Table A.3) and previous studies, such as Engbom et al. (2022) and Lachowska et al. (2022)), which suggest that firm productivity and pay exhibit persistence, albeit not permanently.[31] Theoretical models typically consider firm type as time invariant.

[31] Additionally, for consistency in comparison, we adhere to the firm type construction as outlined by Haltiwanger et al. (2018).

Employing such a classification, we observe a cleansing effect at recession onset by firm TFP (0.26 pp in Table A.4 compared to 0.29 pp in Table 2). Also, the results for high and low wage firms are similar (-0.06 pp in Table A.4 vs. -0.11 pp in Table 2). During the later stages of a recession, high wage firms demonstrate greater cyclical sensitivity than their low wage counterparts (-0.13 pp in Table A.4 vs. -0.17 pp in Table 2). Thus, our findings on the cyclicality of job creation rates remain robust under this alternative analysis.

Another aspect is the impact of firm entry and exit on job creation rates throughout the business cycle. Although empirical documentation of this phenomenon by firm TFP is scarce, it is intrinsically linked to the assumption that recessions have a cleansing effect.[32] In line with Moscarini and Postel-Vinay (2012), we examine the differential job creation rates for continuing firms. The findings indicate that during later periods of a recession, high wage firms contract more significantly than their lower-paying counterparts, similar to our primary estimations. However, when focusing solely on continuing firms, the difference between high and low TFP firms becomes negligible (Table A.5). This observation suggests a business cycle variation in entry and exit rates by firm productivity. Interestingly, when employing value added per worker as a productivity metric (see Table A.6), our estimates show that lower productivity firms shrink more. However, estimates across productivity measures align closely when considering the job creation rate late in a recession. Overall, when we concentrate on continuing firms, we find, in line with Moscarini and Postel-Vinay (2012), a difference in the magnitude of the cyclicality of job creation for high and low type firms.[33]

Summary. Ranking firms based on their rung on the wage or productivity ladder yields different results when it comes to the pace and the cyclicality of employment growth. The difference in growth rates between high and low productivity firms becomes larger during recessions. This suggests that the cleansing effect dominates the sullying effect of recessions. Thus, this is in line with several unemployment models, such as Mortensen and Pissarides (1994) and Lise and Robin (2017), yet in contrast with others (e.g., Moscarini and Postel-Vinay (2013)). In the latter model, low produc-

[32] Lee and Mukoyama (2015) find evidence of the cyclicality of entry and exit firms by firm productivity based on US manufacturing firms. The framework of Audoly (2023) and Acabbi et al. (2023) allow entry and exit to evolve endogenously over the business cycle.

[33] Haltiwanger et al. (2021, 2018) do not provide estimates for continuing firms. Moscarini and Postel-Vinay (2012) find a negative correlation between job creation rates among large and small firms and the unemployment rate, particularly when focusing on continuing firms. Their estimates range from -0.39 to -0.15, depending on the sample selection, and from -0.43 to -0.34 for continuing firms. Consistent with this literature, our analysis also indicates that high type (i.e., wage) firms exhibit more pronounced cyclical sensitivity in the subset of continuing firms.

tivity firms become unprofitable during recessions and lay off workers, causing the net nonemployment flow rate to increase. We confirm this finding 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 cyclically sensitive than the separation rate. This suggests that models should emphasize endogenous hiring rates, which can potentially halt new hiring during a recession since this is cheaper than laying off incumbent workers. Further, the difference between high and low wage firms becomes smaller during a recession. Differences in the poaching channel drive this effect, confirming the importance of distinguishing between poaching and nonemployment channels to understand employment reallocation.

4 Do Recessions Still have a Cleansing Effect with Less Direct Measures of Productivity?

We measure productivity as TFP and estimate it through a production function. This section shows how the pace and cyclicality of job reallocation along the productivity ladder change when we use less direct measures of productivity than TFP.

Additional productivity measures. Theories of labor allocation are at their core about the marginal revenue project of labor (MRPL), which is what a firm gains by employing an additional worker. Measuring MRPL is difficult. In this paper, we estimate firm-level TFP to measure MPRL.[34] However, in order to estimate TFP we make various assumptions when using the Olley and Pakes (1996) procedure.[35] It is therefore useful to compare our results with alternative productivity measures, which uses less assumptions (structure) and are more directly related to data. First, we measure labor productivity as sales per worker. This comparison is informative as sales per worker is used as a measure in several studies based on US data (e.g., Foster et al. (2016); Haltiwanger et al. (2021)). We also measure labor productivity as value added per worker. This is arguably a better measure of labor productivity as it takes into account varia-

[34]Most macro-labor models assume a constant return to scale in the production function and no capital. In this case, firm-level TFP directly measures marginal labor productivity. See, e.g., Moscarini and Postel-Vinay (2013), Coles and Mortensen (2016), Kaas and Kircher (2015), Gouin-Bonenfant (2022), Bilal et al. (2022), Elsby and Gottfries (2022), Acabbi et al. (2023), and Audoly (2023). Note that revenue-based TFP (even if it captures market power) is enough to measure the job ladder (Moscarini and Postel-Vinay, 2018).

[35]See Section 2.3 for details about our estimation procedure. Structure is necessary to deal with econometric issues (i.e., endogeneity issues). Measurement issues for non-labor inputs such as capital may also impact TFP estimation.

tion in intermediate inputs across firms.[36] We compare the pace and cyclicality of job creation rates for these productivity measures.

Cross-sectional patterns: Comparison across measures. We find that the differential growth rate between high and low type firms is about 20% (0.90 pp vs. 0.78 pp) higher using TFP compared to a proxy of labor productivity: sales per worker (see Figure A.2, Panel (a)). The difference is that low TFP firms grow less than low sales firms through the nonemployment margin. Low TFP firms grow marginally (0.08 pp), while low sales firms grow much more (0.19 pp). Interestingly, value added per worker leads to even larger differences than sales. We find that the differential growth rate between high and low type firms is about 40% (1.11 pp vs. 0.78 pp) higher using value added per worker instead of using sales per worker. This difference is consistent with our discussion above on the difficulties of measuring TFP. Overall, our comparison of different productivity measures shows that sales per worker downplays the differential job creation rates by firm productivity by at least 20%.

Business cycle patterns: Comparison across measures. Our second set of results deals with the cyclicality of job reallocation using different productivity measures. Specifically, our purpose is to uncover whether less direct measures of productivity lead to the same conclusion regarding the cleansing or sullying effect of recessions. We use the same regression framework and compare differential job creation rates by TFP and the two labor productivity measures. The results are shown in Table 5.

[36] High TFP firms sell more and use fewer intermediate inputs (e.g., Bloom et al. (2013)). Card et al. (2018) show that their passthrough estimates differ using value added or sales per worker.

Table 5: The Cyclicality of Job Creation Rates: TFP vs. Labor Productivity

	TFP			**Labor productivity**					
	(1)			**(2) Value-added**			**(3) Sales**		
	Total	Poac	Nonemp	Total	Poac	Nonemp	Total	Poac	Non-emp
Change in Unemp.	0.29***	-0.09**	0.38***	0.26**	-0.08	0.34***	0.13*	-0.09	0.21***
	(0.11)	(0.04)	(0.08)	(0.10)	(0.08)	(0.07)	(0.07)	(0.08)	(0.06)
Level of Unemp.	0.07	-0.02	0.10**	0.03	-0.11***	0.14***	-0.08***	-0.16***	0.08***
	(0.05)	(0.02)	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Obs.	82	82	82	82	82	82	82	82	82
Mean of dep. var	0.90	0.74	0.15	1.11	0.91	0.20	0.78	0.73	0.05

Notes: The table shows regression estimates of an increase in the change in unemployment on the employment growth rate of different firms (see Equation (3.5)). 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% level (***,**;* respectively). Each entry in the table reports a different regression.

Estimates in column (1) repeat our baseline results for TFP – these are the same as reported in Table 3. Estimates in (2) use value added per worker to define high and low productivity firms, while estimates in (3) use sales per worker to define high and low productivity firms. Looking first at the results when using the change in unemployment as a cyclical indicator, we find that sales per worker underestimates the cyclicality of differential growth compared to TFP. A 1 pp increase in the change in unemployment increases the differential growth rate by 0.29 pp using TFP, while the effect is only 0.13 pp using sales per worker. Thus, the cyclicality when using sales is only 40% of the rate when using TFP. This is a large difference and it underlines that the distinction between TFP and sales is important.

We find that the difference between TFP and sales is driven by the difference in the nonemployment margin. When recessions begin and unemployment increases, the difference between low and high TFP firms increases by 0.38 through nonemployment compared to 0.21 with sales.

Turning to the level of unemployment as a cyclical indicator, we find that the sign of the estimate on total differential growth *flips* when using sales. Using our baseline ranking in column (1), the point estimate is 0.07 pp, while when using sales per worker, the estimate is -0.08 pp. This result is an important finding, as the signs on our estimates using sales per worker are the same as the signs found in the US data (see Haltiwanger et al. (2021).). Our estimates therefore suggest that we get a different result for TFP when using Danish data, not because Denmark differs from the US, but because sales per worker measures something other than TFP.

Comparing columns (1) and columns (2) is also informative. Contrary to sales per worker, value added per worker also leads to a cleansing effect of recession for both cyclical indicators. The magnitude when using the level of unemployment is smaller for value added per worker (0.03 pp vs. 0.07 pp). Overall, our results suggest that TFP leads to more cyclicality in job creation rates than labor productivity when measured by both sales and value added.

Additional analysis. The Appendix contains additional results showing that our results are independent of the specific definition of high and low productivity types. Recall that we define low types as being in the bottom quintile and high types as being in the top two quintiles, where the type of firm is potentially time variant. Table A.7 shows estimates using time-invariant firm types. Our initial conclusion that differences in productivity measures lead to a different magnitude of the cleansing effect of recession becomes even more striking. Specifically, we do not detect any difference between high and low firm types using sales per worker when there is a one pp increase in the unemployment rate. However, estimates using TFP (0.26 pp) and value added per worker (0.12 pp) are still positive and statistically different from zero. The finding that recessions have a sullying rather than a cleansing effect when using the level of unemployment as a cyclical indicator also remains valid. We reach similar conclusions with different threshold of high and low type firms and assumptions to measure TFP (Tables A.8 and **??**). All in all, these estimates reinforce our findings that a proxy of labor productivity (sales per worker) may lead to the conclusion that recessions have a less cleansing effect than is actually the case.

5 Conclusion

This paper investigates the progression of workers up firm wage and productivity ladders and the cyclicality of this movement. By linking daily employment spell data with firms' financial records over two decades, we provide unique insights into the dynamics of nonemployment and poaching flows, particularly in relation to firm TFP.

Our findings reveal that high productivity firms exhibit more substantial growth relative to their lower productivity counterparts, predominantly through increased hiring from other firms. While this pattern is also observable when ranking firms by wages, the effects are more pronounced with productivity as the metric. This suggests that the productivity ladder is a more accurate representation of the job ladder than the wage ladder.

Echoing US-based studies such as Haltiwanger et al. (2018), we find that high wage firms are more sensitive to economic cycles, particularly towards the end of a recession. This observation aligns with the class of macro-labor models, known as "cyclical job ladder models" (see, e.g, Moscarini and Postel-Vinay (2018)). In these models, the disparity in net job creation across the business cycle between high and low wage firms is primarily driven by the poaching activities of high type firms. Our analysis indicates that the wage ladder breaks down during recessions, since reallocation up the ladder occurs less frequently.

Furthermore, our examination of employment cyclicality by firm TFP uncovers a cleansing effect at the onset of recessions on the productivity ladder. Low productivity firms experience a more pronounced reduction in employment growth compared to high productivity firms, primarily due to the lesser role of the poaching channel in comparison to nonemployment.

Lastly, our analysis indicates that less direct measures of productivity, such as sales per worker, result in an underestimation of the cleansing effect of recessions.

This paper makes a significant contribution to our understanding of labor market dynamics, particularly in terms of job reallocation and the impact of economic cycles on different types of firms. However, there is a need for further research to explore how job flows vary across firm types. Such studies are particularly crucial to understand the diverse impacts of these reallocations on different groups of workers. Moreover, it is important to investigate worker reallocation in labor markets with varying degrees of flexibility, comparing markets like the US and Denmark with those that are less flexible.

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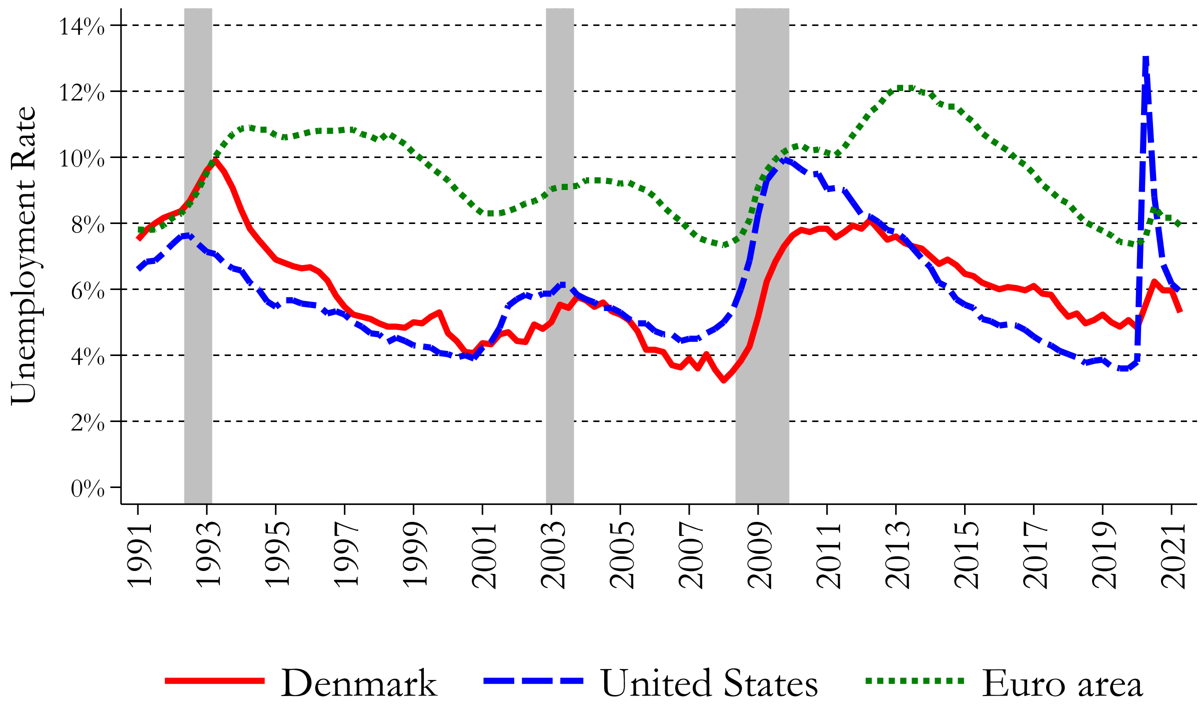
A Additional Tables and Figures

A.1 Figures

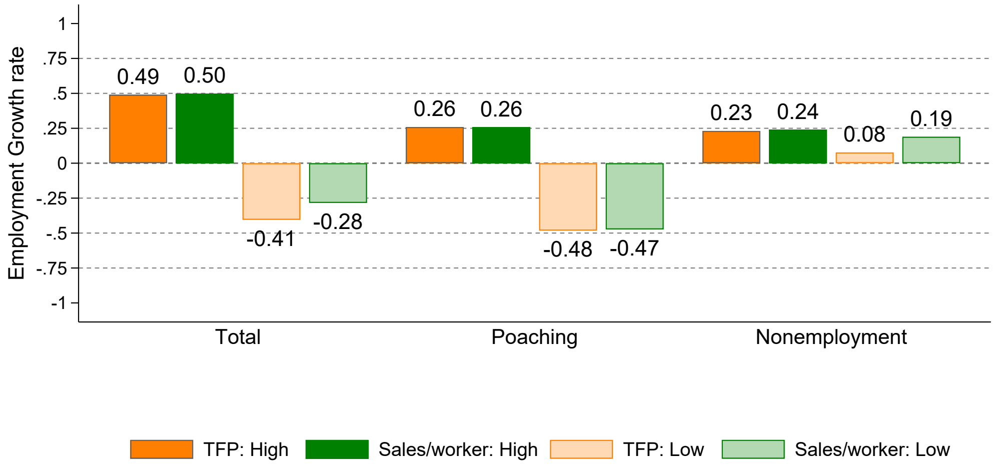
Figure A.1: Unemployment in Denmark, in the US, and in the Euro area



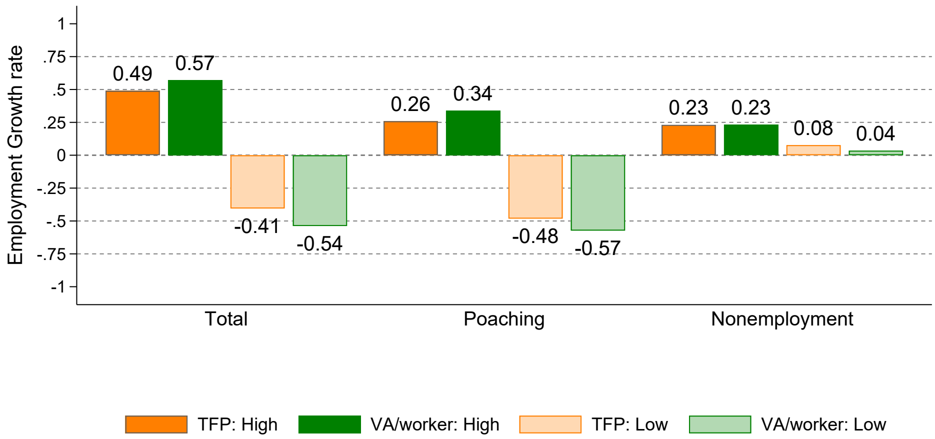
Notes: The figure shows the unemployment rate for Denmark, the US and the Euro area constructed from the OECD series "Quarterly Harmonized unemployment rate". Grey areas denote episode recessions (1992Q3-1993Q1, 2003Q1-2003Q3, and 2008Q3-2009Q4).

Figure A.2: Job Creation Rates by TFP and Labor Productivity

Panel (a): Sales per worker



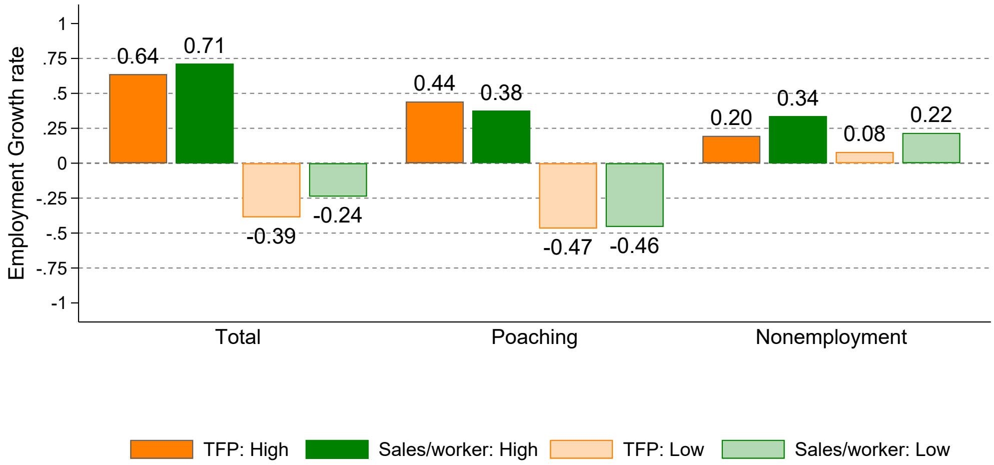
Panel (b): Value added per worker



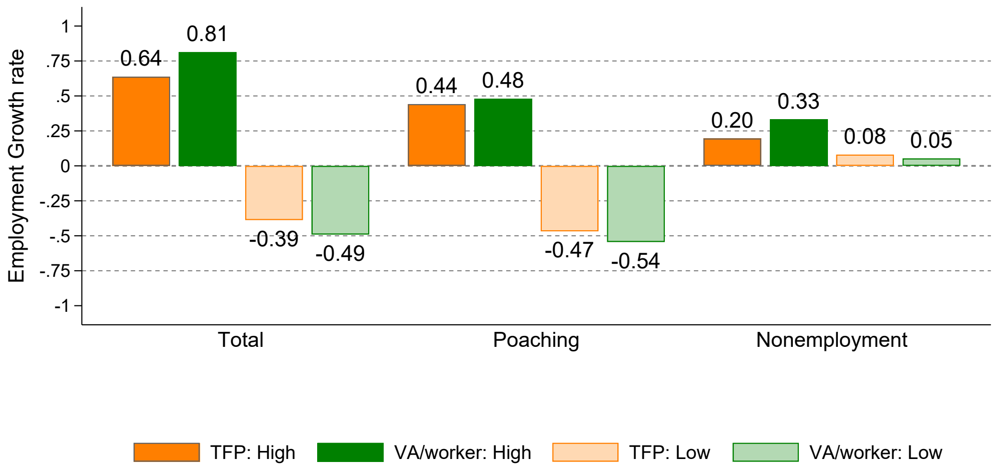
Notes: The figure compares the net job flows (hires minus separations) between TFP and labor productivity (value added and sales per worker).

Figure A.3: Job Creation Rates: Alternative High and Low Firm Types

Panel (a): Sales per worker



Panel (b): Value added per worker



Notes: The figure compares the net job flows between TFP and labor productivity (value added and sales per worker).

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				
VA per worker	0.61	1.00			
Sales per worker	0.44	0.67	1.00		
Wage per worker	0.43	0.51	0.41	1.00	
Size	0.22	0.02	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				
VA per worker	0.59	1.00			
Sales per worker	0.46	0.74	1.00		
Wage per worker	0.32	0.44	0.37	1.00	
Size	0.07	-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	13	7	16	7	20	11	11
Sales per worker	299	206	462	191	528	146	444
Wage	48	33	67	42	57	39	55
Value added per worker	97	69	146	59	174	40	149
Age	15	14	15	14	14	14	15
Manufacturing	16	18	15	17	16	20	13
Services	22	20	23	21	24	20	24
Other services	22	20	23	21	24	20	24
Observations	1581702	604715	483341	559739	386034	380534	700361

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

Table A.3: Persistence of Productivity and Wage

AR(2):				
	TFP	TFP (se)	Wage	Wage (se)
1	0.63	0.027	0.53	0.019
2	0.26	0.026	0.26	0.019
AR(5):				
	TFP	TFP (se)	Wage	Wage (se)
1	0.58	0.031	0.48	0.018
2	0.16	0.024	0.17	0.015
3	0.068	0.014	0.088	0.0091
4	0.059	0.019	0.068	0.0079
5	0.043	0.013	0.038	0.0063

Notes: The table shows regression estimates of an AR(2) and AR(5) models. The sample is a balanced sample of firms (over a 5-year window). The regressions are weighted by firm employment.

Table A.4: The Cyclicality of Job Creation Rates: Time-invariant Types

	Productivity (TFP)			**Wage**		
	Total	Poaching	Nonemploy.	Total	Poaching	Nonemploy.
Change in Unemp.	0.26***	-0.09**	0.35***	-0.06	-0.22***	0.16**
	(0.09)	(0.05)	(0.07)	(0.07)	(0.06)	(0.07)
Level of Unemp.	0.00	-0.05**	0.05	-0.13***	-0.17***	0.04
	(0.04)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Obs.	82	82	82	82	82	82
Mean of dep. var	0.52	0.64	-0.12	-0.15	0.63	-0.78

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 (3.5)). 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).

Table A.5: The Cyclicality of Job Creation Rates: Continuing firms

	Productivity (TFP)			**Wage**		
	Total	Poaching	Nonemploy.	Total	Poaching	Nonemploy.
Change in Unemp.	0.05	-0.20***	0.25***	-0.11	-0.21***	0.11*
	(0.08)	(0.05)	(0.06)	(0.09)	(0.07)	(0.06)
Level of Unemp.	-0.15***	-0.14***	-0.01	-0.24***	-0.16***	-0.08***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Obs.	82	82	82	82	82	82
Mean of dep. var	0.81	0.75	0.07	-0.03	0.58	-0.61

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 (3.5)). 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).

Table A.6: The Cyclicality of Job Creation Rates: Continuing firms

	TFP			Labor productivity: Value added per worker			Sales per worker		
	Total	EE	NE	Total	EE	NE	Total	EE	NE
Change in Unemp.	0.05	-0.20***	0.25***	0.21***	-0.08	0.28***	0.09	-0.13**	0.22***
	(0.08)	(0.05)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
Level of Unemp.	-0.15***	-0.14***	-0.01	-0.08***	-0.13***	0.06**	-0.17***	-0.16***	-0.02
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Obs.	82	82	82	82	82	82	82	82	82
Mean of dep. var	0.81	0.75	0.07	0.93	0.87	0.06	0.60	0.68	-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 (3.5)). 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).

Table A.7: The Cyclicality of Job Creation Rates: Time-invariant Types

	TFP			Labor productivity: Value added per worker			Sales per worker		
	Total	EE	NE	Total	EE	NE Total	EE	NE	
Change in Unemp.	0.26***	-0.09**	0.35***	0.12*	-0.15***	0.28***	0.00	-0.13***	0.13**
	(0.09)	(0.05)	(0.07)	(0.07)	(0.06)	(0.09)	(0.06)	(0.04)	(0.07)
Level of Unemp.	0.00	-0.05**	0.05	0.09***	-0.10***	0.19***	-0.07**	-0.11***	0.05
	(0.04)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Obs.	82	82	82	82	82	82	82	82	82
Mean of dep. var	0.52	0.64	-0.12	0.35	0.64	-0.29	0.27	0.56	-0.29

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 (3.5)). 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).

Table A.8: The Cyclicality of Job Creation Rates: Alternative Ranking

	Productivity (TFP)			**Sales per worker**		
	Total	Poaching	Nonemp.	Total	Poaching	Nonemp.
			Panel (a): 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 (b): 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 (3.5)). 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).

B Institutional Setting and Data Sources

B.1 Institutional Setting

A full-time job in Denmark consists of 37 hours per week and around 1800 per year. Although hours worked are low, the participation rate is around 84 percent in 2021, higher than the EU or the US. 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, implementing a string of workfare reforms in the 1990s has changed the structural level of unemployment (Andersen and Svarer, 2007).

B.2 Construction of Employment Spell Data

The labor market history dataset ("the employment 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 dataset 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 dataset, 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 Sôresen (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.

Theoretical framework. 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. (2018) 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, on average, hire more, face higher marginal costs of hiring (Carrillo-Tudela and Coles, 2016). Audoly (2023) 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, he uses the Business Structure Database, a snapshot of the registry of all British companies. However, this dataset does not contain value-added or labor costs at the firm level. Other models have predictions on net poaching by firm types. In Elsby and Gottfries (2022), 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. Figure 10 (Panel C) shows that the net poaching rate increases with labor productivity and employment growth.

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