

DISCUSSION PAPER SERIES

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and Time Aggregation Bias**

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ABSTRACT

Employer-to-Employer Transitions and Time Aggregation Bias*

The rate at which workers switch employers without experiencing a spell of unemployment is one of the most important labor market indicators. However, Employer-to-Employer (EE) transitions are hard to measure in widely used matched employer-employee datasets such as those available in the US. We investigate how the lack of the exact start and end dates for job spells affect the level and cyclicity of EE transitions using Danish data containing daily information on employment relationships. Defining EE transitions based on quarterly data overestimates the EE transition rate by approximately 30% compared to daily data. The bias is procyclical and is reduced by more than 10% in recessions. We propose an algorithm that uses earnings and not just start and end dates of jobs to redefine EE transitions. Our definition performs better than definitions used in the literature.

JEL Classification: E24, E32, J63

Keywords: labor market flows, employer-to-employer transitions, measurement problems, time aggregation bias

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1 Introduction

The majority of workers switch jobs without experiencing a spell of unemployment. In the US, 2.6% of employed persons change employers each month, a flow that is more than twice as large as employment to unemployment (Fallick and Fleischman, 2004). Moreover, employer-to-employer (henceforth EE) transitions play a key role in job ladder models, the leading framework in labor economics for studying the evolution of wages.

Despite the importance of EE transitions, the lack of the exact start and end dates for employment spells in most datasets limits our understanding of the impact of EE transitions on individual and aggregate labor market outcomes. Misclassified transitions affect not only the direct importance of the EE transition rate compared to the UE rate, but they also affect policy conclusions based on models that use the EE rate as a key input. Indeed, EE transitions are interpreted as coming from search and recruiting efforts that improves the allocation of labor resources (Mortensen, 2003). Misclassifications of EE transitions are referred to as time aggregation bias. It arises when employment relationships (i.e., jobs) are not measured continuously but are aggregated over some time period. Prominent examples are administrative datasets recorded at the annual or quarterly frequency from the US.

How does the EE rate differ when job spells are measured at different frequencies? Is misclassification more severe in loose labor markets? This paper proposes answers to these questions, and proposes a way to correct for time aggregation bias using earnings information and not just start and end dates of employment spells. To do so, we use employment spell data measured at the daily frequency from Denmark for the period 2008-2019. The dataset we exploit is unique in Europe as it covers all jobs in a flexible and dynamic labor market as in the US. For example, American and Danish men are twice as likely to make an EE switch compared to their French and Italian peers throughout their careers (Engbom, 2020).

The main result of this paper is that time aggregation bias overestimates the EE transition rate by up to 30%. Indeed, the quarterly EE transition rate is approximately 3.75% using the daily information. By aggregating to quarterly data, and defining an EE transition as having two jobs in adjacent quarters, the quarterly transition rate is 5.45%, which is 30 % too high. Using a more conservative approach, which defines EE transitions as having two different jobs within the same quarter (within approach), the EE transition rate is around 3.22%, i.e., 14% too low. The reason for the latter result is that the within approach misses true EE transitions that happen right between quarters.

Next, we show that misclassification is procyclical. Increasing the unemployment rate by two percentage points decreases the difference between the quarterly EE and daily EE

rates by 11%. This result is driven by the fact that non-employment spells are shorter in expansions. This makes it more likely to wrongly classify a job change involving a non-employment spell as an EE transition. Our results suggest that, in recessions, the large drop in the EE rate is partly driven by time aggregation bias. This result confirms the conjecture of Moscarini and Postel-Vinay (2018) and Fujita et al. (2020).

Having demonstrated the importance of correcting time aggregation bias in measuring EE transitions, we propose an algorithm that is less prone to measurement errors. The algorithm uses workers' earnings before and after job mobility, and not just start and end dates of jobs, to redefine EE transitions. We exploit workers' earnings as the data reveals that it is highly predictive of EE misclassification. Indeed, we show that jobs that have low earnings in either the origin or the destination firm are likely to be misclassified EE transitions. This is especially true for transitions identified from the quarterly adjacent approach, but not the within approach. This also makes intuitive sense. Jobs present in adjacent quarters, but not in the same quarter and that have low earnings in either the origin or destination firm are likely to have a shorter non-employment spell between them. The algorithm significantly improves the EE rate accuracy using only quarterly data while making fewer misclassification errors. Because it relies solely on earnings information, it can be easily used in other settings, e.g., the LEHD data in the US have the necessary needed to use the algorithm. The algorithm faces a basic trade-off: Reclassifying an EE transition to a non-EE transition can make both a type 1 and a type 2 error. We show that almost all of the additionally identified EE transitions using the adjacent approach at the quarterly frequency, which have low earnings in the last quarter in the origin firm or low earnings in the first quarter in the destination firm, are wrongly classified. Thus, for this group, there is basically no trade-off.

Related literature. This paper contributes to the understanding of employer-to-employer transitions. Engbom (2020) documents large differences in EE rates across countries.¹ We are not aware of a European study that focuses on the measurement of EE transitions. For the US, there are two recent studies. The first study is by economists from the US Census Bureau (Hyatt et al., 2017). Their paper documents the measurement of employer-to-employer by the Census Bureau. Administrative data sources are especially important for the measurement of EE transitions as measuring them in the CPS dataset is challenging since a redesign of the survey questionnaire was redesigned in 2007. Indeed, Fujita et al. (2020) document that an increase in missing answers leads to the spurious

¹The definition of employer-to-employer is the following in Engbom (2020). It is the share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. For male workers of age 25, the EE rate is approximately; 0.07 in Italy; 0.14 in Italy; and 0.16 in the US.

appearance of declining EE transitions after 2007. Mercan (2017) and Mazumder (2007) use the SIPP dataset instead of the CPS. However, the survey design creates additional measurement issues. Respondents are interviewed every four months, which gives rise to recall and response biases (Nakamura et al., 2020).

The importance of EE transitions is motivated by the central role of these transitions in studies of earnings dynamics at the individual and at the aggregate level (Moscarini and Postel-Vinay, 2018; Manning, 2011; Faberman et al., 2017). For example, EE flows in job ladder models can explain wage dispersion for similar workers, or firm dynamics over the business cycle (e.g., Mortensen (2003) Moscarini and Postel-Vinay (2012)). Empirically, Haltiwanger et al. (2018) in the US, and Bertheau et al. (2020) in Europe, document the role of firm heterogeneity to explain EE transition rates over the business cycle. Specifically, Bertheau et al. (2020) uncover a tight link between EE flows and the creation of jobs by the most productive firms.

The paper proceeds as follows. Section 2 describes the data used and the institutional details. In Sections 3 and 4, we present our results and finally, Section 5 concludes.

2 Measuring Employer-to-Employer Transitions

We first describe our definition of what an EE transition is. Then we present the data sources and provide some descriptive statistics. We end the section with an introduction to the institutional setting in Denmark.

2.1 Definition of Employer-to-Employer transitions

We use an administrative matched employer-employee dataset, the *BFL* (*Beskæftigelse for lønmodtagere*). Since 2008, the dataset records the universe of employment spells at the monthly level with exact daily start and end dates for each job. The dataset is constructed from an administrative document that all employers (public and private) report every month to the Danish Tax Authority. In the dataset, an employer is a legal unit that can own many establishments. Thus, employer-to-employer transitions are transitions between different firms and not establishments.²

²A previous version of this work considers additional types of job mobility without experiencing a spell of unemployment. We exclude them in this version. First, we do not consider mobility between establishments. Second, we do not consider job mobility within a business group (i.e., at least two firms connected through an ownership link). Third, we do not consider job changes *within* an establishment (see Bertheau (2021) on this job mobility). Like Fujita et al. (2020), we acknowledge that transitions that do not involve a change of employer are potentially as relevant to a range of labor market outcomes as EE transitions. We leave for future research how workers move within a same employer broadly defined (i.e., across establishments or within a business group).

This is not the case in many matched employer-employee datasets. For example, the widely used LEHD dataset from the US only records whether a worker has been employed at least one day in a quarter.³ We correct for transitions that are due to a change in firm identifiers due to split-ups, mergers, etc.

Different measures of EE transitions. For daily observations, we allow for seven days of non-employment between employment spells. This is the threshold that Bertheau et al. (2020) use in their study of the cyclicity of the job ladder. When we aggregate to lower frequencies, for example, the quarterly level, we define an EE transition in two different ways following Haltiwanger et al. (2018). Our baseline is to define an EE transition as having two different employers in two adjacent periods. This is labelled the "adjacent"-approach. However, this definition allows for a fairly long duration of non-employment spells in between jobs. In fact, EE transitions with non-employment periods of up to 6 months could exist between jobs. A more conservative approach is to define EE transitions when we observe different employers within the same quarter. We call this the "within"-approach.

In all, we have four main measures of EE transitions: (i) daily, (ii) monthly "adjacent", (iii) quarterly "adjacent" and, (iv) quarterly "within".

Misclassifications. There are two types of misclassifications. First, "Type-1" error, which classify a transition as an EE-transition even though it is an ENE-transition. It is a false positive. Second, "Type-2" error, which classify a transition as an ENE-transition even though it is an EE-transition. It is a false negative. Type 1 errors lead to over-estimation of the EE transition rate, while type 2 errors under-estimate it.

As we observe the "true" EE transitions –at a daily level– and those one would observe with quarterly data, it is possible to assess the extent of misclassifications.

2.2 Descriptive Statistics

Table A.1 shows some key statistics for our sample. Notice, that we use all information but we exclude below and above an age threshold. The population is all those in Denmark having a job from age 18 to 60.

First, we show the number of worker-year observations. As we use data from 2008-2019, so the average number of observations in a year is around 3.7 million. Around 30% of all job spells pertain to the public sector, while 23% are in Trade and Transportation,

³Bertheau et al. (2021) provide detailed characteristics of seven European matched employer-employee datasets.

and around 10% are from manufacturing. On average, establishments have 13 employees. Using the daily measure, the quarterly EE hire and separation rate is 4.1%.⁴ The quarterly EN and NE rate is 4.5%, thus, similar to the EE rate.

2.3 Institutional Setting

The Danish labor market is characterized by a so-called flexicurity system with generous social security, low firing costs for firms, and active labor market policies. The unemployment rates in Denmark and in the US are comparable in size and cyclicity (Figure A.1). In the first quarter of 2008, the unemployment rate was 3.2%. In the last quarter of 2010, the unemployment rate reached 8.4%. The unemployment rate peaked in 2010-2012 and gradually went down again until 2020. In the US, the unemployment rate also doubled during the Great Recession (i.e., went from 5% in 2008-Q1 to 9.5% in 2010-Q4). There are few firing regulations, so firms can easily adjust their labor force compared to other countries in Europe. This institutional setting is important for estimating EE flows. For example, notice periods are 20 days for blue-collar workers and 70 days for white-collar workers. The weak regulation implies that we do not expect to find many EE transitions that are triggered by involuntary transitions. Using survey data where workers report whether transitions were voluntary, Taber and Vejlin (2020) find that 80% of EE transitions are voluntarily. In terms of labor market transition rates, Denmark is comparable to the US. American and Danish men are twice as likely to make a voluntary employer-to-employer switch compared to their French and Italian peers throughout their careers (Engbom, 2020) for recent evidence. Also, out of 34 OECD high-income countries, the World Bank ranks Denmark 2nd on the ease of doing business, the U.S is 4th, France 20th, and Italy 31th (World Bank, 2020). Based on these facts, we conjecture that our results would extend to countries with flexible labor markets, such as the US.

3 The Importance of Time Aggregation Bias

This section shows how time aggregation bias affects measured EE transition rates. We show this in two ways. First, we compute the distribution of the non-employment duration between jobs using the exact timing of when jobs begin and end. Second, we replicate "data structures", where the employment relationship is not recorded on a daily basis but on monthly or quarterly levels.⁵

⁴Table A.2 shows the number of firms, establishments, and workers. We do not include hire and separations from recalls, and transitions into and out of the dataset.

⁵By replicating data structures, we collapse our daily information into lower frequency information. E.g., we collapse it into quarterly information such that we mimic other datasets, that do not have daily

3.1 The Duration of non-employment Spells

Figure 1 shows the distribution of the non-employment duration between jobs. First, Figure 1a shows the cumulative distribution function (CDF) of non-employment spell lengths ranging from 0 to 6 months, which begin with an employment spell and end with an employment spell. Hence, the distribution is conditional on a non-employment duration being shorter than 180 days. Around 62% of the transitions between jobs that occur without a long period of non-employment between them (up to 6 months) happen without any non-employment spells in between the two jobs at all. However, 38% have a period of non-employment between them. These are the job transitions that are potentially at risk of being misclassified as EE transitions depending on the observational frequency that jobs are observed at. For example, in the matched employer-employee (LEHD) data for the US, employment relationships are observed at a quarterly frequency. Thus, a non-employment spell of 180 days is potentially not detected. The difference between any non-employment spells and 40 days is roughly 20 percentage point. Next, we investigate how the distribution change over the business cycle. In Figure 1b we take the ratio of the CDF in recession years (2009-2011) to the CDF of expansion years (2016-2018).⁶ We observe that, no matter the numbers of days between the two job spells selected, the fraction of non-employment spells that have ended in a transition before that number of non-employment days is higher in expansions than in recessions. Thus, time aggregation bias is potentially more of a problem in expansions. We quantify it in Section 3.3.

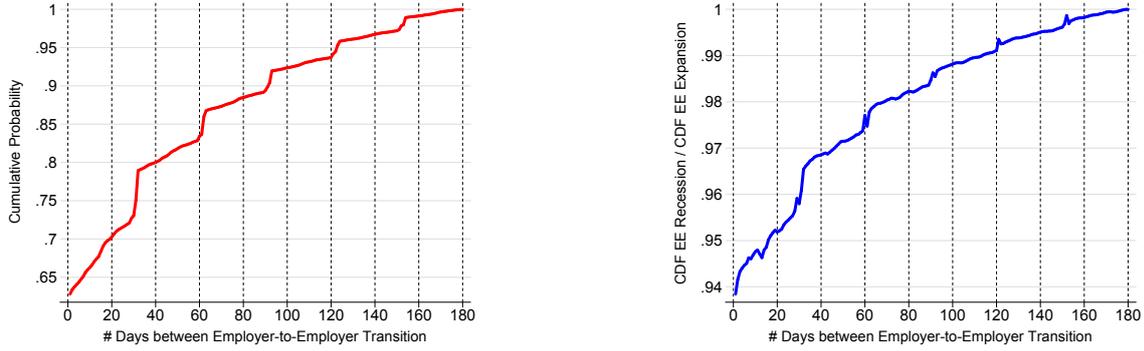
3.2 EE at the Monthly and at the Quarterly Frequencies

While Figure 1 shows the features of the distribution of non-employment spell lengths between job, it is still an open question how it translates into time aggregation bias. This depends on the exact start and end dates of the job spell in conjunction with the frequency of observations in the data. We aggregate daily spells to lower frequencies and use monthly and quarterly frequencies. If we observe that a worker is employed just one day within a period (month/quarter) then we record this as employment in that period. Likewise, we aggregate earnings for each employer within each period. Figure 2 presents the four definitions of EE transitions provided in Section 3.3.

information.

⁶Figure A.1 shows the evolution of the unemployment rate.

Figure 1: Non-employment Duration between Jobs

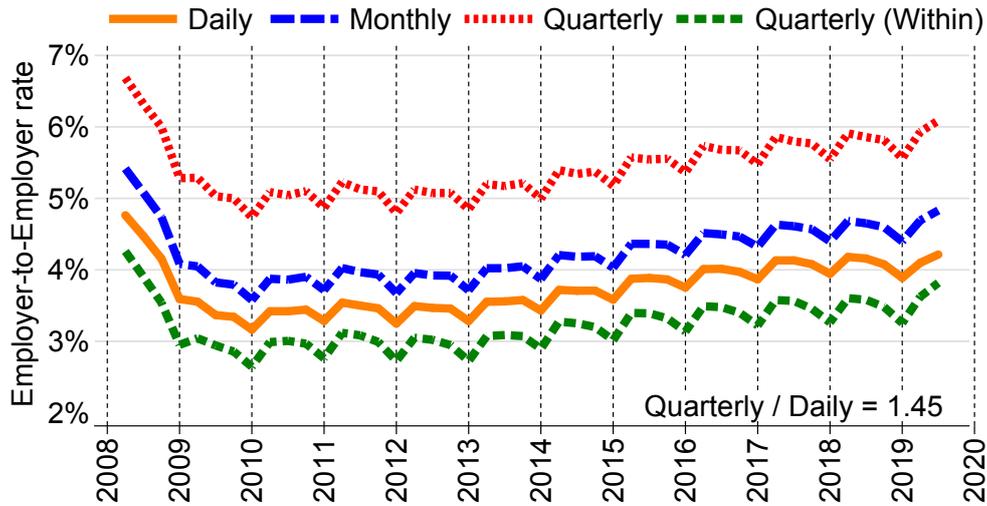


(a) CDF Duration between Jobs

(b) Ratio of CDF

Note: Panel (a) in the figure shows the CDF of non-employment durations conditional on the non-employment duration lasting less than 180 days. In panel (b) we show the ratio of the CDFs for the recession years 2009-2011 to expansion years 2016-2018.

Figure 2: Employer-to-Employer Transitions at Different Frequencies



Note: The figure represents EE transition rates at different levels of time aggregation. See Section 2.1 for definitions.

The quarterly EE transition rate using the daily information is 3.75%. Moving to monthly information using the adjacent approach (i.e., different employers in two adjacent months) results in both type 1 and 2 errors. However, there are more type 1 errors, which occurs when we classify some transitions as EE when they are not. However, the effect is not quantitatively important as it only increases the EE rate to around 4.23% implying

that the EE rate using monthly information is overestimated by around 11%.⁷ This result is comparable to Nordmeier (2014), who uses daily data from Germany and finds that the job-to-unemployment and unemployment-to-job rates, i.e., the job separation and job finding rates, are underestimated by around 10% when moving from a daily to a monthly time period. However, moving to only having quarterly information increases the estimate of the EE transition rate quite a bit, to 5.42%. Thus, time aggregation bias using quarterly data and the adjacent measurement approach causes EE transition rate to be overestimated by around 30%. One of the most widely used datasets, where time aggregation is concern, is the LEHD data for the US. Using LEHD and defining an EE transition as requiring a worker to be employed in two adjacent quarters, which is the definition that we also used above, Haltiwanger et al. (2018) find quarterly EE rates of around 8%. Our results suggest that this rate is around 30% too high since when we move from a quarterly frequency to a daily one, the EE rate drops from 5.42 to 3.75%.

Other definitions of EE transitions are of course possible, as mentioned in Section 2.1. The more conservative approach used in Haltiwanger et al. (2018) is that transitions have to happen within quarters and not between (the "within" approach). This is the strictest restriction in the sense that it gives the lowest quarterly EE transition rate in Haltiwanger et al. (2018) of 4% compared to around 8% using the adjacent approach. Figure 2 presents the EE transition rate using the within approach on quarterly data. We find that we actually underestimate EE transitions using the within approach. The true EE rate is 3.75%, but the within approach calculated on quarterly data gives an estimate of around 3.22%. Thus, it is 14% too low.

3.3 Cyclicalilty of Time Aggregation Bias

Is time aggregation bias more severe in loose or in tight labor markets? Time aggregation is plausibly more severe in expansions because of shorter non-employment spells. Figure 1b indicates that this could be the case. If it is the case, it has important implications for a wide range of models trying to fit business cycle transition rates, e.g., Moscarini and Postel-Vinay (2013). Models of this type make predictions about which types of firms poach from other firms and which hire from non-employment. The focus is typically on how EE transition rates change over the business cycle. Thus, if time aggregation bias is also changing over the business cycle, this needs to be dealt with in order to test the predictions of the models.

To quantify the effect of time aggregation bias on the relationship between the business cycle and EE transitions, we estimate the following model:

⁷This is calculated as $(4.23 - 3.75)/4.23$.

$$y_t = \alpha + \beta Cycle_t + \gamma_t + \epsilon_t. \quad (1)$$

y_t is the quarterly *differential* EE transition rate, where the difference is either quarterly or monthly to daily. γ_t is a linear trend. The parameter of interest is β , which measures the effect of a one percentage point increase of the cyclical indicator on the differential EE transition rate at different observational frequencies. As the cyclical indicator, we use the deviation from the HP filtered trend of unemployment.

Table 1 shows the estimated coefficients for the model both with and without a linear time trend together with the mean of the differential quarterly flows.

Table 1: The Cyclicalities of the Time Aggregation Bias: Unemployment Level

	Quarterly to Daily		Monthly to Daily	
	(1)	(2)	(3)	(4)
Cyclical indicator	-0.090	-0.094	-0.063	-0.065
	(0.016)	(0.016)	(0.008)	(0.008)
Observations	46	46	46	46
Mean Dep. Var.	1.67	1.67	.49	.49
Trend	No	Yes	No	Yes

Notes: The table reports results from a regression where the outcome represents the percentage point difference in employer-to-employer transition rates from quarterly to daily frequency (1 and 2), and from monthly to daily (3 and 4) when the labor market deteriorates (equation (1)). Standard errors in parenthesis. The cyclical indicator is the deviation from the HP filtered trend of the unemployment rate.

First, we see that the average differences in quarterly flow rates are 1.67 percentage points and 0.49 percentage points, corresponding to the results in Figure 2. We detect a statistically significant effect of the cyclicalities of time aggregation bias. For example, looking at the result of the regression using the difference between the quarterly to daily aggregations as an outcome, which is the time aggregation bias, (without a time trend) we find that when unemployment increases by one percentage point, the difference becomes smaller. In particular, the quarterly to daily differential EE rate decreases by 0.090 percentage points for a one percentage point increase in unemployment, see Column (1). The magnitude of the coefficient is not negligible. Indeed, as the mean differential growth rate is 1.67, a two percentage point increase in unemployment reduces the differential EE rate by 11%. Including a time trend leads to the same conclusion, see Column (2). The difference is higher for the difference between quarterly and daily EE rates compared to the difference between monthly and daily EE rates. For EE at the monthly frequency,

the difference is 0.065 percentage points using the model with a time trend. Appendix Figure A.2 plots the data points behind the regression for the model without a time trend. These results are not driven by outliers. Moreover, Appendix Table A.3 reports similar magnitudes of the time aggregation bias when we use the change in the unemployment rate as a measure of labor market condition. These results confirm that time aggregation bias for EE transitions is more severe in expansions.

Our results speak to recent studies, e.g., (Moscarini and Postel-Vinay (2018) and Fujita et al. (2020)), which conjecture that time aggregation bias can impact the cyclicity of EE transitions. To the best of our knowledge, we are the first to show it formally. Nordmeier (2014) investigates time aggregation in job finding and job separation rates. She finds a pro-cyclical time aggregation bias in the job-finding rate, but not in the separation rate.

4 Correcting Employer-to-Employer Transitions

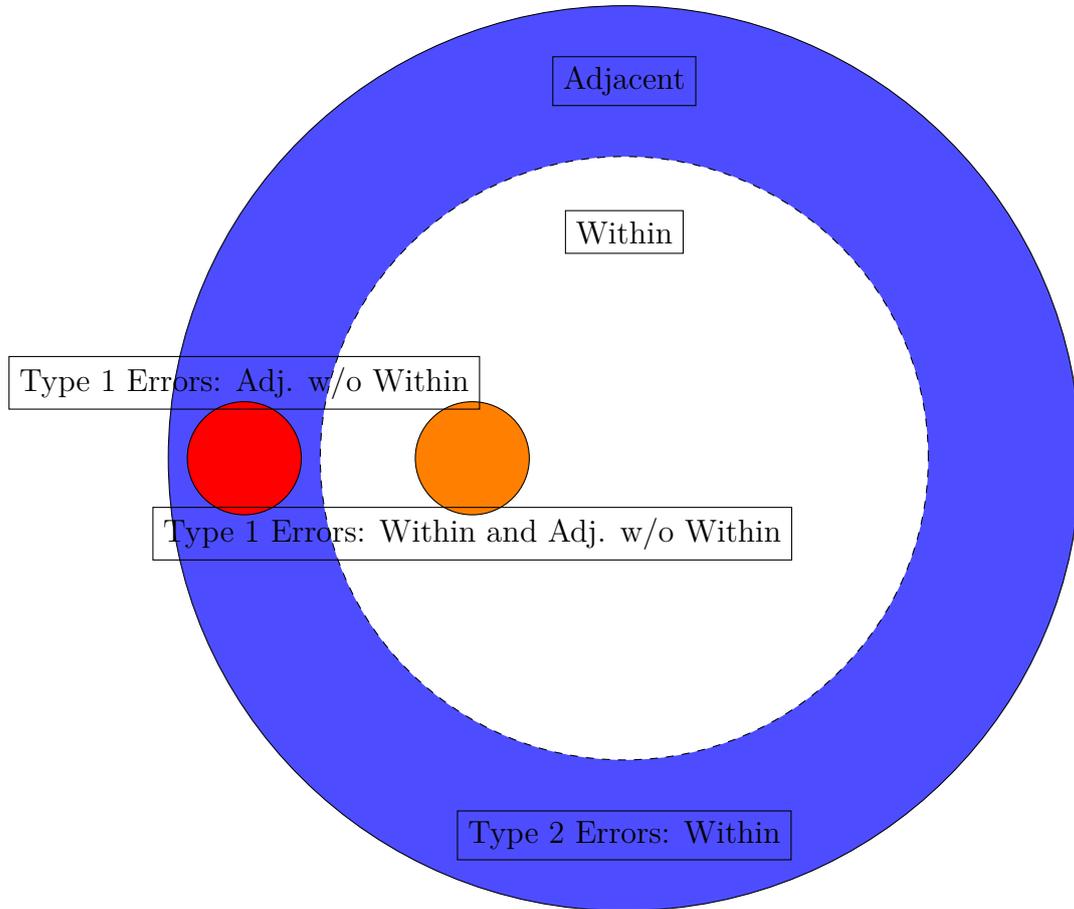
This section shows that some EE transitions, measured at the quarterly frequency, can be reclassified to be closer to the rate of EE transitions measured at the daily frequency. We first document how misclassifications of EE transitions identified by the within and adjacent approaches relate to workers' earnings. Low earnings in either the origin or destination firm are very predictive of misclassifications. Next, we implement an algorithm that reclassifies transitions based on earnings. Specifically, we reclassify transitions with earnings below a certain percentile (threshold) in the earnings distribution. We derive how the threshold values should be set to either 1) minimize the number of misclassified transitions or 2) fit the true EE transition rate.

4.1 Characterizing Misclassifications

As detailed in Section 2.1, there are two types of misclassifications. First, we can classify a transition as an EE transition when it is an ENE (employment-to-non-employment-to-employment) transition. This is similar to a type 1 error (a false positive). Accordingly, we label this type of misclassification a "type 1 error" in what follows. In this case, the transition rate is overestimated. Second, we can classify a transition as an ENE transition when, in reality, it is an EE transition. This is similar to a type 2 error (false negative). In this case, we underestimate the transition rate.

Figure 3 illustrates how the error types are related to the two definitions of EE transitions.

Figure 3: Illustration of Error Types



Notes: The figure shows misclassifications of EE transitions for both the within and the adjacent definitions. The adjacent definition contains the inner white circle and the outer blue circle. The within definition is the inner white circle. Regarding the within definition, the blue area of the outer circle (i.e., excluding the red area) marks the set of type 2 errors (false negative) while the orange area marks the set of type 1 errors (false positive). Regarding the adjacent definition, the orange and red circles marks the set of type 1 errors.

Defining the EE rate using the within approach produces both type 1 and type 2 errors. In Figure 3 the transitions identified from the within approach are those within the dashed-line, i.e., the orange circle and the white circle. The type 2 errors generated by the within approach are those marked by blue. In Section 3.2, we find that the quarterly-within EE rate was lower than the EE rate defined by the daily information. Therefore, type 2 errors dominate. However, it was not clear a priori what the bias would be using the quarterly within definition as it produces both errors. Defining the EE rate using the adjacent approach with quarterly information only produces type 1 errors, i.e., the red and orange circles in Figure 3. The reason is that all true EE transitions are captured

by the adjacent approach. Thus, all the type 2 errors from the within approach are identified as EE transitions by the adjacent approach. However, the adjacent approach additionally adds some type 1 errors (red circle). From this it is clear that the EE rate using the adjacent approach is an upper bound, but as we saw in the previous section (Section 3.2), it overestimates the daily transition rate by around 45%.

Our objective is to reclassify the red and orange circles in Figure 3, without reclassifying any transitions lying in the white and blue areas, under the constraint of only using information available at the quarterly frequency.

As a first step, we characterize how type 1 and type 2 errors using the two approaches relate to earnings.

4.1.1 Earnings Differences

The main idea is that employment spells with low earnings either in the origin or destination firm are likely to be misclassified, since low earnings is an indication that the worker did not work there the full quarter. We measure low earnings as the change in earnings in the firm right before the move and the change in earnings in the firm after the move. We denote t_o as the last quarter in the origin firm and t_d as the first quarter in the destination firm. We define the earnings difference in the origin firm as given by the earnings difference between t_o and t_{o-1} , while the earnings difference in the destination firm is given by the difference between earnings in quarters t_d and t_{d+1} . As we compute earnings differences, we restrict our sample to transitions for which we observe multiple quarters in both the origin and destination firms.⁸

Figure 4 represents the ratio of misclassified transitions to the total number of transitions as a function of the earnings difference one quarter before and after the transition. We group transitions into percentile bins of earnings differences. At each percentile of the earnings difference distribution, we calculate the fraction of errors out of the total number of transitions.

Panels (a) and (b) present results for the within definition, and (c) and (d) present results for additional EE transitions identified from the adjacent approach. We label these transitions "Adjacent without within" transitions as the adjacent approach also contains all the EE transitions identified from the within approach. Thus, below the wording

⁸Appendix Table A.4 presents the size of each of the four mutually exclusive subgroups. EE transitions identified from the within approach consist equally of multi-quarter transitions, i.e., where the jobs in both the origin and the destination firms exist in multiple quarters, and single-quarter transitions. Transitions that are additionally identified from the adjacent approach consist primarily of single-quarter transitions. That is, where the job in either the origin or the destination firm only lasted one quarter (or both).

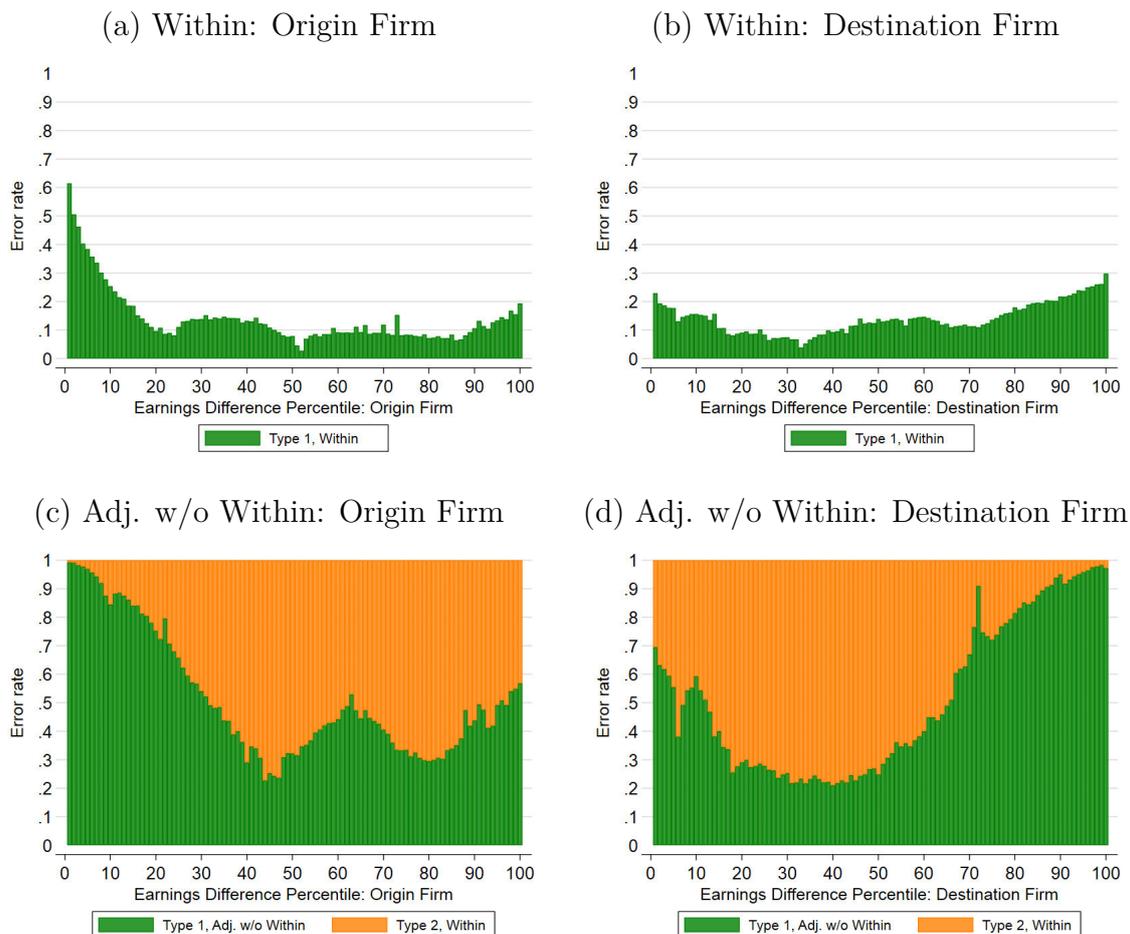
"additionally identified" refers to this sample. Panel (a) plots the earnings difference in the origin firm. We find misclassification of more than 10% in the bottom quintile of the earnings difference distribution. Misclassified transitions reach 60% at the lowest percentile. Turning to panel (b), the expected pattern emerges when we compute earnings differences at the destination firm. When earnings are higher in t_{d+1} compared to t_d , it is more likely that the transition is misclassified. However, the error rate is lower, with only around 20% of the top quintile of earnings differences being type 1 errors.

Panel (c) plots the earnings difference in the origin firm for those EE transitions which are additionally identified from the adjacent approach (blue and red areas in Figure 3). We detect a clear difference in both the general level of type 1 errors and how predictive earnings differences are. While in panel (a) the level of type 1 errors is around 10% and reaches 60% in the lowest percentile, in panel (c) the share of misclassified transitions reaches 40-50%, going up to 100% in the lowest decile in the origin firm. The type 1 error rate is, in general, higher for the transitions additionally identified from the adjacent approach. This result is not surprising, since the adjacent definition overestimates EE transitions because it allows for up to 6 months of non-employment between two jobs.

Figure 3 reveals that the additional EE transitions identified from the adjacent approach are either type 1 errors caused by the adjacent approach or they are type 2 errors if we only used the within approach. That is, those EE transitions identified additionally from the adjacent approach are either true EE transitions, in which case they are type 2 errors if we had only used the within approach, or they are false positive EE transitions, in which case they are type 1 error caused by the adjacent approach.

The trade-off in reclassification of EE transitions is to balance the type 1 and type 2 errors when reclassifying. Reclassifying in order to correct type 1 errors tends to also produce additional type 2 errors. Panels (a) and (b) of Figure 3 indicate that reclassification is hard. That is, if we reclassify the EE transitions identified from the within approach, which have the lowest earnings differences in the origin firm, we get rid of falsely classified EE transitions in 60% of the cases. However, in the remaining 40% we make a mistake and reclassify a true EE transition as an ENE transition, i.e., we produce a type 2 error. Nonetheless, there is more potential in reclassifying those transitions that are additionally identified from the adjacent approach. Reclassifying those with really low (high) earnings differences in the origin (destination) firm almost only corrects type 1 errors.

Figure 4: Type 1 and 2 Errors by Earnings Differences



Note: The percentiles represent the rank of the earnings differences within the group. That is, for panel (a), it is the rank in the earnings differences distribution in the origin firm for those transitions identified using the within approach. Panels (a) and (b) shows the error rates for EE transition rates using the within approach for each earnings difference percentile in the origin and destination firms, respectively. The figure shows the fractions of EE transitions that are of type 1 and 2 errors. The error rate is calculated as the number errors divided by the number of transitions within each percentile of the quarterly earnings difference distribution. For panels (c) and (d), we show the same, but for the transitions identified *additionally* from the adjacent approach.

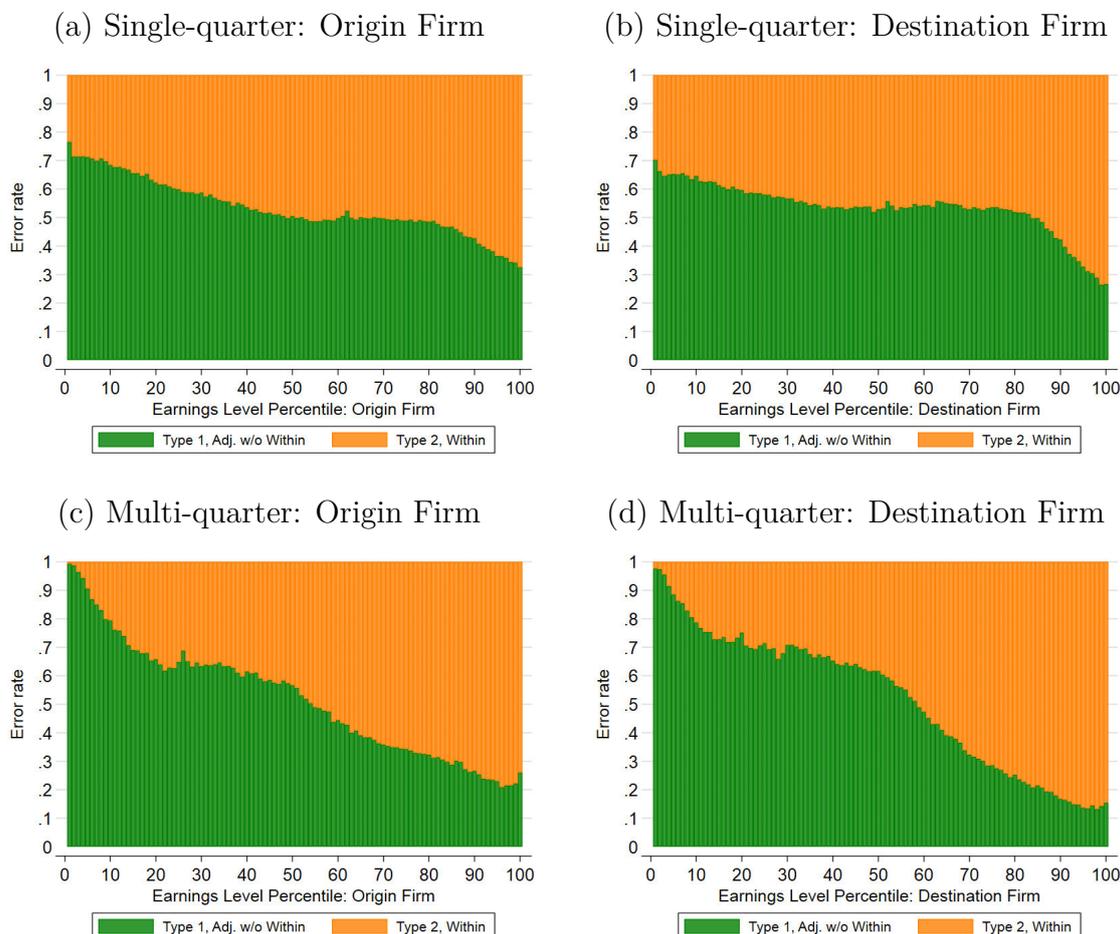
4.1.2 Earnings Levels

Section 4.1.1 shows that earnings differences are a useful predictor of misclassifications. However, it is not possible to measure earnings differences for short employment spells.⁹ To complement our findings, we use earnings levels for short employment spells. Figure 5 shows the same graph for EE transitions additionally identified from the adjacent approach and using earnings levels instead of differences. We additionally split the sample

⁹Note that, employment spells that do not cover at least one employment day in two quarters are excluded in the analysis of earnings differences (Section 4.1.1).

into two. First, the "Multi-quarter" job spells are those where we can construct earnings differences and that were examined in Section 4.1.1, while "Single-quarter" job spells are the remaining spells.¹⁰

Figure 5: Type 1 and 2 Errors by Earnings Levels: Adj. w/o Within EE transitions



Note: The percentiles represent the rank of the earnings differences within the group. I.e., for panel (a) it is the rank in the earnings level distribution in the origin firm for those transitions identified additionally from the adjacent approach and which are single-quarter transitions. Panels (a)-(d) show the error rates for EE transition rates identified additionally from the adjacent approach for each earnings level percentile in the origin and destination firms, respectively, split by single- and multi-quarter transitions. The figure shows the fractions of EE transitions that are type 1 and type 2 errors. The error rate is calculated as the number of errors divided by the number of transitions within each percentile of the quarterly earnings level distribution.

Panels (a) and (b) reveal that the type 1 error rate is around 40-50 % in general. However, the relationship is flatter with only around 70% of EE transitions in the lowest earnings percentile being type 1 errors. Even if the share of misclassified transitions is lower compared to earnings differences, it might still be useful, since it is more than

¹⁰Results for the within approach are reported in Appendix B.1. We find little scope for improving the identification of EE transitions identified from the within approach using earnings levels.

50%. All in all, reclassifying those transitions as ENE eliminates more mistakes than it generates.

Panels (c) and (d) use the same sample as in Section 4.1.1. That is, as the sample with more than one quarter available before and after the EE transition. While the type 1 error rate is still around 100% in the lowest percentiles, the relationship is pretty steep and in the lowest decile, the type 1 error rate is, on average, around 85% compared to around 100% when using the earnings difference.

In conclusion, we find that: (i) earnings differences are better predictors than earnings levels, and (ii) it seems most promising to potentially reclassify those EE transitions additionally identified from the adjacent approach, while those identified from the within approach are harder to reclassify without creating mistakes (type 2 errors).

4.2 Our Correction

We construct an algorithm relying exclusively on quarterly frequency information to correct EE transitions. We evaluate the algorithm using the daily transitions as well as the number of transitions that are either type 1 or type 2 errors.

Ideally, the algorithm should use the adjacent approach and eliminate all type 1 errors (red and orange areas in Figure 3), since the remaining transitions are only true EE transitions. However, the reclassification inadvertently generates type 2 errors, as it reclassifies true EE transitions to ENE (see Section 4.1).

Based on the conclusion of Section 4.1, we reclassify transitions identified as EE to ENE if the earnings differences are below (above) some threshold percentiles in the origin (destination) firm.¹¹ Based on the results in Section 4.1, we allow for separate thresholds for EE transitions identified from the within approach and those additionally identified from the adjacent approach. In particular, we implement the following:

- **Within, Level:** EE transitions that are identified from the within approach, where earnings differences cannot be calculated are then reclassified as ENE if the earnings level in the origin (destination) firm is below the $k_{w,l,o}$ 'th ($k_{w,l,d}$ 'th) percentile.¹²
- **Adj. w/o Within, Level:** EE transitions that are identified additionally from the adjacent approach, where earnings differences cannot be calculated are then

¹¹We use earnings levels if earnings differences cannot be identified. Notice that the way we define differences in earnings in the destination firm implies that earnings differences of high percentiles are most likely to have type 1 errors (Figure 4).

¹²In $k_{w,l,o}$ the first letter in the subscript (w) refers to the approach (within), the second letter (l) refers to the level (as opposed to difference), and the third letter (o) refers to the firm (origin or destination).

reclassified as ENE if the earnings level in the origin (destination) firm is below the $k_{a,l,o}$ 'th ($k_{a,l,d}$ 'th) percentile.

- **Within, Difference:** EE transitions that are identified from the within approach, where earnings differences can be calculated are then reclassified as ENE if the earnings difference in the origin (destination) firm is below (above) the $k_{w,d,o}$ 'th ($k_{w,d,d}$ 'th) percentile.
- **Adj. w/o Within, Difference:** EE transitions that are identified additionally from the adjacent approach, where earnings differences can be calculated are then reclassified as ENE if the earnings difference in the origin (destination) firm is below (above) the $k_{a,d,o}$ 'th ($k_{a,d,d}$ 'th) percentile.

How we choose the thresholds, $k_{w,l,o}$, $k_{w,l,d}$, $k_{a,l,o}$, $k_{a,l,d}$, $k_{w,d,o}$, $k_{w,d,d}$, $k_{a,d,o}$ and $k_{a,d,d}$, depends on the objective. We have two objective functions. First, we seek to minimize the total number of errors. In this case, we give equal weight to type 1 and type 2 errors. Second, we choose the thresholds such that the overall EE transition rate is equal to the true EE transition rate (measured at the daily frequency). This objective has multiple solutions and we choose the solution with the lowest number of total errors. In fact, trying to fit the true EE transitions is equivalent to setting the thresholds such that # type 1 errors=# type 2 errors. We implement both symmetric thresholds, where we use the same threshold for origin and destination firms and asymmetric thresholds, which can vary independently.

For both objective functions, we calculate the EE transition rate and the rate of type 1 and 2 errors. The rate is defined as the total number of errors divided by the total number of true EE transitions. Table 2 reports the results of this exercise. The top panel of the table reports both the within and the quarterly EE transitions as used in Figure 2.¹³ The bottom panel reports the four specifications. In Table A.6 in the Appendix we report the thresholds chosen. Thresholds reflect the patterns found in Figures 4 and 5. In general, only few transitions identified from the within approach are reclassified.

¹³The reason that the within and adjacent approaches do not give the exact same results as previously reported is that the sample is slightly different, since we condition on being able to observe two quarters in order to take differences. That is, we delete the first and last quarter in the sample.

Table 2: Alternative Definitions of EE transitions

	EE rate	% Type 1 Err	% Type 2 Err
Uncorrected Quarterly EE Transition rates			
Within:	3.23	13.9	27.8
Adjacent:	5.44	45.1	0
Corrected Quarterly EE Transition rates			
Min. Tot. Err:	4.22	23.3	10.9
True EE rate:	3.75	17.5	17.5

Note: The table reports EE quarterly transition rate for six different definitions of EE transitions. In the first two rows, we present the uncorrected quarterly EE transition rates using the within and adjacent approaches. In rows three and four, thresholds are chosen to minimize the total number of type 1 and 2 errors. In rows five and six, thresholds are chosen to fit the true (daily) EE transition rate. The fraction of errors is calculated as the number of errors divided by the total number of true EE transitions.

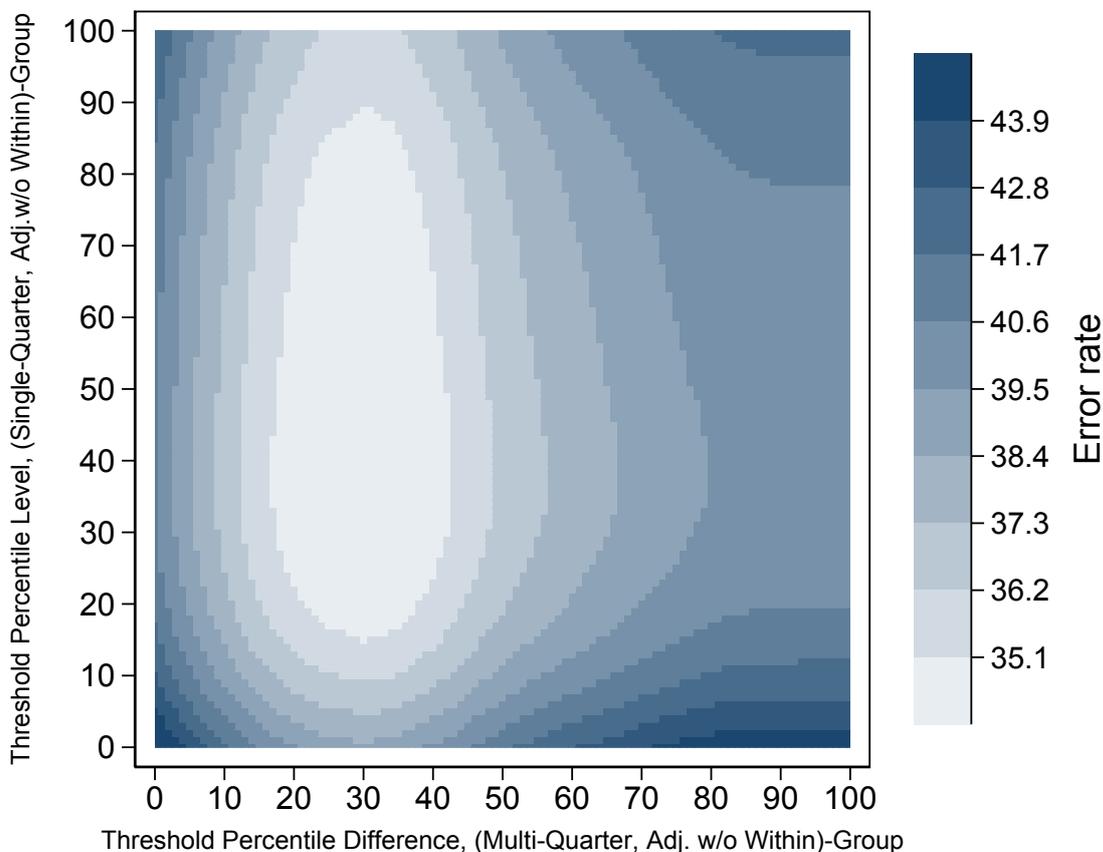
Row (1) shows that using the within approach tends to produce many type 2 errors. However, moving to the adjacent approach in row (2) eliminates type 2 errors completely, but it generates many type 1 errors. Both approaches generate a total error rate of around 45%.

Turning to row (3), we report the results when the objective is to minimize the total number of errors. The total error rate falls from around 45% to around 35%. Notice that the true EE transition rate using daily data is 3.75%. Thus, we are able to both eliminate errors and get closer to the true EE rate. Appendix Table A.5 reports results when we allow for asymmetry in the thresholds. The results are similar.

Figure 6, shows for the symmetric case, how the total error rate changes as the thresholds for the adjacent groups change while holding constant the optimally chosen thresholds for the two within groups.¹⁴ It is clear that there is a minimum at the two optimally chosen thresholds. It is also evident that the thresholds are chosen to be rather high as we reclassify EE transitions with earnings differences in the origin firm below the 30th percentile and with earnings differences in the destination above the 70th percentile. For earnings levels, we reclassify for earnings below the 39th percentile.

¹⁴Since we reclassify almost none of the EE transitions identified from the within approach, we chose to hold them constant.

Figure 6: Trade-offs in the Algorithm: Minimizing Total Errors

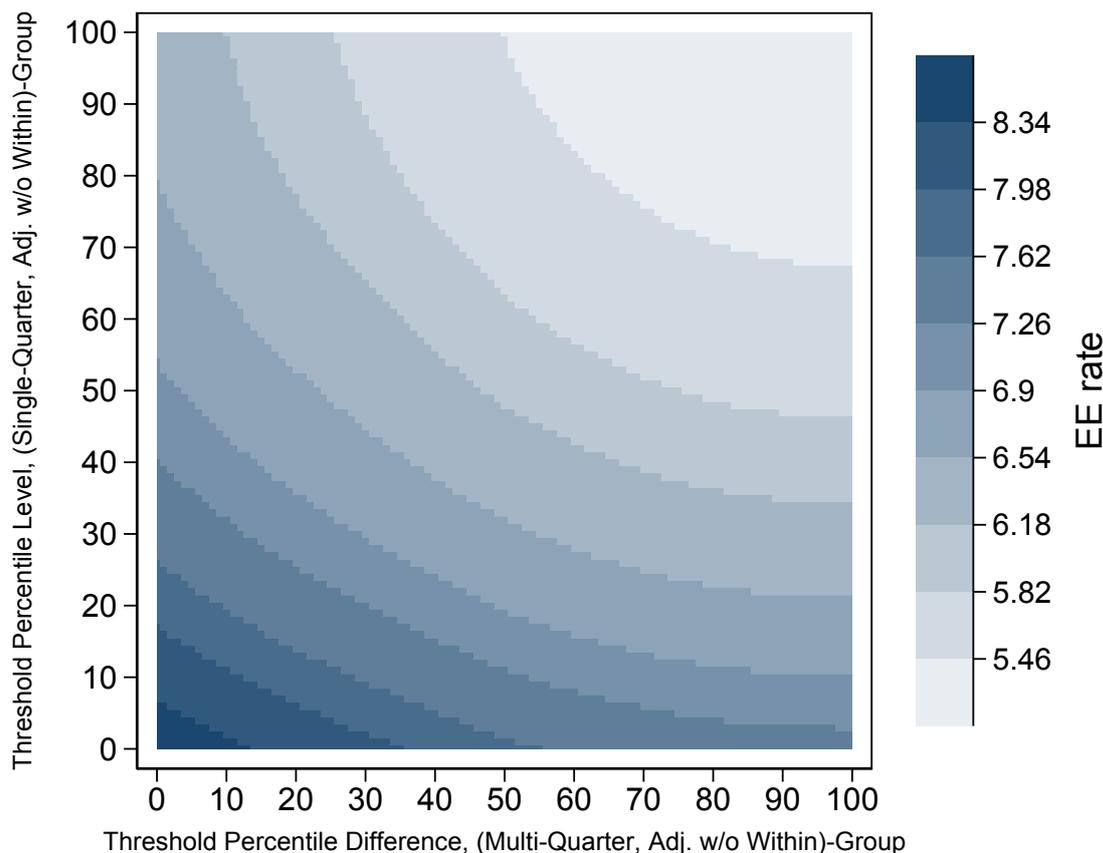


Note: The figure shows the total error rates (type 1 and type 2) holding constant the optimal chosen thresholds for the within groups. The heat map shows how the error rate varies with the symmetric thresholds for the two adjacent groups (multi- and single quarters).

Returning to Table 2 and row (4), we seek to fit the true EE rate conditional on making as few errors as possible. While we fit the true EE rate, the error rate has increased compared to row (3), but only slightly. Appendix Table A.6 reveals that the thresholds have changed quite a bit, so we now reclassify more EE transitions compared to before when the objective is to minimize the number of total errors. This also makes sense. In the case where we minimize the number of errors, we observe that we make more type 1 errors than type 2 errors. That is, we misclassify more true ENE transitions as EE transitions compared to misclassifying EE as ENE. In order to bring down the type 1 error rate, we increase the thresholds and, thereby, also end up making more type 2 errors. This is because we wrongly reclassify some true EE transitions to ENE transitions. This reclassification increases the type 2 error rate more than it decreases the type 1 error rate.

Figure 7 shows how the EE transition rate varies as we symmetrically change the thresholds for the adjacent groups while holding constant the optimal chosen thresholds for the within groups. It is clear from the figure that there are many combinations of thresholds that give the true EE transition rate. We have chosen the thresholds in Table A.6 among the potential candidates that gave the lowest error rate.

Figure 7: Trade-offs in Algorithm: Fitting the EE Rate



Note: The Figure shows the EE transition rate holding constant the optimal chosen thresholds for the within groups. The heat map shows how the EE rate varies with the symmetric thresholds for the two adjacent groups (multi- and single quarters).

5 Conclusions

Employer-to-employer (EE) transitions are important for both individual and aggregate outcomes. For example, recent research demonstrates the weakness of the unemployment rate, which is the leading indicator of labor market conditions, as an indicator measure of aggregate labor market conditions (Bell and Blanchflower, 2021). EE transitions, in

contrast, have been more successful in explaining key statistics, such as aggregate wage growth. However, accurately measuring EE transitions has proven more difficult than first anticipated. This paper deals with important measurement issues regarding how to quantify EE transitions. We use Danish matched employer-employee data from 2008-2019 containing daily information on employment relationships.

Using the daily information, we find considerable time aggregation bias in EE transitions. Defining EE transitions as having different employers in adjacent time periods, we find that the EE transition rate is overestimated by around 14% and 30% for monthly and quarterly aggregations, respectively. By this measure, there is considerable time aggregation bias. Time aggregation bias is significantly larger in expansions than in recessions, since non-employment durations are generally shorter causing ENE transitions to look like EE transitions when employment relationships are only observed at lower frequencies, such as monthly or quarterly.

We analyze how misclassifications of EE transitions relate to earnings differences in the origin and destination firms. Almost all of the EE transitions additionally identified from the adjacent approach with the lowest earnings change in the origin firm and the highest earnings change in the destination firm are false positive. That is, they are true ENE transitions that are misclassified as EE. Based on these findings, we discriminate between the within and adjacent approaches using an algorithm. We derive the data driven optimal thresholds for reclassifying the transitions using the daily EE transition rate as the benchmark. We reduce the error rate from 45% to 35% and additionally the algorithm gives EE transition rates that are closer to the true transition rate compared to both the within and adjacent approaches.

This paper focuses on employer-to-employer transitions without a spell of unemployment. We leave for future research how workers move within a same employer broadly defined (i.e., across establishments or within a business group).

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Appendix

A Additional Tables and Figures

A.1 Tables

Table A.1: Descriptive Statistics

	Sample
Observations (worker-year)	44,597,537
Manufacturing	10.6
Trade and transport	21.4
Other business services	10.6
Construction	6.3
Agriculture	1.5
Finance and Insurance	2.4
Public Admin, Educ. and Health	32.3
Average hourly Wage (real DKK)	207.9
# of Employees Per Estab.	12.7
Quarterly EE Hire Rate	4.1
Quarterly EE Sep. Rate	4.1
Quarterly NE Hire Rate	4.5
Quarterly EN Sep. Rate	4.5

Note: The table shows mean statistics for the sample from 2008Q2 to 2019Q3. EE hire and separation rates are defined using the daily measure (i.e., 7 days of non-employment between subsequent employment spells).

Table A.2: Descriptive Statistics: Details

	Full Sample
Observations (worker-year)	44,597,537
# of Firms	326,786
# of Establishments	417,765
# of Workers	3,691,325
# Of Employees, Cross-Section	2,092,942

Note: The table shows mean statistics for the sample.

Table A.3: The Cyclical­ity of the Time Aggregation Bias: Change in Unemployment

	(1)	(2)	(3)	(4)
Cyclical indicator	0.052	0.090	0.018	0.042
	(0.039)	(0.048)	(0.024)	(0.030)
Observations	46	46	46	46
Mean Dep. Var.	1.67	1.67	.49	.49
Trend	No	Yes	No	Yes

Notes: The table reports results from a regression where the outcome represents the percentage point difference in the employer-to-employer transition rate from quarterly to daily frequency (1 and 2), and from monthly to daily (3 and 4) when the labor market deteriorates (equation (1)). Standard errors in parenthesis. The cyclical indicator is the change in the unemployment rate.

Table A.4: Group Size

	Multi-Quarter Transitions	Single-Quarter Transitions
Within Transitions	1,922,901	1,639,324
Adj. w/o Within Transitions	876,066	1,568,908

Note: The table shows the size of each of the respective groups. The total is the total number of transitions in our data period measured using the adjacent approach. A Multi-Quarter Transition is a transition where the worker is present in multiple quarters in both the origin and destination firms.

Table A.5: Alternative Definitions of EE transitions: Asymmetry in the thresholds

	EE rate	% Type 1 Err	% Type 2 Err
Uncorrected Quarterly EE Transition rates			
Within:	3.23	13.9	27.8
Adjacent:	5.44	45.1	0
Corrected Quarterly EE Transition rates			
Objective:			
Min. Tot. Err (Symmetry):	4.22	23.3	10.9
Min. Tot. Err: None	4.20	23.0	10.9
True EE rate (Symmetry):	3.75	17.5	17.5
True EE rate:	0.0375	17.4	17.4

Notes: The table reports EE quarterly transition rates for six different definitions of EE transitions. In the first two rows, we present the uncorrected quarterly EE transitions rates using the within and adjacent approaches. In rows three and four, thresholds are chosen to minimize the total number of type 1 and 2 errors. In rows five and six, thresholds are chosen to fit the true (daily) EE transition rate. The fraction of errors is calculated as the number of errors divided by the total number of true EE transitions.

Table A.6: Algorithm: Threshold percentiles

Objective	Restrictions	$k_{w,l,o}$	$k_{w,l,d}$	$k_{a,l,o}$	$k_{a,l,d}$	$k_{w,d,o}$	$k_{w,d,d}$	$k_{a,d,o}$	$k_{a,d,d}$
Min. Tot. Err	$k_{.,.,o} = 1 - k_{.,.,d}$	0	0	39	39	0	100	30	70
Min. Tot. Err	None	0	0	42	33	2	100	25	66
True EE rate	$k_{.,.,o} = 1 - k_{.,.,d}$	0	0	73	73	0	100	35	65
True EE rate	None	0	0	67	67	4	100	28	61

Note: The table reports the threshold values chosen in order to minimize the total number of errors and to fit the EE transition rate .

A.2 Additional Figures

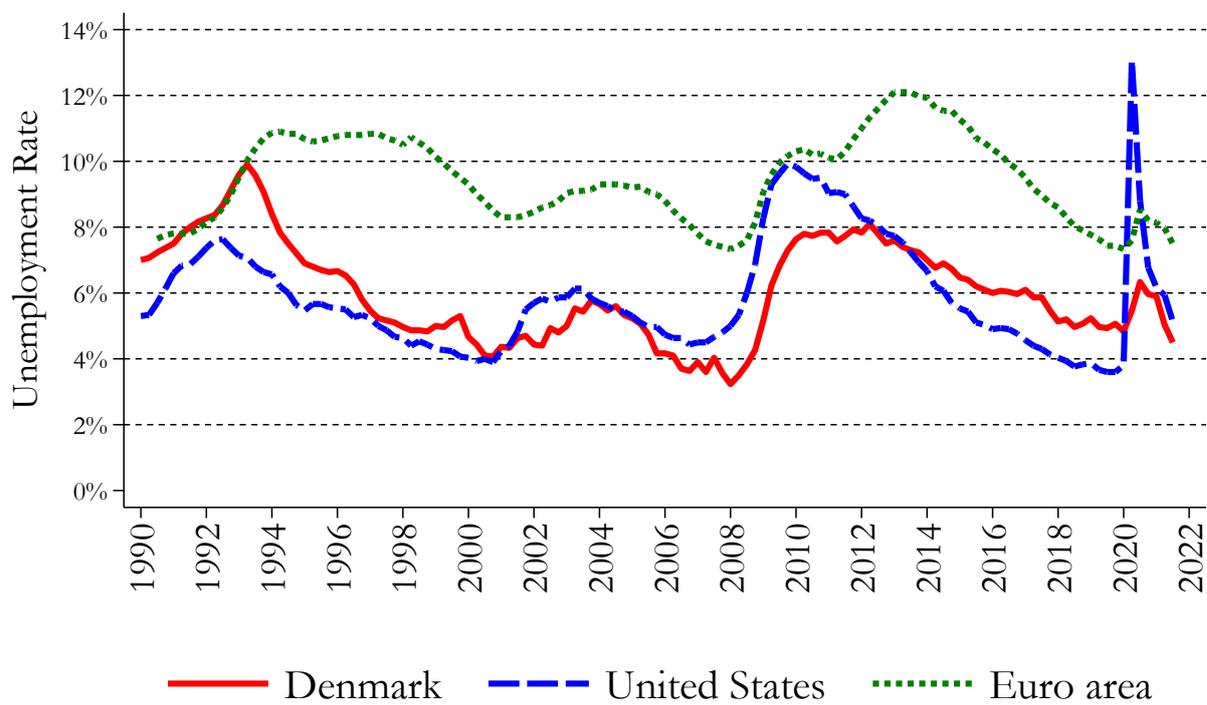


Figure A.1: Business Cycle for Denmark

Note: The figure shows the quarterly unemployment rate.

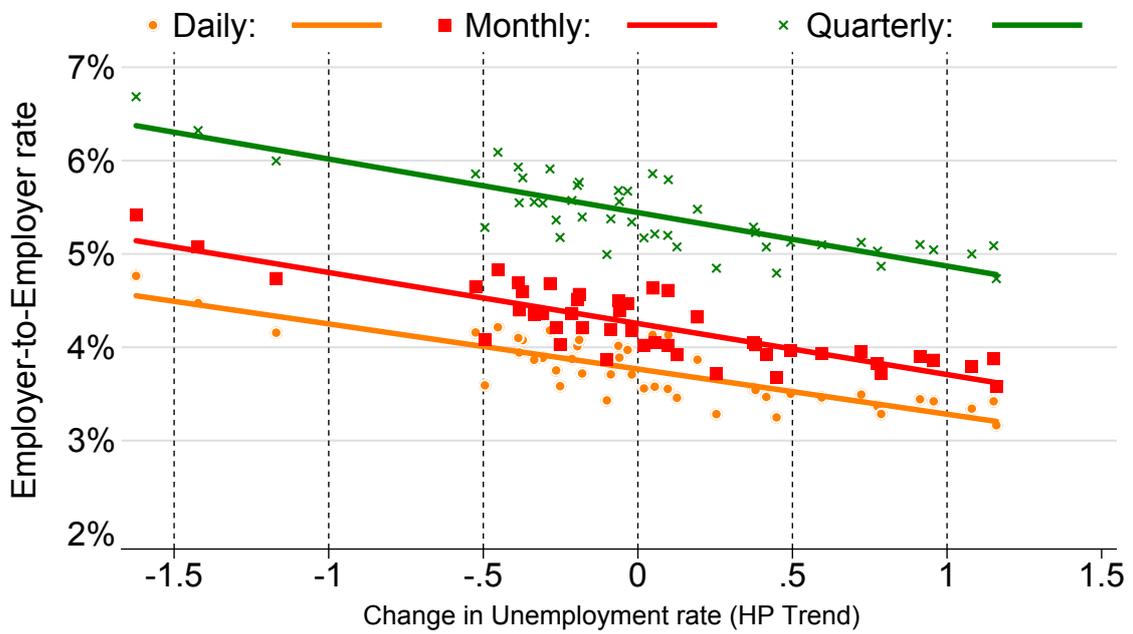


Figure A.2: Scatterplot of Regression

Note: The Figure shows the scatter plot using the daily aggregation measure.

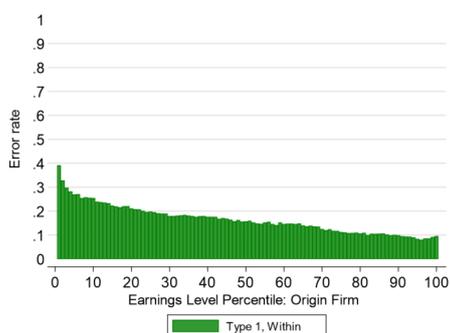
B Additional Analysis

B.1 Misclassification and Earnings Level

We now investigate the errors using the level of earnings, which is all that we can get for a subgroup of transitions, cf. Table A.4. For completeness, we do the figures for all four subgroups including those transitions where we can calculate the difference in earnings. Figure A.3 shows the same graphs as Figure 4, but where we separate the transitions by earnings levels in the quarters t_o and t_d for origin and destination firms, respectively.

Figure A.3: Type 1 and 2 Errors by Earnings Levels

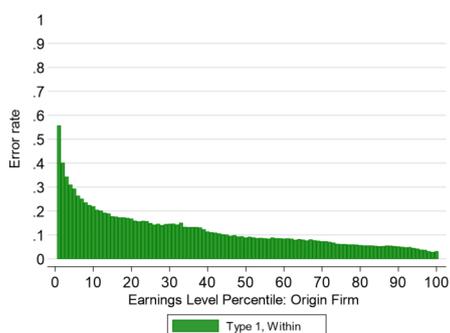
(a) Within, single-quarter: Origin Firm



(b) Within, single-quarter: Destination Firm



(c) Within, multiple-quarter: Origin Firm



(d) Within, multiple-quarter: Destination Firm



Note: The percentile rank is the rank within the group. I.e. for panel (a) it is the rank in the earnings level distribution in the origin firm for those transitions identified using the within approach and which are single-quarter transitions. Panels (a)-(d) shows the error rates for EE transition rates using the within approach for each earnings level percentile in the origin and destination firms, respectively, split by single- and multi-quarter transitions. The figure shows fraction of EE transitions that are of type 1 and 2 errors. The error rate is calculated as the number errors divided by the number of transitions within each percentile of the quarterly earnings level distribution.

In panels (a) and (b) we show the type 1 error rates using the within approach for EE transitions where either (or both) the job in the origin or destination firm is at most one quarter. The type 1 error rate is pretty low for all earnings percentiles. Comparing to panels (c) and (d) where we show the same graph, but for those transitions where we

have multiple quarter in both firms we see that the type 1 error rates are pretty similar, but in general a bit lower for single-quarter observations. It is interesting to compare panels (c) and (d) to panels (a) and (b) in Figure 4, since the population is the same, but the ranking is different. We see that the earnings difference used in Figure 4 is a better predictor of type 1 errors than the level of earnings used in Figure 5.