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Job Reallocation and Wage Structure in the Czech Republic Based on ISPV Data

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Abstract

A component of labor dynamics is attributed to job reallocation. Specifically, job destruction and job creation indicate the structural changes in the labor market and the economy in general. The rates of creation and destruction of occupations differ by industry and reflect the dynamics of the economy. In this paper I employ a job reallocation framework to investigate the structural employment dynamics in the Czech Republic from 2014-2016. I use cross-industry comparisons of job destruction, job creation and job reallocation rates to provide a big picture of the Czech economy via labor market dynamics. Further, I conduct more detailed regional-level analysis of job flows in various industries. I also study wage structure at firm- industry- group-of-industry- and regional- level. The analysis of both job flows and wage dynamics is useful for a more comprehensive assessment of the labor market dynamics. Among other results, I show that manufacturing and trade sectors grew fastest on average in the Czech Republic in 2014-2016. Non-service sectors except for manufacturing consistently shrank on average in 2014-2016. Wages evolved similarly across the majority of industries and grew for all quantiles of the wage distribution. I also find evidence of a strong negative relation between firm-level job flows and average wage

Abstrakt

Složka dynamiky pracovní síly je připisována přerozdělování pracovních míst. Konkrétně destrukce a tvorba pracovních míst naznačují strukturální změny na trhu práce a v ekonomice obecně. Míra vytváření a zániku povolání se liší podle odvětví a odráží dynamiku ekonomiky. V tomto článku používám rámec pro přerozdělení pracovních míst ke zkoumání strukturální dynamiky zaměstnanosti v České Republice v letech 2014-2016. Používám meziodvětvová srovnání míry zániku pracovních míst, tvorby pracovních míst a přerozdělování pracovních míst, abych poskytla ucelený obraz o české ekonomice prostřednictvím dynamiky trhu práce. Dále provádím podrobnější regionální analýzu pracovních toků v různých průmyslových odvětvích. Studuji také mzdovou strukturu na úrovni firmy-odvětví-skupina-odvětví-a regionální-úrovni. Analýza pracovních toků i dynamiky mezd je užitečná pro komplexnější posouzení dynamiky trhu práce. Mimo jiné ukazuji, že v letech 2014-2016 rostly v průměru v České Republice nejrychleji výrobní a obchodní sektory. Sektory mimo služby kromě zpracovatelského průmyslu se v letech 2014–2016 v průměru trvale zmenšovaly. Mzdy se vyvíjely podobně ve většině odvětví a rostly pro všechny kvantily mzdového rozdělení. Rovněž nacházím důkazy o silném negativním vztahu mezi pracovními toky na úrovni firmy a průměrnou mzdou.

Introduction

The dynamics of employment can be attributed to temporary layoffs and recalls or to the destruction and creation of jobs. While the former are short-term changes in employment that can be largely idiosyncratic at an individual level, the latter represent more robust and long-term changes. According to Davis and Haltiwanger (1992), job destruction (hereafter JD) and creation (hereafter JC) are persistent. The authors showed that in the US in 1972-1986 on average 68% of jobs created still existed in the following year, and 81% of jobs destroyed remain so in the following year. JD and JC occured simultaneously, and their rates differed across firms even in the same industry dependent on the size and age of the firm.

JD and JC show the overall condition of the economy, as well as the conditions of particular sectors. If JC is high, intuitively the sector is developing fast and many positions are being created. If JD is high, intuitively the sector is not doing well with many positions being destroyed. If the two rates are balanced and high, employment in this sector is volatile, a lot of occupations are created and a lot of occupations are destroyed. According to economic theory, one example of such a state when both JC and JD are high is the one of transition economies (Haltiwanger et al., 2003a).

A simple analysis of JC and JD allows researchers to make basic inferences about the economy as a whole or about particular industries and obtain a big picture, though not very detailed. JC and JD are a foundation of the basic framework for assessing labor dynamics in any market. However, for a comprehensive analysis more refined and sophisticated methods should be applied. Such more advanced methods would require the detailed analysis of the whole economy in a general equilibrium framework and are out of the scope of my research because of the need for restrictive assumptions and abundant data.

One should distinguish between job flows (Davis and Haltiwanger, 1992), which are the subject of this paper, and worker flows (see, e.g. Burgess et al., 2000). While the analysis of the former needs the firm-level data and indicate structural dynamics of the economy, the analysis of the latter requires more granular worker-level datasets and indicates the movements of workers, as opposed to the dynamics of occupations. In this paper I focus on the job flows exclusively partly because of my goal of the paper concerning structural dynamics of labor markets, and partly because of data limitations.

Job flows, as changes in the number and mix of jobs, can reflect multiple effects. They include the introduction of products and technologies, as well as their interplay with existing goods and processes, the outcomes of research and marketing strategies, negotiations between firms and workers or labor organizations, learning by doing, hiring, training and firing frictions, the availability of inputs and financial resources, competition, regulation, the industrial dynamics (Haltiwanger and Vodopivec, 2003).

JC and JD can be indicative of both the short-term business cycle phase and long-term structural changes in the industrial composition. High JC rate and low JD rate might indicate that a particular industry is growing, while an opposite situation might signal a decline of an industry. In this paper I compute JC, JD and job reallocation rates for two-digit NACE industries, for groups of industries, and for geographical areas of the Czech Republic in 2014-2016. I also analyze wage distributions for all these objects. The goal of this paper is the overall assessment of job flows and wage dynamics for a given period. I also compare the figures across industries, groups of industries, and countries (and time periods) using other papers on JD and JC (e.g. Mitchell et al., 2006, Haltiwanger and Vodopivec, 2003, Lee and Won, 2021). Job flows and wage structure represent real and nominal sides of the economy, so they are useful to analyze together.

In this paper I present job flows indicators and wage distributions for two-digit NACE industries in the Czech Republic in 2014-2016. As a result, one can see comprehensive statistics that describe job dynamics for this period of time. A great number of sectors is not often convenient to analyze because of the multiplicity of possible comparison pairs and a potentially smaller number of degrees of freedom. Therefore, I aggregate two-digit industries into four groups of economic sectors: manufacturing, trade (wholesale and retail), other non-service and other service. Such larger groups allows me to make more reasonable comparisons. I find that manufacturing and trade were the fastest growing group of industries. The majority of industries grew on average in 2014-2016, except for non-service sectors without manufacturing. They consistently shrank in 2014-2016 with their average JD rate higher than their average JC rate. The degree of job reallocation I find is somewhat smaller than the majority of results from the literature.

I also classify all Czech regions into eight districts by their geographical position. The sectoral region-level analysis supports the sectoral country-level results. The most straightforward result of spatial analysis of job flows is that they are highly heterogeneous across geographical areas. It may be driven by different industrial composition and labor market structure in different regions.

I find that wage structure was similar across groups of sectors and the majority of industries. For the most of them the whole wage distribution shifted to the right (positive quantile effects) between 2014 and 2016. Some industries (e.g. those extracting natural resources) exhibited a reverse pattern with the whole wage distribution shifted to the left (negative quantile effects) between 2014 and 2016. At the level of geographical areas the wage dynamics and distributions are heterogeneous. However, the wage distribution in Prague is very similar to the one at the country level. Finally, I estimate the strong negative link between firm-level job flows and firm average wages.

Among research papers on job flows, Jurajda and Terrell (2008) is the closest one for this paper. I also consider the Czech Republic, though I focus on 2014-2016, while Jurajda and Terrell (2008) focus on 1991-1996. Since then, at least to my knowledge, there has been no research of job flows in the Czech Republic that applied the Davis and Haltiwanger's (1992) methodology. A more recent paper by Dvořák et al. (2017) focuses on job creation in the country in 2008-2013. However, it considers only one sector and takes job creation into account in the form of gross changes in employment, which is outside of the JC/JD framework. My paper follows Davis and Haltiwanger's (1992) methodology and aims to contribute to the literature on job flows. Also my paper considers all industries and all regions of the Czech

Republic, which makes it comprehensive by covering the whole economy.

The remainder of this paper is structured as follows. In Section 1, I provide the critical review of the relevant literature. In Section 2, I briefly discuss the data I use, including provision of some descriptive statistics. In Section 3, I present my empirical results on job flows and wage dynamics and their comparisons across sectors, groups of sectors and district-group-of-sectors pairs. In Section 4, I discuss my results in the context of other papers on job flows and wage structure and make some comments about my empirical strategy. Section 5 concludes.

1 Literature Review

1.1 Job Flows Methodology

Davis and Haltiwanger (1992) pioneered the analysis of job flows by suggesting the framework for computing JC and JD rates and applying it to the data. The authors analyzed the U. S. manufacturing sector for the period between 1972 and 1986 and proposed a methodology for calculating JC, JD and job reallocation rates. Reallocation rates are the sum of JC and JD rates. These three indicators show employment dynamics and can be calculated for different degrees of aggregation (with firm-level being the granular one), which makes them a useful tool to determine at which level most job reallocation occurs. One way the paper by Davis and Haltiwanger (1992) was innovative is in the sense of focusing on job flows in contrast to worker flows. The latter had been the focus of many researchers before (see e.g. Blanchard et al., 1990) but the former started conceptually new literature. My paper attempts to be a part of this latter strand of literature and focuses on job dynamics but not on worker flows.

The basis of the methodology proposed by Davis and Haltiwanger (1992) are JC and JD rates.

$$JC_{st} = \sum_{\substack{e \in E_{st} \\ g_{et} > 0}} \left(\frac{x_{et}}{X_{st}} \right) g_{et}$$

is the formula for JC rate in year t and sector s. e is an establishment in the set of establishments E_{st} in year t in sector s. x_{et} is the size of establishment e in year t, defined as the average employment of e in years t and $t-1$. Sector size X_{st} is $\sum_{e \in E_{st}} x_{et}$. Finally, growth rate of establishment e g_{et} is the difference of employment in years t and $t-1$, divided by the size of establishment x_{et}. By construction $g_{et} \in [-2,2]$ with the "death" of a firm corresponding to $g_{et} = -2$ and the "birth" corresponding to $g_{et} = 2$. Hence, JC rate is a firm-size-weighted average of *positive* employment growth rates. Another interpretation is that JC rate is a fraction (approximate as the size of the sector – that is a denominator – is defined as the average number of occupations in two periods) of occupations that were created between two consecutive periods. Note that in case one is interested in the JC rate not in some sector s but for some group in general (can be geographical district or the set of recently opened establishments), she can still use the formula above after properly redefining set E_{st}. Thus, the framework of Davis and Haltiwanger (1992) is flexible in this sense. Similarly, JD rate is

$$JD_{st} = \sum_{\substack{e \in E_{st} \\ g_{et} < 0}} \left(\frac{x_{et}}{X_{st}} \right) |g_{et}|.$$

Analogously, JD rate is a firm-size-weighted average of *negative* employment growth rates or a fraction of occupations that were destroyed between two consecutive periods.

Two remarks on the methodology are in order. First, this formulation does not account for contemporaneous JC and JD at the *establishment level*, though it allows for contemporaneous JC and JD at the *sector level*. Thus, JC_{st} and JD_{st} are lower bounds on true JC and JD rates. For example, in establishment A 10 jobs were created and 8 jobs were destroyed. $g_{At} > 0$, then the information on establishment A contributes to JC_{st} only. However, establishment A is relevant to both true JC and JD rates because it both hired and fired. In this example

JD_{st} and JC_{st} are, respectively, smaller than the true JD and JC rates. Thus, JC_{st} and JD_{st} provide lower bounds for the true rates. The lack of contemporaneous establishment-level JC and JD is a natural limitation for Davis and Haltiwanger's (1992) paper as they used plant-level data.

Second, JC and JD rates are medium-run quantities, so changes in them largely reflect changes in the desired employment level but not temporary changes in the number of vacancies (including temporary layoffs and recalls). Therefore, JC and JD show changes in *job reallocation* but not *workers reallocation*. These two concepts are related but not entirely the same. Suppose the number of vacancies in a particular firm is the same in two consecutive years. In that case the job reallocation rate for this firm is zero. It might be that the same people are employed by the firm in both these years. In that case there was no workers reallocation. However, it might be that some employees were fired and the same vacancies were filled by different workers between the two surveys. In this case workers reallocation happened, though job reallocation did not.

The methodology above gives rise to multiple indicators which are functions of JC and JD rates. The job reallocation rate is one of them:

$$JR_{st} = JC_{st} + JD_{st}.$$

Both JC and JD rates are defined to be positive, which is useful because the job reallocation rate is also positive and increasing in both JC and JD. Job reallocation rate can be interpreted as the fraction of positions that were either created or destroyed between two consecutive periods or a firm-size-weighted average of *absolute* value of employment growth rates. This indicator shows the intensity of job flows in sector s between years $t-1$ and t. One may be interested in gross changes instead of relative ones, which are captured by the job reallocation rate. Consider

$$
\begin{aligned}
X_{st}JR_{st} &= \sum_{\substack{e \in E_{st} \\ g_{et}<0}} x_{et}|g_{et}| + \sum_{\substack{e \in E_{st} \\ g_{et}>0}} x_{et}g_{et} = \\
&= \sum_{e \in E_{st}} x_{et}|g_{et}| = \\
&= \sum_{e \in E_{st}} |\Delta employment_{et}|,
\end{aligned}
$$

which follows from the definition of g_{et}; $\Delta employment_{et}$ is the employment change between years $t-1$ and t in firm e. Note that the gross job reallocation $X_{st}JR_{st}$ is equal to the gross worker reallocation induced by job flows in sector s if the employees whose jobs are destroyed either remain unemployed, or find a job in a different sector $l \neq s$, and the employees whose jobs are created come either from unemployment, or from a different sector $l \neq s$. If some people whose jobs were destroyed quickly (in the same year t, if the data is annual) find a recently created job in the same sector s, total worker movement of workers from/to sector s is smaller than the gross job reallocation $X_{st}JR_{st}$. Hence, $X_{st}JR_{st}$ is the upper bound on worker reallocation induced by job flows.

The lower bound of the worker reallocation induced by job flows can be obtained by $X_{st}\max\{JC_{st},JD_{st}\}$. This indicator eliminates double counting that was present in $X_{st}JR_{st}$, where we could count the same person twice if she is accounted for by both JC_{st} and JD_{st}. However, in the case of $X_{st}\max\{JC_{st},JD_{st}\}$ it is possible that too many worker moves are not taken into account, so both $X_{st}JR_{st}$ and $X_{st}\max\{JC_{st},JD_{st}\}$ are restrictive estimates of worker reallocation but they represent natural bounds on worker flows induced by job flows for a given industry and year. To assess worker reallocation with more precision one would need more granular worker-level data (Burgess et al., 2000). However, one should be aware that the bounds are valid only for worker flows induced by job flows as opposed to total worker flows. The former overlooks worker moves that are not captured by JC or JD: those that are “jointly compensated” in the sense that they do not change employment of firms.

1.2 Applications

There is a strand of the literature that applies the JC/JD methodology to different markets and conduct comparative analyses. My paper aims to contribute to this literature. Davis and Haltiwanger (1992) shows that in 1973-1986 in the U.S. the manufacturing sector exhibited both JC and JD simultaneously, with the economy-level JC rate ranging from 0.064 to 0.132, and the average JD rate ranging from 0.061 to 0.166. In four out of eleven years the JC was more extensive than JD. In a later paper Davis and Haltiwanger (1999) show that in 1972-1993 in the U.S. the average *quarterly* JC rate was on average equal to 0.051, and the JD rate was on average equal to 0.055. Hence, one should be aware if the flows presented are annual or quarterly as the difference between the two is large (almost two times).

Mitchell et al. (2006) apply the JC/JD methodology to Australian data for 1983-2001 and show that manufacturing, construction, and mining sectors together saw the JC rate between 0.002 and 0.028 and the JD rate between 0.004 and 0.035, which are smaller than the job flows rates reported by Davis and Haltiwanger (1992). Lee and Won (2021) use Korean data for 1984-2014 for manufacturing sector (for establishments with at least ten employees) and obtain JD rates between 0.080 and 0.280 and JC rates between 0.130 and 0.260, greater than the respective job flows rates reported by Davis and Haltiwanger (1992). One of the most relevant papers for my research is the article by Jurajda and Terrell (2008). The authors study job flows in the Czech Republic and Estonia. They find that the JC rate in these two countries ranged from almost zero to 0.070 in the old (less efficient state) sector and from 0.100 up to a striking 0.720 in the new (more efficient private) sector. For the JD rate the figure was from 0.050 to 0.240 in the old sector and from almost zero to 0.190 in the new sector. Also OECD (2009) show that job reallocation rates are heterogeneous between industries and are between 0.100 and 0.250 for the majority of industries and the most of member countries.

Among other papers that apply the JC/JD methodology, Haltiwanger and Vodopivec (2003) analyze Slovenian economy in 1997-1999. Their research covers all economic sectors and they find the overall economy-level JC rate of roughly 0.100, with the economy-level JD rate being also very close to 0.100. Haltiwanger and Vodopivec (2003) also present job flows indicators for groups of industries (manufacturing, trade, etc.). Note that Haltiwanger and Vodopivec's (2003) paper is on a transition economy as the paper by Jurajda and Terrell (2008). The results are similar in terms of the results: the former paper shows the (average across 1997-1999) JC rate in Slovenia being close to 0.100, while the latter paper shows that in the Czech Republic in 1996 the JC rate was also close to 0.100. Both rates are similar to one another, which is intuitive as both countries are transition economies, and the labor policies in both Slovenia and the Czech Republic were in some sense similar (unlike in the Czech Republic and Estonia in Jurajda and Terrell, 2008). Both rates are similar to the indicators for the U.S. in 1972-1993 (Davis and Haltiwanger, 1992). At the same time, Haltiwanger and Vodopivec (2003) show that the excess of worker flows above job flows was still lower in Slovenia than in market economies. Haltiwanger and Vodopivec (2003) also show that job flows account for approximately two-thirds of worker flows, while Davis and Haltiwanger (1992) find the fraction of approximately between one-third and one-half. Thus, even though basic job flows indicators in Slovenia and the Czech Republic were similar to the ones of Western economies, more sophisticated indicators of labor market dynamics show that some differences were still present. This observation by Haltiwanger and Vodopivec (2003) suggests that using indicators other than JC and JD rates can be useful for the assessment of labor market dynamics. Finally, note that the results of Jurajda and Terrell (2008) are consistent with the idea that in early transition JD dominates JC, while in late transition JC and JD are approximately balanced (Haltiwanger et al., 2003b), which is similar to Western economies (e.g. Albak and Sørensen, 1998).

Albak and Sørensen (1998) analyze JC and JD in the manufacturing sector of Denmark in 1980-1991. The average JC rate ranged from 0.104 to 0.154 with the average (across years) equal to 0.120, similar to the figures for the U.S. (Davis and Haltiwanger, 1992). The average JD rate ranged from 0.088 to 0.136 with the average (across years) equal to 0.115, also similar to the figure for the U.S. (Davis and Haltiwanger, 1992). It is notable that on average the JC was compensated by JD, such that the overall net job dynamics (JC rate minus JD rate) was close to zero. In five out of eleven pairs of consecutive years the JD rate was higher than the JC rate, which is also similar to Davis and Haltiwanger (1992).

Gómez-Salvador et al. (2004) also examine job flows in Europe in 1990-s but on a larger scale. The authors employ data on thirteen countries (most of which are the countries of Western Europe and none are transition economies) and all economic sectors. The authors find smaller (average) JC and JD rates for all countries in the data than Davis and Haltiwanger (1992): the former rate ranged from 0.044 to 0.086, and the latter – from 0.030 to 0.044. The results are different from the ones for transition economies of 1990-s (Jurajda and Terrell, 2008, Haltiwanger and Vodopivec, 2003) and for the U.S. (Davis and Haltiwanger, 1992). Possible reasons for this discrepancy are that small firms are underrepresented in the sample, or the coverage (in terms of the number of workers) of the data is not large: from 5.3% to 48.6% dependent on the country. Another possible reason is that the data are available at the level of the firm as opposed to the level of establishment. Therefore, the worker moves between different establishments of the same firm are not accounted for, unlike in the administrative firm-level data (as is in Davis and Haltiwanger, 1992). Hence, the job dynamics in Gómez-Salvador et al. (2004) can be underestimated.

Kerr (2018) analyzes job flows in South Africa in 2011-2014 and finds the job flows patterns, which are similar to the literature. The author finds the average (across industries) JC rate ranging from 0.114 to 0.141. The JD rate ranged from 0.096 to 0.108. The importance of this result is that job flows are comparable to other countries (e.g. Davis and Haltiwanger, 1992, Albak and Sørensen, 1998), even though the worker flows are extremely high. Kerr (2018) shows that annual worker flows ranged from 0.527 to 0.541, which is extremely high (compared to 0.368 in Davis and Haltiwanger, 1992).

Davis and Haltiwanger (1992) show the correlation between JC and JD rates *in time* to be -0.864, which is a strong negative association. At the same time the correlation between JC and JD rates *across industries* is shown to be 0.764, which is a strong positive association.

OECD (2009) show that it is true for the majority of member states with an insignificant correlation coefficient for one country only. The authors find the correlation coefficient greater than 0.800 for two-thirds of member states. Hence, economic sectors where more jobs are created are on average also the ones where more jobs are destroyed.

Some papers consider variations of Davis and Haltiwanger's (1992) methodology. The conventional JC/JD analysis considers intra- and intersectoral job flows. Mitchell et al. (2006) conduct the analysis of JD and JC in full-time jobs as opposed to part-time jobs. The authors find that in Australia in 1984-2001 the average JC rate was 0.043 and 0.097 for full-time and part-time occupations, respectively. The average JD rate was 0.037 and 0.063, respectively. Thus, job reallocation in part-time jobs are greater than the overall job reallocation, suggesting higher mobility of such jobs.

Job flows are heterogeneous across establishments. Davis and Haltiwanger (1992) consider variation in job flows by age, size, ownership type, and region. First, they show that single-establishment firms show on average both higher JD and higher JC rates than multi-establishment firms. Therefore, the total job reallocation rate for the former group is also greater than for the latter one. Second, bigger establishment have on average smaller JC, JD and reallocation rates. The average job reallocation rate for establishments with less than 100 workers is 0.304, while for establishments with more than 1000 employees the figure is 0.138. Third, the intensity of job flows tends to decrease with the age of the establishment. The job reallocation rate for establishments that are one year old in the base year the JC and JD rates are 0.270 and 0.206, respectively. At the same time, establishments that are at least fifteen years old on average exhibit the JC rate of 0.065 and the JD rate of 0.097. Haltiwanger and Vodopivec (2003) also find that the job flows are higher for private sector, small, foreign, and young firms.

Job flows are also heterogeneous across countries. Gómez-Salvador et al. (2004) show that differences across countries in the size, age, and industrial distribution of firms are important for cross-country job flows comparisons. Also the authors consider a set of institutional variables. Gómez-Salvador et al. (2004) find that the strictness of employment protection legislation has a negative effect on JC and job reallocation rates. The duration of unemployment benefits and the degree of wage-setting coordination also reduces JC and job reallocation rates. Employment subsidies have a negative effect on a JD rate, while having a positive effect on a JC rate. However, the latter effect is sensitive to the choice of specification.

Job flows are heterogeneous across the phases of a business cycle. Davis and Haltiwanger (1992) show that the job reallocation rate exhibits countercyclic variation. Between the business cycle trough and the business cycle peak (1975 and 1980) the job reallocation rate fell by 0.060. The degree of countercyclicality is on average stronger in magnitude for the establishments that are large, old, belong to multi-establishment firms, and produce durable goods. In a later paper Davis and Haltiwanger (1999) document the different cyclical properties of JC and JD rates. The authors show that recessions are accompanied by sharp increases in JD but milder declines in JC. This asymmetry was more pronounced in the 1970's and the 1980's. In my paper I use the data on the period (2014-2016) when the European economy experienced growth[1], so the issues of cyclical behavior do not directly influence my results as I observe only one part of the business cycle, namely expansion.

The link between job flows and productivity has received much attention in the literature. Theoretically, in a job search framework recently created jobs are more productive than the recently destroyed ones (Mortensen and Pissarides, 1994). Thus, JC and JD indicate efficient reallocation of resources from non-profitable positions to more profitable ones with given prices of a firm-worker match. Hence, JC and JD are connected to productivity of jobs, at least theoretically. This hypothesis is compatible with the idea of creative destruction – high JD is associated with faster productivity growth. Jurajda and Terrell(2008) consider two sectors: old unproductive and new productive. Their results indicate that after the centrally planned economy was discarded in favor of the market economy in both the Czech Republic and Estonia the old public sector grew in terms of new occupations much slower that the new

[1]Eurostat Business Cycle Clock

private sector and occupations in the old sector were being destroyed faster than in the new one, with the most pronounced differences occurring at the beginning of transition.

However, Tyrowicz et al. (2017) find weak and negative correlation between JD rate and productivity growth. Their result might be indicative of the business cycle behavior of JD and productivity that dominates the creative destruction effect. If JD is counter-cyclical, while productivity is pro-cyclical, the correlation between these two variables is likely to be negative. Tyrowicz et al. (2017) show in a metastudy that it is the case for transitional economies. It is worth noting that creative destruction effect is not ruled out by their result. It is possible that it is present, though dominated by cyclical effects. In this case efficient reallocation, which is associated with creative job destruction, works in a different direction to cyclical patterns. Then the correlation between JD rate and productivity would be even more negative in the absence of the creative destruction mechanism.

Empirically, Lee and Won (2021) test the hypothesis of jobs reallocating from less productive firms to more productive ones. They use log of the total factor productivity as a measure of efficiency. At the same time, the authors take into account recessions, so that they separate cyclic components of job flows from the productivity-related components. They find positive significant estimate of the coefficient of total factor productivity in a regression of net job flows in Korea with the coefficient decreasing with time. Thus, the job reallocation is efficient (to more productive firms). Note that Lee and Won (2021) do not consider the link between JD and productivity, but instead consider the link between net job flows (JC rate minus JD rate) and productivity. Another notable feature of Lee and Won (2021) is that the authors find no important role of recessions in efficient job reallocation.

Davis and Haltiwanger (1992) show that both JC and JD at the establishment level are persistent. They find that out of the jobs created in year t, on average 68% are still existent in year $t+1$. Similarly but more strikingly out of the jobs destroyed in year t, on average 81% are still destroyed in year $t+1$ (one-year persistence rates). For year $t+2$, 43-58%% of the jobs created survive, and 62-82%% of the jobs destroyed remain so (two-year persistence rates).

Albak and Sørensen (1998) show a similar result for Danish data. The one-year persistence rates for JC and JD was equal to 71%. Two-year persistence rates for JC and JD were equal to 58%. Thus, the persistence of manufacturing JC was similar in Denmark to the one in the U.S. (Davis and Haltiwanger, 1992), however the persistence of manufacturing JD was smaller in Denmark.

Job flows are only one of the two components of worker flows. The second component is churning flows, which are defined as an employer-specific difference between worker and job flows (Burgess et al., 2000). Later the employer-specific churning flows can be aggregated to, e.g. industry-specific figures. As churning is defined using worker flows, it is out of the scope of the empirical part of my paper because of the nature of the data (see Section 3). As follows from the definition, churning refers to occupation-employee match heterogeneity, which is not captured by job flows. Unlike job flows, churning reflects the evaluation (and reevaluation) of the match by both worker and employer. JC and JD reflect only the employer's side: namely, desirable firm size in certain circumstances. Burgess et al. (2000) show that churning is a highly persistent phenomenon for particular employers. It suggests that churning is an equilibrium phenomenon, but not random. Using quarterly data on the U.S. state of Maryland for 1985-1994, Burgess et al. (2000) find that the churning rate on average smaller for older and bigger employers. Churning constitutes a large fraction of all worker flows. In manufacturing the ratio of the churning rate to the worker flow rate ranges from 0.476 to 0.696, while in non-manufacturing it ranges from 0.368 to 0.791 (Burgess et al., 2000). Thus, churning plays an important role in total worker flows.

Churning is important in terms of business cycles. Lazear and Spletzer (2012) use quarterly U.S. data on 2001-2011 and show that churning is procyclical. During recessions hiring decreases and existing workers become unwilling to quit. As a result, churning also decreases. The authors estimate that during 2007-2009 recession hiring reduction was mostly (four-fifth) due to reduced churning and not to reductions in JC. Lazear and Spletzer (2012) claim that recession-induced decreases in churning are likely to be inefficient in the sense that churning represents reallocation of labor to more productive jobs. Bachmann et al. (2021) also find procyclicality of churning in quarterly German data for 1975-2014. They show that churning is V-shaped in employment growth. The authors also establish that churning is more likely to result from uncertainty about employer-employee match quality, but not from establishment reorganization.

Usually the JC/JD analysis is conducted using firm-level longitudinal databases (e.g. Davis and Haltiwanger, 1992). However, sometimes it is possible to use employer-level data, which is later aggregated to the firm level (e.g. Jurajda and Terrell, 2008). In this paper I follow the latter method – take worker-level data and then aggregate it (for the detailed discussion of data see Section 3). Abowd and Vilhuber (2011) suggest using a different integrated database from the U.S.: The Quarterly Workforce Indicators. It contains quarterly data on worker flows, jobs flows and earnings for demographic subgroups, economic sectors, geographical areas at the level of counties, and ownership type. Such a detailed and comprehensive dataset enriches the set of possible inferences can be done from the data, especially on the connection between worker and job flows. The results of Abowd and Vilhuber (2011) on job reallocation are similar in level, trend, and seasonality to the one obtained using more conventional datasets, including Business Employment Dynamics (BED) data (Spletzer et al., 2004). The contribution of QWI is that it is accurate enough to estimate job flows indicators at a more detailed level (industry by age by gender). Other datasets that are used for job flows analysis are surveys of workers (e.g. Jurajda and Terrell, 2008) and the data on balance sheets of firms (Gómez-Salvador et al., 2004).

1.3 Wage Structure

Haltiwanger and Vodopivec (2003) have also consider the link between wages and job flows. The authors show that firms with higher wage dispersion and higher average wages tend to experience a lower job reallocation rate (and higher worker reallocation). Thus, firm wage policies may be an effective device of reducing worker turnover. The effect on churning is different for mean wage and its dispersion. While the former is associated with higher churning, the latter is associated with lower churning. In this paper I follow the analysis of firm-level wages from Haltiwanger and Vodopivec (2003). However, I also look at the industry-level (and group-of-industries-level) wage structure, following Jurajda and Terrell (2003) in the scope. Jurajda and Terrell (2003) study job flows and wages in Estonia and the Czech Republic in 1990-s for for the less productive old sector, which experienced high JD, and the more productive new sector. The authors find that the ratio of average wages in the new sector relative to the old one starts out high and then gradually diminishes. Belzil (2000) shows that in Denmark in 1980-1991 higher levels of net JC (JC rate minus JD rate) at the firm level are associated with higher male wages. The effect of net JC seems to be independent from the characteristics of an employee, which include education and experience. This effect is stronger for employees with lower tenure.

2 Data

In this paper I use the ISPV (Average Earnings Information System) data on the Czech Republic, which is a firm-level longitudinal dataset. I use the period 2013-2016 for the analysis. The dataset contains information about the employees and firms, including data on the number of hours worked, salary, region, industry and the number of years worked at the same workplace. The survey is general for all large firms (with at least 250 employees) and random for smaller firms, conditional on size (in terms of employment), region and industry. Even though the data are not available on all small firms, the random selection into participation in the survey makes inferences valid for the population of interest.

The survey is conducted quarterly, though for the sake of this paper I use only aggregated annual data. The main reason is that structural dynamics are more pronounced when the data is properly filtered. Higher frequency data might bias results (e.g. because of seasonality or non-linear trends which are not accounted for). When time series are smoothed, the impact of such features of the data is reduced. Furthermore, structural dynamics is not captured by quarterly fluctuations by nature. They are captured in long run, which shows one drawback of this paper; specifically, relatively short time span of the research. Also job flows indicators (JC, JD and job reallocation rates) as defined in Section 2 following Davis and Haltiwanger (1992) are year-to-year statistics, so even though I have the yearly data for 2013-2016, effectively I have three periods (2014-2016) for job flows indicators.

The data are employer-matched, so that the longitudinal nature of the dataset allows me to track job flows for multiple years and to analyze the persistence of JC and JD rates in various firms. Then I aggregate the job flow indicators at the level of two-digit NACE industries in two steps. In the first step, I take more than 5.4 million employee-year observations for 2013-2016 and translate them into firm-level observations. In total, I have 4354 distinct firms in my dataset. In the second step, I aggregate firm-level data into industry-level data, with 82 industries in total. Table 1 shows the size of the largest two-digit industries in the dataset. In this paper I follow Davis and Haltiwanger (1992) and define the size of an industry as the average two-year employment of all firms that operated in the industry in a given year (2014-2016). Table 1, Panel A, shows the largest industries in 2016 in terms of the average total employment in 2015 and 2016. Table 1 Panel B shows the largest industries in terms of the number of firms that operated in these sectors at least for one year. Two panels feature some industries that are the same and some that are different. This difference can be explained by different labor-intensity: e.g. manufacturing of motor vehicles requires more labor than wholesale trade, then in the data we would see a smaller number of firms and higher total employment for the former.

The data are firm-level, but not establishment-level. The difference is that a firm is a legal entity and can control many establishments. One can think of establishments in manufacturing as plants. The original Davis and Haltiwanger's (1992) methodology uses establishment data instead of firm data. There is no difference between the two for small one-establishment firms, while for multi-establishment firms the indicators I obtain overlook moves between

Sector	Size
Panel A: size is defined by the average total employment of firms (in thousands) – 2016	
Manufacture of motor vehicles, trailers and semi-trailers	136.045
Retail trade, except of motor vehicles and motorcycles	119.197
Land transport and transport via pipelines	70.433
Manufacture of machinery and equipment n.e.c.	64.758
Human health activities	63.157
Panel B: size is defined by the number of firms	
Wholesale trade, except of motor vehicles and motorcycles	326
Retail trade, except of motor vehicles and motorcycles	239
Manufacture of fabricated metal products, except machinery and equipment	232
Manufacture of machinery and equipment n.e.c.	201
Manufacture of motor vehicles, trailers and semi-trailers	173

Table 1: Size of Largest Industries

establishments of the same firm, hence can be downward biased if the number of such intrafirm worker moves is non-negligible. However, the magnitude of this bias (and whether it exists or not) is not possible to estimate with the data at hand.

3 Results

3.1 Sector-Level Job Flows

Tables 2-5 show the job flow measures for two-digit NACE industries. I present the results only for the industries that have at least 5 firms in my dataset. I conjecture that for the underrepresented industries with too few firms the indicators are the least accurate and the noise-to-signal ratio is too large to draw definitive conclusions. As a result, I drop observations from 14 out of 82 industries, which together comprise 0.670% of all firms in the dataset. The tables are arranged by groups of economic sectors: manufacturing, trade, other non-service, and other service. In this subsection I discuss results for separate industries. The aggregate analysis of groups of sectors is presented in Subsection 3.2.

Table 4 contains data on firms in agriculture, forestry and fishing, mining and quarrying, electricity, gas, steam and air conditioning supply, water supply, sewerage, waste management and remediation activities, and construction.

Sector	JC 2014	JC 2015	JC 2016	JD 2014	JD 2015	JD 2016	Job Reallocation 2014	Job Reallocation 2015	Job Reallocation 2016
Manufacture of food products	0.078	0.081	0.038	0.076	0.039	0.094	0.154	0.120	0.132
Manufacture of beverages	0.008	0.016	0.029	0.035	0.056	0.024	0.043	0.072	0.053
Manufacture of textiles	0.071	0.109	0.101	0.038	0.102	0.053	0.108	0.211	0.154
Manufacture of wearing apparel	0.032	0.025	0.009	0.032	0.031	0.076	0.064	0.056	0.085
Manufacture of leather and related products	0.298	0.132	0.168	0.112	0.101	0.089	0.410	0.233	0.256
Manufacture of wood and of products of wood and cork, except furniture, of articles of straw and plaiting materials	0.052	0.128	0.207	0.050	0.060	0.160	0.102	0.188	0.367
Manufacture of paper and paper products	0.103	0.096	0.095	0.093	0.032	0.031	0.196	0.128	0.126
Printing and reproduction of recorded media	0.052	0.078	0.097	0.089	0.049	0.025	0.141	0.127	0.122
Manufacture of chemicals and chemical products	0.042	0.041	0.061	0.040	0.009	0.053	0.083	0.050	0.114
Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.016	0.026	0.061	0.032	0.044	0.041	0.048	0.070	0.102
Manufacture of rubber and plastic products	0.098	0.087	0.129	0.020	0.018	0.083	0.118	0.105	0.212
Manufacture of other non-metallic mineral products	0.086	0.071	0.082	0.056	0.025	0.075	0.142	0.095	0.157
Manufacture of basic metals	0.088	0.058	0.023	0.047	0.037	0.065	0.133	0.095	0.089
Manufacture of fabricated metal products,except machinery and equipment	0.101	0.113	0.152	0.053	0.027	0.117	0.154	0.141	0.270
Manufacture of computer, electronic and optical products	0.067	0.076	0.078	0.022	0.032	0.114	0.089	0.109	0.192
Manufacture of electrical equipment	0.083	0.041	0.083	0.036	0.030	0.061	0.119	0.070	0.143
Manufacture of machinery and equipment n.e.c.	0.062	0.093	0.071	0.075	0.040	0.084	0.137	0.132	0.155
Manufacture of motor vehicles, trailers and semi-trailers	0.086	0.079	0.120	0.036	0.023	0.055	0.122	0.103	0.175
Manufacture of other transport equipment	0.085	0.057	0.073	0.025	0.054	0.185	0.110	0.111	0.259
Manufacture of furniture	0.047	0.097	0.247	0.020	0.053	0.104	0.067	0.150	0.351
Other manufacturing	0.043	0.114	0.119	0.030	0.028	0.057	0.073	0.143	0.176
Repair and installation of machinery and equipment	0.118	0.086	0.070	0.113	0.042	0.106	0.231	0.128	0.177

Table 2: Job Flows in Manufacturing Sectors

Tables 5 contains data on firms in transporting and storage, accommodation and food service activities, information and communication, financial and insurance activities, real estate activities, professional, scientific and technical activities, administrative and support service activities, public administration and defence; compulsory social security, education,

Sector	JC 2014	JC 2015	JC 2016	JD 2014	JD 2015	JD 2016	Job Reallocation 2014	Job Reallocation 2015	Job Reallocation 2016
Wholesale and retail trade and repair of motor vehicles and motorcycles	0.126	0.199	0.232	0.073	0.089	0.196	0.199	0.288	0.428
Wholesale trade, except of motor vehicles and motorcycles	0.114	0.076	0.091	0.030	0.082	0.097	0.144	0.159	0.187
Retail trade, except of motor vehicles and motorcycles	0.086	0.072	0.078	0.058	0.069	0.058	0.145	0.142	0.137

Table 3: Job Flows in Trade Sectors

Sector	JC 2014	JC 2015	JC 2016	JD 2014	JD 2015	JD 2016	Job Reallocation 2014	Job Reallocation 2015	Job Reallocation 2016
Crop and animal production, hunting and related service activities	0.030	0.075	0.201	0.064	0.098	0.173	0.095	0.173	0.373
Forestry and logging	0.049	0.089	0.056	0.042	0.044	0.032	0.091	0.133	0.088
Mining of coal and lignite	0.004	0.053	0.006	0.138	0.075	0.072	0.142	0.128	0.077
Other mining and quarrying	0.105	0.021	0.093	0.133	0.061	0.144	0.238	0.082	0.237
Mining support service activities	0.012	0.059	0.000	0.081	0.011	0.096	0.093	0.070	0.096
Electricity, gas, steam and air conditioning supply	0.065	0.014	0.033	0.065	0.038	0.108	0.131	0.052	0.141
Water collection, treatment and supply	0.008	0.005	0.011	0.015	0.007	0.012	0.022	0.012	0.023
Waste collection, treatment and disposal activities; materials recovery	0.016	0.040	0.083	0.032	0.056	0.058	0.048	0.097	0.141
Construction of buildings	0.038	0.038	0.055	0.105	0.081	0.101	0.143	0.119	0.157
Civil engineering	0.046	0.063	0.081	0.090	0.083	0.072	0.136	0.146	0.153
Specialised construction activities	0.045	0.156	0.207	0.347	0.140	0.351	0.393	0.295	0.557

Table 4: Job Flows in Other Non-Service Sectors

human health and social work activities, arts, entertainment and recreation, and other services activities.

The largest sector in the dataset is wholesale trade, except for motor vehicles and motorcycles, with 326 unique firms. The job reallocation rate for this sector slightly increased in 2014-2016 from 0.144 to 0.187. The JD rate also slightly increased from 0.030 to 0.091, while the JC rate fluctuated with the average value equal to 0.094. The second largest sector is retail trade, except for motor vehicles and motorcycles, with 239 firms. It exhibited more or less stable job flows with little fluctuations. The JC rate dominated the JD rate for the

Sector	JC 2014	JC 2015	JC 2016	JD 2014	JD 2015	JD 2016	Job Reallocation 2014	Job Reallocation 2015	Job Reallocation 2016
Land transport and transport via pipelines	0.051	0.043	0.052	0.048	0.019	0.047	0.098	0.062	0.099
Air transport	0.001	0.018	0.101	0.089	0.155	0.005	0.090	0.173	0.106
Warehousing and support activities for transportation	0.031	0.037	0.131	0.017	0.028	0.012	0.048	0.065	0.143
Accommodation	0.073	0.058	0.099	0.176	0.052	0.047	0.250	0.110	0.146
Food and beverage service activities	0.124	0.059	0.078	0.053	0.061	0.061	0.176	0.120	0.138
Publishing activities	0.083	0.376	0.017	0.283	0.212	0.149	0.366	0.587	0.166
Telecommunications	0.050	0.027	0.016	0.077	0.101	0.090	0.127	0.128	0.107
Computer programming, consultancy and related activities	0.093	0.102	0.117	0.118	0.033	0.119	0.211	0.134	0.236
Information service activities	0.122	0.175	0.098	0.011	0.129	0.165	0.133	0.303	0.262
Financial service activities, except insurance and pension funding	0.017	0.015	0.051	0.034	0.030	0.019	0.051	0.045	0.071
Insurance, reinsurance and pension funding, except compulsory social security	0.005	0.011	0.048	0.026	0.050	0.034	0.031	0.061	0.082
Activities auxiliary to financial services and insurance activities	0.063	0.146	0.169	0.110	0.021	0.043	0.173	0.168	0.212
Real estate activities	0.082	0.068	0.226	0.051	0.050	0.095	0.133	0.118	0.321
Legal and accounting activities	0.075	0.092	0.098	0.051	0.019	0.144	0.126	0.110	0.242
Activities of head offices; management consultancy activities	0.202	0.046	0.082	0.043	0.021	0.031	0.245	0.068	0.112
Architectural and engineering activities; technical testing and analysis	0.146	0.058	0.167	0.022	0.061	0.142	0.168	0.119	0.310
Scientific research and development	0.050	0.037	0.065	0.012	0.034	0.062	0.063	0.071	0.128
Advertising and market research	0.302	0.041	0.523	0.133	0.289	0.140	0.435	0.330	0.663
Other professional, scientific and technical activities	0.039	0.066	0.211	0.045	0.051	0.017	0.084	0.117	0.229
Rental and leasing activities	0.006	0.004	0.084	0.051	0.015	0.106	0.058	0.019	0.190
Employment activities	0.284	0.120	0.104	0.133	0.065	0.085	0.417	0.186	0.189
Travel agency, tour operator and other reservation service and related activities	0.070	0.046	0.029	0.042	0.027	0.050	0.111	0.073	0.078
Security and investigation activities	0.081	0.143	0.023	0.147	0.102	0.253	0.228	0.246	0.276
Services to buildings and landscape activities	0.068	0.056	0.066	0.066	0.060	0.072	0.134	0.116	0.138
Office administrative, office support and other business support activities	0.085	0.067	0.180	0.027	0.062	0.052	0.112	0.129	0.232
Public administration and defence; compulsory social security	0.055	0.007	0.006	0.003	0.008	0.000	0.058	0.015	0.007
Education	0.047	0.006	0.006	0.005	0.030	0.031	0.053	0.036	0.037
Human health activities	0.028	0.081	0.043	0.047	0.058	0.029	0.075	0.139	0.072
Gambling and betting activities	0.173	0.044	0.036	0.177	0.039	0.054	0.350	0.083	0.090
Sports activities and amusement and recreation activities	0.118	0.090	0.016	0.116	0.017	0.235	0.234	0.106	0.251
Repair of computers and personal and household goods	0.115	0.124	0.223	0.037	0.079	0.126	0.153	0.203	0.349
Other personal service activities	0.035	0.046	0.053	0.141	0.055	0.049	0.176	0.101	0.102

Table 5: Job Flows in Other Service Sectors

whole period of research with the average values 0.079 and 0.062. The third largest sector is manufacturing of fabricated metal products, except for machinery and equipment. It is comparable in the number of firms with the second-largest one – 232 firms. Note that it is a manufacturing sector, while the other two sectors, discussed above, are service sectors. Manufacturing of fabricated metal products, except for machinery and equipment, exhibited greater JC on average than the previous two sectors, while for the JD rate the pattern is unclear. In 2016 it experienced relatively more JD, while in 2015 – relatively less.

Manufacturing of machinery and equipment is another big sector, which is of interest for my paper. In comparison to manufacturing of other metal products, it exhibited the similar JD rates with the average value of 0.066 that is slightly higher than the one for manufacturing of other metal products. For the JC the situation is qualitatively different. The JC rate is consistently smaller in all periods in the manufacturing of machinery and equipment relative to the manufacturing of other metal products. In contrast to other manufacturing firms discussed in the previous paragraph, machinery and equipment production can be considered as an "old" sector. The former can contain various technological processes, including the innovative technology-intensive ones. This is one possible explanation of such a discrepancy in job flows in the two sectors.

In the manufacturing sector production of motor vehicles, electrical equipment, wood and the products of wood and cork, paper and paper products, chemicals and chemical products, textiles, and leather and related products the JC rate consistently dominates the JD rate in all periods. For other subsectors of manufacturing the picture is mixed. It is notable that no manufacturing subsectors consistently destroyed more jobs than they created. This result is consistent with expansionary dynamics of the economy as 2014-2016 when the European economy overall was growing. The sectors mentioned above grew year-to-year for the whole time span of the research.

3.2 Group-of-Sectors-Level Job Flows

In this subsection I combine the data from Tables 2-5 into groups of sectors instead of using two-digit NACE industries. I combine sectors into four groups: manufacturing, trade (retail and wholesale), other non-service, and other service. The job flows are presented in Table 6. In order to obtain the indicators in Table 6, I weight industry-level job flows indicators by the industry size (which is year-specific as defined in Subsection 1.1), and then divide by the total size of all industries in the group. As a result, I obtain the size-weighted average of industry-level job flows.

Table 6 suggests that in manufacturing the annual job reallocation rate is more volatile with the standard deviation (corrected for the degrees of freedom and unbiased) equal to 0.032, while the standard deviation for trade is 0.011. For other non-service and other service sectors the figures are 0.020 and 0.013, respectively. Hence, non-service sectors, show on average higher volatility of the job reallocation rate in contrast to service sectors, including retail and wholesale trade. High intertemporal volatility of job flows for manufacturing sectors can be partly explained by higher volatility of the JD rate: its standard deviation is 0.023 as opposed to 0.014 in trade and 0.015 and 0.007 in other non-service and other service sectors, respectively. At the same time, high intertemporal volatility of the job reallocation rate for other non-service sectors can be explained by higher volatility of the JC rate: its standard deviation is 0.014 as opposed to 0.09 in manufacturing, 0.007 in trade, and 0.006 in other service sectors.

Table 6 also shows that manufacturing, trade, and other services on aggregate experienced higher JC than JD in all years from 2014 to 2016. Therefore, these three groups of industries grew every year. This fact is consistent with the expansionary dynamics as in 2014-2016 the European economy overall was growing. It is also consistent with (and in fact partly suggested by) one of the observations from 3.1, namely that a large number of manufacturing sectors experienced growth in all periods and no manufacturing sectors experienced contraction in all three years. Both manufacturing and trade groups of sectors exhibited higher JC rates in all years 2014-2016 in comparison to other service sectors. However, for the JD rate the situation is less clear. Manufacturing showed the smaller JD rate in two years out of three than other service sectors. Trade showed the smaller JD rate only in one years out of three than other service sectors.

The comparison of manufacturing with trade sectors is not straightforward. In 2016 manufacturing experienced a slightly higher JC rate than trade, while in 2015 the situation was reversed with a slightly bigger figure for trade. In 2014 trade saw a higher JC rate than manufacturing. Thus, the clear pattern is not visible, I can not tell directly if one of these groups of sectors grew consistently faster than another one. However, note that manufacturing grew consistently year-to-year with the JC rate being larger than the JD rate in all years. At the same time, both trade and manufacturing grew on average faster than other industries.

As for other non-service sectors, they overall shrank in size in 2014-2016 with the JD rate consistently dominating the JC rate. Table 4 shows that it can be driven by mining of coal and lignite, other mining and quarrying, electricity, gas, steam and air conditioning supply, water collection, treatment and supply, and construction, which consistently annually contracted in 2014-2016. At the same time, forestry and logging consistently expanded with the JC rate dominating the JD rate, so the contraction of other non-service sectors was not uniform with respect to individual two-digit NACE industries.

	JC			JD			Job Reallocation		
Group of Sectors	2014	2015	2016	2014	2015	2016	2014	2015	2016
Manufacturing	0.080	0.078	0.095	0.048	0.033	0.079	0.128	0.110	0.173
Trade	0.095	0.081	0.092	0.052	0.074	0.077	0.147	0.155	0.169
Other non-service	0.036	0.048	0.063	0.091	0.064	0.089	0.127	0.112	0.152
Other service	0.074	0.062	0.070	0.059	0.047	0.059	0.133	0.109	0.129

Table 6: Job Flows by Group of Sectors

Now, instead of the evolution of aggregate job flows indicators in time, consider heterogeneity of each group of sectors. Table 7 presents standard deviations of JC, JD, and reallocation rates of industries in the each four groups of sectors. The heterogeneity of job flow measures in manufacturing is smaller than in other service and non-service sectors. It is reasonable as these two are comprised of sectors that are different in many respects, including job mobility. Trade group includes only three sectors, so its standard deviation estimates presented in Table 7 might be imprecise.

	sd(JC)			sd(JD)			sd(Job Reallocation)		
Group of Sectors	2014	2015	2016	2014	2015	2016	2014	2015	2016
Manufacturing	0.057	0.033	0.058	0.029	0.023	0.041	0.078	0.047	0.082
Trade	0.020	0.072	0.085	0.022	0.010	0.071	0.032	0.080	0.156
Other non-service	0.030	0.042	0.071	0.091	0.039	0.092	0.101	0.074	0.154
Other service	0.071	0.070	0.100	0.063	0.060	0.063	0.108	0.110	0.123

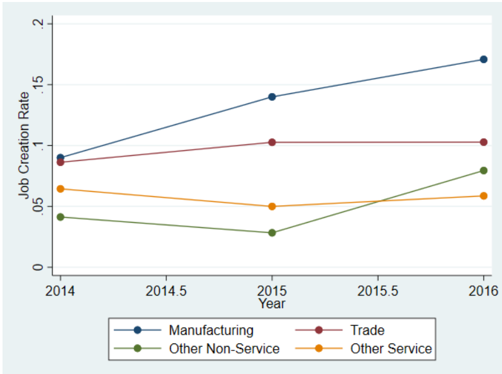
Table 7: Heterogeneity of Job Flows by Group of Sectors

3.3 Group-of-Sectors-by-Region-Level Job Flows

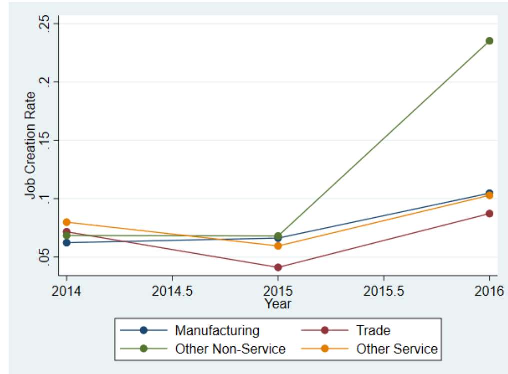
In this subsection I consider job flows at the regional level. I split the whole dataset into eight districts. District one contains Prague, district two contains Central Bohemian Region, both are in the center of the country. District three contains South Bohemian Region, which is in the South-South-West, district four contains Plzeň Region and Karlovy Vary Region, which are in the North-West-West. District five contains Ústí nad Labem Region and Liberec Region, which are situated in the North, district six contains Hradec Králové Region and Pardubice Region in the North-East. District seven contains Zlín Region, South Moravian Region, and Vysočina Region, which are in the South, and district eight contains Olomouc Region and Moravian-Silesian Region in the East.

For each region I look at the evolution of job flows at the level of groups of industries, described earlier in this section. Figure 1 shows JC rates for each district, described above. Graphically, even though the patterns are heterogeneous across districts as different regions have different industrial structure, manufacturing is the most dynamic group of sectors in all regions in terms of job creation. In Prague and Plzeň Region and Karlovy Vary Region manufacturing grew faster than any other group of sectors. In South Bohemian Region and Ústí nad Labem Region and Liberec Region manufacturing grew faster than any other group of sectors in two out of three years. The observation of manufacturing being a dominant group of sectors in terms of JC is consistent with Table 6, columns 1-3. However, lines for manufacturing and trade are overall close, as indicated by very similar JC rates (Figure 1). The largest difference between manufacturing and trade JC rates in 2015 is observed in South Bohemian Region (district three). However, the scale is such that this difference is smaller than 0.050. Figure 1 translates into Table 6 by reweighting the data, so this difference can have smaller impact in Table 6. In 2016 the JC rate in manufacturing is greater than the JC rates in other groups of sectors (column 3). In 2014 trade has higher JC rate (column 1), which is likely to be driven by Hradec Králové Region and Pardubice Region and Zlín Region, South Moravian Region, and Vysočina Region (districts six and seven).

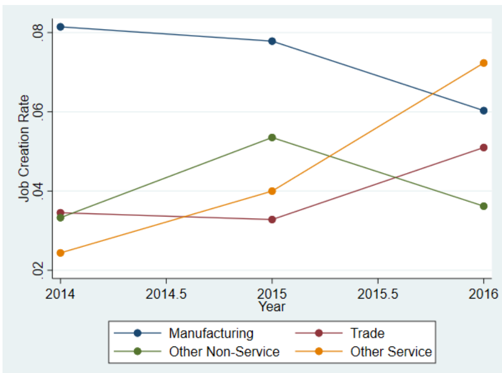
Figure 2 shows JD rates for each district, described above. Among groups of sectors graphical evidence suggests that other (than manufacturing) non-service sectors have substantial JD rates in almost all districts, while other groups of sectors are highly heterogeneous across districts. This observations are consistent with Table 6, where other non-service sectors have highest JD rates in all years (columns 4-6) relative to other groups of sectors. The considerable JD rate of other non-service sectors outweighs JD rates of other groups of industries which in some years and some regions dominated the JD rate of other non-service sectors. Another observation from 2 is unusual movements of job destruction in the trade group of sectors. In the other three groups of sectors the JD rates usually comove, while the JD rate for trade sometimes exhibit a very different pattern. For example, in district eight (Olomouc Region and Moravian-Silesian Region) JD rates of three non-trade sectors clearly comove, while for trade sectors the JD rate moves differently. As the three increase in 2016 by 0.030-0.040, the JD rate for trade sectors decreased by approximately 0.050. Similarly, in district five (Ústí nad Labem Region and Liberec Region) all JD rates are stable across the whole time span, except for the JD for trade sectors in 2016, when it increased by approximately 0.720, while others remained around 0.010. However, in this case (district five) it is likely to be some kind of an outlier, possibly a huge firm closure. The results are unlikely to be driven by small sample size – there 24 firms in trade sectors in district five.



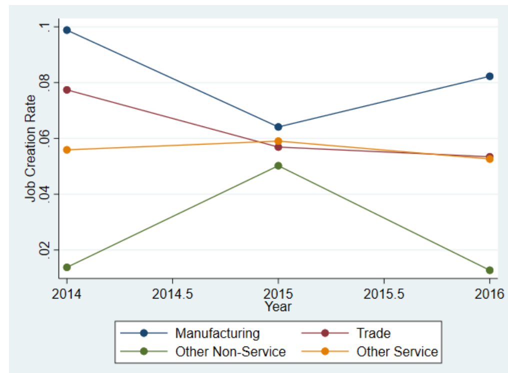
(a) Prague



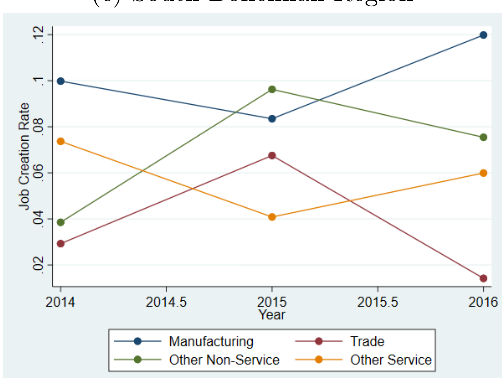
(b) Central Bohemian Region



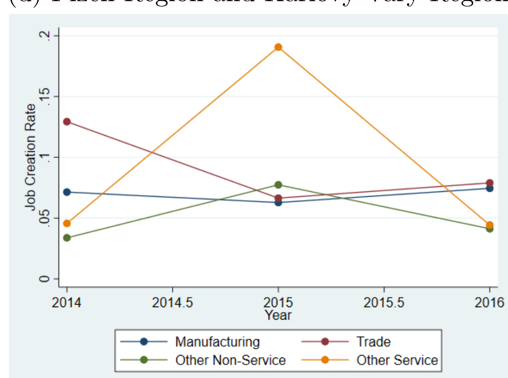
(c) South Bohemian Region



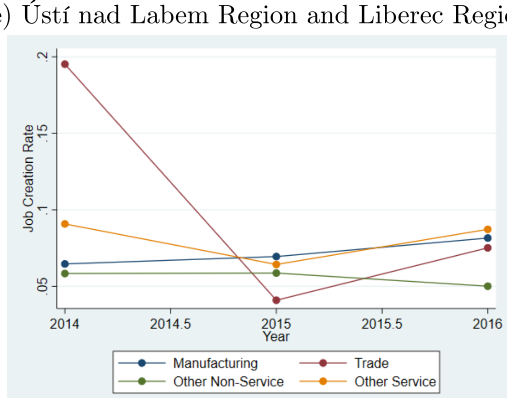
(d) Plzeň Region and Karlovy Vary Region



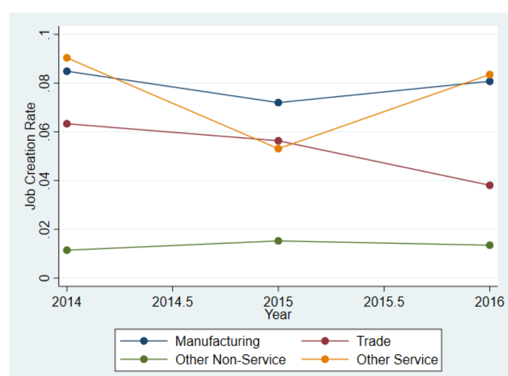
(e) Ústí nad Labem Region and Liberec Region



(f) Hradec Králové Region and Pardubice Region

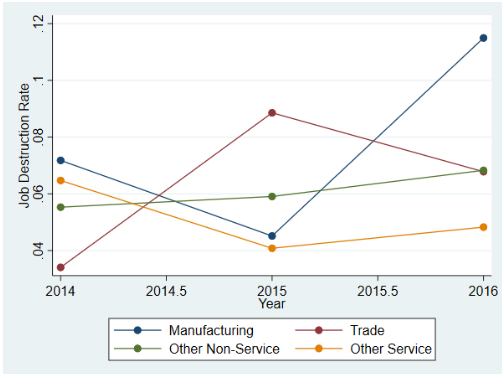


(g) Zlín Region, South Moravian Region, and Vysočina Region

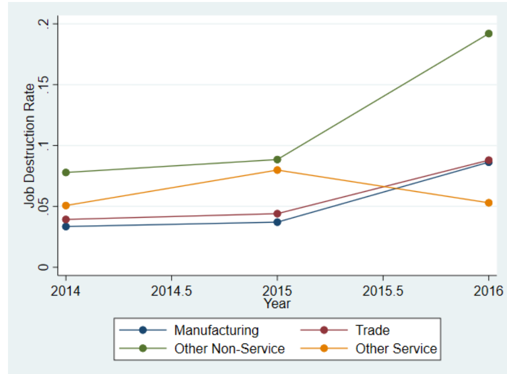


(h) Olomouc Region and Moravian-Silesian Region

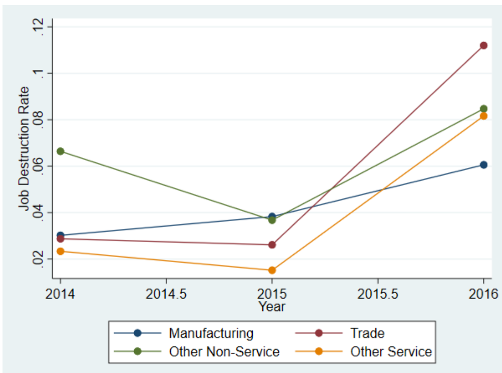
Figure 1: JC Rates by Region and Group of Industries



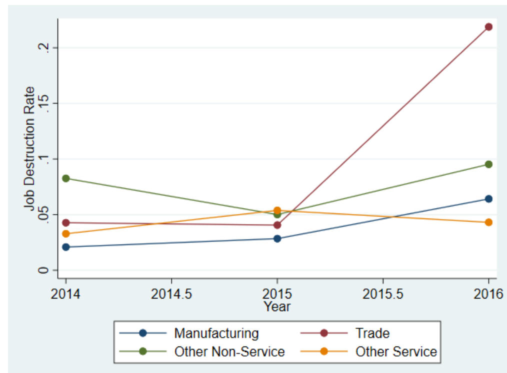
(a) Prague



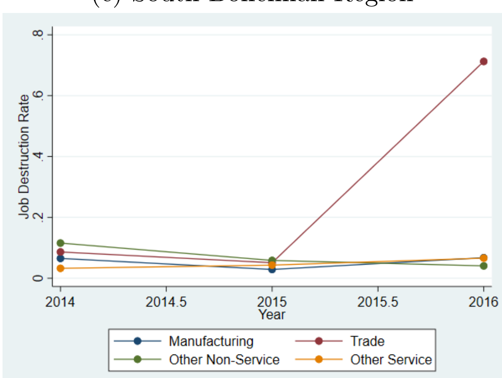
(b) Central Bohemian Region



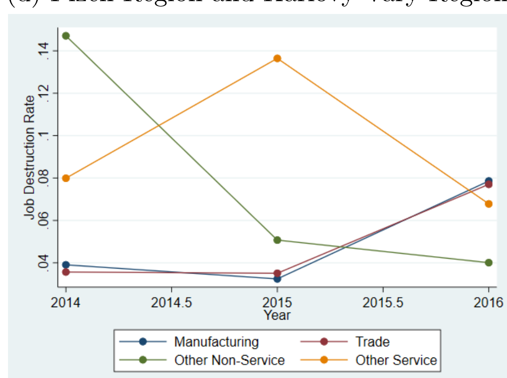
(c) South Bohemian Region



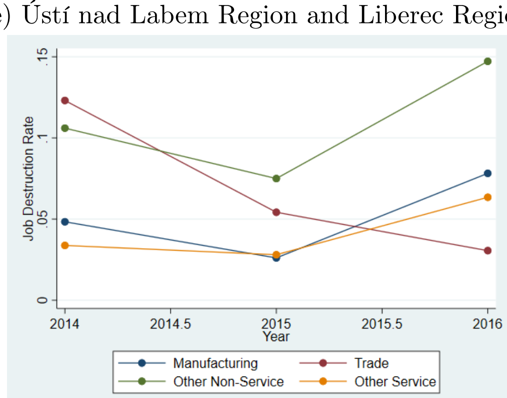
(d) Plzeň Region and Karlovy Vary Region



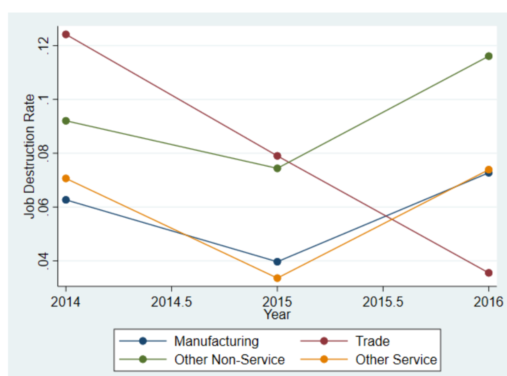
(e) Ústí nad Labem Region and Liberec Region



(f) Hradec Králové Region and Pardubice Region



(g) Zlín Region, South Moravian Region, and Vysočina Region



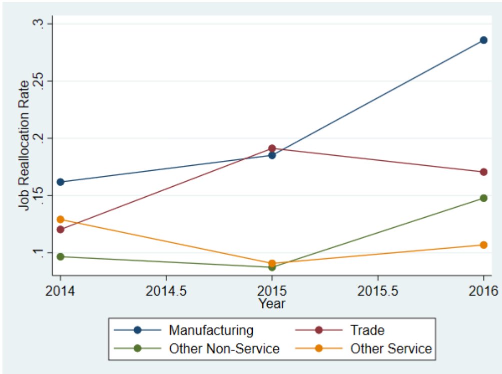
(h) Olomouc Region and Moravian-Silesian Region

Figure 2: JD Rates by Region and Group of Industries

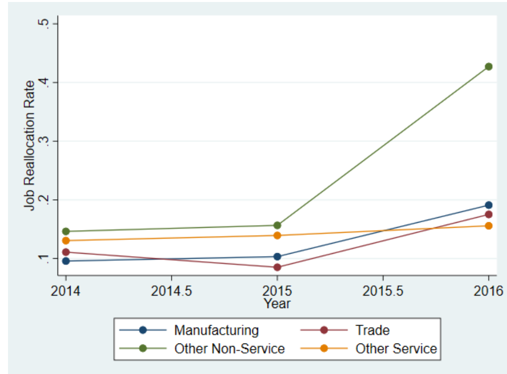
Finally, Figure 3 shows job reallocation rates across districts. Similarly to the case of JC (Figure 1), manufacturing is dominant in many districts, though the dominance is not that strong as it was for the JC rate. In two districts (one and four – Prague and Plzeň Region and Karlovy Vary Region) manufacturing exhibited higher job reallocation rate in all years. In two more districts (three and five – South Bohemian Region and Ústí nad Labem Region and Liberec Region) the job reallocation rate is the highest in manufacturing in at least two years out of three. Overall, job reallocation patterns are highly heterogeneous across districts. This heterogeneity of job flows patterns across districts may be driven by historically different industrial composition. For example, if district D has only one firm that operates in industry I, the entry of the second firm is likely increase job flows (that are defined to be relative to current size) more than the entry of an additional firm with the same employment when there are multiple incumbent firms in district D and industry I. Another possible reason of the heterogeneity of job flows is different labor market structure. It is possible that workers in different regions have different education and different skills. The industrial composition will depend on the available workforce and new jobs will be created such that there are suitable workers on the labor market. This second intuition is expected to be more pronounced when the spatial analysis is done at the level of individual industries as opposed to the level of groups of industries, as in this paper. The reason is that the industry-level heterogeneity is important for differential hiring policies, while the aggregation at a higher level partly removes this heterogeneity by averaging industrial effects.

3.4 Job Flows and Wage Structure

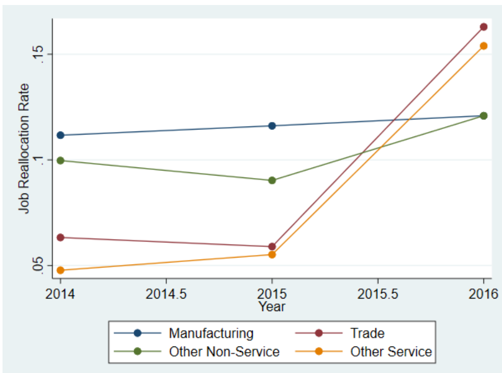
In this subsection I present the analysis of wages in connection to job flows. I define wage for each worker to be the logarithm of the average monthly wage. Figure 4 shows the wage distributions for the four groups of sectors that are defined in Subsection 3.2. Four observations from Figure 4 are in order. First, the wage distributions are more or less stable across 2014-2016. Second, the other service group of sectors has fatter tales than other groups



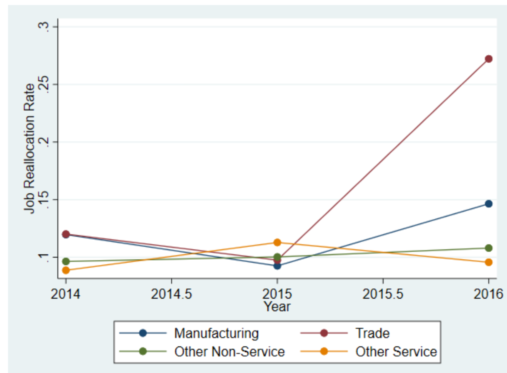
(a) Prague



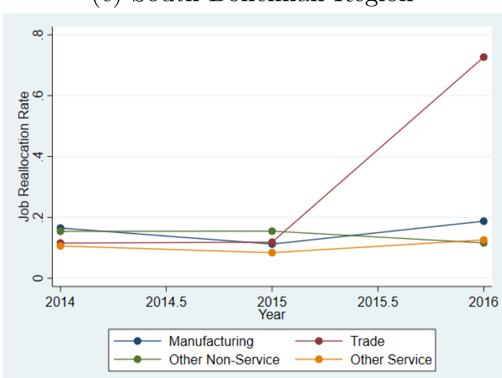
(b) Central Bohemian Region



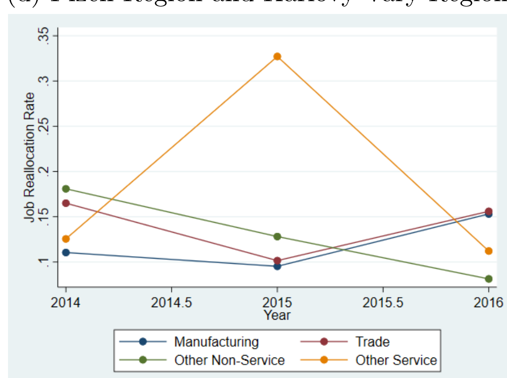
(c) South Bohemian Region



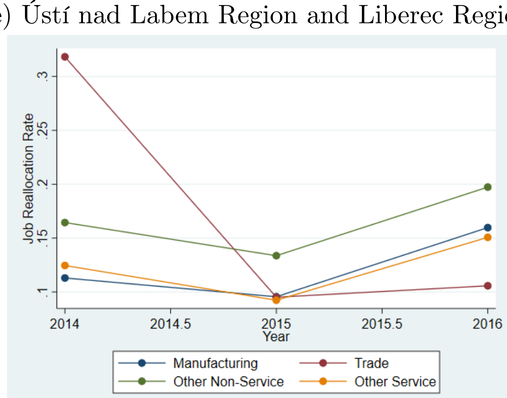
(d) Plzeň Region and Karlovy Vary Region



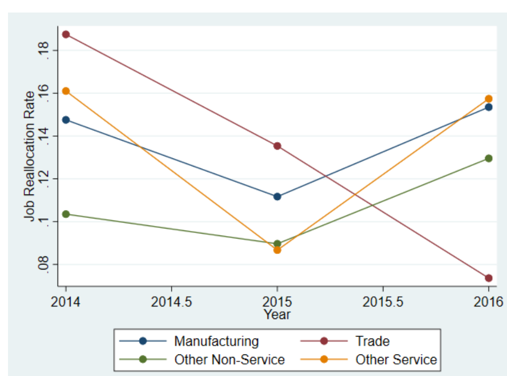
(e) Ústí nad Labem Region and Liberec Region



(f) Hradec Králové Region and Pardubice Region



(g) Zlín Region, South Moravian Region, and Vysočina Region



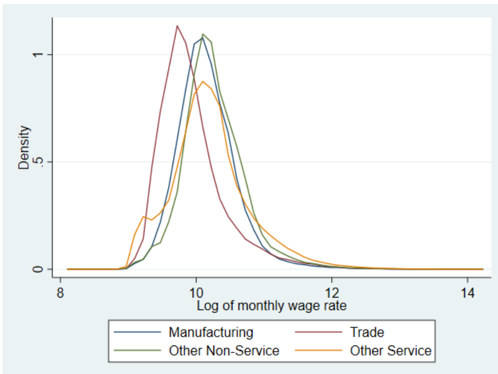
(h) Olomouc Region and Moravian-Silesian Region

Figure 3: Job Reallocation Rates by Region and Group of Industries

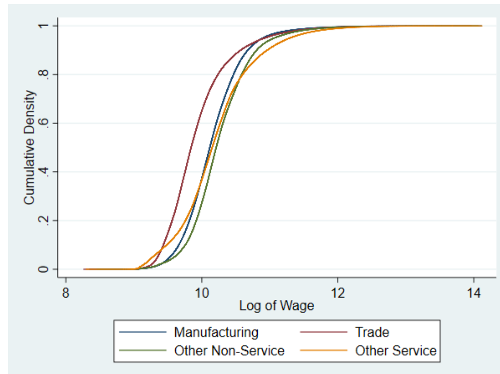
of sectors. It indicates high heterogeneity of this group of sectors, which contains various industries (Table 5). There are relatively more employers in both left and right tales of the wage distribution than in other groups of sectors. This result is stable across all years. Third, the left panel of Figure 4 indicates that the distribution of wages in trade sectors is more skewed to the right than the wage distributions in other groups of sectors. It indicates that the proportion of workers in trade who work for low wage is relatively high.

Fourth, the right panel of Figure 4 suggests that wages in the other non-service group of sectors first-order stochastically dominates wages in manufacturing and trade groups of sectors. At the same time, wages in manufacturing seem to first-order stochastically dominate wages in trade, though the behavior at the upper tail ruins it – graphs suggest that for a small locus of cumulative distribution function very close to one the cumulative distribution function function of wages in manufacturing is dominated by the one in trade. Trade being dominated by all other groups of sectors (except for other service sectors, which have fat-tailed distribution of wages) is consistent with the higher skewness-to-the-right and a higher fraction of people who earn relatively less. Note that testing formally for first-order stochastic dominance (or for the equality of skewness) is out of the scope of my paper, but some observations from the data are still useful for understanding the labor market structure.

Figure 5 shows annual evolution of wage distributions for different groups of sectors. It supports the observation of the fat-tailedness of the wage distribution in other service sectors (left panel, Figure 5g). The time dimension allows me to show that from 2014 to 2016 the hump in the left-tail has decreased in size, suggesting a decrease in the wage heterogeneity. However, even in 2016 the hump is still there, though not that pronounced. It would be interesting to explore the data for years after 2016 to see if the hump is even less pronounced. The right panel, Figure 5h, supports the observation above. Lines for 2014 and 2015 are very close, which suggests that the distribution of wages did not change much between those two years. The only locus of the graph where the lines do not coincide is the one below 10% quantile. For small quantiles of the distribution the wage slightly increased between 2014 and

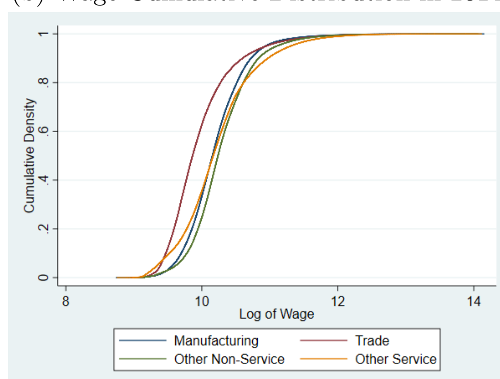


(a) Wage Density in 2014

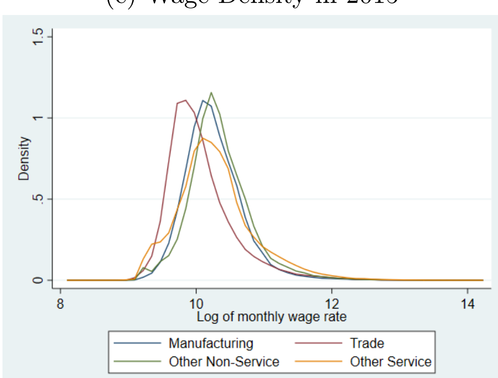


(b) Wage Cumulative Distribution in 2014

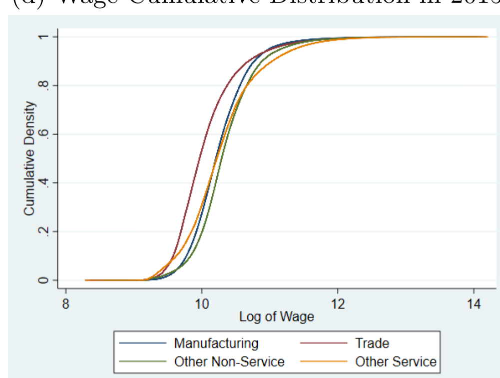
(c) Wage Density in 2015



(d) Wage Cumulative Distribution in 2015



(e) Wage Density in 2016



(f) Wage Cumulative Distribution in 2016

Figure 4: Wage Distributions by Year

2015, which is compatible with a smaller hump in Figure 5g. The lines for 2015 and 2016 are more distinct, the wage distribution seem to have shifted to the right by increasing wage for all quantiles. The most pronounced difference was again experienced by low-wage quantiles. Hence, the hump in the left tail decreased even more.

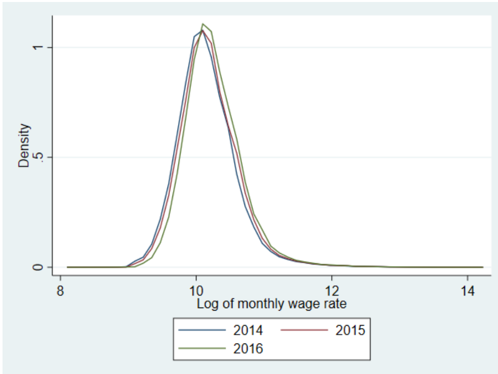
Another observation from Figure 5 concerns the right panel of the graph. In all four groups of sectors the cumulative distribution function of wages seem to be non-decreasing for all quantiles. The difference between wages (in terms of distribution) in 2014 and 2015 is not large, two cumulative distribution function lines (almost) coincide for all groups of sectors except for manufacturing. The difference between the lines for 2015 and 2016 is more pronounced and visible for all groups of sectors. As noted above in the comment on other service sectors, the wages seem to increase for all quantiles. However, one should not confuse quantile effects that I show with the effect on people who were at particular quantiles. For example, consider quantile α. Figure 5 shows that the α-quantile earns more in 2016 than in 2015 (quantile effect). It is possible, though, that a person who was in the α-quantile of the distribution in 2015 received a reduction in wages and now moved to a different quantile $\beta < \alpha$ (mobility effect). The person earns less because of the mobility effect but the quantile effect is still positive, as indicated by the right panel of 5.

The only group of sectors, for which 2014 and 2015 wage distributions are visually different (Figure 5b). One might interpret it as manufacturing experienced smoother wage evolution in contrast to other groups of sectors. It is notable that visually the increase of wages between 2014 and 2015 is more pronounced for high-earners. However, the difference between cumulative distribution function lines is not very big, so that the argument on smoothness is not very strong. Note also that in the left panel of Figure 5 wage distributions in all groups of sectors seem to be skewed-to-the-right, not only trade, as observed above.

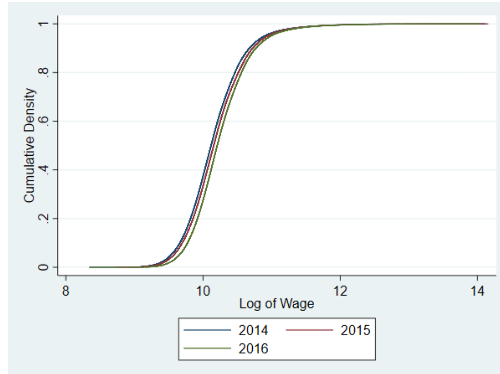
Figure 5 suggests that wage increases (at least weakly) in 2014-2016 for all quantiles in all groups of sectors. However, across two-digit NACE industries in those groups of sectors there might be heterogeneity in terms of wage dynamics. It is possible that different industries in the same group of sectors exhibit different wage structure. I find that for the majority of individual sectors the wage rises in 2014-2016 (e.g. see Table

The wage structure for groups of industries is similar in the sense of non-decreasing quantile effects. However, it is possible that on a less aggregated level the pattern is different. Therefore, I first explore wage structure for groups of sectors in different districts (as defined in Subsection 3.3) in case there is substantial spatial variation captured by my district classification. Second, I explore wage structure for individual two-digit NACE industries.

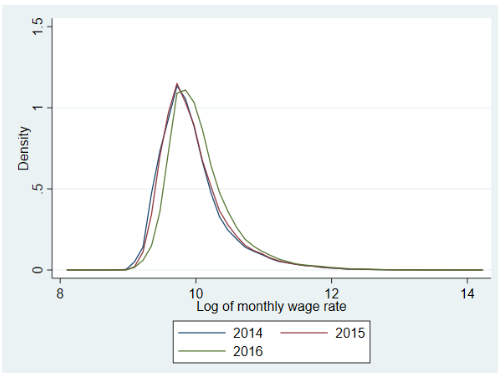
Figure 6 shows that wage structure in different regions exhibits heterogeneous patterns. Figure 4 suggests that the wage structure patterns are similar across years, so for the district level analysis I use data on 2016 exclusively. The results on stochastic dominance of wage in different groups of sectors that hold in the economy in general (Figure 4, right panel) do not hold when districts are explored separately. For example, in Central Bohemian Region (Figure 6b) wage in manufacturing dominates wages in other groups of sectors, except for the right tail, which is fatter for other (than trade) service sectors. In South Bohemian Region (Figure 6c) other (than manufacturing) non-service sectors seem to dominate all other sectors, including other service sectors – unlike in the economy on the whole, even in the upper tail of the wage distribution. In Plzeň Region and Karlovy Vary Region (Figure 6d) trade is dominated by both manufacturing and other non-service groups of sectors, as in the whole economy. However, the relationship between the latter two is not typical of the whole economy. In Plzeň Region and Karlovy Vary Region wages in manufacturing dominate in the upper tail of the distribution (approximately above 70% quantile) and in smaller quantiles other non-service sectors dominate. In the whole economy wages in manufacturing dominate in the left tail (approximately below 10% quantile) and in bigger quantiles other non-service sectors dominate (Figure 4). It indicates that there are relatively less high-earning and low-earning workers in other non-service sectors in Plzeň Region and Karlovy Vary Region together, than in the whole country. In Ústí nad Labem Region and Liberec Region (Figure 6e) the wage distributions in manufacturing and other non-service sectors are very similar. The differences



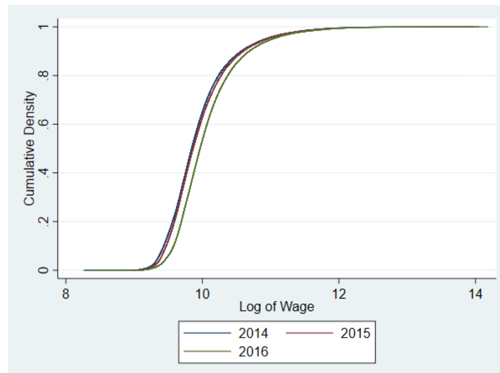
(a) Wage Density in Manufacturing



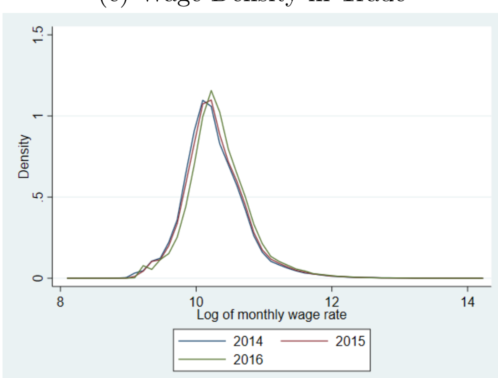
(b) Wage Cumulative Distribution in Manufacturing



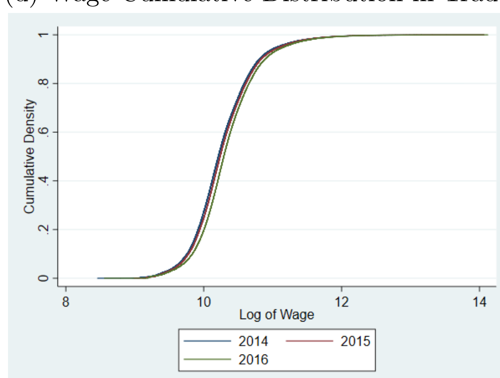
(c) Wage Density in Trade



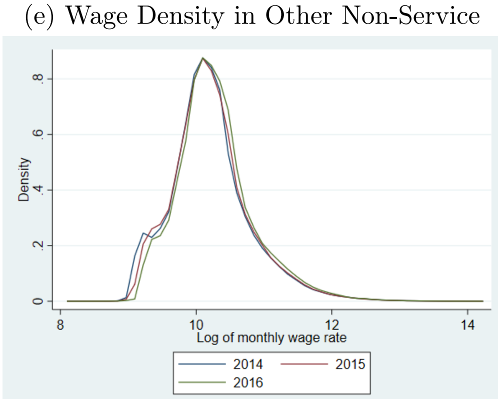
(d) Wage Cumulative Distribution in Trade



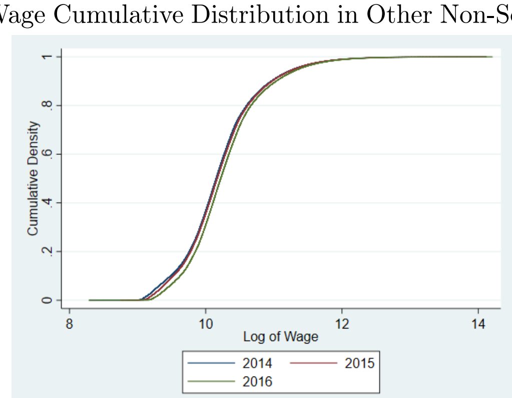
(e) Wage Density in Other Non-Service



(f) Wage Cumulative Distribution in Other Non-Service



(g) Wage Density in Other Service

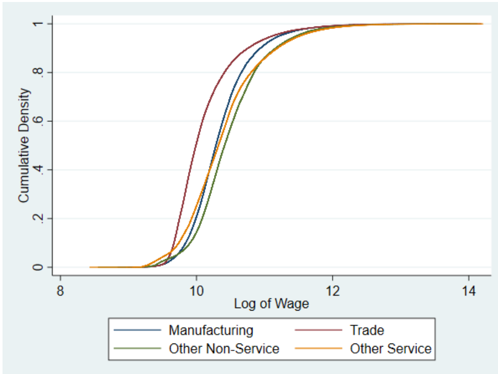


(h) Wage Cumulative Distribution in Other Service

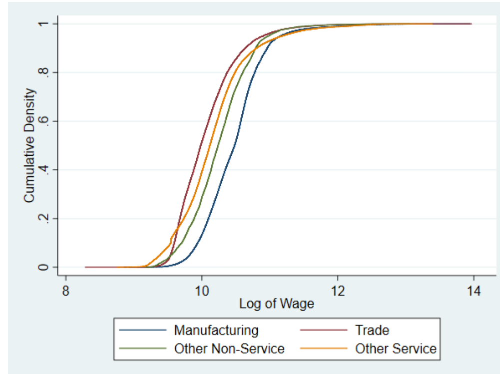
Figure 5: Wage Distributions by Group of Industries

begin at the median earner in both. Above the median, wages in manufacturing dominate the ones in other non-service sectors, while in the economy overall the former is dominated by the latter for the whole distribution except for a small area in the left tail (Figure 4). In Hradec Králové Region and Pardubice Region (Figure 6f) the situation is very similar: wage distributions in manufacturing and other non-service sectors are almost identical, even above the median, unlike in Ústí nad Labem Region and Liberec Region. In Zlín Region, South Moravian Region and Vysočina Region (Figure 6g) wages in other service sectors dominate wages in all other sectors above the median, while in the whole economy they become dominant only in the upper tail of the distribution. It means that there are more high-earners in other service sectors than in other groups of sectors in Zlín Region, South Moravian Region and Vysočina Region. In Olomouc Region and Moravian-Silesian Region (Figure 6h) wages in manufacturing dominate wages in other service sectors almost for all quantiles, while for the whole economy it is true only for quantiles before 50% (the median). Interestingly, in Prague (Figure 6a) the wage dynamics is the most similar to the wage dynamics of the country overall (Figure 4). Some minor differences are only in the tail behavior. For low levels of income wage in trade dominates the one in other non-service sectors. Hence, in Prague there are relatively less low-earning workers in trade than in other non-service sectors. Hence, the wage structure patterns are highly heterogeneous across regions. However, when district-level heterogeneity is averaged out by weighting the picture is more regular (as in Figure 4).

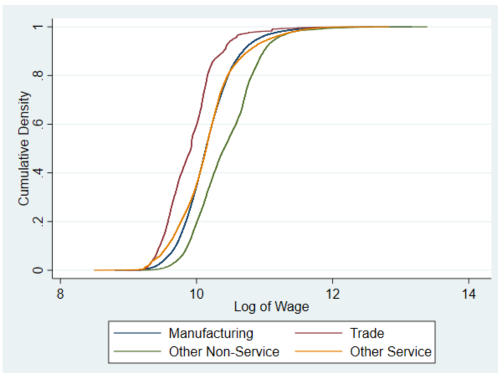
Another possible source of wage structure heterogeneity are the differential patterns of wage structure on the level of two-digit NACE industries. Figure 7 shows wage structure for the biggest sectors in terms of the number of firms. The first line contains biggest sectors in manufacturing, second row – in trade, third row – in other non-service group, fourth row – in other service sectors. The patterns are consistent with the ones at the group-of-sectors-level: wages in 2016 first-order-stochastically dominate wages in 2014 and 2015, wages in 2015 first-order-stochastically dominate wages in 2014. The quantile time effects are positive for all quantiles. Other industries, unreported here, exhibit similar dynamics. In manufacturing



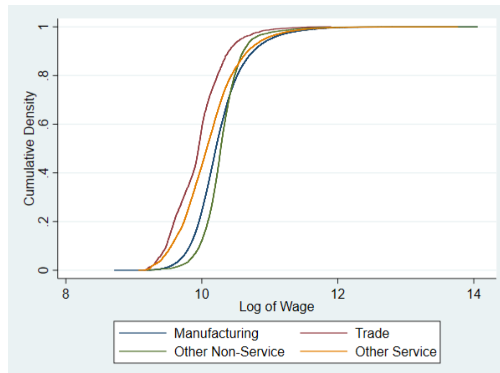
(a) Prague



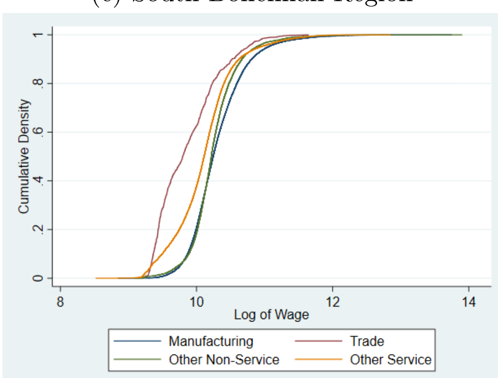
(b) Central Bohemian Region



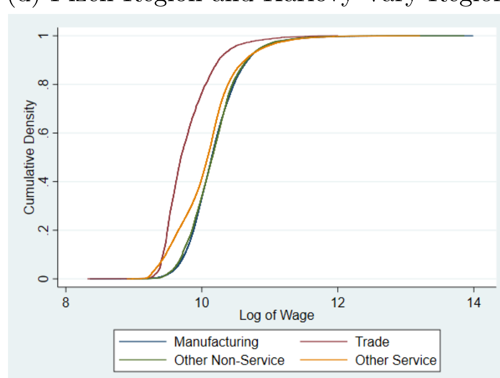
(c) South Bohemian Region



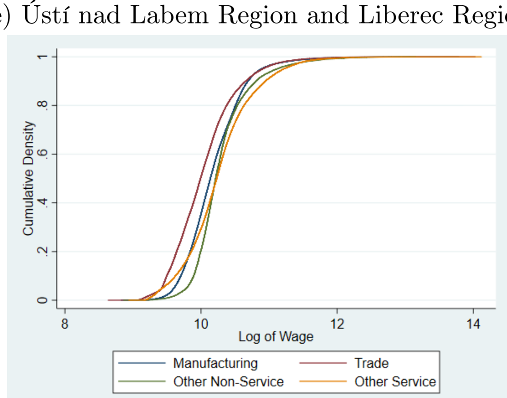
(d) Plzeň Region and Karlovy Vary Region



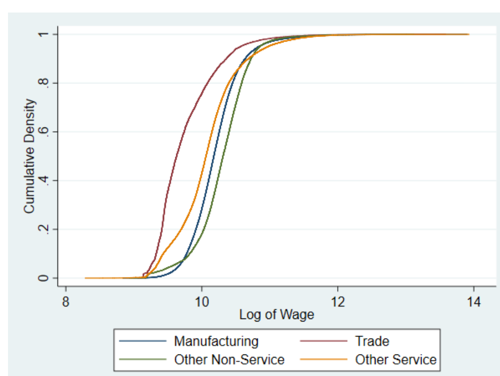
(e) Ústí nad Labem Region and Liberec Region



(f) Hradec Králové Region and Pardubice Region



(g) Zlín Region, South Moravian Region, and Vysočina Region



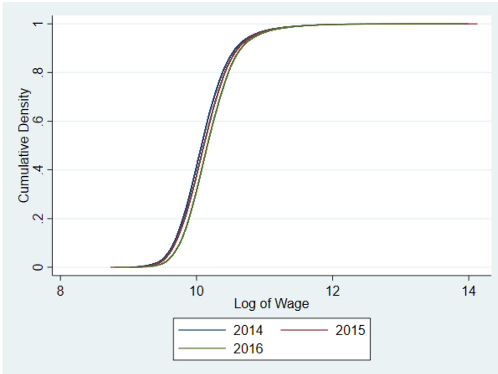
(h) Olomouc Region and Moravian-Silesian Region

Figure 6: Wage Cumulative Distribution Functions by Region and Group of Industries

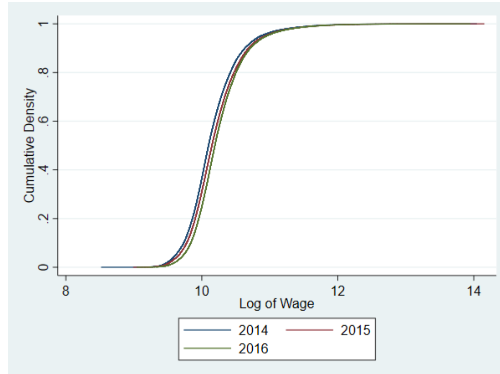
and trade it is true for all industries. Among other non-service sectors four industries exhibit different dynamics (Figure 8). Among other service sectors six industries exhibit different dynamics (Figure 9). Next I describe the patterns that they exhibit.

Figure 8 shows the behavior of wages in three non-service sectors. In extraction of crude petroleum and natural gas wages were stable in 2014 and 2015 and then fell in 2016 for almost all quantiles of the wage distribution (Figure 8a). In mining of metal ores wage first decreased in 2015 for all workers but slightly rebounded in 2016, especially for low-earning workers (Figure 8b). Overall, the wage distribution in 2016 is dominated by the one in 2014. In mining support service activities the wage distribution is more or less stable below the median but above the median workers saw an increase in wages in 2015 but then in 2016 the wage distribution for them moved to the left, so that there are less high-earning workers in 2016 relatively to 2014 or 2015 (Figure 8d). In fishing and aquaculture the pattern of wage evolution is close to standard. Though the cumulative distribution is quite kinky, the line for 2014 is the one to the left, the line for 2016 is the one to the right, and the line for 2015 is in-between, as is consistent with the economy-wide pattern of wages in 2016 dominating wages in 2015 and 2014, and wages in 2015 dominating wages in 2014 (Figure 9a). However, for the very low-earning (10% quantile and below) employees the situation is different: they seem to have their wages reduced in the sense of quantile effects in 2016 (or 2015) relative to 2014. The common feature of the industries discussed in this paragraph is that they are dealing with the extraction of natural resources. Wage on average fall for each of these industries, while in the economy in general the wages rise (Figure 4).

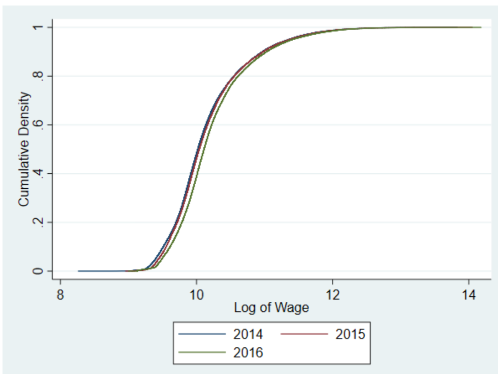
Figure 9 also shows diverse patterns across service industries. Some industries exhibit consistent wage decrease. For example, air transport (Figure **??**) saw an overall decrease of the wage distribution both in 2015 and 2016. Even though some higher quantiles of the wage distribution exhibited some increase in 2015, in 2016 the wage distribution is shifted to the left as compared to 2014. The pattern for residential care activities was similar with the shift of the wage distribution between 2014 and 2016 (Figure 9e). The same is true for



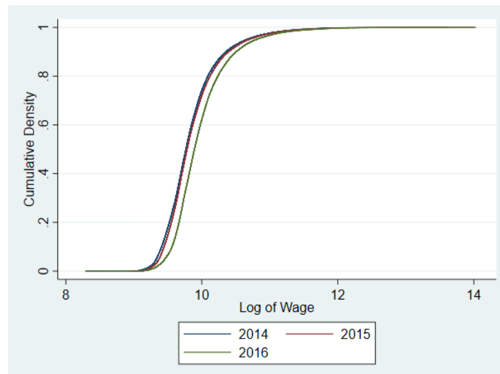
(a) Manufacturing of Fabricated Metal Products, except for Machinery and Equipment



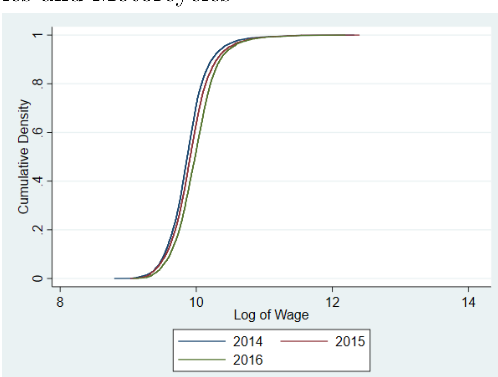
(b) Manufacturing of Machinery and Equipment n.e.c.



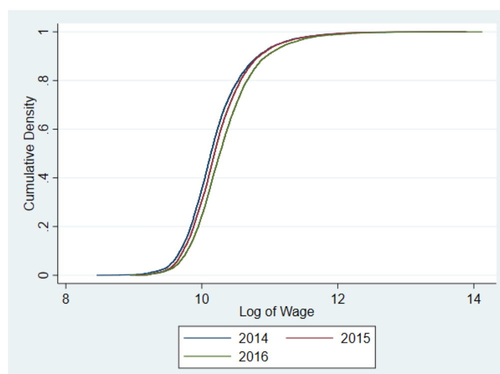
(c) Wholesale Trade, except for Motor Vehicles and Motorcycles



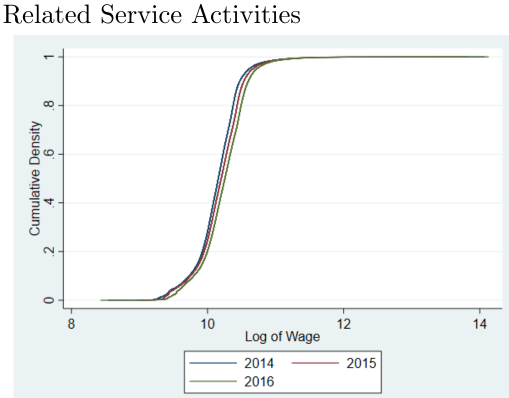
(d) Retail Trade, except for Motor Vehicles and Motorcycles



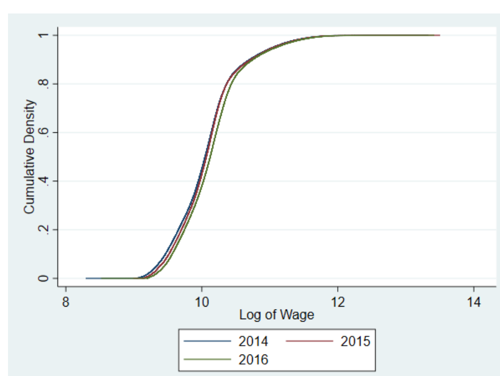
(e) Crop and Animal Production, Hunting and Related Service Activities



(f) Construction of Buildings

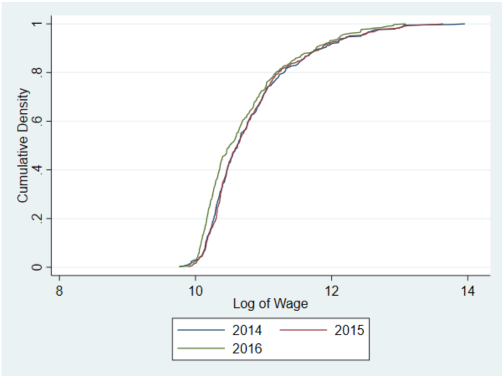


(g) Land Transport and Transport via Pipelines

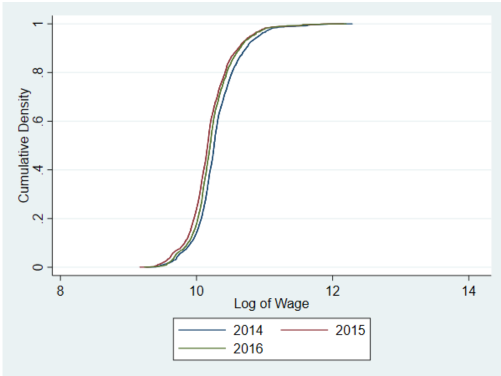


(h) Human Health Activities

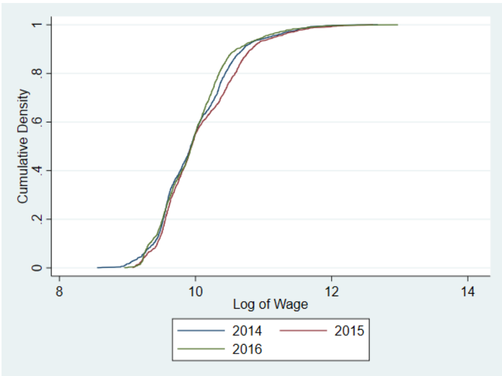
Figure 7: Wage Cumulative Distribution Functions by Industry



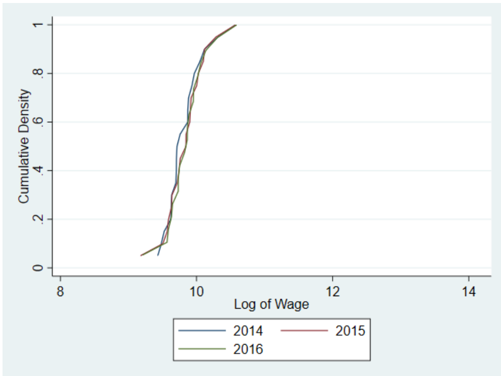
(a) Extraction of Crude Petroleum and Natural Gas



(b) Mining of Metal Ores



(c) Mining Support Service Activities

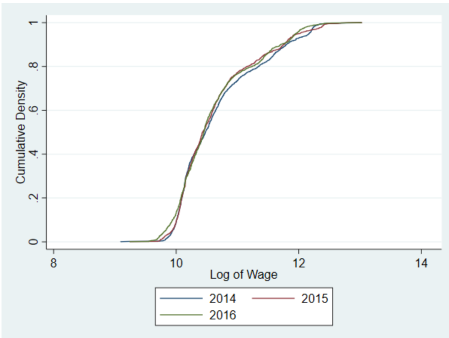


(d) Fishing and Aquaculture

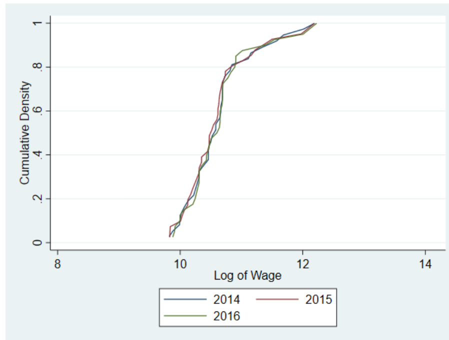
Figure 8: Wage Cumulative Distribution Functions by Industry; Other Non-Service

the repair of computers and personal and household goods, though the wage distribution for this sector was more or less stable (Figure 9f). Advertising and market research showed a similar pattern, but low-earners did not lose as much as high-earners, as for the former the wage distribution was stable, while for the upper tail of wages the cumulative distribution function decreases (Figure 9c). Finally, the most irregular pattern was the one exhibited by motion picture, video and television programme production, sound recording and music, and publishing activities (Figure 9b). The effects were very heterogeneous across quantiles not only in terms of magnitude but also in terms of direction.

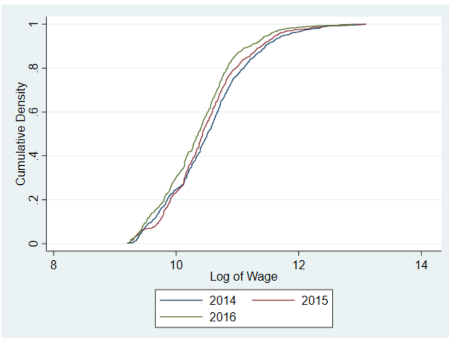
I started this subsection with the aggregate analysis of wage structure at the group-of-sectors-level. The patterns were similar across groups of industries, so in order to analyze the link between job flows and wage dynamics I need to try to find some variation at a different level. Then I followed the path of disaggregation and explored the patterns of wage structure at the level of districts (spatial variation) and at the level of two-digit NACE industries (production variation). In this part I go one step further and look at the firm-level job flows. I follow Haltiwanger and Vodopivec (2003) and analyze firm-level job flows. Firm-level job reallocation rate is defined as either JC rate or JD rate as at the firm level simultaneous JC and JD are not possible to observe from the firm-matched data I have. The dependent variable is the firm job reallocation rate. The set of regressors includes average firm (log) wage, firm wage dispersion, and a set of controls. The controlling variables include year fixed effects, and two-digit industry fixed effects or group-of-sectors fixed effects, dependent on specification. Also certain specifications control for the district. The model is simplistic and is free of causal interpretation. The estimation results are purely descriptive and are presented in Table 8. The standard errors are clustered at the firm level. The highest interest lies in first two lines. The coefficient of average firm wage is negative and stable across specifications. It is also significant at conventional levels across specifications. The coefficient of firm wage dispersion is, on the contrary, insignificant in all specifications I consider. Thus, my results provide some evidence on the link between job flows and wages: firms with higher average



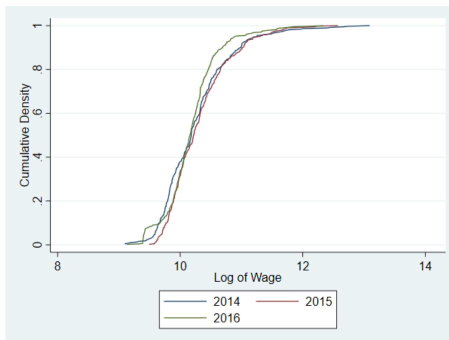
(a) Air Transport



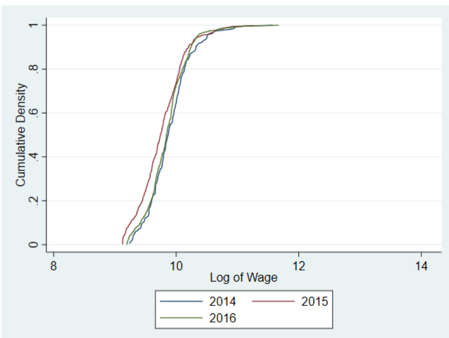
(b) Motion Picture, Video and Television Programme Production, Sound Recording and Music Publishing Activities



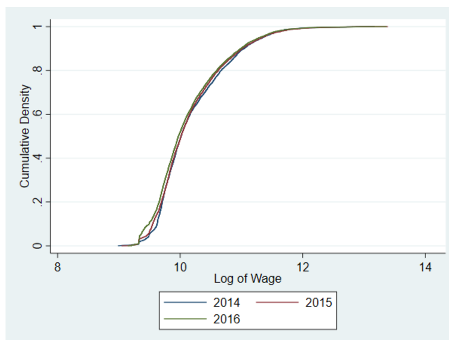
(c) Advertising and Market Research



(d) Other Professional, Scientific and Technical Activities



(e) Residential Care Activities



(f) Repair of Computers and Personal and Household Goods

Figure 9: Wage Cumulative Distribution Functions by Industry; Other Service

wage tend to have lower employment volatility. At the same time, variance of wage does not have strong connection to job flows, conditional on average wage (and control variables). In Subsection 4.4 I discuss my results from Table 8 in connection to the results of Haltiwanger and Vodopivec (2003).

	Job reallocation			
Average firm wage	-0.093 (0.011)	-0.103 (0.013)	-0.102 (0.011)	-0.113 (0.013)
Firm wage dispersion	-0.031 (0.048)	0.020 (0.052)	-0.061 (0.048)	-0.003 (0.052)
Year FE	Yes	Yes	Yes	Yes
Group of sectors FE	Yes	No	Yes	No
Two-digit sector FE	No	Yes	No	Yes
District FE	No	No	Yes	Yes
N	10952	10952	10548	10548
Adjusted R^2	0.028	0.048	0.030	0.051

Standard errors in parentheses

Table 8: Firm-Level Job Flows and Wage

4 Discussion

4.1 Comparison of Indicators with the Literature

My results on job flows indicators are presented in Tables 2-5 by two-digit NACE industries and in Table 6 for four broad groups of sectors. One of them, manufacturing, is of higher interest for this Subsection of the paper than others, as many articles consider manufacturing job flows exclusively.

First, I discuss my results on manufacturing. Table 6 shows that the JC rate for manufacturing ranges from 0.078 to 0.095 in the Czech Republic in 2014-2016, with a (simple unweighted) average being equal to 0.084. Davis and Haltiwanger (1992) find the range of

JC that is larger than the one I find: from 0.064 to 0.132, and the average JC rate of 0.920, which is slightly higher than the one I find. Albak and Sørensen (1998) show the range of the JC rate from 0.104 to 0.154 with the average equal to 0.120. Note that the average JC rate and its lower and upper bounds are higher in Albak and Sørensen (1998) than the ones I find. Haltiwanger and Vodopivec (2003) find the average JC rate to be approximately 0.100, which is also slightly higher than the one I find. With a more extensive dataset Lee and Won (2021) show the range of the JC being approximately 0.130-0.260, which is the highest in the literature I review. Mitchell et al. (2006) find the smallest range of the JC rate: 0.002-0.028. Note that (almost) all average JC rates in manufacturing presented above (except for Mitchell et al., 2006) are bigger than the one I find in this paper. Also note that all the results on JC from the literature (perhaps, with the only exception of Mitchell et al., 2006), though being different numerically, are of the same order of magnitude.

For the JD rate in manufacturing I find the range of 0.033-0.079, with the average of 0.053. Davis and Haltiwanger (1992) show higher JD rates on average. The range they find is 0.061-0.166 with the average of 0.113. Hence, the average JD rate I find is approximately two times smaller than the one found by Davis and Haltiwanger (1992) in the U.S. Similarly, Albak and Sørensen (1998) find the average JD rate equal to 0.115, which is greater than the one I find. The range of the JD rate they find is 0.088-0.115, with both bounds higher than in my data. Note that Albak and Sørensen (1998) find the range of JD smaller than the one in Davis and Haltiwanger (1992), which suggests smaller volatility of JD in Denmark in 1980-1991 than in the U.S. in 1973-1986. The size of the range of JD I find is somewhat between the two. Consistently with two papers above, Haltiwanger and Vodopivec (2003) find the JD rate in manufacturing of approximately 0.100, which is roughly twice as big as the one I find. Lee and Won (2021) show the JD rates between 0.080 to 0.280, such that the lower bound they find is comparable with the upper bound I find. Mitchell et al. (2006) again find the average JD rate in manufacturing, mining, and construction that is the smallest of all I review here, such that the upper bound (0.028) they find is comparable to the lower bound I find.

Thus, the majority of papers reviewed here report the average JD rate in manufacturing being around 0.100, while the average JD rate in manufacturing I find is almost two times smaller. Note that, similar to the JC analysis above, (almost) all average JD rates in manufacturing presented above (except for Mitchell et al., 2006) are bigger than the one I find in this paper. Also similar to the JC analysis above, all the results on JD from the literature, though being different numerically, are of the same order of magnitude.

As the job reallocation rate is just a sum of the JC and JD rates, the average job reallocation rate in manufacturing I find (0.137) is smaller than the average job reallocation rates in the majority of papers reviewed above (Davis and Haltiwanger, 1992, Albak and Sørensen, 1998, Haltiwanger and Vodopivec, 2003, Lee and Won, 2021). It is also smaller than the average job reallocation rate in manufacturing in South Africa in 2011-2014 (0.251) (Kerr, 2018). Kerr (2018) presents only job reallocation rates on manufacturing, so I did not use this paper for the separate analysis of JD and JC above.

Here I present some factors that are possibly responsible for the observed discrepancies in JC and JD rates both between published articles, and between published articles and my paper. First, the straightforward reason of differences in the job flows indicators is that different countries have different institutional conditions and different job flows (Gómez-Salvador et al., 2004). Second, different time periods covered in the articles and in my paper can represent a source of discrepancy if some shock occurred in period t and affected a subset of markets. Third, as suggested by Gómez-Salvador et al. (2004), countries may have different statistical definitions of manufacturing (which sectors to include), so some dissimilarity of the indicators can be attributed to this factor. Third, one possible reason of the results of Mitchell et al. (2006) to stand out is that they contain not only manufacturing, but also construction and mining. However, Table 4 suggests that it is not the only reason. In the Czech Republic in 2014-2016 mining has, e.g., a very low JC rate (on average 0.021), while construction has a moderate JC rate (on average 0.044), so combined with the figures for manufacturing (from Table 6) the JC rate for manufacturing, mining, and construction in my data still would be higher than in Mitchell et al. (2006), though the discrepancy would be smaller. Similar intuition applies to the JD rate. Finally, the time span of my research is relatively short, hence it is possible that with more periods at hand the results would be closer to the ones found in the literature. Nevertheless, the order of magnitude is still the same in my results and (the majority of) the literature.

4.2 Statistical Analysis

One may note that the methodology of this paper is purely comparative without statistical testing of various hypotheses, e.g. on equality of the indicators of job flows (JC rate, JD rate or reallocation rate) for two industries. The major reason for this methodological choice is that for finite samples there is no universally adopted way of testing for the equality of means of two populations. There are simple methods of testing the null hypothesis of equal means for two independent normal populations with equal means. However, this setup is very restrictive and becomes harder to solve as more assumptions are relieved. When two variances are unknown, the setup is called Behrens-Fisher problem (see, e.g., Scheffe, 1970). A number of solutions have been suggested that vary in terms of the assumptions implied and properties of the test (e.g. size control and power control). A recent paper by Counsell et al. (2020) compares a number of testing strategies in terms of power and size control and show the relatively poor performance of the number of methods. Some tend to perform better but in general for the case of heterogeneous variances of two populations of different sizes no method exhibits good testing properties. However, it is exactly the case of my paper. Industries have different size and are likely to have different variances of job flows indicators (as suggested by Table 6 for groups of industries). Note here that the problem above is applicable to my data because my dataset contains a relatively small number of observations (firms) for a given two-digit NACE industry, so that the asymptotic approximation is not valid. As the asymptotic approximation is likely to be unreliable, another possible solution is to use bootstrap confidence intervals.

A possible method of the analysis of the connection between job flows and industries and locations is the regression analysis. The simplest setup in this case would be to use a firm-specific job flow indicator of interest as the dependent variable. The set of regressors consists of dummy variables for years, dummy variables for regions (or districts as defined in Subsection 3.3), dummy variables for industries (or groups of industries as defined in Subsection 3.2), possibly, their interactions for the analysis of industry-by-region job flows (as in Subsection 3.3), and multiple firm characteristics such that there is no omitted variable bias. A straightforward drawback of the regression approach in this context is the lack of degrees of freedom. The data contains information on 4354 firms, 82 industries and 78 geographical entities. The number of observations can still be greater than the number of regressors if some interactions are omitted or if some categories are grouped (e.g. industries into groups of industries). However, some coefficients can be estimated poorly if, e.g. some industry I in region R consists of only one firm and, as a result, the corresponding coefficient is estimated imprecisely.

Another problem of the regression analysis in this context is that for the analysis of job flows by industry it is reasonable to cluster standard errors at the industry-level (or at the level of groups of economic sectors – if the analysis is at their level). Therefore, the "effective" number of observations is equal to the number of clusters (industries or groups of industries), which is much smaller and the precision of estimation of the asymptotic variance-covariance matrix is reduced. Another complication is that a high number of regressors gives rise to non-conventional asymptotic theory and the asymptotic variance becomes more complicated to estimate (see Anatolyev, 2019 for a review), even without clustering.

On the contrary, in the context of the wage structure analysis regression approach is suitable. In this case only two coefficients are of interest (contrary to many JC/JD indicators) and they can be consistently estimated, given certain exogeneity conditions hold. For them to hold I add covariates, hoping that the set of controls is sufficient for the exogeneity of two variables of interest (average firm wage and firm wage dispersion).

4.3 Classification of Industries and Regions

In Subsection 3.2 I group all two-digit NACE industries into four groups: manufacturing, trade, other non-service, and other service. The first group, manufacturing, corresponds to the Eurostat classification (Eurostat, 2008). It contains sectors that physically or chemically transform inputs into new products. The inputs can be raw materials or the products of other manufacturing activities. Therefore, the output can be either final goods, or intermediary output. A separate analysis of manufacturing is particularly useful in the context of placing this paper in the literature: many other papers concentrate on the analysis of job flows in manufacturing (e.g. Caballero and Hammour, 1996, Lee and Won, 2021), and provide useful benchmarks for comparison (Subsection 4.1).

Similarly, the second group of sectors, trade, corresponds to "wholesale and retail trade; repair of motor vehicles and motorcycles" group of sectors in the Eurostat classification (Eurostat, 2008). The shorter version of the group name was chosen for convenience. Such a shorter name can be misleading by overlooking the repair of motor vehicles but I believe it is not a problem for two reasons. First, Table 3 indicates that the repair of motor vehicles is included in the trade group of sectors. Second, the data includes 662 firms in the trade group of sectors, out of which only 36 (approximately 5.4%) are the subdivision "Maintenance and repair of motor vehicles". Therefore, the repair of motor vehicles accounts for a minor part in this group of sectors as opposed to wholesale and retail trade. The reason for distinguishing trade from other service sectors is twofold. First, the trade group contains sectors that are different from other service sectors in the sense of also being an intermediary between economic agents. Therefore, they are expected to exhibit dynamics other than other service sectors. Second, the trade group of sectors is big enough in terms of the number of firms (Table 1), so that the precision of estimated indicators is more credible.

Finally, other two groups are broad as their names suggest. Various industries with various job dynamics are included in both these groups, especially in the other service one. Other non-service sectors group contains production of raw materials, energy, water and waste treatment, and construction. Other service sectors group contains many more sectors and they are more diverse. Therefore, my results do not make emphasis on the last group of sectors. Industries that it contains are highly heterogeneous in terms of job flows (Table 7). One possible direction for future research is to split the other service group of sectors into smaller groups (possibly, using the Eurostat classification from Eurostat, 2008) and investigate job flows for each of those smaller groups in detail.

The grouping of regions into eight districts is more arbitrarily than the grouping of industries. It is made on the basis of geographic proximity and might capture the effects of some common shocks, which affect spatially connected regions. At the same time, the robustness of my results to different groupings of regions is questionable. One can view my strategy as the analysis of *weighted combination of job flows* of some regions. For example, the fact that in district five (see Subsection 3.3) in 2016 the JC rate of manufacturing is higher than the JC rate of trade (Figure 1) means that the (weighted) average JC rate of manufacturing in Ústí nad Labem Region and Liberec Region was higher that the (weighted) average JD rate. It is possible that in one of them manufacturing grew and in another one it shrank but as a result of reweighting the overall JC rate in manufacturing for the district is higher than the overall JD rate in the same group of sectors. The somewhat ideal way is to look at the region-by-industry job flows. However, there are

4.4 Wage Structure

I present my results on the connection between firm-level job flows and wages in the Czech Republic in 2014-2016 in Table 8. My estimate of the coefficient of the average firm wage is around -0.100 depending on the specification. One can view the last column as the final specification as it controls for the largest set of covariates as compared to other specifications I consider. Then the estimate is -0.113 with the standard error of 0.011. This result is in line with Haltiwanger and Vodopivec (2003), who in a similar regression finds the coefficient to be equal to -0.133 with the standard error of 0.005 in Slovenian data for 1997-1999. The magnitudes of coefficients and standard errors are similar. However, the second coefficient of interest is the coefficient of firm wage dispersion. I find it to be around 0.000, changing signs across specifications, and robustly insignificant. However, Haltiwanger and Vodopivec (2003) find this coefficient significant and estimate it to be -0.194 with the standard error of 0.011. The data I use and Haltiwanger and Vodopivec (2003) use are different in terms of the country and years of research. Also Haltiwanger and Vodopivec (2003) regress employment weighted variables, while I do not reweigh the data. Possibly, these reasons together explain the different estimates. Nevertheless, the differences are really huge and require a closer look.

5 Conclusion

The JC and JD framework of Davis and Haltiwanger (1992) allows researchers to better understand the labor market in particular and the economy in general. It moves the focus from the reallocation of workers to the reallocation of jobs. Therefore, JC and JD are connected to other fields, including industrial organization and the macroeconomics of business cycles. These indicators provide insights into the relative performance of different sectors from the job dynamics perspective.

Another useful characteristic of an economic sector is the wage distribution. While it represents the nominal side of the economy, job flows measures, including JC and JD rates, represent the real side of the economy. Hence, the combination of the evidence on job flows and wage dynamics provide a comprehensive picture of the economy.

I investigate job flows and wage structure in the Czech Republic in 2014-2016 with employer-matched ISPV data. I present results at the level of two-digit NACE industries, groups of industries, and geographical districts. I find that manufacturing and trade grew the fastest on average. The majority of industries expanded in 2014-2016, except for non-service sectors without manufacturing, which annually shrank. I find the degree of job reallocation that is somewhat smaller than the most of the literature report.

I find that wage distributions were homogeneous across groups of sectors and the majority of industries. For the most of them the wage distribution increased for all the quantiles of wages. Some industries exhibited a reverse pattern with the wage decreased for all the quantiles of wages. The wage distribution in Prague is similar to the one at the country level. In line with Haltiwanger and Vodopivec (2003) I find the strong negative association between firm-level job flows and firm average wages.

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