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Wage Growth, Urbanization, and Firm Characteristics – Evidence for Germany

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Markus Kelle[1]

Wage Growth, Urbanization, and Firm Characteristics – Evidence for Germany

Abstract

I use German administrative data for 2001-2010 to analyse the impact of urbanization and firm characteristics on wage growth of workers. I find a statistically highly significant higher within-job wage growth rate for workers in counties with a higher population density. This provides evidence that workers' productivity growth is higher in denser regions, which could be explained by faster learning or human capital accumulation of workers. However, this effect turns insignificant once I account for the number of employees of the workers' firms, the share of highly educated workers in the firm and wagelevel firm fixed effects. This indicates that such a learning effect may occur rather within firms than between workers in a region. Beyond this, the paper presents evidence that workers in denser areas also benefit more from job changes within counties. One reason for that is that workers in denser regions match more often with high-wage firms. Furthermore, I find evidence that also the efficiency of the worker-firm matches is higher in denser areas.

JEL Classification: R11, R23, J24

Keywords: Wage growth; learning; urbanization; firm characteristics

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1 Markus Kelle, UDE. – I thank Marcel Henkel for many helpful comments and discussions about the paper. Furthermore, I thank the staff of the research data center (FDZ) at the IAB for support in handling and for providing the data. I am solely responsible for any errors. – All correspondence to: Markus Kelle, University Duisburg-Essen, Mercator School of Management, Lotharstrasse 65, 47057 Duisburg, Germany, e-mail: markus.kelle@uni-due.de

1 Introduction

The urban economics literature provides ample evidence that wages of workers are higher in more urbanized regions. However, the understanding of the economic reasons for this wage premium is still incomplete. Among others, Glaeser and Maré (2001), De la Roca and Puga (2015), and Wheeler (2006) point out that the urban wage premium is not only a static premium but has also an important dynamic component. Thus, workers moving to cities do not receive the entire wage premium immediately. It is growing over time as workers spend several years in cities instead of a rural area. The economic interpretation of this result is that workers may benefit from higher learning benefits and knowledge accumulation in denser regions which lead to higher productivity growth and thus to higher wage growth rates. However, it is both theoretically and empirically still not entirely clear how this potential learning in urban areas may indeed occur.

To shed some more light on this issue, I do two things in the present paper: First, I analyse whether wage growth rates of workers in Germany are higher in counties with a higher population density. Second, I analyse whether the relationship between urbanization and wage growth can be explained by the characteristics of the firms in which workers are employed.[1] This second part of the analysis is rather new to the literature, most likely because of data limitations. One exception is the analysis of Lehmer and Möller (2010). They find that wages of workers in Germany are growing faster in cities. However, this effect decreases once they control for the size of the firms. This is because workers have larger wage growth rates in larger firms and these larger firms are more often located in cities. The latter result is also emphasized by the agglomeration literature, which shows that firm characteristics are heterogeneous across regions. For instance, Combes et al. (2012) find that firms have significantly higher total factor productivities (TFP) in areas with higher population density. Thus, the existing evidence suggests that it is indeed useful to consider the role of firm characteristics to understand the link between urbanization and the dynamics of worker wages.

To conduct this analysis in the present paper, I use the 'SIAB 7510' dataset, which is provided by the German institute for labor and occupation research (IAB). The dataset provides administrative information about several characteristics of workers in Germany, their daily wages and also information about the firms in which workers are employed. I use four firm variables to account for potential sources of wage growth of workers at the firm level: the log number of employees, the age of firms in years, the share of highly educated workers and wage-level fixed effects estimated by Card et al. (2013).[2] To the best of my knowledge, using these different

[1] I use the term 'firm' for convenience in the entire paper. However, the provided information in the applied data is actually at the plant-level, which is a finer measurement than the firm-level.

[2] Card et al. (2013) have access to the full population of workers and firms. I can use only a 2%-sample, which does not allow estimating firm fixed effects. However, the IAB provides these

types of firm information, I go beyond all other existing related studies.

Methodologically, I follow the approach of D'Costa and Overman (2014) (DO in the following). I regress the annual growth rates of real daily wages on the population density in the county of the workers' workplace. In the second step, which is going beyond DO's analysis, I add also the firm variables to the regression to see whether this has an impact on the size of the estimated coefficient of density. Furthermore, I focus in the main part of the analysis on the so-called within-job wage growth of workers, by restricting the sample to the observations of workers' wage growth in the same job.[3] For instance, Wheeler (2006) argues that this approach is mostly suited to understand the local economic channels that have an impact on learning rates of workers, because the measured wage growth is not affected by the changing economic conditions through job changes of workers. DO denote the estimated effect of urbanization on the within-job wage growth as the 'pure growth effect'.

Without firm-level controls, I find that population density has a highly significant positive relationship with wage growth rates. Thus, I find evidence for an existing 'pure growth effect' in Germany. This result is robust to a large set of control variables, accounting for worker fixed effects and is robust in different time periods. Furthermore, I find that the effect is positively related to the education levels of workers. However, when I account for firm-charactertistics the estimated coefficient of population density becomes much smaller. The estimated pure growth effect is reduced by about 60% and is not statistically significantly different form zero anymore in the most important specifications. Instead, the number of employees and the share of highly educated workers of the firms have highly significant and positive coefficients. Thus, workers in denser regions benefit significantly from working in larger firms with high-shares of skilled workers. This explains nearly the entire 'urban wage growth premium'.

Beyond the results for the within-job wage growth of workers, I also analyse the impact of urbanization on the 'between-job wage growth' of workers. First, I find that workers show higher wage growth rates when they start a new job in another county which has a higher population density. This effect is also denoted as 'mobility' or 'wage level effect'. However, this effect vanishes when I account for the wage-level firm fixed effects. Thus, workers obviously benefit from moving to 'better' firms when they move to denser counties. Second, workers in denser regions have significantly higher wage growth rates when they change jobs within the county. This effect decreases by about 40% when I control for firm characteristics. Thus, workers in denser regions obviously benefit from moving to firms with rather high wage levels. However, the reamining effect is still significant, which might be explained by more efficient matches of workers and firms in denser areas (e.g., Wheeler, 2006

fixed effects in a separate dataset, which are called 'CHK-effects' (compare also CHK, 2015).

[3] I define a 'job' as the specific firm in which a worker is employed. By this definition, workers change their job when the ID of their firm is changing in the data.

or Yankow, 2006).

In total, the results emphasize that it is an important issue for future research to understand, why firms are different in more urbanized areas and how these firm characteristics affect wage growth of workers. I find that firm-specific determinants might be more important for the development of workers' productivity and wages than regional characteristics. This dimension has been largely neglected in the previous urban wage premium literature considering the producitivity growth of individual workers in denser regions.

The rest of the present paper is organized as follows: first, I present the dataset, its preparation and some descriptive facts. Second, I introduce the applied regression approach and briefly discuss its motivation. Third, I show results for the usual urban wage premium. Fourth, I analyse in the main part of the paper the within-job wage growth of workers. Fifth, I briefly analyse also job changes of workers. Finally, I conclude in section six.

2 The dataset

2.1 Construction

This study uses the weakly anonymous Sample of Integrated Labour Market Biographies (Years 1975-2010). Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access. The dataset is a 2% random sample from the entire amount of German workers subject to social security payments. It provides detailed information about daily wages of workers, their occupation and several bibliographical variables like age, education, gender and nationality. Furthermore, one can distinguish also different types of employment like part- and full-time jobs.[4]

Beyond the worker characteristics, the dataset includes also information about the firm in which workers are employed. For instance, these are the county of the firms location, the sector, the number of employees, different types of education of workers and the date of foundation.[5] Furthermore, I use the firm identifiers to merge wage-level fixed effects to the data. These fixed effects are generated by Card et al. (2013) (CHK) and are provided in a spearate dataset by the IAB. The so-called CHK fixed effects are generated in a Mincer-type regression. Log wages of workers are regressed on workers' age and education and worker and firm fixed effects. Thus, the firm fixed effects capture all characteristics of firms that affect the wages of their workers beyond the worker controls and the worker fixed effects.

[4]For more detailed information about the dataset see also vom Berge et al. (2013).

[5]As already mentionend above, the data is provided at the plant-level, but I use the term 'firm' for convenience.

The SIAB dataset covers the period from 1975 till 2010. However, I focus the main analysis on the time period 2001-2010 for at least two reasons. First, this ensures comparability with other related studies like DO and De la Roca and Puga (2015), which also focus mainly on observations for this century. Second, restricting the covered time span accounts for the possibility that some economic relationships may change over time. To check this, I make a robustness check of my main results for the earlier time period 1991-2000.

I use only German male workers that have full-time jobs and are between 21 and 60 years old. Because some workers have information about daily wages for more than one time period within a year, I use only observations that rely on more than 185 days of employment within a year. Furthermore, I focus the analysis on the former Western Germany to avoid that results are affected by structural differences between the East and West of Germany. This selected sample should ensure that the individual workers and their observed behavior should be highly comparable. The results should be affected only to a small extent by structural changes in the labor market towards higher employment of women and more part-time employment. However, it is important to note that the sample is more homogeneous than in DO, for instance, who account also for part-time workers. To avoid that the results are affected by outliers in the dependent variable, I drop observations from the data with wage growth rates above 200 percent and below minus 75 percent.

One important shortcoming of the data is the right-censoring of the daily wages. In Germany, there is an upper earnings limit in the statutory pension insurance scheme. Daily wages are only reported up to this limit (see also vom Berge et al. (2013)). In the applied sample, about 15% of the wages are affected by the censoring. To be able to use a better information about the wages than the censoring limit, I apply the imputation method of Gartner (2005). Given the observed variables for individuals, daily wages are predicted by a Tobit regression, which accounts for all variables that I use later in the regression analysis (see section three). Furthermore, I add the share of high-skill workers in a county and interation terms of the education level dummy variables for the individual worker and the population density of the county. Thus, the predictions use a quite large set of available information. Since the observed wages should vary randomly around the 'true' value, a second term is added to the prediction in the second step, which is drawn from a truncated normal distribution. For more details of this method, see Gartner (2005). To use real daily wages of workers, I deflate wages with a price index from 'Destatis' (Federal Statistical Office) after the imputation with 1995 as the base year.

Finally, I use data from 'Destatis' about the population and the area of the counties to calculate the population density of the counties. For the descriptive facts in the following sub-section, I distinguish also between cities, suburban and rural counties using data from the BBSR (Federal Institute for Research on Building, Urban Affairs and Spatial Development). Furthermore, I define different city size classes. Cities which have more than 500,000 citizens in 2010 are denoted as large cities. Medium-sized cities (called 'medium cities' for convenience) have a population between 200,000 and 500,000. Small cities have a population between 100,000 and 200,000 citizens.

2.2 Descriptives

Table 1 shows the average population density in different types of regions and the average annual wage growth rates of workers. The counties are classified into five groups as described above. These groups are similar to those used in DO. The mean population density for the region-types shows that population density increases with city size. This suggests that the population density is a useful measurment of a county's urbanization. The mean real wage growth rate of the 1,408,332 observations in the sample is 2.15 percent. This is clearly larger than usual statistics show for the total German economy. This result should be driven by the fact that I use only a very selected sample. Many workers that are relevant for the entire economy like women, foreigners, and part-time workers are ignored in the analysis.

Table 1: Poulation density of counties and annual real wage growth rates of workers, mean values, 2001-2010

Region-type	log popul. density	no. of counties	wage growth	no. of obs.
large city	7.88	10	3.16	246,744
medium city	7.46	18	2.34	124,862
small city	7.18	29	2.63	124,372
suburban	5.92	130	1.94	601,408
rural	4.98	138	1.50	310,946
total	6.31	325	2.15	1,408,332

Furthermore, table 1 shows that the mean wage growth rate is positively related to population density. The only exception are small cities, which show a relatively high wage growth compared to medium-sized cities. However, a simple regression of wage growth rates on population density shows a highly significant positive correlation of these two variables. The regression analysis below shows whether this result is still robust when I control for worker and firm characteristics.

Table 2 shows firm characteristics in the different region-types. There are 167,950 firms in the sample with 704,611 observations for firms per year. The displayed variables are the four variables that I use later in the regression analysis: the log number of employees, the age of the firm in years, the share of workers with high education (university or terchnical university degree)[6], and the wage-level firm fixed

[6]I denote this variable as the 'high-skill share' for convenience.

effects. In general, the stylized facts confirm the agglomeration literature and show that firm characteristics differ across regions. The firms in more urbanized regions are larger, younger, have higher share of skilled workers and show larger wage fixed effects. Regressions of these firm characteristics on population density, 2-digit sector dummies and year dummies show that these relationships are statistically highly significant for all firm variables at the 1%-level.

Table 2: Characteristics of firms, mean values, 2001-2010

Region-type	log empl.	firm age	high-skill share	firm wage-level FE	firm-year obs.
large city	5.61	20.06	0.175	0.713	104,535
medium city	5.31	20.25	0.116	0.684	56,695
small city	6.06	21.64	0.124	0.714	48,199
suburban	4.85	21.31	0.088	0.681	320,764
rural	4.63	21.65	0.051	0.633	174,418
total	5.08	21.11	0.101	0.679	704,611

Table 3 finally shows that it is useful to distinguish between the within- and between-job wage growth in the analysis. The largest wage growth rates can be found when workers change their jobs across counties (7.78 percentage points). However, this occurs in only 3.5% of all observations. The second largest value occurs when workers change the firm within a county (4.88 percentage points). These observations present 4.5% of the sample. The by far largest share of the sample (92%) consists of observations in which workers stay within the same firm in the same county. In years, in which workers do not change their jobs, the growth rate is clearly smaller than in years of a job-change, but on average still positive with a value of 1.81.

Table 3: Mean wage growth rates for different types of observations, 2001-2010

Types of observ.	wage growth	no. of observ.	share
within job	1.81	1,295,845	92.0%
job changes:			
between counties	7.78	49,027	3.5%
within counties	4.88	63,460	4.5%
total	2.15	1,408,332	100.0%

Altogether, it is important to note that worker mobility is relatively low in Germany. In total, there are 234,787 workers in the applied sample. Thus, I can use on average about six observations per worker. Only 17.4% of the workers in the sample (40,737 of 234,787) move at least once across counties in the period 2001-2010. 22.2% of the workers (52,051) change the firm within a county at least once in this period. 66% of the workers do not change their job in the ten year period at all.

3 Regression approach

3.1 Regression equation

The basic regression approach in the paper is that I regress real annual wage growth rates of workers on the population density of the county of a worker's workplace and several control variables. In the second step, I add firm variables to the regression to see whether this changes the estimated effects of population density on wage growth rates. The regression equation can be written as follows:

$$\Delta w_{ijct} = dens_{ct}\delta + z_{jt}\theta + x_{it}\beta + \lambda_t + \alpha_i + \epsilon_{ijct} \tag{1}$$

I follow the approach of DO and use the annual wage growth in percentage points of workers' daily wages, Δw_{ijct}, as the dependent variable.[7] The variable is indexed for worker i in firm j in county c at time t. This measurement of wage growth is highly correlated with the first difference of log wages, which is used for instance by Yankow (2006) as the dependent variable. The correlation coefficient of these two variables is 0.97.

3.2 Within- and between-job wage growth

The main purpose of the paper is to analyse whether productivity growth of workers is accelerated in more urbanized areas by learning of workers or human capital accumulation. To identify this effect, I further restrict the sample to the observations of workers' wage growth within the same job.[8] For instance, Wheeler (2006) and Yankow (2006) argue that the benefits from learning should be rather reflected in this within-job wage growth, because it should mainly reflect the learning of workers from their local economic environment, which can be both regional- and firm-sepcific effects. Also the descriptive facts in section 2.2 were showing that the growth rates are much larger when workers change their jobs. This indicates that wage growth is affected also by other economic forces when workers change their jobs. Thus, I regress in the first step the wage growth rates of workers within the same job on the population density of the county to see whether growth rates are indeed larger in

[7] $\Delta w_{ijct} = 100 * (w_{ijct} - w_{ijc(t-1)})/w_{ijc(t-1)}$.

[8] As mentioned already above, I define job-changes as a change of the ID of the firm in which a worker is employed.

more urbanized areas. This estimated effect is denoted by DO as the 'pure growth effect'. Adding the firm variables in the second step shows whether and to which extent this effect can be explained by the characteristics of the firms in which the workers are employed.

In the second and minor part of the regression analysis, I use the observations of the job changes to analyse the between-job wage growth of workers. Here, I further distinguish between job-changes within and between counties. The cases in which workers start jobs in another county should give some insights whether there is a 'mobility effect' in workers' wages. This effect is also denoted as the 'wage level effect', because it describes to which extent the wages of workers shift up immediately when they start a new job in a more urbanized area. Generally, one would expect that wage growth is larger when workers move to counties with higher densities because of the presumingly higher productivity in denser areas. From the worker perspective, one would expect that wage growth rates are larger when they move to denser areas because the costs of living should be relatively higher there (e.g., DO).

Finally, I also run regressions for the years in which workers change jobs within the same county. This approach should show whether workers benefit more from changing jobs in denser areas. This could occur for at least two reasons: first, workers may find more easily employers which pay higher wages in denser areas, because the number of very productive firms with high wages is larger there (e.g., Combes et al., 2012). Second, workers may benefit from lower search costs which result in more productive matches of workers and firms (e.g., Yankow, 2006 and Wheeler, 2006). These better matches should result in relatively higher productivity of workers and thus higher wages. This effect is denoted as the 'matching effect'.

3.3 Explanatory variables

3.3.1 Population density

In the regression analysis, I use population density, $dens_{ct}$, as the measurement of counties' urbanization. For instance, DO use instead dummy variables for different types of city sizes in Britain (small cities, large cities and London). Lehmer and Möller (2010) use a dummy variable that distinguishes between cities and other counties. I prefer the population density variable instead, first, because it provides a single effect that can be easily compared across different regression specifications. Second, population density is highly related to city size in Germany. Table 1 in section two shows that the population density is increasing with city size even for larger cities. Furthermore, this measurement can capture also differences in counties' densities between rural and sub-urban areas or even within these two groups. This is not possible when using only dummy variables. I check my main results also with dummy variables for the different region-types shown in section two. The regression results for the R-squared and the coefficients of the firm variables hardly change.

One problem that may arise using population density as regressor is that there might be a simultaneous causality of wage growth and population density, because regions with higher wage growth should attract also more workers. However, the variation of population density over time within counties is only quite small compared to the variation between counties. The variance share of the within component is only 0.01% of the total variance. Nevertheless, I check also the results with only the population density in 2005 as regressor. The results are still nearly the same. Furthermore, I focus in the regressions for the 'pure growth effect' only on workers who change the county in which they work at least once (county-movers). This approach should ensure that the estimated effects are driven by the between variation in the variables of interest. As I use worker fixed effects also in some regressions, a large share of the between variation would otherwise be captured in the fixed effects.

3.3.2 Firm characteristics

As discussed above, I add also firm-sepcific variables, z_{jt}, to find whether these have an impact on wage growth rates of workers and the estimated urbanization effect. I use the log of firms' number of employees, the age of the firm in years, the share of workers with high education (university or technical degree) and wage-level firm fixed effects from Card et al. (2013). Using these different types of firm characteristics in an analysis of wage growth and urbanization is, to the best of my knowledge, new to the literature.[9] I choose these four variables, because I suppose that these are the most important among the available variables.

It is quite common in the literature that larger firms should have higher wages for different reasons (e.g., Oi and Idson, 1999). However, the impact of firm size on wage growth, controlling for the three other variables, is not entirely clear. One reason for a positive link might be that large firms provide larger learning potentials within the firm as an individual worker can benefit from knowledge exchange with many other workers. Knowledge spillovers should occur much easier within a (large) firm than between workers of distinct firms (e.g., Nix, 2015).

Concerning the age of firms, Brown and Medoff (2003) find, controlling for other firm and worker characteristics, a U-shaped relationship between firm age and wages. However, they neither analyse wage growth of workers explicitly nor provide clear theoretical ideas to explain the observed pattern. Nevertheless, the age of firms might be a useful control variable. Nix (2015) analyses the impact of high-skill workers in firms on wages of other workers. She finds that indeed other workers benefit from having highly educated colleagues. This result is line with the human capital literature which suggests that a higher share of highly educated workers in a location leads to higher spillovers of knowledge and ideas (e.g., Moretti, 2004).

[9]For instance, Lehmer and Möller (2010) account only for the firm size with a dummy variable for large firms with more than 500 employees.

Thus, I expect that the share of highly educated workers per firm should have a positive impact on wage growth of workers.

Finally, the wage-level fixed effects from Card et al. (2013) should capture all factors, excluding the three other variables, that affect the general wage level within a firm. These could be export or import activities, TFP, R&D expenditures, FDI activities or the implementation of innovations. Furthermore, also the union coverage of firm should have an impact on wages. Thus, this variable can potentially capture a lot of factors and a clear interpretation is difficult. Nevertheless, it should be useful to account for the general ability to offer high wages to workers. If firms reached already high-wage levels in the past they might be able to provide high wage growth rates also in the future. Thus, it seems to be useful to account for the wage-level fixed effects in the analysis.

3.3.3 Control variables

Going beyond population density and firm characteristics, I control in all regressions for the usual Mincer controls, x_{it}. These are the age of workers in years, the age squared and education of workers. The data provides six dummy variables for the education levels of workers. Furthermore, I control for the log number of years that workers have spent already in their present firm. Wage growth rates are usually higher in the first years in a new firm (e.g., Stephani, 2013). In most specifications, I use also dummy variables for workers' occupation and the firm's sector classification. Both set of variables rely on 2-digit level classifications, which provides finer measurements than in most other related papers in the literature (e.g., DO and Lehmer and Möller, 2010).

In all specifications, I control for year-specific effects by adding year dummies, λ_t. Finally, I use in some regressions also worker fixed effects, α_i. This is important to control for unobserved worker characteristics. As often discussed in the urban wage premium literature, there is evidence for a sorting of workers' with high unobserved abilities into more urbanized regions (e.g., Combes et al., 2008). Thus, it might be the case that the impact of urbanization on wage growth is over-estimated when workers with the highest growth rates self-select into urban regions. Worker fixed effects can account for those unobserved worker characteristics that may affect the wage growth rates.

4 Urban wage premium

Before I start to analyse wage growth, I also run regressions with log wages of as the dependent variable. This should provide insights how the usually estimated urban wage premium looks like in the applied dataset. The regression equation can then be written as follows, simply replacing the dependent variable in (1) with the log wages:

$$log(w_{ijct}) = dens_{ct}\delta + z_{jt}\theta + x_{it}\beta + \lambda_t + \alpha_i + \epsilon_{ijct}. \quad (2)$$

Table 4: Regressions for log wages of German workers, 2001-2010

Explanatory Variables	(1) OLS	(2) OLS	(3) OLS	(4) FE	(5) FE
log density	0.048***	0.035***	0.008***	0.013***	0.004***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)
log empl	-	-	0.020***	-	0.014***
			(0.001)		(0.000)
firm age	-	-	-0.001***	-	-0.000***
			(0.000)		(0.000)
hs share	-	-	0.180***	-	0.100***
			(0.008)		(0.004)
firm FE	-	-	0.779***	-	0.440***
			(0.008)		(0.006)
indiv. contr.	yes	yes	yes	yes	yes
year dummies	yes	yes	yes	yes	yes
sec. dummies	no	yes	yes	yes	yes
occ. dummies	no	yes	yes	yes	yes
worker FE	no	no	no	yes	yes
Obs.	1,408,332	1,408,332	1,408,332	1,408,332	1,408,332
R^2	0.362	0.565	0.670	0.091	0.163

Standard errors in brackets are clustered at county-level in OLS regressions. Robust standard errors are used in FE regressions. ***, **, and * indicate significance at 1%-, 5%- and 10%-level, respectively.

Table 4 shows that the population density of the counties shows in all specifications positive and highly significant coefficients. Denser regions have signifcantly higher wage levels than rural regions. The estimated effects of population density become smaller the more control variables are accounted for. In particular, I find that accounting for firm variables reduces the effect by about 70-80%. The impact of the firm controls is slightly larger in the OLS specification (3) compared to the approach with individual fixed effects (5).

I find that all firm variables have significant coefficients. Workers have significantly higher wages in large firms with high shares of high-skill workers, which are rather young and have high values of the firm-fixed effects. This result underlines the importance of firm heterogeneity to understand the differences in wages across regions. Finally, I find as usual in the literature that including workers fixed effects further reduces the urban wage premium. Nevertheless, the density effect remains statistically highly robust.

5 Urban wage *growth* premium

5.1 Total sample

Going beyond the 'classical' urban wage premium, I now analyse the urban wage growth premium by running the regression equation (1) presented above for the total sample of observations.[10] The results in table 5 show that more urbanized regions show significantly higher wage growth rates than rural areas when firm variables are neglected. Population density has a positive and highly significant coefficient in specification (2) and (4), which account for sector and occupation dummies.

This result changes once firm variables are included. The estimated coefficients shrink substantially for both the OLS regression (3) as for the fixed effects approach (5). The decrease is about 85% in the OLS case and 75% with worker fixed effects. In the fixed effects approach (column (5)), the estimated coefficient turns even insignificant. All firm variables show positive and significant coefficients instead. Thus, workers have higher wage growth rates in firms that are larger, older, have many high-skilled workers and generally higher wage levels.

The results provide evidence in favor of the idea that wage growth of workers is rather determined by firm characteristics than by regional characteristics. However, before drawing stronger conclusions from these results, it should be noted that the regressions still comprise the entire amount of observations of workers' wage growth. The estimated effects are a combination of the within- and between-job wage growth. I disentangle these different channels in the following subsections.

5.2 Within-job wage growth

5.2.1 All workers

As described already in section three, I focus on the within-job wage growth to ensure that the identified effects are indeed driven by the local economic environment that affects productivity growth of workers, for instance through learning (e.g., Wheeler, 2006). To do this, I drop the years from the data in which workers start a new job. Table 6 shows the regression results.

[10] I do not show in the entire paper the estimated coefficients of the worker control variables, for convenience. The results for these variables are in line with other papers and the expectations. Workers have higher wage growth rates when they are young. The education of workers is positively related to their wage growth. Furthermore, wage growth rates are higher when workers have spent only few years in the current firm.

Table 5: Regressions for annual wage growth of German workers, total sample, 2001-2010

Explanatory Variables	(1) OLS	(2) OLS	(3) OLS	(4) FE	(5) FE
log density	0.270***	0.198***	0.032**	0.338***	0.078
	(0.026)	(0.022)	(0.016)	(0.051)	(0.050)
log empl	-	-	0.180***	-	0.402***
			(0.014)		(0.028)
firm age	-	-	0.030***	-	0.055***
			(0.002)		(0.003)
hs share	-	-	2.211***	-	3.802***
			(0.160)		(0.350)
firm FE	-	-	3.155***	-	10.825***
			(0.109)		(0.252)
indiv. contr.	yes	yes	yes	yes	yes
year dummies	yes	yes	yes	yes	yes
sec. dummies	no	yes	yes	yes	yes
occ. dummies	no	yes	yes	yes	yes
worker FE	no	no	no	yes	yes
Obs.	1,408,332	1,408,332	1,408,332	1,408,332	1,408,332
R^2	0.020	0.027	0.030	0.009	0.012

Standard errors in brackets are clustered at county-level in OLS regressions. Robust standard errors are used in FE regressions. ***, **, and * indicate significance at 1%-, 5%- and 10%-level, respectively.

The estimated coefficients of population density are similar and highly significant when firm controls are excluded. The coefficient is 0.155 in the OLS approach (column (1)) and 0.190 with workers fixed effects (3). In both specifications, the firm variables have significant and positive coefficients (column (2) and (4)). The only exception are the wage-level firm fixed effects in specification (4). However, the impact of the firm variables on the estimated coefficient of population density is quite different in the two-types of specifications. Including the firm variables leads to a reduction of the density effect by about 80% in the OLS case (column (1) and (2)), but only by about 40% in the fixed effects regressions (column (3) and (4)).

Thus, accounting for worker fixed effects leads to a much smaller explanatory power of the firm controls for the identified effect of urbanization. To understand this result, it is important to note that the fixed effects capture the entire between-variation in the variables for workers that always work for the same firm in the same county. As the descriptive facts were showing, this is the majority of workers. Thus, this approach uses mainly the within-variation in the data for the wage growth,

Table 6: Regressions for annual wage growth of German workers, without job-change years, 2001-2010

Explanatory Variables	(1) OLS	(2) OLS	(3) FE	(4) FE
log density	0.155***	0.030**	0.190***	0.115**
	(0.019)	(0.013)	(0.047)	(0.047)
log empl	-	0.241***	-	0.230***
		(0.011)		(0.026)
firm age	-	0.007***	-	0.024***
		(0.001)		(0.003)
hs share	-	2.098***	-	1.381***
		(0.157)		(0.356)
firm FE	-	0.569***	-	-0.159
		(0.087)		(0.179)
indiv. contr.	yes	yes	yes	yes
year dummies	yes	yes	yes	yes
sec. dummies	yes	yes	yes	yes
occ. dummies	yes	yes	yes	yes
worker FE	no	no	yes	yes
Obs.	1,295,845	1,295,845	1,295,845	1,295,845
R^2	0.023	0.025	0.004	0.004

Standard errors in brackets are clustered at county-level in OLS regressions. Robust standard errors are used in FE regressions. ***, **, and * indicate significance at 1%-, 5%- and 10%-level, respectively.

population density and the firm variables to identify the effects.

This has two consequences for the estimated coefficients: first, as discussed in section three, using the within-variation may lead to an upward bias of the estimated coefficient of population density through a reversed causality between wage growth in a county and the population density. Second, also the estimates of the firm variables (column (4)) are smaller with worker fixed effects than in the OLS regressions (column (2)). Thus, the variation of the firm characteristics over time may have a smaller impact on wage growth rates of workers than differences in the levels of the firm variables.

To provide a clearer estimate of the analysed relationships and to facilitate the interpretation, I further reduce the sample. I include only the workers that change at least once the county of their workplace anddenote these workers as 'county-movers'. Using this method, the estimated effects are identified by workers that start working in another county. This approach should ensure that indeed the estimated effects are driven by the between-variation in the data, which should provide more robust and clearer results.

5.2.2 Only county-movers

Table 7 shows the results for the reduced sample with only the county-movers. The number of observations is strongly reduced because only few workers are moving across counties (compare section two). Nevertheless, the estimated coefficients of population density remain highly significant when firm variables are neglected in both the OLS and the FE regressions (column (1) and (3)). This result provides quite robust evidence that there is a 'pure growth effect' of urbanization in Germany. The within-job wage growth of workers is significantly higher in denser regions controlling for many individual variables, sector- and occupation dummies and worker fixed effects. Also economically, the estimated effects are sizable. If workers move to a region with a one standard deviation higher population density (1.15), they benefit from an about 0.19 percentage points higher annual wage growth rate (the coefficient is 0.169 in column (3)). Accumulated over a ten year period this leads to about 2% higher wages.

However, the effect of population density turns insignificant once I take the firm variables into account. I find that the high-skill share and the size of firms have significantly positive coefficients. The wage-level firm fixed effects are only significant in the OLS regressions. The age of the firms does not have significant coefficients. The reduction of the estimated coefficient of density is again stronger for the OLS regressions. Here, including the firm controls reduces the coefficient by 80%. In the fixed effects regression the coefficient shrinks by about 60%. However, the difference between these two approaches is smaller than above in table 6 when all workers were included. This can be explained by the fact that all firm variables, except the coefficient of the age of firms, have in table 7 larger coefficients when accounting only for the county-movers compared to the sample including all workers in table 6. This confirms the idea that indeed the between-variation in the data leads to larger estimates for the firm variables than the within-variation.

Nevertheless, the reduction of the density effect through the firm variables is still smaller when using worker fixed effects than in the OLS regressions. One reason for this is that the share of highly educated workers, the wage-level fixed effects and the number of employees have smaller coefficients in the fixed effects regression ((4)) than in the OLS regression ((2)). This result can be explained by a positive correlation of the worker fixed effects with these firm variables. Thus, this indicates that workers with higher wage growth rates because of unobserved characteristics work more often in firms with rather high wage growth rates. Obviously, there is some kind of positive assortative matching of firms and workers with respect to wage growth rates. This result confirms Card et al. (2013) who emphasize that there is a positive correlation of worker and firm fixed effects concerning wage levels, which partially explains increasing wage inequality in Germany.

Table 7: Regressions for annual wage growth of German workers, without job-change years, only county-movers, 2001-2010

Explanatory Variables	(1) OLS	(2) OLS	(3) FE	(4) FE
log density	0.190***	0.038	0.169***	0.071
	(0.027)	(0.023)	(0.057)	(0.058)
log empl	-	0.351***	-	0.344***
		(0.017)		(0.043)
firm age	-	-0.003	-	0.000
		(0.003)		(0.006)
hs share	-	2.130***	-	1.533***
		(0.286)		(0.559)
firm FE	-	0.945***	-	0.654
		(0.206)		(0.405)
indiv. contr.	yes	yes	yes	yes
year dummies	yes	yes	yes	yes
sec. dummies	yes	yes	yes	yes
occ. dummies	yes	yes	yes	yes
worker FE	no	no	yes	yes
Obs.	211,682	211,682	211,682	211,682
R^2	0.023	0.024	0.005	0.006

Standard errors in brackets are clustered at county-level in OLS regressions. Robust standard errors are used in FE regressions. ***, **, and * indicate significance at 1%-, 5%- and 10%-level, respectively.

Altogether, I conclude from the specification with workers fixed effects (column (3) and (4)) that workers in denser regions benefit from significantly higher wage growth rates. This effect is reduced by about 60% when firm variables are included in the regression. In particular, workers in denser regions benefit from working in larger firms with higher shares of highly educated workers. The remaining effect of population density is not significantly different from zero and also economically small. These results underline that it is important to understand why characteristics of firms are different in denser regions to understand why wages of workers grow faster in denser regions.

Finally, it is worth to note that the finding of a significant ‘pure growth effect’ is different compared to DO and Wheeler (2006). DO only find weak effects of urbanization on within-job wage growth rates for young workers. Wheeler (2006) finds no significant impact of urbanization once controlling for worker fixed effects. These contrasting results might be driven by different sample characteristics. For instance, DO use a less restricted sample than I do and account also for part-time workers. Furthermore, these two papers use survey data instead of adminsitrative data that I use. This might produce some measurement error in the wage variable which leads to increased standard errors of the estimated effects.

5.3 Robustness of the *pure* growth effect

In the present section, I intend to further disentangle the sources of the identified impact of urbanization on within-job wage growth rates of workers. To do this, I check whether the age of workers or their education have an impact on the link between urbanization and wage growth. The literature suggests that for young and more educated workers the learning opportunities might be larger and thus the wage growth rates should be more affected by the local economic environment of workers (e.g., DO). Additionally, I re-run the regressions from above for the period 1991-2000 to see whether the results are also robust for different time periods. All sub-samples have the same characteristics as in table 7 in the previous section. Thus, I use only the observations of workers within the same job (within-job wage growth) and account only for workers that changed the county of their workplace at least once (county-movers).

5.3.1 Age of workers

To analyse the impact of the age of workers on wage growth, I re-run the regressions with only county-movers from the previous section for workers which are between 21 and 30 years old in the year of the observation. The estimated coefficients of population density in table 8 are similar to these in table 7 for the total sample of workers. The coefficient of density slightly increases in specification (3) from 0.169 in the total sample to 0.211 for young workers. The number of employees per firm and the high-skill share of workers have positive and significant coefficients also for the young workers. The estimated coefficients are also larger than for the entire sample. Consequently, including the firm controls leads to a large decrease of the coefficient of population density (80%). This suggests that young workers might benefit more from their working environment than older workers, but that this is effect occurs in particular at the firm level.

I run also regressions for workers in other age groups, which I do not show for convenience. The results for workers that are between 31 and 50 years old confirm the result that the impact of the age is rather small. The estimated coefficient for population density in specification (3) is 0.23 and thus even slightly larger than for the youngest workers. The impact of the firm variables on the estimated effects is smaller than for the young workers. Thus, the reduction of the density effect from 0.23 to 0.14 is also smaller (40%). Finally, I run regressions for workers in the ages between 51 and 60 years, which account for about 26,000 observations. Here I do not find any significant effects for population density. When accounting for worker

Table 8: Regressions for annual wage growth of German workers aged 21-30, without job-change years, only county-movers, 2001-2010

Explanatory Variables	(1) OLS	(2) OLS	(3) FE	(4) FE
log density	0.208***	0.034	0.211	0.033
	(0.061)	(0.059)	(0.162)	(0.163)
log empl	-	0.409***	-	0.560***
		(0.045)		(0.131)
firm age	-	-0.003	-	0.018
		(0.007)		(0.016)
hs share	-	2.608***	-	3.797*
		(0.790)		(2.074)
firm FE	-	0.668	-	-0.442
		(0.434)		(0.624)
indiv. contr.	yes	yes	yes	yes
year dummies	yes	yes	yes	yes
sec. dummies	yes	yes	yes	yes
occ. dummies	yes	yes	yes	yes
worker FE	no	no	yes	yes
Obs.	32,235	32,235	32,235	32,235
R^2	0.054	0.058	0.022	0.024

Standard errors in brackets are clustered at county-level in OLS regressions. Robust standard errors are used in FE regressions. ***, **, and * indicate significance at 1%-, 5%- and 10%-level, respectively.

fixed effects, the estimated coefficients turn even negative. Furthermore, none of the firm variables has a significant coefficient. Altogether, these results suggest that the age of workers does play a role to understand the identified effects. But the impact seems to be rather small and becomes mainly relevant when workers are older than 50 years.

5.3.2 Education of workers

Also in line with the learning hypothesis, one could expect that workers with high education benefit more from urbanization than workers with low education (e.g., DO). To check this hypothesis, I analyse a sub-sample of highly educated workers (university or technical university degree). In table 9, I find for high-skill workers clearly larger coefficients of population density than for the total sample. Comparing the coefficients in specification (3) the coefficient increases from 0.169 in the total sample to 0.325. Thus, the magnitude of the effect nearly doubles for highly educated

Table 9: Regressions for annual wage growth of German high-skill workers, without job-change years, only county-movers, 2001-2010

Explanatory Variables	(1) OLS	(2) OLS	(3) FE	(4) FE
log density	0.401***	0.118*	0.325*	0.173
	(0.072)	(0.067)	(0.176)	(0.178)
log empl	-	0.527***	-	0.482***
		(0.046)		(0.126)
firm age	-	-0.020**	-	-0.011
		(0.008)		(0.018)
hs share	-	2.644***	-	2.340**
		(0.405)		(0.950)
firm FE	-	1.639***	-	2.300
		(0.549)		(1.420)
indiv. contr.	yes	yes	yes	yes
year dummies	yes	yes	yes	yes
sec. dummies	yes	yes	yes	yes
occ. dummies	yes	yes	yes	yes
worker FE	no	no	yes	yes
Obs.	50,704	50,704	50,704	50,704
R^2	0.012	0.014	0.006	0.007

Standard errors in brackets are clustered at county-level in OLS regressions. Robust standard errors are used in FE regressions. ***, **, and * indicate significance at 1%-, 5%- and 10%-level, respectively.

workers. Furthermore, I find also that the firm variables have larger coefficients for highly educated workers than for the total sample. However, the remaining effect of density is still rather large. This underlines that indeed the high-skill workers benefit more from learning potentials in their local work environment.

To check whether there are any effects at all for workers without the highest education levels, I run also regressions for workers with medium-levels of education[11] and lowest education, which I do not show for convenience. The results for medium-skilled workers show that the estimated coefficients of population density are clearly smaller than for highly educated workers and for the total sample. In the fixed effects regression without firm variables (specification (3)), the coeffcient of population density is only 0.114 compared to 0.169 in the total sample and 0.325 for high-skill workers. Nevertheless, the estimated coefficient is significant at the 5%-level. Including the firm variables, I find that the only variable with a significant coefficient

[11]These are workers with an university-entrance diploma.

is the number of employees of a firm. In total, the estimated effects of both the density and the firm variables are clearly larger for highly educated workers.

Finally, I run also regression for low-educated workers, which is only small subgroup with 15,000 observations. I do not find any significant effects of population density. The magnitude of the estimated coefficients is much smaller than for the total sample and turn even negative when using worker fixed effects. Also the firm variables have only small coefficients. Thus, I conclude from the analysis of the impact of education that benefits from working in a denser area are positively related to the eduaction of workers. The same applies to the impact of the firm variables on workers' wage growth. These results suggest that the estimated effects are indeed related to the learning of workers in their local economic environment.

5.3.3 Time period of analysis

One important robustness check is to see whether the main results are robust also for another period of time or not. Since I use wage data as a proxy for productivity, one should keep in mind that wages reflect also demand and supply shocks in the local labor markets. Thus, the results could be misleading if they would represent rather structural changes in the labor market than productivity growth of individual workers. As those shocks might be more pronounced in specific periods, it seems to be useful to analyse whether the results are robust in earlier years. Thus, I run the same regressions as shown in table 7 for the years 1991-2000.

The results presented in table 10 do not show large differences compared to the results for the period 2001-2010 presented above. The estimated coefficients of population density have a similar size (0.175 compared to 0.169) and are significant at the 1%-level. The impact of firm characteristics is also comparable for the two time periods. I find in both periods that firm controls reduce the density effect by about 80% in the OLS regressions. For the specification with worker fixed effects the reduction is nearly 70% and thus slightly larger than in the baseline period (60%). Altogether, the evidence for the period 1991-2000 supports that there is a pure growth effect in urban regions, which is mainly explained by firm characteristics.

Using again sub-samples with young and highly educated workers for the period 1991-2000, which I do not show for convenience, I find that the effects of urbanization on wage growth are clearly larger for highly educated workers. Furthermore, I find also a rather small impact of the age of workers on the results. Again, education seems to be more important than the age of workers to understand the higher wage growth of workers in denser areas.

Altogether, the robustness of the results over time suggests that the identified effects are indeed related to workers' learning from the local environment and not driven by structural labor demand changes. Those structural changes should less likely occur over a 20 year time period. However, it could in principle be that there was an increasing demand for high-skill workers in large firms with high shares of

Table 10: Regressions for annual wage growth of German workers, without job-change years, only county-movers, 1991-2000

Explanatory Variables	(1) OLS	(2) OLS	(3) FE	(4) FE
log density	0.160***	0.034*	0.175***	0.056
	(0.025)	(0.021)	(0.050)	(0.052)
log empl	-	0.255***	-	0.234***
		(0.020)		(0.036)
firm age	-	0.005	-	0.021***
		(0.004)		(0.007)
hs share	-	2.183***	-	2.434***
		(0.294)		(0.607)
firm FE	-	0.547***	-	0.642
		(0.269)		(0.436)
indiv. contr.	yes	yes	yes	yes
year dummies	yes	yes	yes	yes
sec. dummies	yes	yes	yes	yes
occ. dummies	yes	yes	yes	yes
worker FE	no	no	yes	yes
Obs.	226,404	226,404	226,404	226,404
R^2	0.032	0.034	0.012	0.013

Standard errors in brackets are clustered at county-level in OLS regressions. Robust standard errors are used in FE regressions. ***, **, and * indicate significance at 1%-, 5%- and 10%-level, respectively.

highly educated workers, which are more often located in cities. This would be an alternative interpretation of the observed pattern of within-job wage growth of workers, which I cannot exclude completely.

5.4 Between-job wage growth

The main part of this paper deals with the analysis of the within-job wage growth of workers. However, to understand the role of urbanization in the working life of workers more deeply, it is helpful to analyse also the between-job wage growth. The descriptive facts in section two were showing that the wage growth rates are clearly larger when workers change their jobs and are consequently economically quite important to understand the wage dynamics of individual workers. I analyse the between-job wage growth in the present section and distinguish between job-changes between counties and within counties.

5.4.1 Between counties

I start by restricting the sample to the years in which workers start a new job in a new county. This allows to analyse the so-called 'mobility effect' (e.g., DO). This is the wage increase that workers receive potentially immediately after moving to a denser region, which is also denoted as the 'wage level effect'.

Table 11: OLS regressions for annual wage growth of German workers, job-changes between counties, 2001-2010

Explanatory Variables	(1)	(2)	(3)
log density	0.068	0.554***	-0.141
	(0.198)	(0.140)	(0.148)
log empl	-	-	0.031
			(0.109)
firm age	-	-	0.064***
			(0.014)
hs share	-	-	1.963
			(1.238)
firm FE	-	-	30.437***
			(1.091)
indiv. contr.	yes	yes	yes
year dummies	yes	yes	yes
sec. dummies	no	yes	yes
occ. dummies	no	yes	yes
Obs.	49,027	49,027	49,027
R^2	0.037	0.066	0.099

Standard errors in brackets are clustered at county level in OLS regressions. ***, **, and * indicate significance at 1%-, 5%- and 10%-level, respectively.

Specification (1) in table 11 shows no significant coefficient of population density. On average, wage growth in a move-year seems to be rather independent of the urbanization of the destination region. This picture changes once I account for sector and occupation dummies in (2). Now, density has a highly significant positive coefficient. Thus, the types of occupations and sectors in which people start working obviously depend on the density of the destination counties. Controlling for this, I find a significant higher wage growth when workers move to denser regions. This result indicates that there is static wage premium for workers in denser regions. Wages immediately shift up when workers move to more urbanized areas compared to moving to less urbanized areas. A one standard deviation increase in population density (1.15) of the destination county leads to about 0.6 percentage points higher wage growth rates.

However, the estimated effect becomes insignificant and even weakly negative once I account for firm characteristics in (3). In particular, the wage-level firm fixed effect have a very large and significant coefficient. Workers that move to denser regions benefit from moving to firms with relatively high wages. As firms have higher wage levels in denser regions, this effect completely explains the mobility effect of moving to more urbanized regions. Thus, it is an interesting and relevant issue for future research, to understand why wage levels at the firm level are higher in cities. In particular, sources of higher productivity at the firm level may provide an important issue for future research (e.g., Combes et al., 2012). However, Ehrl (2014) claims that wage-level fixed effects and firm TFP are only weakly correlated with each other. Thus, also other factors like the internationalization of firms, for instance, should also be accounted for.

Nevertheless, comparing the coefficient of population density in column (2) (0.554) and coefficient for the pure growth effect in table 7 column (3) (0.169) shows that the potential impact of the wage level effect is rather small compared to the wage growth effect that I analysed above. The coefficient of the mobility effect is only about three times larger than the pure growth effect. When workers work more than three years in a denser region, the wage growth effect already exceeds the level effect. This result is in line with Lehmer und Möller (2010) who also find a relatively larger wage growth effect in Germany. But of course my results must be interpreted with caution as the estimation of the wage level effect of course has some important shortcomings. For instance, the applied approach does not account for the characteristics of the job that workers had before starting their new job in another county.

5.4.2 Within counties

A second reason why workers may benefit from higher wage growth in more urbanized areas is that they benefit from changing their jobs within counties. To analyse this possible channel, I focus the sample on the years in which workers start a new job in another firm in the same county and regress the wage growth rates again on population density.

The results in table 12 show that the wage growth rates are larger in denser regions when workers change jobs within a county. The coefficient of population density is positive and highly significant in all specifications. Without firm controls in specification (2) the coefficient is 0.869. This means that workers in a county with a one standard deviation higher population density benefit from job changes within the county by a nearly one percentage points larger wage growth rate. Compared to the 'pure growth effect' in section 5.3, the coefficient is about 5 times larger. Thus, the effect is important to understand higher wage growth of workers

Table 12: OLS regressions for annual wage growth of German workers, job-changes within counties, 2001-2010

Explanatory Variables	(1)	(2)	(3)
log density	0.584***	0.869***	0.502***
	(0.117)	(0.132)	(0.126)
log empl	-	-	-0.262***
			(0.074)
firm age	-	-	0.180***
			(0.010)
hs share	-	-	-0.993
			(0.774)
firm FE	-	-	23.173***
			(0.983)
indiv. contr.	yes	yes	yes
year dummies	yes	yes	yes
sec. dummies	no	yes	yes
occ. dummies	no	yes	yes
Obs.	63,460	63,460	63,460
R^2	0.034	0.056	0.089

Standard errors in brackets are clustered at county level in OLS regressions. ***, **, and * indicate significance at 1%-, 5%- and 10%-level, respectively.

in denser regions, which underlines that it is useful to distinguish between within- and between-job wage growth. However, as workers do not change their jobs very often, the pure growth effect is altogether most important to understand the higher wage growth of workers in cities.

The estimated effect of populaton density gets clearly smaller once I account for firm characteristics of the new employer of the workers (column (3)). The coefficient shrinks by more than 40% from column (2) to (3). This result is again mainly driven by the large and highly significant coefficient of the wage-level firm fixed effects. This indicates that workers in denser regions benefit from starting to work in firms with higher wage levels. As these firms are more frequent in urban regions, workers can more easily improve their wages by changing jobs.

Interestingly, the remaining effect is nevertheless still significantly different from zero. Thus, workers that change their jobs within denser counties benefit not only from working at 'better' firms. There is a remaining effect which could potentially be explained by a better match of workers and firms. The literature suggests that denser regions lead to more efficient outcomes in the search and matching process of firms and workers (e.g., Wheeler, 2006 or Yankow, 2006). Those more efficient matches may lead to higher worker productivity which is reflected in higher wage levels. The provided evidence supports this idea. However, it is of course unclear whether this effect would persist if one could control for further characteristics of the firms and workers. Nevertheless, the fact that this effect is not present when workers start working in a new county underlines the idea that the matching efficiency might be indeed increasing with lower geographical distances between firms and workers.[12]

6 Conclusions

The present paper analyses the relationship between wage growth of German workers, urbanization and firm characteristics. Most importantly, I find a higher within-job wage growth of workers in counties with a higher population density (pure growth effect). This result is robust to an inclusion of a large set of control variables and worker fixed effects. Furthermore, the estimated effects of population density on wage growth are positively related to the education level of workers. These results are robust in a rather large time period. Thus, the provided evidence supports the idea that learning and human capital accumulation is fostered in denser regions.

To shed some more light on this issue, I account also for firm variables in the regression analysis. This perspective is hardly analysed so far in the literature, most likely because of data limitations. I find that workers have higher wage growth rates in larger firms with higher shares of highly educated workers. In some regressions, also firms with generally higher wage-levels show higher wage growth rates. Including the firm variables reduces the estimated impact of urbanization on wage growth by about 60% and the effect turns in the most important specifications statistically insignificant. Thus, the higher wage growth can mainly be explained by the fact that firms have different characteristics in urbanized areas. These firms characteristics may foster productivity and wage growth of workers rather than the regional characteristics.

The characteristics of firms play also an important role to understand the link between urbanization and wage growth when workers change their jobs (between-job wage growth). When workers start working in a new county, I find that the wage growth rate in the year of the move is the larger the higher the density of the destination county is. However, this effect disappears once I add wage-level fixed effects of the firms to the regression. Thus, workers benefit from working for the high-wage firms within sectors when they move to denser areas.

Furthermore, workers also benefit significantly from changing jobs within coun-

[12] I also check the robustness of the mobility and matching effect in the time period 1991-2000. I find that the pattern of the main results is still valid. The mobility effect vanishes when firm variables are included. The matching effect remains statistically robust also with firm variables. I do not show the results for convenience.

ties with higher densities. Again, the positive effect of density decreases (by about 40%) once I account for the wage-level in firms as control variable. Thus, workers benefit from new jobs at firms with higher wage levels also within the same region. This is plausible as the density of highly productive firms with high wages should be higher in denser areas (e.g., Combes et al., 2012). However, there is a remaining significant effect of population density also when controlling for firm variables. This effect could be attributed to higher efficiencies of the matches of workers and firms in denser areas (matching effect), which is also identified by Wheeler (2006) as an important source of higher wage growth of workers in the US.

Altogether, the results emphasize that it is quite important to consider the characteristics of the firms to understand regional differences of workers' wages and their evolution over time. The approach used by Card et al. (2013) or Dauth et al. (2016) to decompose the wages of workers into a worker and a firm component seems to be useful for future research efforts. The productivity of workers should not be independent of the productivity of the entire firm and the other workers within the firm. Furthermore, both the worker and firm producitivities are affected by other firms and workers in the same region. Thus, workers' productivity and consequently wages are influenced by several local economic forces, which make the analysis more complex. But the present paper suggests that this is necessary to understand more about the determinants of workers' wages and the role of agglomeration and urbanization in this process.

I see two important directions for future research: First, the impact of urbanization and agglomeration on firm characteristics should be more deeply analysed. Second, it is also necessary to collect more evidence about the channels how firm characteristics affect worker productivity and wages. In particular, it would be important to account for further firm characteristics beyond the four variables that I analyzed in the present paper. For instance, R&D activities, capital intensities, TFP of firms, export or import activities, implemented innovations etc. would be important further firm-level information that should be considered in future research.

Finally, it is worth to note that my finding of significantly higher within-job wage growth rates in more urbanized areas is in contrast with the analyses of D'Costa and Overman (2014) for the UK and Wheeler (2006) for the US. They find only weak effects for young workers. One reason for these different results might be that I use only data for full-time workers. Furthermore, the applied dataset relies on administrative data while the other studies use survey data instead. Those differences in the basic construction of the datasets should be taken into account in future research efforts.

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