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Agglomerations, Tasks and Wage Growth

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Maximilian Perl[1]

Agglomerations, Tasks and Wage Growth

Abstract

Wage growth is stronger in larger cities, but this relationship holds exclusively for non-manual workers. Using rich German administrative data, I study the heterogeneity in the pecuniary value of big city experience, a measure of dynamic agglomeration economies, and its consequences for the city-size wage gap. After 15 years of work experience in Munich the cumulative earnings premium relative to a median-sized city is 15% for workers in the most manual occupations, 25% for workers in the least manual occupations and 30% for workers in the most analytical occupations. This cumulative wage premium is 3 to 5 times the magnitude of the static city-size wage gap.

JEL-Codes: R10, J31, R23

Keywords: Cities; agglomeration; tasks; wages; wage growth; Germany

January 2023

1 Maximilian Perl, UDE and DFG RTG 2484 Regional Disparities and Economic Policy. *– I am extremely grateful to Martin Karlsson and Jens Wrona for their guidance and supervision. I am also thankful to Thomas Bauer, Anja Grujovic, Michael Haylock, Daniel Kühnle, Frederic Robert-Nicoud and Tobias Seidel as well as my colleagues at the University of Duisburg-Essen and at the Research Training Group for helpful comments and discussions and to Thomas Bauer for providing me access to digitized data on historic population counts.* *– All correspondence to: Maximilian Perl, University of Duisburg-Essen, Lotharstr. 65, 47057 Duisburg, Germany, e-mail: maximilian.perl@uni-due.de*

1 Introduction

Wages grow faster in larger cities. Mean annual earnings in Munich grew by 10% between 2013 and 2019, twice the rate of median-sized West-German cities.[1] But these benefits accrue largely to workers in non-manual jobs. This city-size wage *growth* gap is persistent across countries (Glaeser and Maré, 2001; de la Roca and Puga, 2017; Eckert et al., 2022b) and consistent with dynamic agglomeration economies (Glaeser, 1999). That is, mechanisms through which the city population raises worker productivity over time. I argue that a task bias in agglomeration economies, in particular in learning, can explain the heterogeneity in the data.

For this purpose, I study the heterogeneity in the value of big city experience, a measure of dynamic agglomeration economies, across tasks. I quantify the impact of big city experience on the cumulative city-size wage gap, which I define as the sum of the static and dynamic city-size wage gap, in West Germany. The analysis uses comprehensive German administrative data including the employment biographies of over 1,800,000 workers between 1975 and 2019. Using data on workers' employers and their occupational rank, I provide evidence consistent with task biased learning. In answering these questions, I provide new evidence on (i.) which dimensions are most relevant for explaining heterogeneity in the city-size wage gap and (ii.) the magnitude of the city-size wage growth gap. The results also point to possible explanations for intra- and interregional income inequality. Moreover, the long observation period allows me to study how the static and cumulative city-size wage gap has developed over time.

I estimate the static city-size wage gap as the wage elasticity with respect to city population. Following the literature, I define cities as local labor markets (LLMs), which are roughly equivalent to commuting zones. In my specification, I allow the value of experience to vary by city-size and task intensity. Following de la Roca and Puga (2017), I use these estimates to construct measures for the cumulative city-size wage gap for West Germany. In addition to prior work, my measure of the cumulative city-size wage gap is occupation-specific varying with task intensities. To address endogeneity concerns, I instrument my regressor of interest, city size, with newly digitized historic population data from the 19th century. Finally, I exploit the rich information on workers' employment histories and their employers to identify potential mechanisms explaining the heterogeneity of the city-size wage gap across workers.

[1] I use the terms city and local labor market interchangeably referring to the location in which residents live and work.

I find that, in line with previous studies (de la Roca and Puga, 2017; Eckert et al., 2022b), big city experience provides sizeable additional wage benefits. A considerable part of these wage benefits is transferable to other locations. Accounting for these dynamic benefits raises the city-size wage gap far beyond previous estimates. For instance, the static city-size wage gap for Munich relative to median median-sized cities is around 5%. In contrast, earnings premia for individuals who have worked in Munich for 15 years are over 20% relative to workers who gained all of their experience in median-sized cities. Additionally, the dynamic component of the city-size wage gap displays strong heterogeneity. I find that workers in the most (least) manual occupations earn 15% (25%) higher wages after 15 years in Munich relative to workers with the same experience in a median-sized city.

This paper relates to a wider literature quantifying agglomeration economies.[2] Early studies were restricted on estimating net agglomeration benefits (Ciccone and Hall, 1996). Since the advent of large administrative data, the focus has shifted to the mechanisms of the city-size wage (growth) gap such as worker (Combes et al., 2008) and firm sorting (Gaubert, 2018; Bilal, 2021), firm selection (Combes et al., 2012), matching (Dauth et al., 2022) and learning (de la Roca and Puga, 2017; Moretti, 2021).

I bridge two substrands of this literature. First, I contribute to a growing literature on dynamic agglomeration economies. That wages grow faster in larger cities is a well-known fact (Glaeser and Maré, 2001) and its magnitude is substantial driving much of the spatial variation in wages between cities of different sizes (Baum-Snow and Pavan, 2011). It is also consistent with two distinct agglomeration mechanisms: learning and matching (Glaeser, 1999). On the one hand, workers become more productive over time because larger cities facilitate knowledge exchange or offer more valuable experience. On the other hand, thicker labor markets offer more job openings at any point in time thereby reducing earnings losses due to layoffs or expediting moves up the job ladder.

Empirically, both mechanisms appear to play a role. Larger local labor markets do increase the frequency of job switches (Wheeler, 2006; Yankow, 2006; Eckert et al., 2022b). This raises wage growth in larger cities because the between-job wage growth is similar across cities of different sizes. Similarly, within-job wage growth is stronger in larger cities (Wheeler, 2006;

[2] For a comprehensive review of the theoretical foundations I refer the reader to Duranton and Puga (2004) and for a review on empirical results to Rosenthal and Strange (2004) and Combes and Gobillon (2015).

Yankow, 2006) suggesting that learning plays some role. In the most comprehensive study to date, de la Roca and Puga (2017) find that the fraction of the city-site wage gap previously attributed to worker sorting, should instead be attributed to higher returns to experience gained in larger cities. This paper contributes to this literature by analysing the heterogeneity of dynamic agglomeration economies and by providing further evidence on individual mechanisms behind the dynamic city-size wage gap.

Second, I provide new evidence on the heterogeneity of the city-size wage gap. Previous studies found that the city-size wage gap is more pronounced for college graduates and white-collar workers than those without a college degree in the United States (Gould, 2007; Bacolod et al., 2009a; Abel et al., 2012), Italy (Addario and Patacchini, 2008), Sweden (Andersson et al., 2013) and the Netherlands (Groot and de Groot, 2014). Similar results suggest that agglomeration economies may be task biased. Workers with routine tasks receive lower wage premia for residing in larger cities (Koster and Ozgen, 2021). In contrast, the city-size wage gap is stronger for workers with abstract non-routine occupations (Grujovic, 2018). This heterogeneity appears to be a relatively recent phenomenon as urban labor market opportunities for non-college workers have deteriorated (Autor, 2020). I extend this literature by providing new evidence on the heterogeneity of *dynamic* agglomeration economies.

Finally, following Autor et al. (2003), who document a task bias in structural changes since the 1980s, urban economists have become interested in the role of task-biased structural change for regional inequality. The findings of this literature are as follows; first, over the past century cities have shifted towards jobs with a higher share of interactive non-routine and analytical non-routine tasks (Michaels et al., 2018). This development has been more pronounced in larger cities.[3] Second, since the 1980s commuting zones specializing in routine tasks were more susceptible to information and communication technologies (ICTs) replacing medium-skill workers. The fall in prices for ICTs has increased wage polarization across counties (Autor and Dorn, 2013) benefiting the largest agglomerations whose workers were less threatened by the new technologies(Michaels et al., 2018; Eckert et al., 2022a). This trend was exacerbated by the fact that ICTs are often complementary with workers in abstract non-routine tasks, which are predominantly located in the largest LLMs (Eckert et al., 2022a).[4]

[3]Dutch data similarly displays that the average local routine task intensity decreases in employment density (Koster and Ozgen, 2021).

[4]These findings that workers with higher skill or more abstract non-routine occupations benefit most contrasts

The paper is organized as follows; section 2 discusses the data and sample selection. Sections 3 and 4 present the empirical strategy and the results. In section 5 I provide robustness checks for my empirical strategy. Section 6 concludes.

2 Data & Descriptive Statistics

2.1 Data Description

The primary data for this paper is the the Sample of Integrated Employment Biographies (SIAB) from the German Institute for Employment Research (IAB). It contains individual employment biographies for a 2% sample of private workers excluding the self employed from 1975 to 2019.[5] That is, it provides daily top-coded wages, age, sex, education, job skill level, occupational group and establishment for all employment spells of 1,893,291 individuals since 1975. A disadvantage of the German data is that wages are top-coded at the social security contribution limit (86,000 Euros in West-Germany in 2019). Thus, to prepare the SIAB for my analysis, I adopt Dauth and Eppelsheimer (2021)'s code to construct an annual panel and to impute top-coded wages by sex-education-year-subsamples. The imputation is inspired by Dustmann et al. (2009) and Card et al. (2013), but I include additional variables which are used as regressors in the main analysis. I also include city fixed effects rather than firm fixed effects in the imputation. Finally, I merge information from the IAB's Establishment History Panel (BHP) on the skill and education level of every establishment's workforce to the SIAB.

The units of analysis are cities. To ensure that workers work and reside in the same location, I define cities as local labor markets. Because spells in the SIAB only contain the district of employment (i.e. Kreise or Kreisfreie Städte), I map each of the roughly 400 districts to 141 LLMs as defined by Kosfeld and Werner (2012). This definition is comparable to commuting zones from the US Census Bureau. To measure contemporary LLM population and density, I use district population and land area statistics from the German statistical office (DeStatis) for the years 1975 to 2019 and aggregate the information to the LLM level. For the historic

with the observations that these are also the workers, which are most likely to move to larger cities (Bacolod et al., 2009b; Michaels et al., 2018; Rossi-Hansberg et al., 2019). If workers with different tasks are imperfect substitutes one would expect the local wages for worker types, that are locally overrepresented, to fall. That this is not the case strongly hints at externalities.

[5] Frodermann et al. (2021) provide a detailed description for the version I use in my analysis.

population counts I rely on the digitised 1867 census of the German customs union (for Prussia) and the 1871 census of the German Empire (for other regions). With few exceptions historical counties map consistently into contemporary districts.

Mapping Occupations to Task Group I assign each 3-digit occupation code five task intensities corresponding to one of five task groups (*manual routine*, *manual non-routine*, *interactive non-routine*, *cognitive routine* and *analytical non-routine*) and a main task based on Dengler et al. (2014)'s occupation-task mapping. These intensities measure the share of tasks belonging to one task group a typical worker of a given occupation has to complete. The main task is simply the task group with the highest task intensities for each occupation. I construct two further task groups *manual* and *routine*, which I define as the sum of manual non-routine and manual routine or cognitive-routine and manual routine task intensities, respectively.

I briefly outline how Dengler et al. (2014) construct their occupation-task mapping. They start with the German Federal Employment Agency's occupation database containing the core requirements for 3900 occupation titles. For instance, a cook's requirements include (among others) cooking according to recipes. Each occupation title's requirements are assigned by experts rather than determined from surveys of workers. This stands in contrast to the Qualification and Career Surveys used to map occupation to tasks in German data previously. Each of these core requirements is assigned to one of the five aforementioned task groups.

In Table 1 I present for each task group the five occupations with the highest and lowest task intensity in that task. The analytical non-routine and interactive non-routine task group contain mostly academic and customer service jobs respectively. The cognitive routine task group comprises jobs that, in contrast to analytical non-routine jobs, are less abstract and require repairing or using complex technology. Such jobs include pilots or surveying & mapping. The two manual task groups *manual routine* and *manual non-routine* contain mostly low and medium skill jobs. They differ from one another in that manual non-routine occupations are most often outside industrial production such as cleaners, train drivers and traffic control, artists or actors. In contrast, manual routine jobs include mostly jobs in industrial production such as construction and welding, ceramic production and processing or (industrial) wood work.

Table 1: Top and Bottom Five Occupations By Task Intensity

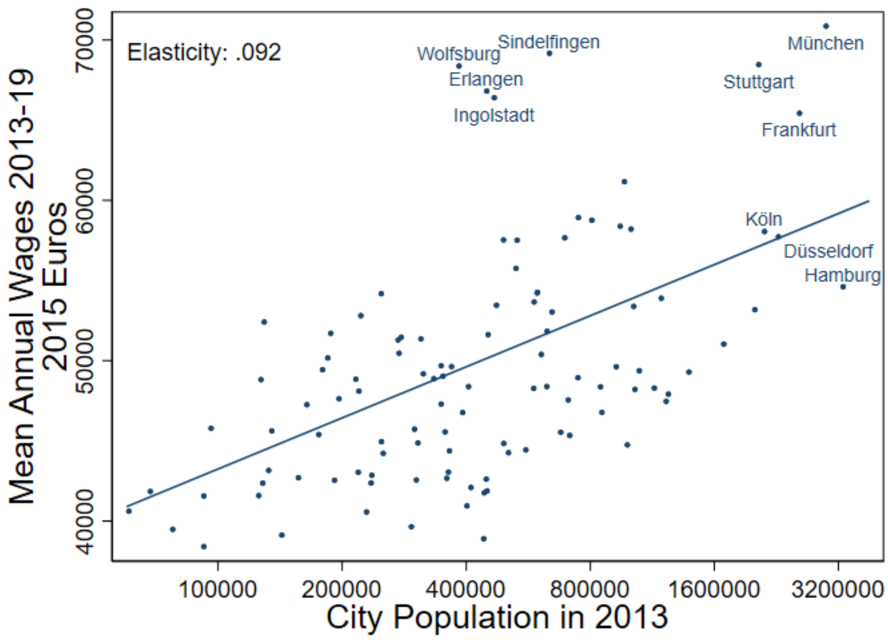
	Analytical Non-Routine	*Manual Non-Routine*	*Manual Routine*	*Interactive Non-Routine*	*Cognitive Routine*
Top 5					
1	Humanities	Train Driver & Traffic Control	Ceramic Manufacturing	Presenters & Entertainers	Tax Consulting
2	Mathematics & Statistics	Building Construction	Plastic & Rubber Manufacturing	Marketing	Mechatronics & Automation
3	Language- & Literature Studies	Underground Construction	Glass manufacturing	Book, Art, Antique & Music Stores	Electrical Engineering
4	Veterinarians & Related	Control & Maintenance in Transport	Printing & Bookbinding	Service staff in Passenger Transport	Technical Drawing & Related
5	Geology, Geography & Meteorology	Jobs in Body Care	Metal Production	Education & Social Work	Auditing & Accounting
Bottom 5					
136	Metal Production	Pharmacy	Biologist	Ceramic production/processing	Driving & Sports Instructors
137	Floor Installation	Tax Consulting	Tax Consulting	Metal Construction/welding	Teaching & Research at Universities
138	Operators of Construction Machinery	Accounting & Auditing	Computer Science	Stage and Costume Design	Veterinarians & Related
139	Ceramic Production/Processing	Finance & Insurance	Presenters & Entertainers	Beverage Production	Train Drivers & Traffic Control
140	Train Drivers & Traffic Control	Marketing	Marketing	Paper & Packaging Technology	Actors & Dancers

Notes: This table lists the least and most task intensive occupations at the level of 3-digit occupation codes for the five task groups as defined by Dengler et al. (2014).

2.2 Sample Selection

I restrict my analysis to German nationals aged 20 to 60 born since 1953 working full time. I drop the part-time employed, because I cannot calculate their full-time equivalent wage, as well as the marginally employed and the unemployed.[6] I drop workers from the primary sector, because their employment opportunities often strongly depend on natural resources and exogenous location characteristics. I drop public employees not exempt from social security contributions and workers who have ever worked in East-Germany. This leaves me with 108 cities, excluding Berlin. I count Berlin as belonging to East-Germany for the analysis, because I cannot differentiate between East- and West-Berlin, because prior to Germany's reunification extensive government subsidies overrode market forces, and because the current LLM Berlin covers areas of East-Germany. Finally, I drop foreign nationals, and workers born before 1953, because I observe these workers full labor market biographies. Between 1978 to 2019 my restricted sample contains 407,881 men (337,702 women). I split the sample into 6 disjoint periods of seven years (1978-1984, 1985-1991, 1992-1998, 1999-2005, 2006-2012 and 2013-2019) and estimate my specifications for each period-sex cell separately. This preliminary draft presents results on male worker only. However, my empirical analysis of female workers leads me to the same conclusions. Splitting the sample into disjoint periods allows me to observe how the city-size wage gap developed over time.

Figure 1: The Urban Wage Premium



Mean annual earnings between 2013 and 2019 for German nationals between the ages of 20 and 60 in 2015 Euros. Population numbers from DeStatis for 2013. Definitions of Local Labor Market from Kosfeld and Werner (2012).

2.3 Descriptive Analysis

I begin by presenting descriptive evidence on the city-size wage (growth) gap for Germany. Figure 1 plots mean annual wages for all 108 West-German LLMs between 2013 and 2019 against LLM population in 2013.[7] The unconditional wage elasticity with respect to LLM population is 9% suggesting a strong relationship between population and local wage levels. Put differently mean wages in Munich are 23% higher than in Aalen a median-sized LLM, or almost 70% than in Vechta, Freyung and Uelzen, the LLMs with the lowest wages.

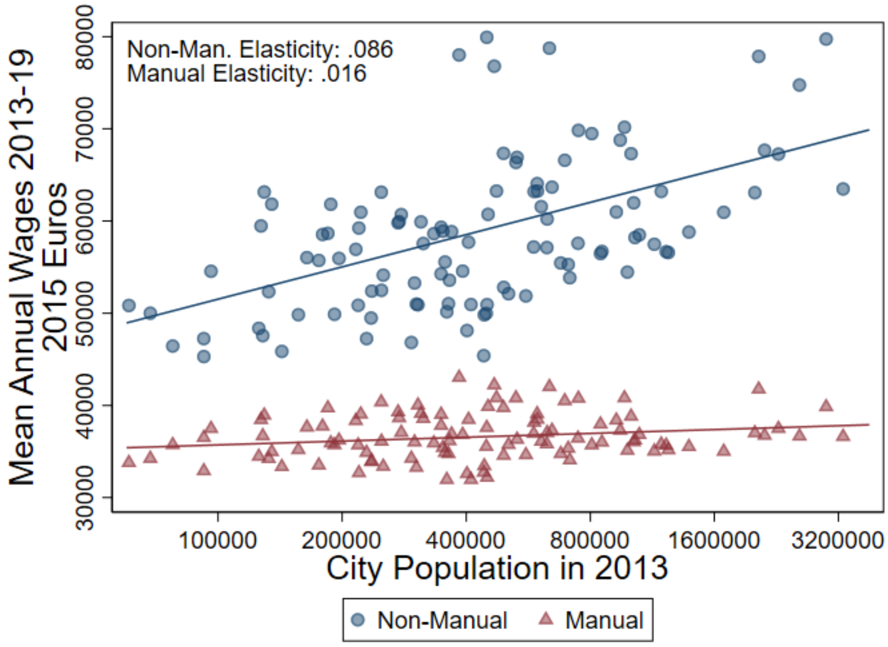
The figure displays four outliers; Erlangen, Ingolstadt, Sindelfingen and Wolfsburg. These medium-sized agglomerations pay wages on par with or higher than Frankfurt, Munich and Stuttgart, because they host headquarters, R&D departments and major production sites for Siemens, Audi, Mercedes-Benz and Volkswagen, respectively.[8] These corporations are highly profitable, employ many high-skill workers and have a large trade union coverage. Accordingly

[6]Marginal employment (german: *geringfügig beschäftigt*) refers to employment contracts with monthly earnings below 450 Euros or no more than 70 working days per calendar year (regulations from 2019). These workers are not subject to social security contributions.

[7]The qualitative results are robust to changing LLM population for LLM density, which I define as population per square kilometer.

[8]In most countries one would expect such companies to relocate to larger cities. In Germany, however, the firms opted to stay or move to smaller locations for a variety of reasons including the country's division after the second world war.

Figure 2: Heterogeneity of the Urban Wage Premium



Mean annual earnings from 2013 to 2019 for German nationals between the ages of 20 and 60 in 2015 Euros by task group. Population numbers from DeStatis for 2013. Definitions of Local Labor Market from Kosfeld and Werner (2012). Task groups as defined by Dengler et al. (2014).

they pay relatively high wages.[9]

Figure 2 displays the heterogeneity of the city-size wage gap plotting mean annual earnings between 2013 to 2019 for the manual and non-manual work force for each West-German LLM against LLM population. Effectively, there exists no (unconditional) city-size wage gap for manual workers. In contrast, workers belonging to any of the non-manual task groups receive strong city-size wage premia.[10]

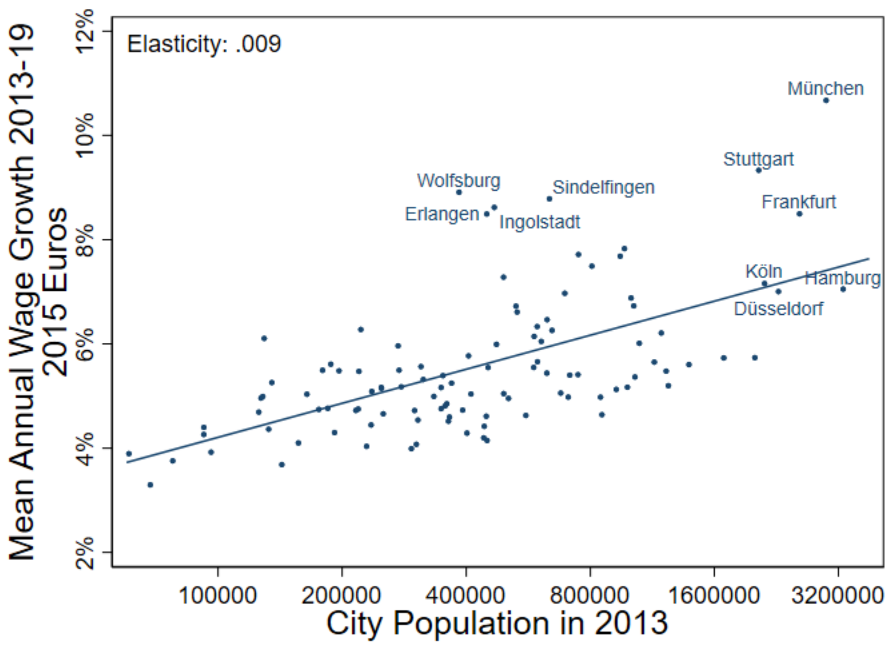
Moving on to differences in wage growth across LLMs figure 3 plots the mean annual wage growth for West-German LLMs between 2013 and 2019 against LLM population.[11] The unconditional elasticity of wage growth with respect to population size is 15%. This association is stronger than the relationship between city-size and wage levels. The average worker in Munich

[9]The plot based on the CZ definitions of the BBSR displays nine such locations; Darmstadt, Erlangen, Friedrichshafen, Heidelberg, Heilbronn, Ingoldstadt, Karlsruhe, Leverkusen, Regensburg and Wolfsburg. ZF Zahnrad's headquarter lies near Friedrichshafen, SAP sits in Heidelberg, Schwarz Gruppe, Europe's largest consumer retailer, has its headquarters in Heilbronn and Bayer's headquarter is located in Leverkusen. Darmstadt and Karlsruhe are the seat for several smaller corporations including Merck, Software AG, Schenk, DM or United Internet. Regensburg has no individual large company dominating its economy, but hosts factories by BMW and other corporations and has a particularly strong labor market. Leverkusen and Wolfsburg are a particularly extreme cases; both cities were build around Bayer's and Volkswagen original factories solely to accommodate the workers.

[10]The wage-population elasticity is 6.6%, 8.9% and 6.6% for analytical non-routine, cognitive routine and interactive non-routine, respectively and 1.6% for manual workers.

[11]I do not distinguish between wage growth arising within or between jobs.

Figure 3: Urban Wage Growth Premium



Mean annual earnings growth from 2013 to 2019 for German nationals between the ages of 20 and 60 in 2015 Euros. Population numbers from DeStatis for 2013. Definitions of Local Labor Market from Kosfeld and Werner (2012).

experiences 9% wage growth compared to only about 5% wage growth in median sized cities.

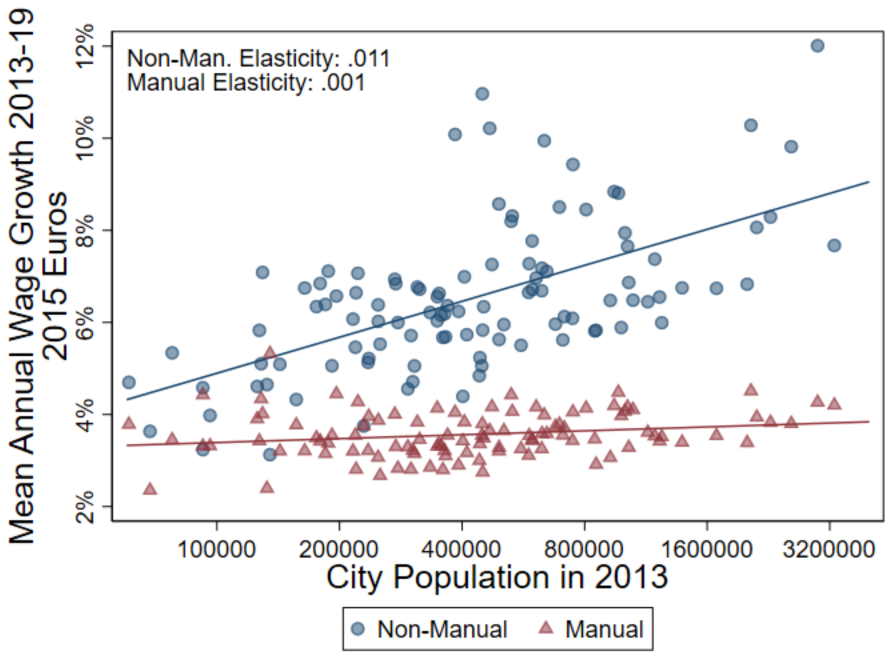
In Figure 4 I plot the city-size wage growth premium splitting the local workforce in each LLM by manual and non-manual occupations. It is notable that the wage growth elasticity with respect to population is almost zero for manual workers and strongly positive for non-manual workers (strongest for those in analytical non-routine occupations).

I have thus shown that the city-size wage gap as a phenomenon also exists in West-Germany, that individual wage growth is larger in larger LLMs, and that the city-size wage gap differs markedly across the tasks workers complete.

3 Empirical Methodology

Because I aim for my estimates to be comparable to the literature, I conduct my empirical analysis in three steps. First, I estimate agglomeration economies without controlling for big city experience gradually adding worker fixed effects. This specification follows the previous literature. Second, I extend the specification controlling for big city experience (thereby controlling for differences in wage growth across cities with different sizes) and calculate the dynamic

Figure 4: Heterogeneity of the Urban Wage Growth Premium



Mean annual earnings growth from 2013 to 2019 for male German nationals between the ages of 20 and 60 in 2015 Euros by task group. Population numbers from DeStatis for 2013. Definitions of Local Labor Market from Kosfeld and Werner (2012). Definitions for task group from Dengler et al. (2014)

city-size wage gap. Finally, I allow the value of big city experience to vary with various task intensities and construct estimates of cumulative agglomeration economies, i.e. static plus dynamic agglomeration economies.

Static Agglomeration Economies I follow the literature estimating the wage elasticity with respect to city-size with administrative employee panels and use a two-way fixed effects specification of the following form:

$$\log w_{i,t} = \gamma \log D_{c(i,t)} + \lambda_{c(i,t)} + \mu_i + \phi_t + x'_{i,t}\beta + \varepsilon_{i,t}, \tag{1}$$

where $\lambda_{c(i,t)}$ are city fixed effects for worker i residing in city c in period t, μ_i and ϕ_t are worker and year fixed effects, $w_{i,t}$ is worker i's, $x_{i,t}$ are time-varying controls (e.g. experience, industry, occupation), $D_{c(i,t)}$ is city c's population and $\varepsilon_{i,t}$ is an error term.[12,13] In what follows I refer to equation 1 as the *static specification*.

[12]Indexing city-level variables with $c(i,t)$ indicates that this specification does not model potential outcomes for different cities. Instead, the econometrician observes realized location choices by worker i in period t. For the same reason city subscripts are omitted for wages and the error term.

[13]Note that it is not necessary to control for firm fixed effects. The establishments identified in the SIAB are immobile. Thus, the city fixed effects capture the cross-city variation in establishment specific wage premia.

The coefficient of interest is γ, which measures the wage elasticity with respect to agglomeration size conditional on observable worker characteristics as well as location and time fixed effects. The model's parameters are estimated consistently under the identifying assumption discussed further below.

This econometric model implicitly assumes away dynamic agglomeration effects but accounts for unobserved ability and allows for the commuting zone specific wage premia to vary over time. This assumption contradicts the empirical literature and my own descriptive results for Germany. Thus, I now extend the model to account for dynamic agglomeration economies.

Dynamic Agglomeration Economies To derive a specification that explicitly allows for dynamic agglomeration benefits, I extend the static specification 1 to include measures of big city experience:

$$\log w_{i,t} = \gamma D_{c(i,t)} + \lambda_{c(i,t)} + \mu_i + \phi_t + x'_{i,t}\beta + \sum_{j=1}^{J} \kappa_{c(i,t),j} exp_{c(i,t),j,t} + \varepsilon_{i,t}, \tag{2}$$

where $exp_{c(i,t),j,t}$ denotes the experience gained by worker i up to period t in city j applied in the current location $c(i,t)$. The coefficient $\kappa_{c(i,t),c(i,t-1),t-1}$ denotes corresponding coefficient measuring the pecuniary value of an additional year of city specific experience $exp_{c(i,t),j,t}$. Finally, $\varepsilon_{i,t}$ denotes an error term. This model is flexible in that I allow the value of city specific experience to depend on the current location. That is, $\kappa_{c',c,t}$ depends not only on where the worker has gained experience, but also where she is applying that experience c' (where c' may equal c).[14]

To further simplify the model in Eq. eq:twfedynamic, I group cities into two tiers; Top 5 and Other. Top 5 refers to the five largest West-German local labor markets by population, i.e. Hamburg, Munich, Frankfurt, Cologne, Dusseldorf, and Other refers to all other local labor markets.[15] Grouping the cities by size, reduces the number of parameters drastically, because I do no longer have to estimate $\kappa_{c(i,t),j}$ for all 108^2 pairs of cities. I refer to model in equation

[14]We do include nonlinear terms for location specific experience, but omit them from equation (2) for clarity.

[15]Two comments are in order. First, I consider 12 alternative groupings. I split the sample of LLMs into two groups for the 2 to 10 largest LLMs versus smaller markets. I also vary this definition slightly for the 2, 3 and 4 largest LLMs swapping Hamburg, which has a fairly low wage for its size, for Frankfurt/Dusseldorf. My estimates for the wage elasticity and the coefficients on controls are remarkably robust to this variation. Second, I group my LLMs based on population and not density, because density is affected both by the size of the labor market and by the number of surrounding cities.

(2) as the *dynamic specification*.

Accounting for Big City Experience One can think of γ in specifications (1) and (2) as a measure of the immediate or static city-size wage gap due to agglomeration economies.[16] However, to estimate the dynamic city-size wage gap caused by both static *and* dynamic agglomeration economies, I must account for big city experience. I follow de la Roca and Puga (2017) estimating γ in a two stage procedure.[17]

1. Regress log wages on city fixed effects on all worker characteristics.

$$\log w_{i,t} = \lambda_{c(i,t)} + \mu_i + \phi_t + x'_{i,t}\beta + \sum_{j=1}^{J} \kappa_{c(i,t),j} exp_{c(i,t),j,t} + \eta_{i,t}.$$

2. Regress the city fixed effects, which are in effect

$$\lambda_c = \gamma_c D_c + \nu_c.$$

By the Frisch-Waugh-Lovell Theorem the estimates of the regression coefficients from the two stage procedure are the same (up to an estimation error) as the estimates from a joint estimation of all coefficients.

The key difference in estimating the dynamic city-size wage gap now lies in the second stage, where I change the dependent variable to account for big city experience

$$\lambda_c + \sum_{j=1}^{J} \hat{\kappa}_{c,j} e\bar{x}p_{c,j} = \gamma_c D_c + \nu_c, \tag{3}$$

where $e\bar{x}p_{c,j}$ is the mean experience of the population in location c gained in location j.

Heterogeneity in Big City Experience I have provided descriptive statistics that the extent of the city-size wage growth premium varies across tasks. To test this task-dependency, I allow for big city experience to vary with the occupation specific manual task intensity and

[16] Admittedly, any estimate of γ in the static specification 1 would be biased, if big city experience would correlate with city-size and affect log wages. Hence, we control for big city experience in the dynamic specification.

[17] This two-stage approach has previously been used in the literature to correct standard errors (Combes et al., 2008). Specifically, specifications 1 and 2 include both group- and individual-level regressors which biases standard errors downwards (Moulton, 1990). Proceeding in two stages I can consistently estimate standard errors for γ without relying on the bootstrap.

analytical non-routine task intensity. I select these task dimensions, because the descriptives indicate that the city-size wage (growth) is strongest for analytical non-routine occupations and because it accrues almost exclusively to non-manual workers.

$$\log w_{i,t} = \lambda_{c(i,t)} + \mu_i + \phi_t + x'_{i,t}\beta + \sum_{j=1}^{J} \kappa_{c(i,t),j} exp_{c(i,t),j,t} + \sum_{m=1}^{M} \theta exp_{m,t,\tau(\sigma(i,t),\sigma(i,t-1),\dots)} + \delta_{i,t}, \tag{4}$$

where $exp_{m,t,\tau(\sigma(i,t),\sigma(i,t-1),\dots)}$ denotes big city experience with each year weighted by an occupation specific-task intensity. The subscript $\sigma(i,t)$ denotes the occupation of worker i in year t.[18] I adjust the second stage accordingly

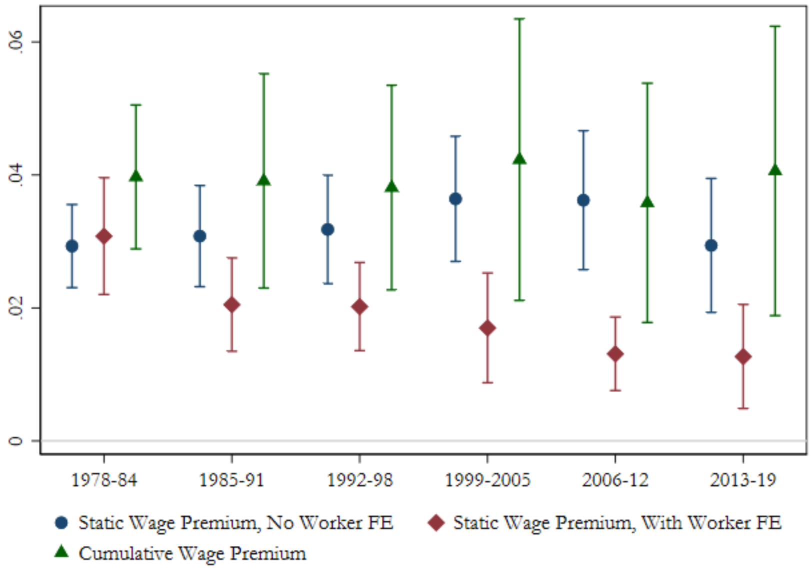
$$\lambda_c = \gamma_c D_c + \nu_c \tag{5}$$

$$\left(\sum_{j=1}^{J} \hat{\kappa}_{c,j} e\bar{x}p_{c,j} + \theta e\bar{x}p_{m,t,\tau(\sigma(i,t),\sigma(i,t-1),\dots)} \right) + \lambda_c = \gamma_c D_c + \nu_c, \tag{6}$$

where equation (5) estimates the immediate and equation (6) the dynamic city-size wage gap.

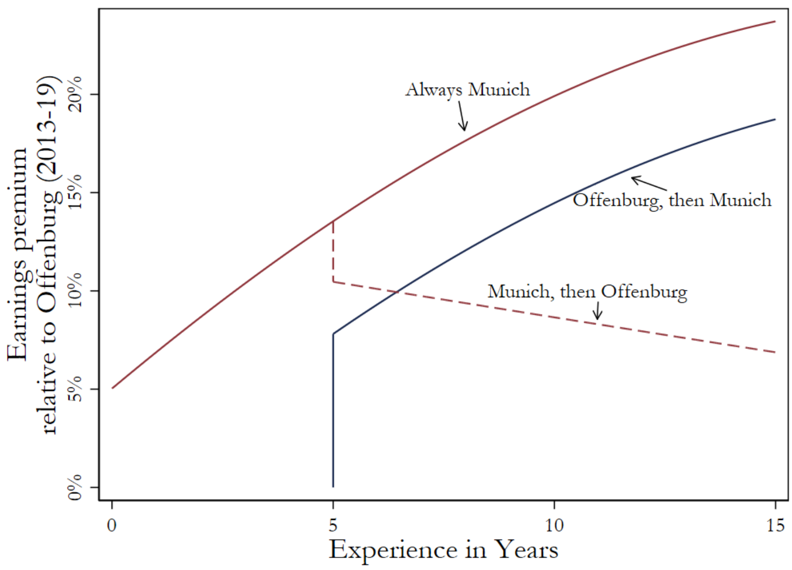
Identifying Assumption To identify the parameter γ I rely on the parallel trends assumption. That is, agglomeration size has to be strictly exogenous conditional on fixed effects (worker, city, occupation as well as industry) and time-varying worker-level controls. Put differently, there may be no time varying factors which are correlated with agglomeration size and also influence worker wages. In the specification controlling for dynamic agglomeration economies the assumption has further consequences. Specifically, D'Costa and Overman (2014) show that this assumption fails, if the unobserved heterogeneity in returns to big city experience are not proportional to the worker fixed effects. In my robustness checks I relax the parallel trends assumption with instrument variables.

Figure 5: OLS Estimates of the Urban Wage Premium



OLS estimates of the second stage regression of LLM specific wage premia (static and cumulative) on LLM population by 7-year periods with their 95% confidence intervals. The blue estimates are from the static specification (as described in section 3) omitting worker fixed effects from the first stage. The red estimates are also from the static specification, but the first stage now includes worker fixed effects. The green estimates plot the cumulative city-size wage gap as specified in section 3 changing the second stage to allow for the average value of big city experience.

Figure 6: Experience Premium By Location



Earnings premia in big city relative to median-sized city by years of labor market experience. Straight red line: earnings premium of working in Munich relative to Offenburg, a median-sized city whose city fixed effect was normalized to 0. Dotted red line: earnings premium of working in Munich for 5 years and subsequently moving to Offenburg relative to working in Offenburg for all years. Blue straight line: earnings premium of working in Offenburg for the first five years of ones career and subsequently moving to Munich. The x-axis represents the wage path of a worker based in Offenburg. Results based on the estimates for LLM fixed effects and the coefficients for big city experience.

4 Results

4.1 Big City Experience and the Cumulative Urban Wage Premium

To ensure that my results are comparable to those of other studies, I first estimate the static specification without worker fixed effects, i.e. without controlling for sorting. The corresponding OLS estimates from the first and second stage are summarised in Tables 3 and 5, respectively. I also plot the second stage estimates, i.e. estimates of the static city-size wage gap, in Figure 5 in blue.

Our estimates are around 3% and remarkably constant across periods. The magnitude is comparable to estimates of previous studies on Germany. Estimating the static specification with worker fixed effects does not change the city-size wage gap in earlier periods. Again, I summarise the first and second stage estimates in Tables 3 and 5 and plot second stage estimates in Figure 5 in red. In later periods estimates of the city-size wage gap reduce down to 1% for the 2013 to 2019 periods. That the estimates of the city size wage gap fall as I include worker fixed effects suggests that sorting has increased in importance over time, which is in line with the literature (Diamond and Gaubert, 2022).[19]

4.2 Cumulative Urban Wage Premium

Next, I estimate the dynamic specification without allowing for heterogeneity of big city experience across tasks. The first and second stage estimates are summarised in Tables 6 and 7, respectively. The second stage estimates are of the cumulative agglomeration economies, I plot the latter in green in Figure 5.

I find that the cumulative city-size wage gap is similar in magnitude as the static city-size wage gap without controlling for sorting, but also that the estimates are imprecise.[20] The results suggest that sorting may play a smaller role, and that the fraction of the city-size wage gap previously attributed to sorting, could be due to learning. However, the imputation procedure makes a comparison of the fixed effects densities across specifications unreliable.

[18]We do include a nonlinear version of task-dependent big city experience as a control, but omit it from equation (4) for clarity.

[19]In section 5 I show that alternative explanations such as a change in sample do not drive these results.

[20]I estimate my specification without interacting big city experience with current location dummies. I vary my big city classification defining the largest second up to the largest 10 LLMs as *big cities*. The conclusion remains the same.

Nevertheless, the earnings premia gained by working in big German cities are similar to those found for Spain. In Figure 6 I plot the earnings premium of different location choices relative to Offenburg a roughly median-sized LLM as a function of experience.[21] Workers who always live in Munich earn an immediate age premium of roughly 5% and experience additional wage growth. If the worker moved to Offenburg after five years, she would lose the static wage premium of 5%, but partially keep the additional value of her previous big city experience. That is, big city experience is transferable to smaller cities. The partial transferability of the wage premium is consistent with either self-selection or human capital accumulation theory. However, the benefit of previous big city experience shrinks over time. Finally, a worker who moves to Munich after having previously worked in Offenburg for five years experiences immediate wage gains consisting of the static Munich specific city premium and a higher valuation of her small city experience in Munich. The wage paths show that the dynamic component of the city-size wage gap is substantial. Over time residents in Munich may receive a cumulative city-size wage gap in excess of 20% over a rich median-sized city such as Offenburg.

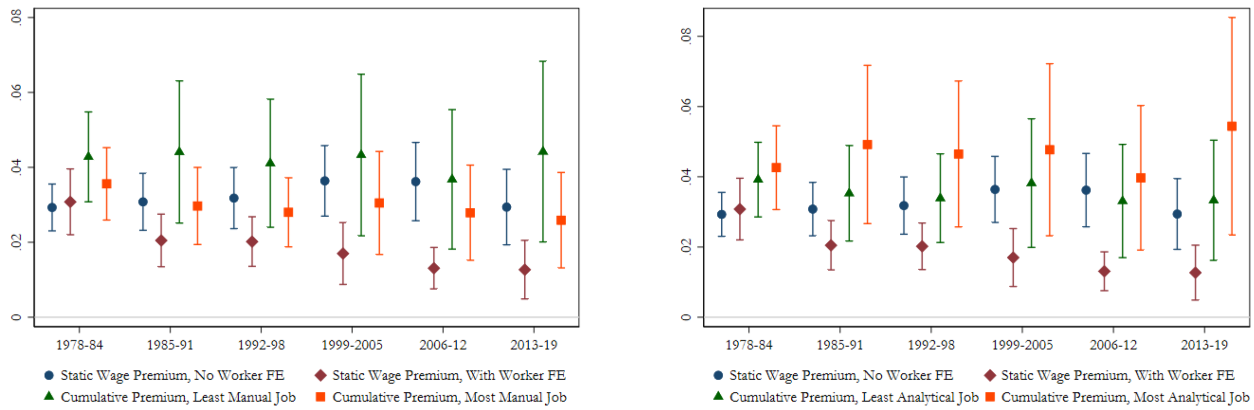
4.3 Task-Biased Big City Experience

I now move to my heterogeneity analysis estimating four cumulative wage elasticities. For the manual task intensity I estimate the cumulative elasticity for the least and the most manual task intensive occupations. I proceed analogously for the analytical non-routine task intensity. The first stage estimates of either specification do not differ substantially from the estimates of the dynamic specification without heterogeneity along the task dimension. I plot the second stage results along with the static elasticities in figure 7. Tables 15 (11) and 14 (10) provide the exact values for the least and most manual (analytical non-routine) occupations, respectively. I find that workers in the most manual (analytical non-routine) occupations receive a smaller (larger) cumulative wage premium. However, again the estimates for the cumulative wage premium are statistically not significantly different from the static elasticities after conditioning on fixed effects.

The differences in earnings premia between the least and most manual (analytical non-

[21] To plot the wage paths accurately I must select a specific city fixed effect requiring me to fix my comparison to a distinct big-small-city pair. Offenburg is a relatively high income city given its population. Thus, my estimates are closer to the lower bound of the cumulative city-size wage gap. I select Offenburg because its fixed effect is standardized to zero and it is a median-sized city for all periods.

Figure 7: 2nd Stage Results: Heterogeneity (Males only)

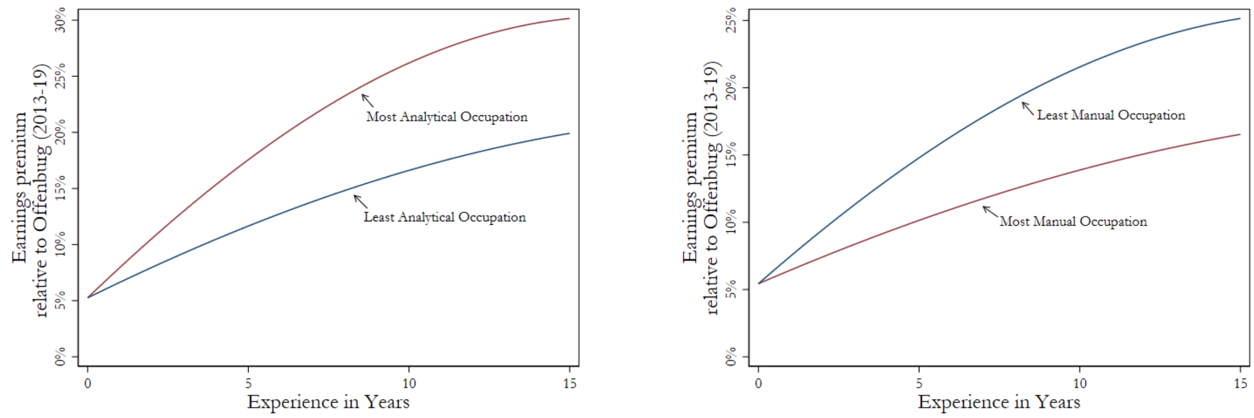


(a) Manual Task Intensity

(b) Analytical Non-Routine Task Intensity

OLS estimates of the second stage regression of LLM specific wage premia (static and cumulative) on LLM population by 7-year periods with their 95% confidence intervals for the least and most analytical non-routine (manual) occupations. The blue estimates are from the static specification (as described in section 3) omitting worker fixed effects from the first stage. The red estimates are also from the the static specification, but the first stage now includes worker fixed effects. The green and orange estimates plot the cumulative city-size wage gap as specified in section 3 changing the second stage to allow for the average value of big city experience for the least and most task-intensive occupation.

Figure 8: Experience Premium By Location and Occupation



(a) Analytical Non-Routine Occupations

(b) Manual Occupations

Earnings premium for working in big city over working in smaller cities by labor market experience in years for workers in the least and most manual (analytical non-routine) occupations. Panel (a): The red line presents the earnings premium for working in Munich in the most analytical non-routine occupation relative to a worker in the least analytical non-routine occupation in Offenburg over time. The blue line displays the earnings premium for working in Munich in the least analytical non-routine occupation relative to a worker in the least analytical non-routine task occupation in Offenburg. The most analytical non-routine occupation is *Humanities* and has a analytical non-routine task intensity of 0.93, whereas the least analytical non-routine task occupation is that of train conductors with an analytical non-routine task intensity of 0. Panel (b): The red line presents the earnings premium for working in Munich in the most manual (both routine and non-routine) occupation relative to a worker in the least manual occupation in Offenburg over time. The blue line displays the earnings premium for working in Munich in the least manual occupation relative to a worker in the least manual task occupation in Offenburg. The most manual occupation is train conductors and has a manual task intensity of 1, whereas there are a several occupations with a manual task intensity of 0 including Management, Audit Accounting, Programming or Computer Science.

routine) occupations become substantial over time. In Figure 8 I plot the earnings premia for workers in Munich relative to workers in Offenburg with the least manual and analytical non-routine occupations without big city experience. After 15 years in Munich a worker in the least (most) analytical non-routine occupation receives an earnings premium of almost 20% (30%). The results are the opposite for manual workers. Workers in the least (most) manual occupation earn almost 25% (only 15%) more in Munich.

5 Robustness Checks

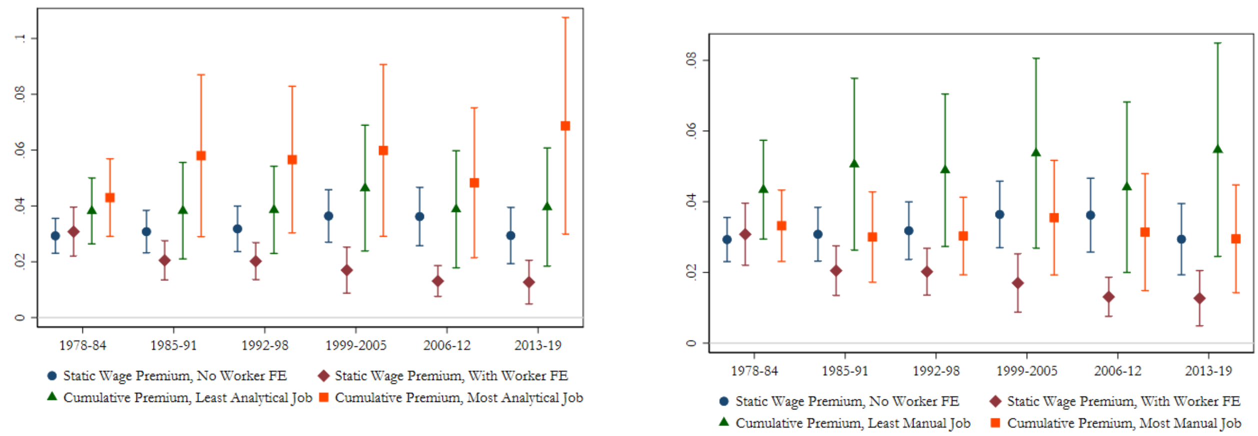
Several concerns plague my analysis. First, my fixed effect specification may still suffer from reverse causality or omitted variable bias caused by time-varying unobserved heterogeneity. I deal with this concern by instrumenting current agglomeration size with historic population from 1867 and 1871. Second, restricting my analysis to workers born since 1953 changes the sample composition over time, as workers in earlier periods are on average younger and less experienced. The observed trends in the city-size wage gap could be driven by sample composition. Thus, I construct an alternative measure for experience based on age and education.

5.1 Instrumenting Population

I can control for sorting on worker ability with worker fixed effects. However, my estimates of agglomeration economies may still be inconsistent, e.g. because high local wages attract more workers, or if time-varying omitted factors are correlated with agglomeration size and also influence local wages (e.g. infrastructure projects). The literature generally finds that these issues are negligible (Ciccone and Hall, 1996; Combes et al., 2010). Still I instrument agglomeration size with historic population to check the robustness of my estimates. The 1867 census by the German customs union provides the data for Prussia. Data for other states, e.g. Bavaria, Baden or Hessia, come from the 1871 census of the German Empire.

For 2SLS to estimate the static and the cumulative wage elasticity with respect to population size consistently, I require that the instruments satisfy the relevance condition and exclusion restriction. Historic population is strongly correlated with current population. For instance, the F-statistic for a regression of population in 2013 on population in 1867 and 1871 is 266.49 with similar values for the other periods, far exceeding Stock and Yogo (2005)'s rule-of-thumb.

Figure 9: Robustness Checks: IV Estimation (Males only)



(a) Analytical Non-Routine Task Intensity (2SLS)

(b) Manual Task Intensity (2SLS)

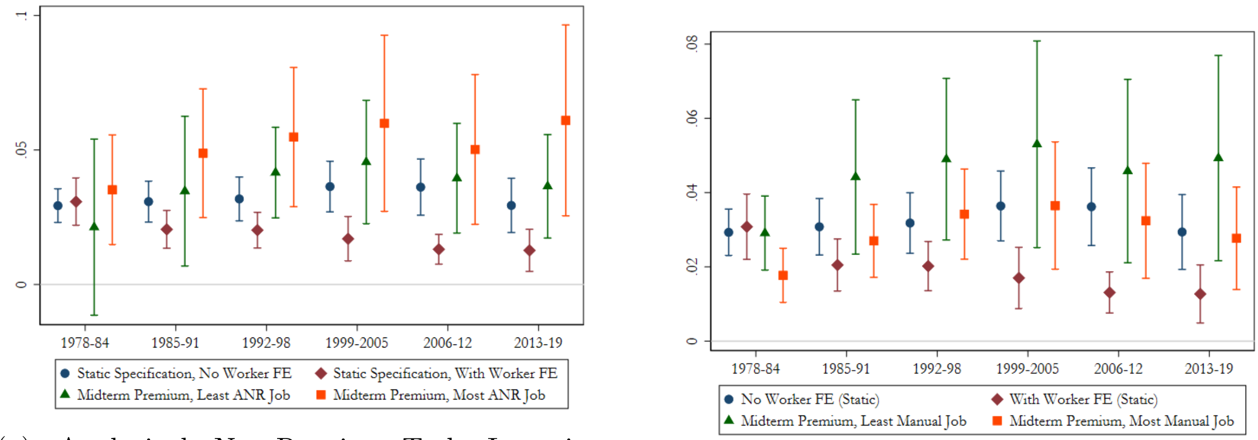
2SLS estimates of the second stage regression of LLM specific wage premia (static and cumulative) on LLM population by 7-year periods with their 95% confidence intervals. The blue estimates are from the static specification (as described in section 3) omitting worker fixed effects from the first stage. The red estimates are also from the the static specification, but the first stage now includes worker fixed effects. The green and orange estimates plot the cumulative city-size wage gap as specified in section 3 changing the second stage to allow for the average value of big city experience for the least and most task-intensive occupation.

The F statistics and the coefficients for the first stage of my 2SLS are summarised in Table 9. The exclusion restriction is untestable and would be violated, if historic population affected present local productivity through past local productivity. Figure 9 plots the 2SLS estimates for the wage elasticity. Table 8 provides the corresponding values. The estimates are close to the OLS estimates and the conclusions remain unchanged.

5.2 Sample Composition Effects

By restricting the analysis to workers born since 1953, the sample composition differs over time with the average worker being younger and having less work experience in earlier periods. To ensure a comparable sample composition across periods I replace my experience measure based on the number of days employed by age minus labor market entry age. I follow Dauth and Eppelsheimer (2021) and define entry age as 25 if a worker has a college degree, 22 if she has a vocational degree and 18 otherwise. I repeat my imputation for the new extended sample. Figure 10 plots the corresponding OLS and 2SLS estimates. My conclusions are robust to changes in measuring experience. First, sorting seems to have increased over time. Second, for all but the first period, cumulative urban wage premia are larger than the static urban wage premia.

Figure 10: Robustness Checks: Extended Sample (Males only)



(a) Analytical Non-Routine Task Intensity (OLS)

(b) Manual Task Intensity (OLS)

OLS estimates of the second stage regression of LLM specific wage premia (static and cumulative) on LLM population by 7-year periods with their 95% confidence intervals. In contrast to previous coefficient plots the sample has changed; experience is no longer based on the number of days workers are observed in the SIAB but as age minus x, where x is education dependent. Moreover, I no longer restrict the sample to workers born since 1958, but allow for workers to be born in any year. The imputation for censored wages was run separately under these sample restrictions.

6 Conclusions

I establish that there exists substantial heterogeneity in the city wage growth gap with much larger gains for non-manual workers and especially for those in analytical non-routine occupations. I estimate the cumulative wage elasticity with respect to local labor market population. After 15 years of big city experience differences in wage growth can create an earnings premium 3 to 5 times larger than the static city-size wage gap. Finally, I establish the existence of a strong heterogeneity in wage premia across task intensities. I find that workers in the most (least) manual occupations earn 15% (25%) higher wages after 15 years in Munich relative to workers with similar experience in a median-sized city. Workers in analytical non-routine occupations receive the highest premium. 15 years of experience in Munich or other large cities may increase their earnings by up to 30% relative to workers who gained all of their experience in a median-sized city.

The strong heterogeneity in the value of big city experience, which we find, points to two future avenues for research. First, the extent of the heterogeneity suggests that dynamic agglomeration economies are severely restricted to a sub-population. Numerous studies have discussed this heterogeneity with regard to static agglomeration economies (Gould, 2007; Bacolod et al., 2009b; Abel et al., 2012; Addario and Patacchini, 2008; Andersson et al., 2013; Groot and de Groot, 2014; Grujovic, 2018; Koster and Ozgen, 2021; Rossi-Hansberg et al., 2019). Counterfactual analyses predict huge welfare gains, if the largest cities were to mostly host those industries and workers benefiting most from agglomeration economies (Rossi-Hansberg et al., 2019). For such policies to be successful, the literature must first identify the precise mechanisms as well as the occupations and industries benefiting most from agglomeration economies. Second, the size of dynamic agglomeration economies suggests that much of the heterogeneity in the overall city-size wage gap may be driven by heterogeneity in wage growth. This narrows down the mechanisms displaying heterogeneity to learning and matching. Future research should quantify the extent to which the city size wage gap is driven by dynamic as opposed to static agglomeration economies. Such research should also aim to identify the mechanisms through which city size raise wage growth in detail and explain why these externalities display such strong heterogeneity.

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Appendix

Table 2: Data Description for Selected Variables

Variable Name	Description
exp	Experience in years calculated from days worked.
ten	Tenure at the current establishment in years.
educ	Educational attainment; college degree, vocational training or neither.
skill	Skill level of job (Low, Medium, High, Very High)
age	Age of employee
wage_imp	Daily wages in 2015 Euros. Imputed for observation with top-coded wages.
jahr	Year of observation
urban_top	Binary variable equal to 1, if the employee was working in the five largest LLMs.
uexp_top	Experience in years gained in the five largest LLMs.
uexp_top_top	Experience in years gained in the five largest LLMs times urban_top.
uexp_rest	Experience in years gained outside the five largest LLMs.
uexp_rest_top	Experience in years gained outside the five largest LLMs times urban_top.
population	LLM population
density	LLM population divided by LLM area in square kilometers.
TaskAnalytical	Equal to 1, if the occupation is primarily involved with analytical non-routine tasks.
TaskManual	Equal to 1, if the occupation is primarily involved with manual tasks.
TaskRoutine	Equall to 1, if the occupation is primarily involved with routine tasks.
TaskCognitive	Equal to 1, if the occupation is primarily involved with cognitive routine tasks.
TaskInteractive	Equal to 1, if the occupation is primarily involved with interactive non-routine tasks.
TaskManualNonRoutine	Equal to 1, if the occupation is primarily involved with manual non-routine tasks.
TaskManualRoutine	Equal to 1, if the occupation is primarily involved with manual routine tasks.

Table 3: First Stage Estimates of Static Specification

	1978-84		1985-91		1992-98		1999-2005		2006-12		2013-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Experience	0.0464***	0.00599***	0.0335***	0.0112***	0.0269***	0.0301***	0.0288***	0.0431***	0.0266***	0.0311***	0.0209***	0.0250***
	(0.000414)	(0.00182)	(0.000229)	(0.00139)	(0.000207)	(0.00116)	(0.000220)	(0.00148)	(0.000223)	(0.00156)	(0.000191)	(0.00152)
Experience^2	0	0	-0.0720***	-0.0583***	-0.0552***	-0.0399***	-0.0552***	-0.0450***	-0.0448***	-0.0493***	-0.0333***	-0.0491***
	(.)	(.)	(0.00156)	(0.00100)	(0.00101)	(0.000636)	(0.000808)	(0.000584)	(0.000647)	(0.000536)	(0.000495)	(0.000459)
Tenure	-0.0000579	-0.00880***	0.00768***	-0.00136***	0.0109***	0.00218***	0.0112***	0.00230***	0.0124***	0.00212***	0.0117***	0.00164***
	(0.000381)	(0.000435)	(0.000234)	(0.000225)	(0.000203)	(0.000150)	(0.000197)	(0.000140)	(0.000199)	(0.000147)	(0.000175)	(0.000138)
Tenure^2	0	0	-0.0482***	-0.0264***	-0.0446***	-0.0110***	-0.0347***	-0.0111***	-0.0298***	-0.00649***	-0.0233***	-0.00562***
	(.)	(.)	(0.00194)	(0.00109)	(0.00123)	(0.000699)	(0.000928)	(0.000602)	(0.000727)	(0.000554)	(0.000564)	(0.000483)
Medium Skill Job	0.0919***	0.191	0.117***	0.0267**	0.151***	0.0554***	0.171***	0.0681***	0.121***	0.0227***	0.149***	0.0564***
	(0.00970)	(0.0133)	(0.00792)	(0.00945)	(0.00695)	(0.00960)	(0.00702)	(0.0114)	(0.00295)	(0.00176)	(0.00246)	(0.00293)
High Skill Job	0.248***	0.0479**	0.331***	0.0811***	0.374***	0.108***	0.426***	0.112***	0.333***	0.0559***	0.309***	0.0913***
	(0.0114)	(0.0150)	(0.00892)	(0.0104)	(0.00787)	(0.0105)	(0.00810)	(0.0121)	(0.00438)	(0.00282)	(0.00372)	(0.00429)
Very High Skill Job	0.349***	0.115***	0.486***	0.126***	0.534***	0.134***	0.589***	0.146***	0.494***	0.0700***	0.471***	0.138***
	(0.0130)	(0.0208)	(0.00976)	(0.0136)	(0.00836)	(0.0123)	(0.00834)	(0.0133)	(0.00496)	(0.00357)	(0.00448)	(0.00535)
Vocational Training	0.0799***		0.0802***		0.0799***		0.0878***		0.0873***		0.0583***	
	(0.00270)		(0.00241)		(0.00238)		(0.00251)		(0.00268)		(0.00262)	
College Degree	0.376***		0.419***		0.405***		0.436***		0.435***		0.343***	
	(0.00751)		(0.00547)		(0.00429)		(0.00402)		(0.00387)		(0.00355)	
N	318175	300917	612576	590435	826004	806231	965873	947020	1024037	1003469	1137100	1123964
R^2	0.395	0.827 0.515	0.859	0.531	0.879	0.573	0.889	0.593	0.900	0.611	0.901	
Worker Fixed Effects		✓		✓		✓		✓		✓		✓

Standard errors in parentheses. Estimated with male workers only. All specifications include a constant and year, industry and occupation fixed effects.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Static Urban Wage Premium (Static Spefication 2nd Stage, OLS)

	1978-84		1985-91		1992-98		1999-2005		2006-12		2013-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log Population	0.0293***	0.0308***	0.0308***	0.0205***	0.0318***	0.0202***	0.0364***	0.0170***	0.0362***	0.0131***	0.0294***	0.0127**
	(0.00319)	(0.00448)	(0.00388)	(0.00358)	(0.00416)	(0.00338)	(0.00480)	(0.00421)	(0.00533)	(0.00282)	(0.00514)	(0.00399)
N	107	107	107	107	107	107	107	107	107	107	107	107
R^2	0.378	0.370	0.329	0.254	0.359	0.275	0.357	0.189	0.316	0.175	0.218	0.124
Worker Fixed Effects		✓		✓		✓		✓		✓		✓

Standard errors in parentheses. OLS estimates for the second stage regressions. All regressions include a constant and include all 107 West-German LLMs.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Static Urban Wage Premium (Static Spefication 2nd Stage, 2SLS)

	1978-84		1985-91		1992-98		1999-2005		2006-12		2013-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log Population	0.0241***	0.0278***	0.0274***	0.0173***	0.0294***	0.0188***	0.0332***	0.0168***	0.0307***	0.0103**	0.0252***	0.0.101**
	(0.00427)	(0.00453)	(0.00487)	(0.00428)	(0.00481)	(0.00371)	(0.00572)	(0.00416)	(0.00637)	(0.00343)	(0.00595)	0.00378)
N	107	107	107	107	107	107	107	107	107	107	107	107
R^2	0.367	0.366	0.325	0.248	0.357	0.274	0.354	0.189	0.308	0.167	0.214	0.119
Worker Fixed Effects		✓		✓		✓		✓		✓		✓

Standard errors in parentheses. OLS estimates for the second stage regressions. All regressions include a constant and include all 107 West-German LLMs.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: First Stage Estimates of the Dynamic Specification

	1978-84 (1)	1985-91 (2)	1992-98 (3)	1999-2005 (4)	2006-12 (5)	2013-19 (6)
Big City Experience	0.0574***	0.0557***	0.0291***	0.0311***	0.0251***	0.0232***
	(0.0143)	(0.00404)	(0.00240)	(0.00174)	(0.00141)	(0.00125)
Big City Experience × Experience	-0.00702***	-0.00342***	-0.00126***	-0.00106***	-0.000789***	-0.000660***
	(0.00203)	(0.000316)	(0.000129)	(0.0000690)	(0.0000469)	(0.0000383)
Big City Experience × Now Big City	-0.00675	-0.0168***	-0.00608*	-0.00700***	-0.00871***	-0.00528***
	(0.0143)	(0.00406)	(0.00239)	(0.00169)	(0.00134)	(0.00118)
Big City Experience × Experience × Now Big City	0.000547	0.000978**	0.000362**	0.000314***	0.000316***	0.000193***
	(0.00204)	(0.000319)	(0.000129)	(0.0000684)	(0.0000463)	(0.0000378)
Small City Experience × Now Big City	0.00230	0.0164***	0.0136***	0.0100***	0.00815***	0.00649***
	(0.0129)	(0.00364)	(0.00216)	(0.00150)	(0.00125)	(0.00110)
Small City Experience × Experience × Now Big City	-0.000373	-0.00145***	-0.000844***	-0.000471***	-0.000315***	-0.000253***
	(0.00190)	(0.000285)	(0.000111)	(0.0000576)	(0.0000433)	(0.0000353)
Experience	0.00799***	0.0111***	0.0289***	0.0413***	0.0297***	0.0236***
	(0.00182)	(0.00139)	(0.00116)	(0.00148)	(0.00156)	(0.00152)
Experience^2	0	-0.0454***	-0.0319***	-0.0362***	-0.0428***	-0.0426***
	(.)	(0.000989)	(0.000640)	(0.000587)	(0.000550)	(0.000470)
Tenure	-0.00872***	-0.00138***	0.00213***	0.00231***	0.00231***	0.00171***
	(0.000439)	(0.000226)	(0.000151)	(0.000141)	(0.000148)	(0.000139)
Tenure^2	0	-0.0223***	-0.0102***	-0.0108***	-0.00693***	-0.00569***
	(.)	(0.00109)	(0.000703)	(0.000605)	(0.000557)	(0.000485)
Medium Skill	0.0200	0.0265**	0.0556***	0.0680***	0.0222***	0.0566***
	(0.0133)	(0.00938)	(0.00960)	(0.0113)	(0.00176)	(0.00293)
High Skill	0.0488**	0.0797***	0.108***	0.112***	0.0545***	0.0910***
	(0.0149)	(0.0104)	(0.0105)	(0.0121)	(0.00282)	(0.00428)
Very High Skill	0.115***	0.125***	0.134***	0.145***	0.0694***	0.137***
	(0.0206)	(0.0134)	(0.0122)	(0.0132)	(0.00357)	(0.00533)
N	300917	590435	806231	947020	1003469	1123964
R^2	0.828	0.860	0.880	0.889	0.900	0.901
Worker Fixed Effects	✓	✓	✓	✓	✓	✓

Standard errors in parentheses. Estimated with male workers only. All specifications include a constant and year, industry and occupation fixed effects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Static and Cumulative Urban Wage Premium (Dynamic Spefication 2nd Stage, OLS)

	1978-84		1985-91		1992-98		1999-2005		2006-12		2013-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log Population	0.0294***	0.0313***	0.0186***	0.0229***	0.0184***	0.0227***	0.0150***	0.0215***	0.0120***	0.0177***	0.0113**	0.0186***
	(0.00451)	(0.00453)	(0.00354)	(0.00399)	(0.00328)	(0.00371)	(0.00414)	(0.00492)	(0.00265)	(0.00351)	(0.00402)	(0.00466)
N	107	107	107	107	107	107	107	107	107	107	107	107
R^2	0.348	0.376	0.221	0.285	0.244	0.310	0.155	0.240	0.157	0.249	0.101	0.207
Worker Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Including Big City Experience		✓		✓		✓		✓		✓		✓

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Staticand Cumulative Urban Wage Premium (Dynamic Spefication 2nd Stage, 2SLS)

	1978-84		1985-91		1992-98		1999-2005		2006-12		2013-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log Population	0.0255***	0.0283***	0.0150***	0.0211***	0.0160***	0.0221***	0.0138***	0.0231***	0.00883**	0.0169***	0.00842*	0.0184***
	(0.00447)	(0.00457)	(0.00408)	(0.00490)	(0.00349)	(0.00421)	(0.00397)	(0.00524)	(0.00323)	(0.00463)	(0.00373)	(0.00507)
N	107	107	107	107	107	107	107	107	107	107	107	107
R^2	0.342	0.373	0.213	0.283	0.239	0.310	0.154	0.239	0.146	0.248	0.094	0.207
Worker Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Including Big City Experience		✓		✓		✓		✓		✓		✓

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Robustness Checks: First Stage of 2SLS Estimation

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Log City Population in					
	1978	1985	1992	1999	2006	2013
Historic Population	0.0157***	0.0156***	0.0156***	0.0155***	0.0157***	0.0154***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0034)
N	107	107	107	107	107	107
R^2	0.713	0.712	0.712	0.716	0.714	0.720
F statistic	266.46	265.08	265.86	270.05	276.33	276.33

Standard errors in parentheses. Historic city population in areas belonging to Prussia from 1867, other other cities from 1871.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Heterogeneity: Most Analytical Occupation (OLS Estimates)

	1978-84 (1)	1985-1991 (2)	1992-98 (3)	1999-2005 (4)	2006-12 (5)	2013-19 (6)
Log Population	0.0329***	0.0256***	0.0253***	0.0232***	0.0182***	0.0221***
	(0.00475)	(0.00447)	(0.00417)	(0.00520)	(0.00366)	(0.00540)
N	107	107	107	107	107	107
R^2	0.383	0.316	0.336	0.259	0.255	0.240

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Heterogeneity: Least Analytical Occupation (OLS Estimates)

	1978-84 (1)	1985-1991 (2)	1992-98 (3)	1999-2005 (4)	2006-12 (5)	2013-19 (6)
Log Population	0.0321***	0.0223***	0.0219***	0.0209***	0.0172***	0.0170***
	(0.00472)	(0.00384)	(0.00354)	(0.00474)	(0.00342)	(0.00442)
N	107	107	107	107	107	107
R^2	0.373	0.281	0.300	0.238	0.244	0.187

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Heterogeneity: Most Analytical Occupation (2SLS Estimates)

	1978-84 (1)	1985-1991 (2)	1992-98 (3)	1999-2005 (4)	2006-12 (5)	2013-19 (6)
Log Population	0.0301***	0.0250***	0.0257***	0.0253***	0.0177***	0.0232***
	(0.00481)	(0.00564)	(0.00491)	(0.00567)	(0.00482)	(0.00620)
N	107	107	107	107	107	107
R^2	0.380	0.316	0.336	0.257	0.255	0.239

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Heterogeneity: Least Analytical Occupation (2SLS Estimates)

	1978-84 (1)	1985-1991 (2)	1992-98 (3)	1999-2005 (4)	2006-12 (5)	2013-19 (6)
Log Population	0.0290***	0.0202***	0.0209***	0.0220***	0.0163***	0.0162***
	(0.00473)	(0.00468)	(0.00396)	(0.00496)	(0.00448)	(0.00461)
N	107	107	107	107	107	107
R^2	0.370	0.279	0.300	0.237	0.244	0.187

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Heterogeneity: Most Manual Occupation (OLS Estimates)

	1978-84 (1)	1985-1991 (2)	1992-98 (3)	1999-2005 (4)	2006-12 (5)	2013-19 (6)
Log Population	0.0317***	0.0214***	0.0208***	0.0193***	0.0161***	0.0154***
	(0.00472)	(0.00370)	(0.00338)	(0.00455)	(0.00316)	(0.00422)
N	107	107	107	107	107	107
R^2	0.365	0.269	0.284	0.218	0.229	0.164

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Heterogeneity: Least Manual Occupation (OLS Estimates)

	1978-84 (1)	1985-1991 (2)	1992-98 (3)	1999-2005 (4)	2006-12 (5)	2013-19 (6)
Log Population	0.0331***	0.0248***	0.0240***	0.0225***	0.0182***	0.0197***
	(0.00478)	(0.00424)	(0.00387)	(0.00510)	(0.00363)	(0.00487)
N	107	107	107	107	107	107
R^2	0.384	0.309	0.325	0.251	0.255	0.218

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Heterogeneity: Most Manual Occupation (2SLS Estimates)

	1978-84 (1)	1985-1991 (2)	1992-98 (3)	1999-2005 (4)	2006-12 (5)	2013-19 (6)
Log Population	0.0284***	0.0187***	0.0193***	0.0199***	0.0146***	0.0141***
	(0.00472)	(0.00445)	(0.00370)	(0.00459)	(0.00409)	(0.00423)
N	107	107	107	107	107	107
R^2	0.361	0.265	0.282	0.218	0.227	0.163

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Heterogeneity: Least Manual Occupation (2SLS Estimates)

	1978-84	1985-1991	1992-98	1999-2005	2006-12	2013-19
	(1)	(2)	(3)	(4)	(5)	(6)
Log Population	0.0305***	0.0235***	0.0239***	0.0244***	0.0176***	0.0200***
	(0.00486)	(0.00530)	(0.00445)	(0.00545)	(0.00477)	(0.00539)
N	107	107	107	107	107	107
R^2	0.381	0.309	0.325	0.250	0.255	0.218

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$