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City size, employer concentration, and wage income inequality

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Abstract: This study investigates the relationship between the urban wage premium and employer concentration using Swedish full population employer-employee data. Departing from an AKM modeling framework to distinguish worker from firm specific heterogeneity – a measure of rent-sharing – we then measure the urban wage premium using differences in the estimated firm fixed effects at the level of local industries, nested within local labor markets. Our results suggest that labor market employer concentration, as calculated using the Hirschman-Herfindahl index and a leave-one-out instrumental variable design, can account for a significant share of the estimated urban wage premium (UWP). Addressing city-level wage income inequality by applying our model to different segments of the local labor market income distribution, we find that while the UWP pertains to all income segments, it is largest for top-income levels (above the 90th percentile), and within this segment employer concentration also has the largest explanatory power. Thus, while being an important explanatory factor for all percentiles of the local income distribution, a relatively lower employer concentration within larger cities, and vice versa, higher concentration within smaller cities, primarily help explain the variance of top wages within these cities/labor markets.

JEL-codes: D22, J31, J42, R12

Keywords: wage distribution, rent sharing, monopsony, linked employer-employee data, local labor markets

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1. Introduction

In the field of income inequality there has recently been a push to extend the more traditional explanatory approaches related to factor input supply- and demand changes (arising from new technology, trade patterns and immigration, see Acemoglu & Autor, 2011; Katz, 1999; Wright, Goldin, & Katz, 2009) to include the potential effects of firm level factors and increasing inequality in firm productivity. In a seminal paper, Barth, Bryson, Davis, & Freeman (2016) decompose US individual log earnings into dispersion in-between- and within establishments and estimate that in-between dispersion is related to as much as 79 percent of total increase in variance in income among all workers, 1992 to 2007. Similar results are also found in Dunne, Foster, Haltiwanger, and Troske (2004), and Faggio, Salvanes, and Van Reenen (2010).

This extension of the inequality literature builds upon three distinct strands of research on worker and firm productivity. Firstly, it is a long since established fact that there is considerable heterogeneity in firm-level total factor productivity (TFP), even as measured among observably similar firms and establishments. For example, the 90-10 TFP percentile ratio for US manufacturing firms is estimated as being in the order of two, and even larger gaps are found for firms in China and India (see Syverson, 2011, for a review). Secondly, previous research has documented the relationship between this variation in productivity across firms and wage differences among workers within those firms (see e.g. Cardoso, 1997; Davis & Haltiwanger, 1991; Skans, Edin, & Holmlund, 2009; Slichter, 1950, among many), but due to challenges in capturing selection and unobserved heterogeneity among workers, researchers have been cautious in attributing firm-level differences in TFP as the sole cause of wage variation. Lastly, empirical studies on rent-sharing have explored the connection between worker wages and various measures of firm profits or rents, where a typical finding is that a 10 percent increase in value-added per worker corresponds to a 0.5 to 1.5 percent average increase in wages (for a recent review, see Card, Cardoso, Heining, & Kline, 2018).[1]

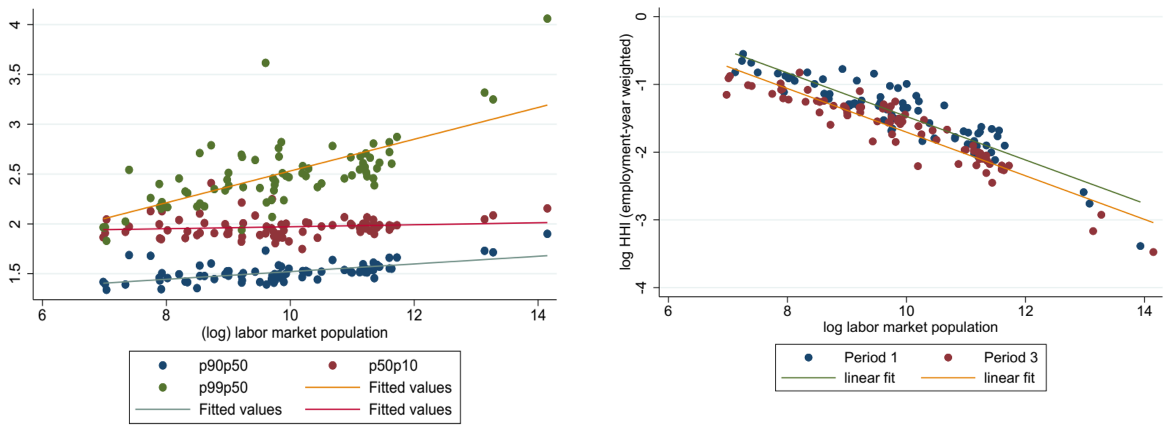
However, despite recent progress as to how these wage increases are partitioned between different types of workers, there is still a lack of both theoretical and empirical work explaining how firm level profits or rents may spill into wages for different worker categories, and by extension, how this may affect income inequality. In this paper, we build upon a monopsony

[1] In the text, the two terms "establishment" and "firm" refer to place of work and a legal entity (owning and operating the establishment), respectively. Thus, a firm can have more than one establishment but not vice-versa. In our discussion of previous studies, since research papers differ as to which of these two entities are analyzed, we use these terms interchangeably. In section 2, we define our use of the two terms for the data analysis that follows.

framework, first developed by Joan Robinson (1933), and seminal work by Manning (2003, 2011) which links various degrees of monopsony and firm wage-setting power to the level of wages for different worker categories. Our aim is to analyze *i)* the extent to which the urban wage premium, i.e. the premium associated with work in higher populated labor markets, can be accounted for by lower degrees of industry-specific employer concentration within the respective labor markets. Additionally, we also aim to analyze *ii)* the positive link between local labor market population size and local labor market earnings inequality (at the level of local industries nested in the respective labor markets), and test to what extent the interaction between population size and employer concentration helps explain this well-known pattern.

As we will further argue below, our paper hereby addresses an evident gap between two still largely separate literatures: On the one hand, the above-mentioned research efforts to address the root causes of macro level changes in dispersion in wages and income, now extended to include firm level factors related to firm productivity and employer concentration. On the other, the vast and still growing literature in regional science as concerns the causes and effects of agglomeration and explanations of the so-called urban wage premium (i.e., why larger cities pay more, even while controlling for observable and non-observable worker characteristics).

Figure 1. Earnings inequality and local labor market employer concentration as related to local population size.



Panel A: Earnings inequality within labor markets

Panel B: Average labor market concentration within labor markets

Notes: Source: Mona database, Statistics Sweden. The Herfindahl-Hirschman index is calculated using firm employment size for the number of firms in a given industry nested in a labor market. The HHI corresponds to a weighted average of HHI taken across all industries within a particular labor market (see Section 2, p. 9 as to how we calculate the HHI). Fitted values correpond to the OLS regression line.

In this regard, Figure 1 below neatly illustrates our research problem. In Panel A, we see that earnings inequality as measured by percentile ratios at the level of the local labor market increases with local population size (x-axis). This increasing inequality is related to rising top- and upper income levels, as exemplified by the 99/50 and 90/50 coefficients, whereas bottom level income inequality (the 50/10 ratio) remains constant across the population size distribution. Panel B, in turn, illustrates how average local industry employer concentration (as measured by the Herfindahl index) decreases with local population size.

Resting on the assumption that wages correctly reflect the marginal productivity of workers, explanations of the patterns found in Panel A (higher wages and inequality in larger cities) usually focus on individual level productivity of workers in urban environments. Beyond mere geographical sorting of industries and educational worker categories, the source of this higher individual productivity is most often related to three basic factors. Either *a)* to learning (sharing of knowledge), i.e., a situation in which human capital accumulation is faster in larger more population dense cities due to facilitated social interaction (Glaeser 1999; Glaeser & Maré 2001; Moretti 2004; Baum-Snow & Pavan 2012; De la Roca & Puga 2012); or to *b)* coordination effects, the "matching hypothesis", which suggests that cities create a context in which there is a better chance of bringing about a good match between workers and firms (Dauth, Findeisen, Moretti, & Suedekum, 2022; Kim, 1990; Korpi & Clark, 2019; Wheeler, 2006; Yankow, 2006); or, finally, to *c)* sorting and self-selection, i.e. the notion that relatively higher worker productivity in larger cities is largely due to different types of innate abilities of workers living in and moving into these larger cities (see e.g. Combes, Duranton, & Gobillon, 2008; Combes, Duranton, Gobillon, & Roux, 2012; Matano & Naticchioni, 2012, 2013).

Out of these three factors – while there is still debate – there is an emerging consensus that the largest share of this urban wage premium can be ascribed to matching and geographical sorting of individuals with differences in underlying ability (for overviews, see Rosenthal & Strange 2004; Puga 2010).

Given the many recent studies suggesting that employer wage-setting power is non-negligible in many industries (see further discussion below), the implicit underlying model in much of the UWP literature – which views firms essentially as price takers – may however be faulty. If so, wages in any given industry may not only reflect workers' individual marginal productivity but also a mark-down from the marginal productivity of workers, a mark-down which in turn is positively corelated with employer concentration. And such employer concentration, as illustrated in Panel B in Figure 1, clearly decreases with population size of the local labor market. Thus, even though their dependence on one another is yet to be determined, the potential relationship between inequality and employer concentration is central to our basic research question: To what extent can higher average worker earnings and wage income inequality in larger local labor markets (and vice-versa) be explained by decreasing industry-specific employer concentration within those labor markets?

To allow for a comparison of our analysis to more traditional explanatory approaches to city-size wage differences and income inequality, we start our analysis by first estimating the Swedish urban wage premium (UWP) by way of common estimation methods in the literature. Other than controlling for basic industry level fixed effects, this traditional approach to UWP estimation does however not take any firm level factors (e.g., rent sharing) into account. To address such firm level factors and their impact on both the urban wage premium and urban inequality (as depicted in Panel A of Figure 1), we then employ an AKM modeling framework which allows us to distinguish between worker- and firm-level fixed effects (or firm pay premia), by local industry and local labor market. On the basis of this partition, we then continue our analysis by *i)* estimating how the average firm pay premium (a common measure of rent-sharing, see Card et al. 2018) varies with local labor market population, and the degree to which employer concentration within local industries contributes to the variation in these firm pay premia; and *ii),* applying our model to different income segments of the local labor market income distribution to hereby assess how employer concentration contributes to wage income inequality within these local labor markets.

Our results suggest that, firstly, the urban wage premium as measured by the firm-pay premia (firm fixed effects) is largely equivalent to outcomes as when basing the estimates on more standard estimators such as the Mincer equation. That is, as with the ordinary UWP estimates, these firm pay-premia also increase on average with urban population size, a result which suggests that a substantial share of the UWP as measured by way of traditional estimation approaches is related to firm level factors influencing wages, rather than merely consisting of different types unaccounted for individual level characteristics as is most often assumed in the literature.

Second, when we introduce employer concentration to our UWP estimator, this variable accounts for a substantial share – around 30 percent – of the UWP. Thus, differences in employer concentration across local industries helps explain income differences across the city size distribution. This result is further underlined by adding an interaction effect between employer concentration and population size, the outcome of which clearly suggests that the average UWP decreases with increasing employer concentration, and vice versa.

Third, addressing wage income inequality by applying our model to different segments of the local labor market income distribution, our analysis suggests that firm pay premia (firm FEs) play a relatively larger role in explaining upper and top-level income rather than lower- level income. As for the role of employer concentration in explaining this outcome, we find the largest reduction in the UWP coefficient estimate for income above the 90th percentile (explaining some 33 percent of the outcome), whereas the reduction in the UWP estimate is rather uniform for the lower income segments, at 20-25 percent. Our interpretation of this result is that relatively lower employer concentration within larger cities, and vice versa, higher concentration within smaller cities, primarily help explain the variance of top wages within these cities/labor markets.

Our paper contributes to the literature as follows: Firstly, we corroborate findings by Rinz (2022) to the extent that employer concentration affects inequality within local labor markets. However, whereas his study finds a significant positive link between inequality and employer concentration (stemming from a negative effect on lower-level wage income), our results point to a negative effect on top wage income which instead reduces wage inequality, primarily in smaller local labor markets. In this regard, our results are very much in line with predictions from the yet limited theoretical work on employer concentration and inequality outcomes (see Card et al., 2018, although this work of course lacks a geographic dimension). Second, our results adds to the literature that analyzes the role of employer concentration in explaining the urban wage premium (Hirsch, Jahn, Manning, & Oberfichtner, 2022; Luccioletti, 2022), in that we show that the urban wage premium as measured by the firm-pay premia is largely equivalent to outcomes as when basing the estimates on more standard estimators, and that employer concentration explains a substantial share of the this firm pay premia based measure of the UWP. Finally, our results corroborate the findings of studies that address employer concentration within local labor markets and average wage income. Similar to our results, these papers find negative elasticities between employer concentration and wages (Azar, Marinescu, & Steinbaum, 2022; Rinz, 2022).[2]

[2] The literature on the effects on wages of a concentration of a small number of employers (to which we can also add studies focusing on the effects of mergers and acquisitions, see e.g. Arnold, 2019; Prager & Schmitt, 2021), is but one category of the empirical evidence on the potential effects of firm wage setting power. Other studies

Our paper is organized as follows. We discuss data and variable definitions in Section 2 and our chosen empirical strategy in section 3. Section 4 details our results while section 5 concludes.

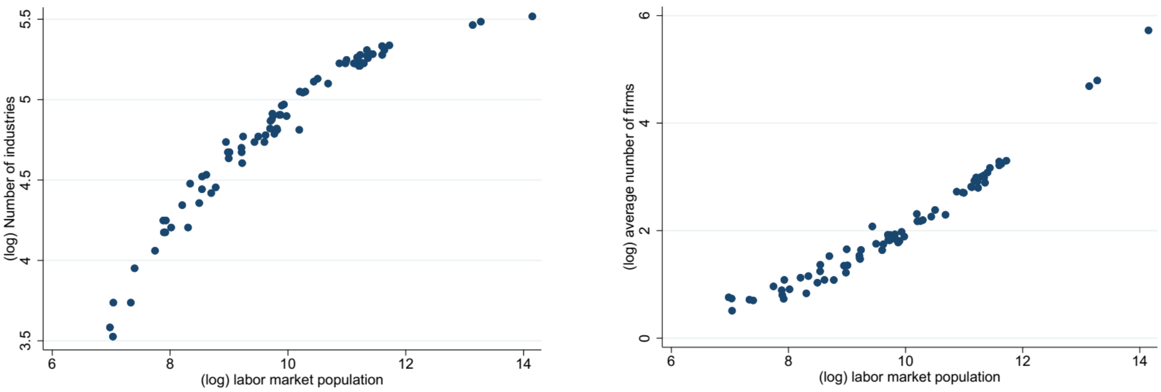
2. Data and variable definitions

Our analysis builds upon full population data from Statistics Sweden's Linda database, in which we have access to individual level data as concerns educational attainment, employment status and place of work, as well as demographic information such as age and marital status. Necessary for the study at hand, our data also includes geo-coded firm- and establishment level employer information, including revenue, value added and industrial classification codes. The data stretches from 1996 to 2015, but since we estimate both individual- and firm fixed effects and recent evidence suggests such estimators as error-prone using longer time stretches (Millimet & Bellemare, 2023), we instead study three separate six-year time periods, 1996-2001, 2003-2008 and 2010-2015. By choosing shorter periods, the estimated fixed effects not only include more information, but also allows for constructing stacked panels and tracking changes over time.

Our main unit of analysis are establishments, either as one of many establishments within a firm or a separate firm entity, which are nested within industries which in turn are nested within local labor markets. For our purposes and the time-period that we analyze, Sweden can be divided into 75 local labor market regions which essentially correspond to commuter zones (Statistics Sweden, SCB). Based on these 75 larger geographical regions, we then define an industry specific local labor market as given by employers (establishments) belonging to the same 3-digit industry. From these industries we exclude the public- and financial sector which leaves us with 258 industries in total, including both manufacturing, services, and construction.

have focused on *i)* quit- and recruiting responses to different wage levels; on *ii)* the link between wages and firm productivity; on *iii)* various forms of collusion and firm behavior aimed at suppressing employer mobility between firms. In sum, all these strands of the literature suggest non-negligible employer wage setting power. Where the effects of this power are most easily quantified (categories one and two above), estimates suggest a mark-down of marginal revenue product of around 20-25% (for recent literature reviews, see Ashenfelter, Card, Farber, & Ransom, 2022; Berger, Herkenhoff, & Mongey, 2022; Lamadon, Mogstad, & Setzler, 2022; Sokolova & Sorensen, 2021).

Figure 2. The number of industries and average number of establishments by industry across local labor market population size



Panel A: The number of industries across labor market size

Panel B: Average number of firms across labor market population size

Notes: Source: Mona database, Statistics Sweden. The number of industries refers to the number of 3-digit industries with a labor market, and the average number of firms corresponds to the average number of firms in the 3-digit industries.

Taking all 258 industries and the 75 labor market regions together would leave us with about 19 350 separate industry specific local labor markets. However, since far from all industries are represented in all the 75 regions, we end up with a total of 11 792 industry specific local labor markets in the final sample. These industry specific labor markets are distributed unevenly across regions, but as a rule the number of industries increases with local population size, from the smallest regions accommodating 32 separate industries to the largest containing 249 industry categories (see Figure 2, Panel A). The total hereby amounts to 30 136 industry specific local labor market observations across our three time-periods. These industry specific labor market regions also vary starkly in terms of the average number of establishments represented locally within each industry, an average number which also clearly is positively related to population size of the local labor market (Figure 2, Panel B).

Turning to our measure of employer concentration, we use the Herfindahl-Hirschman index (HHI) as estimated for the number of employees in establishments within each of our industry specific local labor market categories. For a given market, the HHI is commonly defined as the sum of the squared market shares for either firms or establishments within a market. In our case, the HHI is given by

$$HHI_{klt} = \sum_{j=1}^{m} \left(\frac{Emp_{jklt}}{\sum_{j=1}^{m} Emp_{jklt}} \right)^2 \quad (1)$$

where Emp_{jklt} represents the number of employees in establishment j, in industry k, and region l for time t, where m gives the total number of firms in that labor market during time-period t. Since we seek to model cross sectional relationships for three separate time periods, we opt for calculating each yearly HHI_{klt} and average these yearly measures over each of our three separate time periods p. Hence, our period specific measure of HHI is given by $HHI_{jklp} = \frac{1}{T}\sum_{t=1}^{T} HHI_{jklt}$, where $T = 6$.[3]

3. Empirical strategy

As to provide a backdrop and motivation to our own empirical strategy, we begin our analysis by estimating the Swedish UWP by way of more traditional approaches. We then highlight and discuss potential problems when employing this estimator and suggest an alternative analysis which allows us to gauge the potential role of firm level factors and labor market employer concentration in explaining the UWP. In a third stage of the analysis, based on our suggested approach, we then move on to address the role of these two factors (labor market concentration and UWP) in explaining local wage income inequality.

Since both observed and unobserved individual worker heterogeneity varies across regions, and estimation of the UWP aims to capture regional level wage determinants that go beyond such variation, the standard procedure when estimating the UWP is to, firstly, run a fixed effect regression (mincer) that controls for both observed and unobserved worker characteristics (as well as broad industry categories), while also including regional dummy variables to capture any income differences *not* picked up by these other controls. The hereby estimated regional earnings differentials are then in a second stage used as dependent variable, where they in turn are regressed on log population size (or log density). The final estimated UWP is then equivalent to the coefficient of the population size variable, capturing the elasticity between regional earnings differentials and local population (see e.g. Combes et al., 2008; Combes, Duranton, & Gobillon, 2010; De la Roca & Puga, 2017).

For an individual i working in the local labor market l at year t, we thus start by estimating the following model:

[3] As a robustness check, we also calculate an alternative HHI measure based on the *average* number of employees for each firm (and not establishment??) as well as *average* number of firms over each separate time-period, given by $HHI_{kl\overline{p}} = \sum_{j=1}^{m}\left(\frac{\overline{Emp}_{jkl}}{\sum_{j=1}^{m}\overline{Emp}_{jkl}}\right)^2$, where $\overline{Emp}_{jkl}$ gives the average number of employees in firm j, in industry k, and local labor market l within the period p. This does however not change the outcome significantly.

$$ln\,Earnings_{ilt} = \alpha_i + \beta_0 X_{ilt} + D_l Market_{lt} + \epsilon_{ilt}, \tag{2}$$

where α_i capture worker fixed effects, X_{ilt} include time-varying observable characteristics as well as industry dummy variables, and where $Market_{lt}$ is a vector of dummy variables which takes the value of 1 if an individual works in local labor market l or is zero otherwise. When estimating (2), in the presence of worker fixed effects, the effect emanating from workers staying within the same market (l) during the whole period gets absorbed by α_i. Hence, the identification of D_l (representing our local labor market earnings differential) comes solely from individuals that move between labor markets, *l,* to a job within either the same or a different industry.

When using worker mobility to identify the regional earnings differentials, note that mobility in this sense also requires the worker to change jobs (employment in a firm). Thus, part of an explanation behind the earnings differential potentially stands to be found in the characteristics that reside at the firm level (e.g., firm specific pay premia). Without taking such firm fixed effects into account, we risk having variables in X be correlated with the firm fixed effects, which in turn may affect the β_0-estimate in (2). If the same variables (in X) are also correlated with the local labor market dummy variables, the estimates of the latter may clearly also be affected. Furthermore, if we also suspect that such potential firm fixed effects (firm pay premia) may be meditated by competition for workers taking place locally and within industries (which recent studies in the monopsony literature strongly suggest), it is immediately clear that such effects cannot be captured using equation (2). The regional unit of analysis (local labor markets) is simply too high in terms of aggregation level to allow for adding such controls.

We choose therefore to extend current urban wage premium estimation approaches in two ways. Firstly, we introduce a firm fixed effect directly into the model (2). Abstracting a moment from the regional dummy variable ($D_l Market_{lt}$) in equation (2), introducing such firm level factors results in the well-known AKM-model which stipulates that log earnings can be written as a loglinear function of fixed unobserved characteristics at both the worker- and firm level, together with an index of time varying covariates (Abowd, Kramarz, & Margolis, 1999). Doing so allows us to estimate to what extent both individual- and firm level factors contribute to wage income, and by extension – as we further argue below –it also allows for an analysis where not only individual level factors, but also firm fixed effects are considered when estimating the UWP. Secondly, to be able to model the way in which the degree of local competition for workers may affect variation in firm FEs (often referred to as *firm pay premia*), we assign individuals to firms nested within locally situated industries (industry-by-regions). As compared to using local labor markets as in (2), we thus shift the unit of analysis to individuals working in firms nested in industries within local labor markets (as e.g., in Rinz, 2022).

When adding these two aspects mentioned above, for individual *i* working in firm *j* within industry-by-region *kl*, equation (2) thus reads as:

$$ln\ Earnings_{ij(kl)t} = \alpha_i + \psi_{j(kl)} + \beta_1 X_{ij(kl)t} + D_{kl} Markets_{klt} + u_{ij(kl)t} \tag{3}$$

where (as in equation 2) α_i and $X_{ij(kl)t}$ capture worker fixed effects and possible time varying observable worker characteristics, $\psi_{j(kl)}$ is the firm fixed effect, and $Market_{(kl)t}$ is our industry-by-region dummy variable which takes the value of 1 if an individual works in firm *j* operating in industry *k* located in labor market *l*.

In this alternative AKM approach to UWP estimation, where firm fixed effects are accounted for in addition to individual level factors, the new estimate of beta (β_1) does likely not suffer from the same problem as when using (2). Note however that on the basis of model (3) we cannot directly estimate the earnings differential between industry-by-regions conditional on both individual and firm-level fixed effects, since the industry-by-regions fixed effect (D_{kl}) is subsumed by the average firm fixed effect by construction (i.e., there is no individual level variation – job changes – on which basis such differences can be estimated). But instead, following the same logic as in traditional UWP estimation approaches using (4) below, we can now arrive at a new estimate of the earnings differential across local labor markets by regressing our estimated firm fixed effects ($\psi_{j(kl)}$) on our region categorical dummy variables (industry-by-regions).

$$\widehat{\psi_{j(kl)}} = a + D_{kl} Market_{kl} + e_{j(kl)}. \tag{4}$$

Since these firm fixed effects were estimated conditional on β_1, estimates of these local labor market differentials do not appear to be affected by the source of endogeneity as outlined previously (estimating equation 2).

Due to the large number of *kl*-dummy variables (around 11 000 separate categories), however, running this regression is not feasible. Instead, the estimate $\widehat{D_{kl}}$ can simply be arrived at by taking the average of the estimated firm fixed effects within each industry-by-region category. We repeat this procedure for each of the three period estimates of the AKM model, leaving us a stacked panel with at most three period observations for each industry-by-labor market. [4]

Using the above regional earnings differentials (based on firm fixed effects, captured by our industry-by-region categorical variables) as a basis for UWP estimation in equation 5 below, and comparing these estimates to those arrived at by way of ordinary UWP estimation in equation 2 (in Table 2), we are hereby able to gauge the extent to which these firm level factors may exert influence within ordinary UWP estimation. On the basis of equation (5), following a similar approach as in Hirsch et al. (2022), we can then also address potential causes of this variation in firm pay premia, specifically the potential role of local labor market employer concentration.

$$\widehat{D_{klp}} = a + b \ln Pop_{lp} + cHHI_{klp} + d_{kp} + e_{kl} \tag{5}$$

In (5), $\widehat{D_{kl}}$ is the average firm fixed effects at the local industry-by-region level (as estimated using model no. 4 above), a is the intercept, and b, since we use the log of local population size, captures the percentage change in average firm fixed effects from a percentage change in local labor market population. In a stepwise regression fashion, we then add within-industry employer concentration ($cHHI_{klp}$) and examine its effect on the variation in firm pay premia by analyzing how b thereby changes. We should note that the using (5), we include separate industry fixed effects for each period, and thereby control for differences that may be due to e.g., different national or international level of competition, capital intensity, industry specific human capital or differences in unionization rates.[5] Lastly, and importantly, these controls should also capture industry specific shocks in a period, which is not accounted for using our leave-one-out instrument. All regressions are weighted by the size of the labor force in each *kl*-market.

To conclude, our estimation of the urban wage premium is thus equivalent to the more standard approaches in the literature insofar that it is based on the variation in wage income that cannot

[4]Note that, compared to the model without firm fixed effects (our Mincer model, equation 2), identification of the market fixed effects in (4) does not rely on individuals who move between markets. Instead, it reflects the differences in the (employment weighted) average of the (estimated) pay-premia across industry-by-regions once individual specific fixed heterogeneity has been accounted for. In the data treatment- and modelling do-file syntax that accompanies this paper (available upon request) we show that these two estimation methods yield the same results when applied to a smaller sample of the full population data.

[5] This control is therefore important, since the Swedish labor market is a highly regulated affair encompassing more than 700 collective agreements, governing the bargaining power between the mostly unionized employees (around 90%). These collective agreements are however mostly organized around industry categories, which simplifies our estimation strategy.

be explained by *individual level* observed or unobserved factors. Our extension of these estimation approaches, however, allows for taking observable and unobservable firm level factors into account, and to further analyze how these firm pay premia vary across urban population size and factors that may influence this variation. [6]

Local labor market earnings inequality

In our final focus of the paper, addressing the potential role of employer concentration in explaining local labor market inequality, we face a dilemma. On the one hand, if we chose to relate employer concentration to a model in which the dependent variable, in the form of a local inequality measure, is based on ordinary income, we cannot account for the potential influence of unobserved heterogeneity at the worker level. On the other hand, if we choose to model inequality estimates solely based on firm fixed effects (derived by way of AKM estimation), and thereby taking individual fixed effects into account, we lose the direct link to local levels of income inequality, the focus of our analysis.

We therefore opt for an analysis where we focus on individuals within different segments of the local income distribution, either corresponding to the tails of the distribution (below the 10^{th} and above the 90^{th} percentile) or two broader income segments below and above the 50^{th} percentile (10><50, 50><90). Estimating model no. 5 using these four subsets of the local income distribution instead of the full sample, we can establish a link between earnings outcome, firm pay premia, and employer concentration and assess the role of employer concentration in accounting for local levels of the average firm premia for workers in the different segments of the earnings distribution. We further discuss our strategy below in the results section.

Causality identification and interaction effects

There is a potential problem with our second step specification using (5) above in that earnings and local labor market concentration may be endogenous. That is, if there are shocks to the local industry which affect both earnings among firms and labor market concentration, HHI

[6] In specifying the AKM model, we follow Card, Cardoso, and Kline (2016) and control for the square and cube of worker age centered at 40, not including the linear term in the model. Following Dauth et. al. (2022) we also separate demographic variables based on five educational categories, which are all interacted with the squared and cubed age variable in the model. Finally, when estimating the AKM model including all fixed effects, we adopt the iterative approach as suggested by Guimaraes and Portugal (2010).

becomes endogenous and any attempt to causally interpret our findings becomes problematic. To remedy this problem, following Rinz (2022) and Azar et al. (2022), recent studies that address highly similar topics, we instrument our HHI$_{klp}$ for a given industry k located in labor market l by predicting HHI from a weighted average of the HHI for the same industry but over all other labor markets. The instrument is thus given by

$$HHI_{kl\overline{p}}^{IV} = \sum_{s \neq l} HHI_{ksp} \frac{\overline{Emp}_{ksp}}{\sum_{s \neq k} \overline{Emp}_{ksp}} \tag{6}$$

where – for time-period p – the summation is taken within industry k overall regions s except for the l-region. Each HHI_{ksp} is here weighted by its relative employment share of the total number of employees working in industry k except for in the l-region, where $\overline{Emp}_{ksp}$ refers to the average number of employees in industry k, labor market s over the years in period p. Our IV estimation strategy thereby represents a typical "leave-one-out" instrument (see further discussion below as related to the results, in section 4).

Finally, to further probe the role of HHI, we extend the basic specification in (5) by incorporating the interaction between HHI and our population size variable into the model (thereby allowing the UWP to be dependent of the level of HHI). We thus also consider the following model,

$$\widehat{D_{klp}} = a + b \ln Pop_{lp} + cHHI_{klp} + d \ln Pop_{lp} HHI_{klp} + d_{kp} + e_{klp}. \tag{7}$$

In this model, UWP is expressed as a possible function of HHI such that $UPW = b + dHHI$, where b gives the UWP when $HHI = 0$ and $b + d$ the UWP when $HHI = 1$. As we move from less to more populated labor markets, we expect that workers in less concentrated local industries to have higher UWP compared to workers in more concentrated industries. In terms of the estimated UWP, we thus expect $d < 0$.

4. Results

In this section, we present results for the estimates of the urban wage premium and local labor market concentration, both at the level of local labor markets and at the level of industry-by-regions. Results represent average estimates for the periods 1996-2001, 2003-2008 and 2010-2015. Panel A in Table 1 shows the estimates for average earnings using model 2, estimates which are equivalent to the more common methods of UWP estimation. Panel B, in turn, shows the results of using the same estimator (2) but changing the level of analysis to locally situated industries (industry-by-regions). Finally, Panel C shows the average firm fixed effects from our main modelling approach using model 5.

The first column of all three panels shows the correlation between labor market population for the respective dependent variable, i.e., an elasticity corresponding to either of our two measures of the urban wage premium, one based on individual earnings and another on firm fixed effects. In column (2), we show the correlation between each of our earnings measure and labor market concentration as given by the HHI. To the extent the UWP depends on the level of concentration in industries within the local labor market, we estimate the UWP in column (3) when controlling for the HHI. To deal with the potential endogeneity of HHI, in column (4) we show estimates of the same model but instrumenting for HHI using the "leave one out" instrument as defined in specification (6).

Starting with our UWP estimates in column (1), we see – firstly – that estimates of the traditional UWP using individual earnings but changing the level of aggregation from local labor markets in Panel A to industry-by-regions in Panel B, are fully equivalent (both at 0.0126). Thus, importantly for our subsequent reasoning, changing the level of analysis in this regard does not affect the outcome, and the use our industry-by-regions rather than local labor markets as unit of analysis (our preferred specification 3) is only consequential in terms of the questions we can address and the controls we can add when estimating the outcome.

Second, note that when substituting earnings (Panel A and B) for firm fixed pay premia as dependent variable (Panel C), the outcome is about the same, and even slightly higher, than when using individual earnings as dependent variable (0.0143 as compared 0.0126).[7] Importantly, since all three of these estimators take the same individual level factors into account (observed and unobserved), and the resulting UWP estimates are largely similar, this result suggests that a substantial share of the UWP as measured by way of traditional estimation approaches is related to firm level factors influencing wages rather than merely unaccounted for individual level characteristics.

[7] Note: The estimated elasticities imply that a 1 percent increase in local population size is associated with 0.0126 and 0.0143 percent increase in earnings and the firm wage premium, respectively. Using Panel C estimates, and going from a population size of e.g., 10 000 to 100 000, and 100 000 to 1 000 000, translates into a premium of 0.143 percent and 1.43 percent for each tenfold increase in the underlying size of the local labor market.

Table 1. Results for the urban wage premium and labor market concentration

	(1)	(2)	(3)	(4)
Panel A: UWP estimate based on local labor markets and first stage regression with worker fixed effects (mincer equation)				
Dependent variable: average earnings (log)	OLS	OLS	OLS	IV
Labor market population (log)	0.0126***		0.0315***	0.0816***
	(0.00181)		(0.00979)	(0.0162)
Herfindahl-Hirschman index		-0.123***	0.194**	0.708***
		(0.0223)	(0.0940)	(0.169)
Constant	-0.161***	0.0503***	-0.482***	
	(0.0212)	(0.0120)	(0.163)	
Observations	225	225	225	225
R-squared (adj.)	0.650	0.599	0.678	0.478
Kleibergen-Paap				9.110
Panel B: UWP estimate based on industry-by-regions and first stage regression with worker fixed effects (mincer equation)				
Dependent variable: average earnings (log)	OLS	OLS	OLS	IV
Labor market population (log)	0.0126***		0.0147***	0.0100***
	(0.00166)		(0.00144)	(0.00120)
Herfindahl-Hirschman index		-0.0428***	0.0266**	-0.0326
		(0.0160)	(0.00716)	(0.0120)
Constant	-0.161***	0.0102	-0.194***	
	(0.0196)	(0.00944)	(0.0176)	
Observations	30,219	30,219	30,219	30,219
R-squared (adj.)	0.584	0.540	0.587	0.096
Kleibergen-Paap				81.28
Panel C: UWP estimate based on industry-by-regions and average firm fixed effects (AKM model estimates)				
Dependent variable: average firm fixed effects	OLS	OLS	OLS	IV
Labor market population (log)	0.0143***		0.0168***	0.0100***
	(0.00197)		(0.00167)	(0.00254)
Herfindahl-Hirschman index		-0.0475**	0.0321***	-0.0545**
		(0.0191)	(0.00956)	(0.0256)
Constant	-0.183***	0.0112	-0.223***	
	(0.0231)	(0.0112)	(0.0208)	
Observations	30,219	30,219	30,219	30,219
R-squared (adj.)	0.632	0.618	0.657	0.077
Kleibergen-Paap				81.27

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-(Correia, 2017)Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

Turning to industry specific local labor market concentration (in Column 2) there is a negative association between HHI and our individual earnings' measure in Panel A and B, as well as between HHI and the firm pay premia in Panel C. Thus, traversing the full range of the HHI from 0 to 1 (from low to high employer concentration) is associated with lower earnings, by approximately -12.3 percent for earnings in Panel A and by -4.75 percent in terms of the firm pay premium in Panel C.

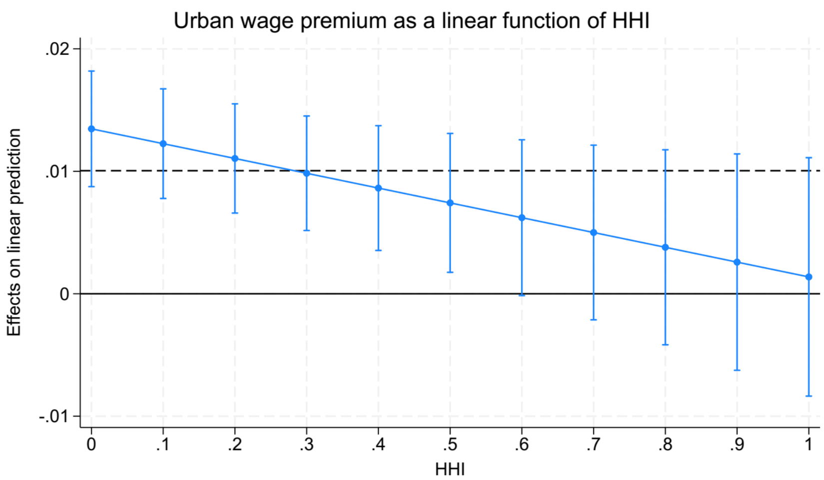
Henceforth focusing on the results from our main specification in Panel C, when controlling for both population size as well as the level of labor market concentration, in Column (3), the UWP increases slightly with the coefficient on HHI turning positive. At the face of it, labor market concentration thus seems to be of limited importance for the UWP. As discussed in the previous section, however, a central concern using our primary specification lies in the potential endogeneity of the Herfindahl-Hirschman Index (HHI). The risk stems from the HHI's possible correlation with unobserved variables, such as productivity shocks, which could simultaneously influence both concentration and earnings. Specifically, in case of a productivity shock within a given industry-location, it could alter firms' recruitment strategies, thereby affecting both the industry's concentration ratio and its average wage rates.

To mitigate the bias stemming from this endogeneity, we deploy an instrumental variable (IV) approach that capitalizes on geographical variation within industries to instrument for the HHI. Specifically, we construct a 'leave-one-out' instrument, an approach substantiated by recent works by Rinz (2022) and Azar et al. (2022), from the weighted average HHI of the same industry across all other local labor markets. The instrument is designed to be orthogonal to any local industry-specific shocks, given its reliance on national-level variations in the HHI for a particular industry. Nevertheless, the independence of the instrument from local shocks introduces certain limitations that warrant discussion. For instance, the instrument is ill-suited for addressing a national-level shock affecting an entire industry, which would invariably influence both labor market concentration and average earnings across various local markets. Similarly, the instrument is inadequate for capturing the effects of spatially correlated productivity shocks, which may propagate from one local labor market to adjacent markets, thereby retaining endogeneity concerns.

In Table 1, Column 4 in Panel C, when using our instrument HHI variable (as outlined in model 6 above), we recover a negative coefficient on HHI, and slightly larger in size as compared to Column 2. For the UWP on the other hand, adding the instrumented HHI to the regression reduces the UWP to a statistically significant point estimate of 0.01. Thus, employer concentration captures a substantial share – around 30 percent – of the variance of the UWP. Note also that results both in Panel B – the Mincer equation estimate of the UWP – and results in Panel C are very similar, something which further strengthens our conclusion that modelling the average UWP by way of firm FEs is largely equivalent to traditional Mincer type UWP estimation.

To further shed light on this outcome, to our main model we also add an interaction effect between HHI and population size (model no. 7), capturing the way in which the predicted UWP varies with local industry concentration (HHI). As highlighted in Figure 3 below, although the estimate turns statistically insignificant for very high levels of HHI, the result clearly suggests that the average UWP decreases with increasing employer concentration, and vice versa.

Figure 3. The urban wage premium as predicted by local industry level concentration (HHI)

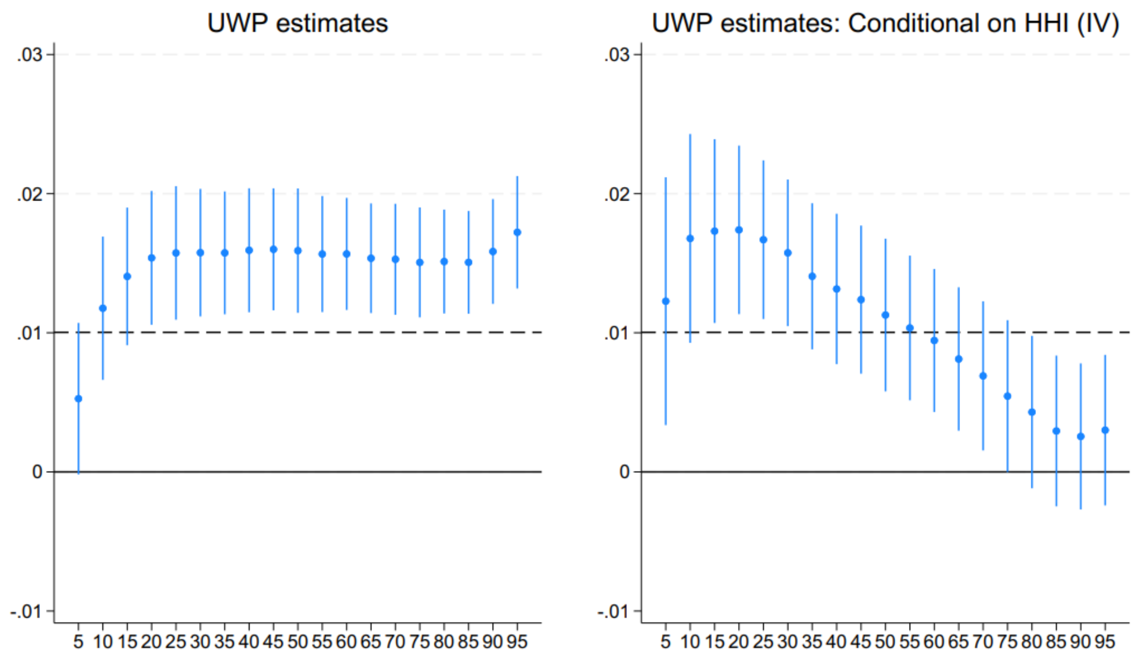


Notes: The figure shows the predicted effect of UWP as a linear function of HHI. The model corresponds to the IV-model as presented in column (4) in Table 1 Panel C fitted with an additional interaction term as described in equation (7). The bars here correspond to 95 percent confident intervals and where the dashed horizontal line shows the UWP estimate in the IV model from Table 1 and Panel C as a reference. The dependent variable in the regression is the industry-by-region differences in firm fixed effects, estimated in a first-step AKM model. The model includes fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI.

Heterogeneity analysis

Finally, it is important to probe the heterogeneity the firm-fixed effect outcomes arrived at when using our main specification. To do so, we refocus model no. 5 on different percentiles of the distribution of firm fixed effects (rather than the mean) to gauge *i)* whether and to what extent the average effects in Table 1 (Panel C) can be accounted for by differences in the tails of the firm fixed effect distribution, and *ii)* in more detail analyze how employer concentration accounts for the size distribution of these firm fixed effects.

Figure 4. Outcomes from model no. 5 as conditioned on percentiles rather than the mean, without (left hand plot) and with (right hand) controlling for employer concentration. Note: the dotted horizontal line signifies the average estimate.



Panel A: Percentile estimates without HHI control **Panel B:** Percentile estimates with HHI

Notes: The figure shows the UWP estimates from several regressions without (Panel A) and with (Panel B) control for HHI. The dependent variable in these regressions refers to the corresponding percentile firm fixed effects at the industry-by-region level, estimated in a first-step AKM model. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model (Panel B) uses the "leave-one-out" instrument to account for potential endogeneity of HHI. The bars correspond to 95-percent confidence intervals, and where the dashed horizontal lines the estimate for the average model from Table 1 in Panel C column (1) Panel A and column (4) in Panel B.

We present the main results in Figure 4 above. Along with their 95 percent confidence intervals, the first plot (left) shows the parameter estimates for log population elasticity corresponding to the model in column 1 in Table 1, Panel C, but where separate regressions are run for different percentiles of the firm fixed effect distribution, starting from the 5th percentile up to the 95th (where each rightward step on the x-axis corresponds to a 5-percentile shift). The second (right hand) plot corresponds to the same elasticity but using the IV model, controlling for the level of HHI as instrumented with the leave-one-out instrumental variable, and where the estimates correspond to that of column 4 of Table 1 above (in Table A1, Appendix 1, we also present the results with full details for a select number of percentiles).

Although there are clear differences in the tails of the distribution, the results (left-hand plot) point to a situation where the estimated urban wage premium is fairly constant across the percentiles of the firm fixed effect distribution across industry-by-regions. However, once we control for employer concentration (HHI, in the right-hand plot), we see a clear tapering off for the wage premium within industry-by-regions with large firm FEs, i.e. for the higher percentiles if firm FEs. In other words, the higher percentile of firm FEs, the larger is the effect – or explanatory power – of labor market concentration as measured by the HHI.

Noteworthy also, as we see in Panel B in Table A1, which contains the underlying tables for select percentile estimates shown in Figure 4, coefficient estimates for the instrumented HHI are positive for the 5th and the 25th but statistically insignificant (and adding the control actually *increases* the original UWP coefficient somewhat, rather than reducing it as previously using our main model, as shown in Table 1). From the median and upwards, however, the estimated HHI coefficient is negative, and above the median of the firm FE distribution, its' addition to the regressions also renders the UWP estimates insignificant. Applying our reasoning from our analysis of average effects in the prior section, following Hirsch et al (2022), it thus seems as if employer concentration plays a relatively larger role in explaining the largest firm pay premia.

So, to conclude, from Table 1 and the negative association between HHI and firm FE (Panel C), we know that a higher concentration leads to a lower firm pay premium, or reversely, that lower labor market concentration is related to higher such premiums. As we showed earlier in Figure 1 (Panel B), when we move from smaller to larger labor markets the degree of labor market concentration in local industries is on average lower. Hence, across the city size distribution, the average local industry concentration decreases as we move from smaller towns to larger cities. As we interpret the population size elasticity, any larger income that is associated with this drop in concentration rates is contained in the raw UWP estimate, and as we control for HHI, we effectively remove from the UWP estimate the (positive earnings) effect that comes from lower HHI (and the remaining UWP coefficient is therefore smaller).

When we instead look at different percentiles of the firm FE distribution, the interpretation is analogous. However, it is only for the higher percentiles that we observe a significantly lower

UWP when we control for HHI. Our interpretation is that labor market concentrations are more relevant in explaining differences in higher levels of firm fixed effects. Thus, the reason for why a particular labor market (industry-by-region) has a higher p95 than other labor markets market is closely connected to it having a lower HHI. This connection appears to be less relevant (weaker) for differences between labor markets in terms of their p50 and below (where one market e.g. having a higher p50 is much less related to it having a lower HHI).

Because of the stronger negative effect from HHI for the highest percentiles of firm fixed effects, we can also conclude that HHI negatively affects the dispersion in firm-fixed effects by way of curbing the highest premia. In other words, the higher the employer concentration within local labor markets, the lower is the firm pay premia within those labor markets. Thereby, local labor-market size and local industry concentration affect the dispersion of firm fixed effects (firm pay premia), i.e., both these factors affect its variance across the across the city size distribution. Further, because the variance of firm fixed effects constitutes one component of the variance in earnings, the above analysis also suggests a possible a channel through which labor-market size and local industry concentration can impact earnings inequality, the final research question to which we now turn.

Inequality and employer concentration

Next, we turn the focus to inequality in earnings outright and address the potential role of firm pay premia and employer concentration in explaining local levels of wage income inequality.

To gauge this question, by directly linking firm fixed effects to the different parts of the local[8] wage distribution and specifically modelling the role of employer concentration in explaining these firm fixed effects, we choose to estimate our main model no. 5 using four subsets of the sample of individual workers that figured in the AKM model; two of which pertain to workers in either tail of the (local) income distribution (individuals earning either below the 10^{th,} or above the 90th earnings percentile, respectively); and two that contain individuals within two broader income segments, either below or above the 50th percentile (i.e., 10th < 50th, 50th >90th). For each segment of the workforce, we then calculate the average firm fixed effect for each industry within each of the 75 labor markets. By using the same model as previously used in our full sample analysis (as in Table 1) but substituting the four respective subsets for the full sample, we can now assess the role of employer concentration in accounting for local levels of

[8] By local we refer to the level of a specific industry within a given labor market.

the average firm premia for workers in the different segments of the earnings distribution. Thereby, we establish a link between earnings outcome, firm pay premia, and employer concentration.

Hereby, we can gauge *i)* whether the UWP (as measured by way of firm fixed effects) is uniform across different segments of the earnings distribution, and *ii)* analyze to what extent employer concentration helps explain potential differences in UWP that we find within these different income segments. [9]

Although this analysis is potentially problematic in terms of sample selection on the outcome variable, something which limits the degree to which we can draw exact inference, we believe that this analysis constitutes our best available option in seeking to link an individual's placement within the local earnings distribution – in broad categorical terms – to firm pay premia, and employer concentration.

The results are contained in Table 3 below, showing estimates of two versions of model no. 5 for each of our four subsets of the sample (as outlined per the above). In Panel A, we include only the variable for population size while our control for employer concentration (the instrumented Herfindahl-Hirschman index) is added in Panel B. Focusing on results using the first estimator, shown in Columns 1, 3, 5 and 7 in Table 4, we see that the UWP (as measured by the firm pay premium) pertains to all segments of the income distribution, and that it is larger for the higher income segments (at 0.009 and 0.012 for the two lowest income categories, and at 0.016 for the 50^{th}-90^{th} percentile and 0.021 for those with earnings above the 90^{th}).

[9] Because of how our data is structured, we cannot link each individual's *placement* within the industry-by-region earnings distribution to a particular firm fixed effect, since all workers within a firm are assigned the same firm fixed effect, regardless of their wage level. Because of this, we cannot – for instance – run a percentile regression of the full local labor market earnings distribution and control for our firm FEs and other variables of interest.

Table 3. Urban wage premium from second-step regressions population categories

	INC <10		10> INC <50		50> INC <90		INC >90	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES:	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Labor market pop.	0.009***	0.007**	0.012***	0.009***	0.016***	0.011***	0.021***	0.014***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Industry conc. (HHI)		-0.028		-0.044*		-0.063**		-0.088***
		(0.030)		(0.026)		(0.024)		(0.028)
Constant	-0.165***		-0.171***		-0.187***		-0.023***	
	(0.018)		(0.021)		(0.025)		(0.03)	
Observations:	27,419	27,419	30,173	30,173	29,618	29,618	30,219	30,219
R-squared:	0.659	0.019	0.664	0.050	0.641	0.094	0.582	0.136
Kleibergen-Paap		80.60		81.26		81.18		81.28

Notes: Dependent variable refers to the industry-by-region average in firm fixed effects for workers in the corresponding earnings categories. Fixed effects are estimated in a first-step AKM model. All models here include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the “leave-one-out” instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

Thus, what this analysis so far suggests is that firm FEs play a relatively larger role in explaining upper and top-level income rather than lower-level income.

Turning to our IV estimates in Columns 2, 4, 6 and 8, and the potential role in of employer concentration in accounting for the increasing UWP estimates, we find that there is a negative effect of the Herfindahl-Hirschman index for all our income segments, and that adding HHI reduces the UWP regardless of the income bracket that we focus on. Even though the largest reduction is linked to top income, the reduction in the UWP estimate is fairly uniform across the income distribution: below the median it is between 20-25%, while the equivalent numbers for the 50^{th}-90^{th} and above the 90^{th} percentile income segment is 25 and 33 percent, respectively. The size of the HHI coefficient also increases for higher income segments, but only turn statistically significant for income above the 10^{th} percentile and only weakly so for both the 10^{th}-50^{th} percentile and the 50^{th}-90^{th} percentile income bracket.

Thus, we find that firm FEs on average increase with the income segment that we focus on. As for the role of employer concentration in explaining this outcome, following Hirsch et al (2022) and our reasoning as earlier in the text regarding the average UWP estimates, we find the largest reduction in the UWP coefficient estimate for income above the 90^{th} percentile (explaining some 33 percent of the outcome), whereas the reduction in the UWP estimate is rather uniform for the lower income segments, at 20-25 percent. Our interpretation here is that for higher wage income, a larger share of the urban wage premium can be accounted for by differences in labor market concentrations as measured by the HHI.

To conclude, our analysis above suggests that while firm pay premia increase with population size rather uniformly across the local wage income distribution, we find that employer concentration captures more of the variation of (i.e., it plays a larger role in explaining) top-level income as compared to below the 90^{th} percentile and below the median. Our interpretation of this result is that relatively lower employer concentration within larger cities, and vice versa, higher concentration within smaller cities, primarily help explain the variance of top wages within these cities/labor markets.

Finally, it is important to note that even though these firm pay premia increase with the size of local population, and the levels of monopsony explain an important part of the variance in these firm fixed effects, a question remains as to what relative role these two factors have in explaining the totality of the positive population size - income inequality relationship. To address this final issue, we estimate a bivariate regression using the ratio between the local labor market variance in firm fixed effects and the local labor market variance in earnings as dependent variable, and the UWP variable of population size. What we obtain (in Table A2 in the appendix) is a slightly negative coefficient estimate, a result which suggests that while the variance in firm fixed effects increases with population size, the variance in raw earnings increases to an even larger degree. Thus, while larger firm pay premia in larger cities, related to – and likely enabled by – lower levels of employer concentration, are an important part of the explanation of higher wages in larger local labor markets, they are by no means the whole story: The variance in firm fixed effects is fairly constant across the city size distribution, and the increasing inequality and variance in total earnings as we move from smaller to larger cities is also – which we of course know from previous research – closely related to increasing variance in individual level income determinants.

5. Concluding discussion

In this paper, we build upon recent progress within the literature on firm productivity, rent sharing and firm wage setting power and analyze to what extent the urban wage premium and wage income inequality within Swedish local labor markets can be explained by varying degrees of local labor market employer concentration, as measured by the number of employers for locally situated industries across the urban hierarchy (the geographic city-size distribution) and over time.

As we argued by way of introduction, our paper hereby addresses an evident gap between two still largely separate literatures: On the one hand, the many research efforts to address the root causes of macro level changes in dispersion in wages and income, now extended to include firm level factors related to firm productivity and employer concentration. On the other, the vast and still growing literature in regional science as concerns the causes and effects of agglomeration and explanations of the so-called urban wage premium (i.e., why larger cities pay more).

We start our analysis by addressing the urban wage premium and its potential links to varying degrees of employer concentration in local labor markets. Instead of using a more traditional approach of estimating the urban wage premium (UWP) by way of a Mincer equation, explaining wage levels in terms of observable and unobservable individual level characteristics, we build upon an AKM-framework (Abowd et al., 1999) which also allows for estimating the contribution of firm fixed effects (or firm pay premia) when addressing the causes of different wage levels.

Thereby also controlling for individual level characteristics, we find that the contribution from firm level factors (firm productivity and rents) to earnings increases with local labor market size (in the order of around 0.014 percent increase for every 1 percent increase in population size). Further, our results also suggest that measuring the urban wage premium by the firm-pay premia (firm fixed effects) is largely equivalent to outcomes as when basing the estimates on more standard estimators such as the Mincer equation. That is, as with the ordinary UWP estimates, these firm pay-premia also increase on average with urban population size, a result which suggests that a substantial share of the UWP as measured by way of traditional estimation approaches is related to firm level factors influencing wage income (rather merely reflecting unaccounted for individual level characteristics, such as selection and matching as is most often discussed in the literature.

Further, when we explore to what extent this average urban wage premium pertains to different segments of the local income distribution, in Table 3, we find that it is larger for workers with higher wages. Our analysis hereby suggests that firm pay premia (firm FEs) play a relatively larger role in explaining upper and top-level income rather than median and lower- level income.

In terms of explaining the empirical findings, we find that adding employer concentration to our UWP estimator, this variable accounts for a substantial share – around 30 percent – of the UWP. Thus, differences in employer concentration across local industries helps explain income differences across the city size distribution. As illustrated in Figure 3, this result is further underlined by adding an interaction effect between employer concentration and population size, the outcome of which clearly suggests that the average UWP decreases with increasing employer concentration, and vice versa.

As for the role of employer concentration in explaining differences in wage income inequality, we find the largest reduction in the UWP coefficient estimate for income above the 90th percentile (explaining some 33 percent of the outcome), whereas the reduction in the UWP estimate is rather uniform for the lower income segments, at 20-25 percent. Our interpretation of this result is that relatively lower employer concentration within larger cities, and vice versa, higher concentration within smaller cities, primarily help explain the variance of top wages within these cities/labor markets.

We should note that the results of our analysis likely constitute a lower bound of the association between employer concentration and the UWP. For example, since we add local industry period fixed effects (industry-by-period FEs) in all our estimates, our estimated coefficient for employer concentration solely reflects dynamics within local industry-specific labor markets. As we illustrate in Panel B in Figure 2 (page 8), since there are clear differences in terms of the geographic spread of industries (some industries are represented only in the largest or larger cities, i.e., furthest to the right in the figure), while some are represented in every city or local labor market (furthest to left in the figure) there is also a possible employer concentration dynamic that is non-local and happening on a national level across all regions. Indeed, when dropping our industry-by-period dummy variables the coefficient estimates of HHI (our employer concentration variable) increases in size substantially. We leave an analysis of this separate dynamic for future research efforts.

Lastly, it is worth pointing out that our results are in line with studies which point to increasing dispersion in firm productivity and rent sharing as a potentially important factor when explaining changes in wage inequality over time (as found in e.g., Barth et.al., 2016). The results also strongly suggest that employer concentration is important for understanding regional income differences and the urban wage premium, a hitherto largely overlooked factor in this context.

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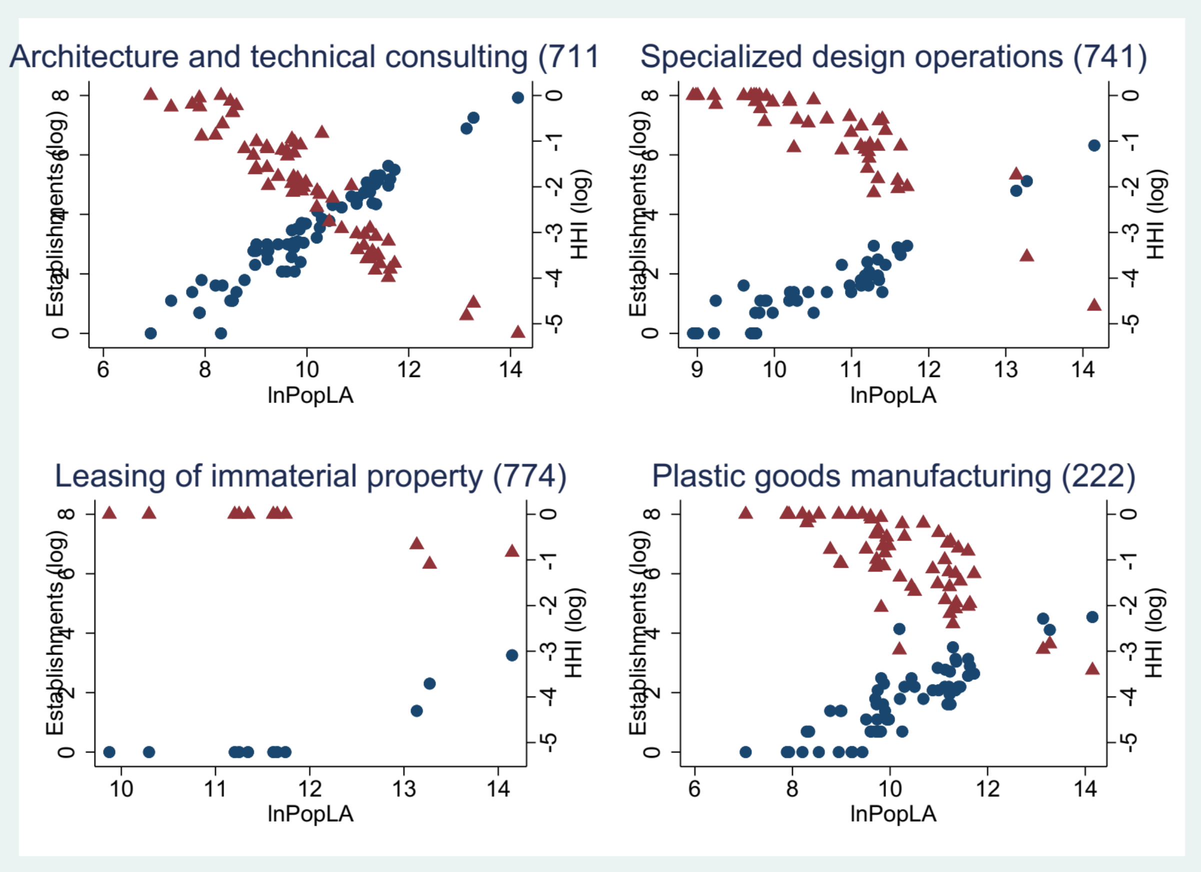
Appendix 1:

Figure A1. Examples of between-industry variation in the number of local firms represented within a certain industry (y-axis, left), and the local Herfindahl-Hirschman Index (y-axis, right) as related to local population size (x-axis).



NOTE: Tringles (red) signify the log Herfindahl-Hirschman Index, and dots (blue) the log number of local establishment represented within the industry.

Table A1. The percentile distribution of the UWP as measured by way of firms FEs, with and without controls for employer concentration (Panels A and B)

	(1)	(2)	(3)	(4)	(5)
Firm FE distribution:	P(5)	P(25)	P(50)	P(75)	P(95)
Panel A	OLS	OLS	OLS	OLS	OLS
Labor market pop. (log)	0.005*	0.016***	0.016***	0.015***	0.017***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-0.288***	-0.251***	-0.190***	-0.127***	-0.048*
	(0.035)	(0.029)	(0.027)	(0.024)	(0.026)
Panel B	IV	IV	IV	IV	IV
Labor market pop. (log)	0.012***	0.017***	0.011***	0.005*	0.003
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Local industry conc.	0.090*	0.012	-0.059**	-0.123***	-0.182***
	(0.050)	(0.030)	(0.024)	(0.021)	(0.029)
Observations	30,219	30,219	30,219	30,219	30,219
R-squared	0.065	0.095	0.075	0.096	0.145
Kleibergen-Paap	81.28	81.28	81.28	81.28	81.28

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2. Bivariate regression estimate of the ratio of the local labor market variance in firm fixed effects and the local labor market variance in earnings (dependent variable), and population size (control).

	(1)
	Var fe/Var y
	OLS
Labor market pop. (log)	-0.0132***
	(0.00225)
Constant	0.303***
	(0.0287)
Observations	30,187
R-squared	0.044

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 2.

In this appendix, we gauge the robustness of the main results presented in Table 1 and Table A2 by discussing results from several alternative specifications.

Exclude monopsony markets with HHI = 1

For our definition of markets as 3-digit industry by 75 labor market regions, we document a significant share of the observations (units) with a single firm employer. Out of a total of 30,219 industry-by-region observations, 8,512 (or 28%) are monopsony markets in the sense that HHI = 1. In Table AA.1, we show the results from estimation the main model in equation (3) without monopsony markets. The results are very much in line with those presented in Table 1. Comparing the UWP estimate when instrumenting for HHI to the results from our main specification in column 4 of Table 1, we find an estimate of 0.010 in both models, with a difference that arises only at the fourth decimal.

Table AA1. Estimates when excluding monopsony markets (HHI=1)

	(1) ols	(2) ols	(3) ols	(4) IV
Labor market population (log)	0.0145***		0.0172***	0.0103***
	(0.00197)		(0.00166)	(0.00252)
Local industry HHI		-0.0454**	0.0395***	-0.0598**
		(0.0215)	(0.0111)	(0.0268)
Constant	-0.186***	0.00922	-0.230***	
	(0.0233)	(0.0114)	(0.0208)	
Observations	21,707	21,707	21,707	21,707
R-squared	0.711	0.672	0.714	0.086
Kleibergen-Paap				68.04

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

Accounting for any assortative matching

In a recently published paper, Dauth et al. (2022) argue that wages are higher in larger cities partially due to the stronger assortative matching. Considering the AKM model, assortative matching is usually captured by the correlation between the individual- and firm fixed effect component. The correlation measures the degree to which high quality workers work in high quality firms. To investigate whether and to what extent our results can be ascribed to assortative matching that is positively correlated with population size, we make the following alteration of our main model. First, we regress the estimated firm fixed effects ψ_{jp}^{AKM} on the individual fixed effects α_{ip}^{AKM}, and recover the residual

$$\hat{\varepsilon}_{ip}^{AKM} = \psi_{jp}^{AKM} - \hat{a}_p - \hat{\alpha}_{ip}^{AKM}, \tag{A1}$$

which corresponds to the firm fixed effects coefficient devoid of any assortative matching. We then substitute this “cleaned" new firm fixed effect measure for our ordinary firm fixed dependent variable when estimating the differences between industry-by-regions using equation (2). Results from estimating our main model in equation (3) on the basis of this alternative new measure is presented in Table AA2.

Table AA2. Estimates controlling for first-stage assortative matching

	(1) OLS	(2) OLS	(3) OLS	(4) IV
Labor market population size (log)	0.0151***		0.0175***	0.0105***
	(0.00199)		(0.00171)	(0.00259)
Local industry HHI		-0.0520**	0.0308***	-0.0591**
		(0.0199)	(0.0100)	(0.0265)
Constant	-0.193***	0.0123	-0.231***	
	(0.0234)	(0.0116)	(0.0213)	
Observations	30,219	30,219	30,219	30,219
R-squared	0.695	0.658	0.697	0.087
Kleibergen-Paap				81.28

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the “leave-one-out” instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

We observe a slightly elevated estimate of log of population size in column 1, i.e. UWP, but for the preferred specification corresponding to the IV estimate (in column 4), we find very similar results with regards to both the log of population size and the HHI, at 0.011 and -0.059 respectively. Our estimated effects, that we argue are driven by varying degrees of employer concentration, do not appear to be greatly affected by assortative matching.

Population size or population density?

As outlined in the data section, we choose to rely on the log of population size in the respective geographical labor market to estimate the urban wage premium. In the previous literature, other variables are sometimes used for the same purpose, primarily the log of population density. In Table A3, we therefore present the results from re-estimating our main model using log of population density (achieved by dividing local labor market population with their geographical size in terms of 1000 square meters) instead of the log of population size.

Table AA3. Estimates using log population density

	(1)	(2)	(3)

	OLS	OLS	IV
Population density (log)	0.0189***	0.0202***	0.0114***
	(0.00381)	(0.00342)	(0.00389)
Local industry HHI		0.0131	-0.0756***
		(0.0102)	(0.0265)
Constant	-0.0738***	-0.0820***	
	(0.0111)	(0.0105)	
Observations	30,219	30,219	30,219
R-squared	0.658	0.658	0.050
Kleibergen-Paap			81.95

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

Compared to using population size, the log density estimates in the first column display a higher urban wage premium of 0.019, compared to 0.014 using the former. However, when we control for HHI in the IV model, the difference in the two urban wage premium estimates is very slight, 0.011 compared to 0.010. Aside from a slightly elevated point estimates using the log of density, the two models thus yield qualitatively the same result.[11]

Unweighted regressions

All presented results so far in the paper are weighted using the size of the industry-by-region labor market in terms of their employees as weights. The weighted results thus give the estimates from the perspective of the average worker, giving larger weights to the more populated industries in e.g., Stockholm. For the average industry-by-region market on the other hand, the situation may look different. Therefore, we have also estimated the main models in Table 2 without weights, see Table AA4.

For the average market, we observe slightly higher point estimates for log of population size of 0.018, which decreases to 0.011 once we control for HHI and are strikingly similar to the weighted result. However, in contrast to the weighted regression, the unweighted IV model in column 4 reports no significant results. Looking at the Kleibergen-Paap statistic of 17, the results likely suffer from weak instruments, which is exacerbated by the two-level clustering. Cluster only at the industry level instead yield a statistic of 180 and a significant UWP estimate at the 95% level.

Table AA4. Estimates from unweighted regressions

	(1)	(2)	(3)	(4)

	ols	Ols	ols	IV
Labor market population size (log)	0.0179***		0.0144***	0.0107
	(0.00171)		(0.00206)	(0.0102)
Local industry HHI		-0.0693***	-0.0235***	-0.0483
		(0.00886)	(0.00671)	(0.0715)
Constant	-0.259***	-0.0223***	-0.207***	
	(0.0192)	(0.00618)	(0.0256)	
Observations	30,219	30,219	30,219	30,219
R-squared	0.151	0.148	0.152	0.014
Kleibergen-Paap				16.68

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model. All models include fixed effects at the industry-by-period level, and estimates are unweighted in contrast to all other results. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

Outliers

Since the firm fixed effects, underlying the dependent variable in the second step analysis, are estimated there is always a risk that certain observations are poorly estimated, leading to large deviations. Hence, we have also estimated the main models after winsorizing the estimated firm fixed effect before computing the industry-by-region average. Results are presented in Table AA5.

Table AA5. Estimates from first staged winsorized firm fixed effects in

	(1)	(2)	(3)	(4)
	ols	ols	ols	IV
Labor market population size (log)	0.0128***		0.0150***	0.00875***
	(0.00183)		(0.00158)	(0.00240)
Local industry HHI		-0.0423**	0.0289***	-0.0515**
		(0.0177)	(0.00898)	(0.0235)
Constant	-0.160***	0.0133	-0.196***	
	(0.0215)	(0.0102)	(0.0195)	
Observations	30,219	30,219	30,219	30,219
R-squared	0.701	0.665	0.704	0.082
Kleibergen-Paap				81.28

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

After winsorizing the estimated firm fixed effects at the 5th and 95th percentile, point estimates of the UWP comes back very close to the main results, but slightly smaller.

Excluding large metropolitan areas

There are three larger predominant metropolitan areas in Sweden, namely Stockholm, Malmö, Gothenburg, below which – in terms of population size – there is a significant gap to the next big city. This fact is well known and has given rise to a discussion in the previous economic geography literature of "missing middle", or a "dent", in the city size rank distribution. By excluding the three larger metropolitan areas from the sample we test whether and to what extent our main findings are driven by the larger cities in the sample. For these estimations, sample size decreases to 22,659. Note that we present two IV models in this case, the first being the same preferred specification as in Table 1, whereas the second also excludes the three large metropolitan areas from the leave-one-out instrument, thus ensuring that any exogenous shock affecting any of these do not propagate to other parts of the country.

Table AA7. Estimates excluding the three largest metropolitans

VARIABLES	(1) ols	(2) ols	(3) ols	(4) IV	(5) IV[a]
Labor market population size (log)	0.00639**		0.0110***	0.0172***	0.0145***
	(0.00255)		(0.00295)	(0.00396)	(0.00328)
Local industry HHI		0.0163**	0.0402***	0.0953***	0.0678***
		(0.00748)	(0.00806)	(0.0247)	(0.0222)
Constant	-0.0892***	-0.0222***	-0.156***		
	(0.0289)	(0.00317)	(0.0352)		
Observations	28,130	28,020	28,020	28,020	8,118
R-squared	0.515	0.514	0.520	-0.002	0.015
Kleibergen-Paap				63.35	57.87

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI.[a] In this model the three largest metropolitans are excluded from the instrument. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

The findings as shown in Table AA7. are, however, very much in line with the main results in Table 1, suggesting that there is no large metropolitan effect solely driving the findings. The UWP estimate in column (1) is about half the size of the finding in Table 1, and in contrast to the Table 1, increases when controlling for HHI. It is because the HHI turns out to be positively correlated with the firm pay premium when excluding the largest metropolitan areas. In the IV models, the UWP thus increases to 0.017 and 0.0145 respectively. However, we note that the Kleibergen-Paap statistic shows up lower when we look at this part of the sample. For completion, we also present the results from only including the three largest metropolitans in Table 8.

Table AA8. Estimates for the three largest metropolitans

	(1) Ols	(2) ols	(3) ols	(4) IV
Labor market population size (log)	0.0340**		0.0335*	0.0302*
	(0.00696)		(0.00786)	(0.00724)
Local industry HHI		-0.0514	-0.0160	-0.122*
		(0.0260)	(0.0342)	(0.0318)
Constant	-0.463**	0.0215	-0.454*	
	(0.0991)	(0.0109)	(0.115)	
Observations	2,144	2,142	2,142	2,142
R-squared	0.931	0.910	0.931	0.179
Kleibergen-Paap				137

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

Turning to the results for the largest labor markets, i.e. Malmo, Gothenburg, and Stockholm, we see that the UWP is considerably larger with 0.034 in model (1), which is reduced to 0.03 in the IV model. Despite the relative few numbers of observations of 2,142, R-square and the Kleibergen-Paap statistic is almost twice as large, but significance level is also smaller (less significant).

Alternative IV-specification

To deal with the endogeneity of HHI, we rely on the leave-one-out instrument where each observation for an industry-by-region is instrumented with the weighted average of HHI within the same industry but over all other labor-market regions. This IV is not entirely unproblematic and works insofar that local shocks to any single market do not promulgate to nearby markets. Insofar that the local shocks may spread across space, we can expect them first and foremost to affect labor market concentration through changing the demand for certain types of workers, thereby also affecting earnings. Herein we present the results from several alternative IV specifications, in Table AA9.

As a first step in model (1), we consider the instrument introduced in the previous section above, where the three largest metropolitan areas were left out from the leave-one-out instrument for all market observations.

Next, we note that our preferred measure of HHI, defined as yearly HHI averaged over the period in equation (1), can also be calculated differently. In model (2), we instead consider the yearly average of firm size within each period and based on this singular firm measure the HHI for the period. Although, we don't have any reason to except it to perform differently, it is better suited for considering additional instruments.

Thus, based on the average firm size version of HHI, we consider as a further robustness check, the leave-one-out instrument of 1/M, where M here refers to the number of firms in the market. It is directly connected to the HHI by

$$HHI = \frac{1}{M}[cv(Firm\,Size)^2 + 1], \qquad \text{(A2)}$$

where $cv(Firm\,Size)^2$ refers to the squared coefficient of variation in firm size (in a given market), which captures concentration through a measure of inequality or dispersion. The use of 1/M was also considered by Azar et al. (2020) as instrument, with the only exception that they consider the logarithm, i.e., $\log(1/M)$. Here we consider two versions, one unweighted and one weighted by the size of the respective market in terms of number of employees. The results are presented in the models (3) ad (4) respectively.

Table AA9. Estimates using alternative instrumental variable

	(1)	(2)	(3)	(4)
	IV	IV	IV:1/M	IV:1/M
Labor market population size (log)	0.00990***	0.0116***	0.00904**	0.0148***
	(0.00264)	(0.00213)	(0.00359)	(0.00191)
Local industry HHI	-0.0565*	-0.0408	-0.0815	0.00911
	(0.0284)	(0.0288)	(0.0509)	(0.00894)
Observations	8,421	30,205	30,205	30,205
R-squared	0.112	0.086	0.042	0.114
Kleibergen-Paap	64.94	78.59	17.14	387.2

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV models use different variations of the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

For the models (1) to (3) there is little differences between the UWP estimates, which lies close to the 0.01 we observed for the IV model in Table 1. Looking at the Kleibergen-Paap estimates, we see that, if anything, the alternative instruments is weaker, which translates into insignificant estimates of the HHI variables, although we observe negative point estimates. Turning to the model in (4), which show the results from instrumenting HHI using the employment weighted 1/M (the number of firms), we find that UWP comes out as somewhat higher, with 0.0148 log points and a substantially higher Kleibergen-Paap statistic. But overall, our conclusion for trying different instruments, is that our key findings mostly hold.

Limited mobility bias

There is a considerable empirical literature that evolves around the workhorse AKM model. One potential problem when estimating the firm fixed effects is that the quality of the estimates depends on the amount of movement of workers between firms. All AKM based estimates in our paper are done using the largest connected group of workers and firms. Due to limited mobility, however, these fixed effects estimates can be biased. To remedy (or at least limit) such concerns, we also present AKM estimates when restricting our sample to those firm-periods that at minimum experience 15 workers either entering or exiting the firm (from or to another firm) during any of our three considered six-year periods.

Table AA10. Estimates from firms with high worker mobility

	(1)	(2)	(3)	(4)
VARIABLES	OLS	OLS	OLS	IV
Labor market population size (log)	0.0147***		0.0173***	0.0109***
	(0.00217)		(0.00183)	(0.00265)
Local industry HHI		-0.0473**	0.0317***	-0.0482*
		(0.0201)	(0.00986)	(0.0247)
Constant	-0.189***	0.0119	-0.229***	
	(0.0255)	(0.0119)	(0.0223)	
Observations	22,831	22,831	22,831	22,831
R-squared	0.651	0.612	0.653	0.086
Kleibergen-Paap				85.41

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model, here only including firms with at least 15 worker-moving events. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

Despite lowering the total industry-by-region count from 30,219 to 22,831, this measure does not change the results meaningfully. In Table AA10, we see that the urban wage premium estimate in column 1 is 0.015 and 0.011 in the IV model when conditioned on the HHI (column 4). Although this exercise does not fully rule out the possibility of limited mobility bias, we nonetheless consider the very similar results comforting as regards our main models and conclusions.

Part time work of women

In contrast to our study, the sample in much of the previous literature is most often restricted to men only, excluding women because their hard-to-control-for higher incidences for part time work and labor market absence associated with the childbirth. To make our findings study more in line with these previous studies, we therefore also estimate the models on a sample of men only, re-running the AKM model on the largest connected set of make workers and firms. The results, presented in Table AA.11, are however very much in line with the main result presented in Table 1, with one possibly exception, namely that HHI does not turn out significant in model (4).

Table AA.11. Estimates for the sample of male workers

	(1) OLS	(2) OLS	(3) OLS	(4) IV
Labor market population size (log)	0.0132***		0.0157***	0.00977***
	(0.00176)		(0.00160)	(0.00241)
Local industry HHI		-0.0412**	0.0310***	-0.0448
		(0.0182)	(0.0111)	(0.0302)
Constant	-0.168***	0.0102	-0.206***	
	(0.0210)	(0.0102)	(0.0211)	
Observations	28,514	28,514	28,514	28,514
R-squared	0.591	0.561	0.593	0.055
Kleibergen-Paap				93.03

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model, only including the largest connected set of male workers and firms. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors.

Quality of the individual-firm match

A related strand of literature building on the original AKM model also accounts for the quality if the worker-firm match effect. Usually conceptualized as the interacted worker and firm fixed effects, the matched effect model was first considered by Woodcock (2015). While also considering a fixed effect match model, Woodcock (2015) favored a random effects approach, which was developed in Card, Cardoso and Klein (2018). For the purpose here, however, we consider the fixed effect version of the model following Raposo, Portugal, and Carneiro (2019).

The problem with introducing the interactive fixed effect alongside the worker- and firm fixed effects, is that the model gets over-parametrized, i.e., without additional assumptions there is no way of separating the worker- and firm fixed effect from the match effects. One such assumption is that the match effect is orthogonal to both the worker and firm fixed effect. Although potentially restrictive, the assumption leads to a parsimonious decomposition of the worker, firm, and match effect. It is also the same assumption used by Mittag (2019) in developing an alternative estimator of the extended AKM model with match effects.
Instead of estimating the AKM model in equation (5), we consider the following specification for each period,

$$\log Earnings_{ij(kl)t} = \phi_{ij} + \beta X_{it} + \varepsilon_{ij(kl)t}, \qquad \text{(A3)}$$

where ϕ_{ij} represents the time-invariant characteristics of the match between each worker and the employing firm, e.g. how well the worker's skills fit within the job description. On the largest connected set of worker and firms, we proceed by estimate ϕ_{ij} using the same estimator as before as outlined in Guimarães and Portugal (2010). With the orthogonality assumption Rapasso, Portugal and Carneiro recovers the worker, and for our purpose, the firm fixed effect by the following regression

$$\hat{\phi}_{ij} = \alpha_i + \psi_j + \eta_{ij}, \tag{A4}$$

where α_i is the worker fixed effect, and ψ_j the firm fixed effect, and η_{ij} a measure of the match fixed effect, all of which to be estimated. The importance of including match effects in the model for labor market outcomes is researched in e.g., Mittag (2019), who finds significant bias in the estimate of several individual characteristics, such as the wage gap. For our purpose here, accounting for match effect yields a potentially more accurate estimate of coefficient to worker characteristics in X_{it} vector of variables, and by extension potentially also to the estimated firm fixed effect. The results are presented in Table AA.12, which corresponds to the same models as estimates in Table 1 in the paper.

Table AA12. Estimates from AKM model with worker-firm match fixed effects

	(1) ols	(2) Ols	(3) ols	(4) IV
Labor market population size (log)	0.0137***		0.0156***	0.00831***
	(0.00199)		(0.00167)	(0.00248)
Local industry HHI		-0.0484**	0.0234**	-0.0690***
		(0.0193)	(0.00990)	(0.0249)
Constant	-0.175***	0.0120	-0.205***	
	(0.0234)	(0.0111)	(0.0203)	
Observations	27,249	26,470	26,470	26,470
R-squared	0.464	0.432	0.466	0.039
Kleibergen-Paap				91.31

Notes: Dependent variable is industry-by-region differences in firm fixed effects, estimated in a first-step AKM model, estimated with a worker-firm "match" fixed effect. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors

Thus using $\hat{\psi}_j$ as recovered from the match effect estimate we proceed with the analysis from equation (3). The results from this model are presented in Table A11. Overall, the results point in same directions. However, we notice the match effect model delivers slightly lower point estimates with an urban wage premium of 0.008 in the IV model, compared to an equivalent estimate of 0.010 in AKM specification. Thus, once accounting for match effects in the AKM model, there appears to be smaller differences across markets with respects to earnings that goes through the firm channel. However, the resulting difference between the two AKM specifications are not large, which we primarily take as sign of robustness of the preferred specification.

Plant fixed effects instead of firm effects

Our AKM model's firm fixed effects are calculated for workers in all establishments within a given industry-by-region labor market. If there are many establishments in a geographical area in the same industry, workers at these establishments are assigned to the same firm and receive the same estimated firm fixed effect in the regression. Instead of aggregating over establishments within markets we can equally also consider using each establishment within our industry-by-region categories as its own unit in the AKM model, thus estimating separate plant fixed effects. This may e.g. be useful in so far that firms have different offices dealing with separate tasks or employing workers with different occupations. Using this specification, we also estimate our main models in Table 2, here shown in the Table AA13, but these outcomes are however in no way strikingly different from those from our main specification.

Table AA.13. Estimates with local plant fixed effects in the AKM model

	(1) OLS	(2) OLS	(3) OLS	(4) IV
Labor market population size (log)	0.0142***		0.0167***	0.00983***
	(0.00180)		(0.00159)	(0.00251)
Local industry HHI		-0.0471**	0.0318***	-0.0557**
		(0.0185)	(0.00995)	(0.0265)
Constant	-0.181***	0.0111	-0.221***	
	(0.0214)	(0.0108)	(0.0203)	
Observations	30,316	30,205	30,205	30,205
R-squared	0.670	0.636	0.672	0.073
Kleibergen-Paap				81.33

Notes: Dependent variable is industry-by-region differences in plant fixed effects, estimated in a first-step AKM model. All models include fixed effects at the industry-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors

Occupation-by-region definition of a market

Instead of considering geographically separated industries as a unit of analysis, we can equally consider geographically separated groups of occupations. Arguably, in some sense a specific occupation within a confined region is a directly relevant market for many workers. Take for instance accountants, who can be said to perform roughly the same tasks whether he or she works for a manufacturing firm or in a high-tech service firm.

When testing this alternative unit of analysis, however, we lose one of our time periods since occupational statistics is only available to us from 2001 and onwards. Otherwise, we use the same 3 digits for occupations, yet the resulting occupation-by-region cells falls short of the number of 3-digit industry counts. Together, these two data limitations result in a sample reduced by more than half, i.e., we have 12,710 occupation-by-region observations in two periods compared to 30,219 industry-by-region observations in three periods.

Table A.14. Estimates for occupation-by-region definition of markets

	(1) OLS	(2) OLS	(3) OLS	(4) IV
Labor market population size (log)	0.0131***		0.0147***	0.00623
	(0.00169)		(0.00171)	(0.00414)
Local industry HHI		-0.0727***	0.0246**	-0.106**
		(0.0204)	(0.00942)	(0.0452)
Constant	-0.168***	0.00972	-0.192***	
	(0.0209)	(0.00829)	(0.0220)	
Observations	14,145	12,710	12,710	12,710
R-squared	0.734	0.687	0.740	0.102
Kleibergen-Paap				23.90

Notes: Dependent variable is occupation-by-region differences in firm fixed effects, estimated in a first-step AKM model, estimated with a worker-firm "match" fixed effect. All models include fixed effects at the occupation-by-period level, and estimates are weighted using employment weights. The IV model uses the "leave-one-out" instrument to account for potential endogeneity of HHI. Robust standard errors are presented in parentheses with 2-way clusters at the industry and labor market level, where *,**,*** corresponding to 10%, 5%, and 1% level of significance. Kleibergen-Paap refers to the rk Wald F Statistic for weak instruments test when using cluster-robust standard errors

Thus, shifting the definition of market to occupations instead of industries, and calculating the occupational based HHI, we re-estimate the AKM model and show the results from the second step in Table AA13. As we can see in the table, the estimates are surprisingly similar, although we find a lower estimate for the urban wage premium in the IV model, at 0.006 compared to the 0.01 for the industry definition of markets. In the current specification, the UWP estimate of 0.006 does not turn out significant either, which is partly because of the smaller sample, and the requirements of using two level clustering, here at the occupational and labor market level.