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Labor Market Concentration, Remunerations, Inequality, and Institutions: A Dynamic Approach

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Tommaso Nannicini

Labor Market Concentration, Remunerations, Inequality, and Institutions:

A Dynamic Approach

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Labor Market Concentration, Remunerations, Inequality, and Institutions: A Dynamic Approach†

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Abstract

Using local projections and Italian administrative data, we find that the effect of Labor Market Concentration (LMC) increases over time and is more pronounced for annual earnings, mainly due to its impact on employment-intensive margins (worked weeks, part-time, and temporary contracts). The effect is also stronger in remote areas and the service sector. Similar patterns emerge for inequality, with LMC having a greater impact at the bottom of the distribution, regardless of whether unskilled workers are located in cities or remote areas. LMC also directly influences firms' choices of collective bargaining contracts, a mediating factor for the observed findings.

Keywords: employer concentration, labor market outcomes, inequality, local projections, instrumental variable.
JEL Codes: J31, J42, C23, C26.

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La concentrazione del mercato del lavoro, retribuzioni, disuguaglianza e istituzioni: un'analisi dinamica

Abstract

Utilizzando le local projections e dati amministrativi italiani, questo lavora mostra che l'effetto della concentrazione del mercato del lavoro (LMC) aumenta nel tempo ed è particolarmente evidente sui redditi annuali, soprattutto a causa dell'impatto esercitato sui margini legati all'intensità lavorativa (settimane lavorate, contratti part-time e a termine). Un effetto più marcato viene osservato nelle aree periferiche e nel settore dei servizi. Andamenti analoghi vengono rilevati per la disuguaglianza, con un'incidenza maggiore della LMC nella parte bassa della distribuzione, indipendentemente dal fatto che i lavoratori non qualificati risiedano nelle aree urbane o in aree remote. Anche le scelte delle imprese in materia di contrattazione collettiva risultano influenzate direttamente dalla LMC, che agisce come fattore di mediazione dei risultati osservati.

Parole chiave: concentrazione del mercato del lavoro, outcome del mercato del lavoro, disuguaglianza, local projections, variabili strumentali

1 Introduction

In recent years, there has been growing interest in the literature regarding the effects of labor market concentration (LMC), which measures the concentration of employees among employers. LMC can serve as a proxy for firm pricing power in traditional monopsony and oligopsony models (Robinson, 1933; Boal and Ransom, 1997; Manning, 2003), as well as in more recent frameworks that relate bargaining power to search and matching frictions, where workers do not have access to all available jobs (Jarosch et al., 2024) or exhibit heterogeneous preferences for jobs (Berger et al., 2022).

A well-documented finding in the literature is the negative relationship between LMC and worker remuneration measures (annual earnings or "unitary" wages, i.e., hourly, daily, or weekly). Bassanini et al. (2024) conducted a cross-country analysis of several European countries, estimating elasticities between LMC and daily wages ranging from -0.019 in Germany to -0.022 in France, -0.025 in Portugal and -0.029 in Denmark. As for the US, Azar et al. (2022) reported larger estimates (-0.127) for posted annual earnings, with other studies confirming similar findings, albeit with lower magnitudes (Arnold, 2019; Benmelech et al., 2022; Marinescu et al., 2021; Rinz, 2022; Schubert et al., 2024).

In this framework, using unique Italian administrative data, our paper makes three contributions to the literature.

First, we argue that the dynamics of labor market responses to changes in LMC has to be taken into account, since understanding this dynamics sheds light on the different adjustment channels and the associated timing. Most existing literature estimates the effects of LMC shocks on contemporaneous (or one-year-forward) labor market outcomes.[1] This issue may be particularly relevant for highly regulated labor markets, given that labor market institutions may represent an additional channel that affects the timing of LMC effects.

Second, in a dynamic setting, we claim that the choice of the remuneration variable matters. In the literature, some studies utilize unitary wages while others annual earnings; however, no research has systematically investigated the differential impacts of LMC across these measures using the same data and methodology. This contribution is particularly relevant, as it helps clarify the distinct impacts LMC has on workers' ability to achieve adequate living standards in a year (earnings), and on firms' capacity to reduce labor costs for a given amount of labor (unitary wages).

Third, LMC can directly affects labor market institutions, in particular firms' choices of the adopted collective bargaining contract, and this channel might represent one of the mediating factor for the increasing dynamic impact of LMC.

We believe that Italy is a proper case study. In addition to regulations to firing costs and collective dismissals, Italy is characterized by a pervasive collective bargaining system, with nearly 100% of employees formally covered, and where all workers, depending on their occupation and tenure, are associated with a minimum wage that firms must adhere to. Nonetheless, in Italy firms are free to choose their collective bargaining contract, without restrictions related to the sector in which they operate or to the use of agreements signed by the most representative unions and employers' associations. Accordingly, in Italy there has been a massive increase in the creation

[1] To the best of our knowledge, only Thoresson (2024) employs a dynamic approach, estimating the impact of LMC on wages by leveraging a reform in Sweden's pharmacy market using an event-study framework.

of new collective bargaining agreements (from around 300 in the 2000s to around 1000 in recent years), also because of increase of the so-called "pirate" contracts, signed by unions and employers' associations that do not represent any collective interest, usually associated with lower wages. In this institutional framework, labor regulations might clearly mediate and interfere with an increase in LMC. Labor market regulations could slow the impact of LMC, as in Italy, for example, to end a temporary employment relationship one must wait until the closing date (only about 0.5% terminate early, due to dismissal costs and the risk of legal action). Further, an increase in LMC could clearly affect in a dynamic perspective the firm strategy in the adoption of the collective contract, increasing the probability of opting out from the most representative collective contracts[2]

In such a framework, different adjustment mechanisms might apply in case of a LMC shock. Initially, just after the shock, workers remain bound by their collective contracts, employment levels and composition, and firms can plausibly only influence the variable components of compensation (such as bonuses and overtime). Afterward, firms may respond by firing and hiring workers (even with different contractual arrangements) and deciding whether to renew temporary contracts. Over the long term, a wider portion of a firm's workforce may be affected by a LMC shock, since the LMC shocks may additionally affect adoption of a possibly different collective bargaining contract, with more favorable conditions for firms. Therefore, as time goes by after the shock, the range of strategies available to firms to leverage their increased monopsonistic power expands, including channels related to labor market institutions, leading us to expect that the impact of LMC might increase over time.

We use unique employer-employee administrative data covering the universe of Italian employees and firms in the private sector, provided by the Italian National Social Security Institute (INPS) through the VisitInps program.[3]

Leveraging the richness of individual data, we generate cell-level data defined considering the interplay between the 611 local labor markets (LLMs), provided by the National Statistical Institute (Istat), and industries (21 sections of the NACE Rev.2 classification).[4] Notably, the Italian definition of LLMs is not based on administrative boundaries but on self-contained areas defined by commuting patterns, with the key criterion being the minimization of the proportion of commuters crossing LLM boundaries to get to work. Hence, our LLM definition is consistent with the recent literature on data-driven local markets (Nimczik, 2023), to better capturing the bulk of relevant job opportunities available to workers, in line with evidence that most workers seek jobs locally (Manning and Petrongolo, 2017; Marinescu and Rathelot, 2018).

Using cell-level data for the period 2005-2018, we compute the Herfindahl-Hirschman Index (HHI), showing that in Italy the HHI has significantly increased over time, by approximately 25% in this period, and this trend is more pronounced in services and remote LLMs.[5]

Apart from considering the LCM effect on remuneration levels, distinguishing between annual

[2]For an in-deep explanation of the Italian collective bargaining system see Matano et al. (2022).

[3]See https://www.inps.it/it/it/dati-e-bilanci/attivit–di-ricerca/programma-visitinps-scholars.html

[4]Some studies in the literature use occupation instead of industry, e.g Bassanini et al. (2024) and Martins and Melo (2024). There is no consensus on whether industry or occupation is the preferred dimension. To cover the entire analysis period (2005-2018), we must use the industry dimension since the occupation variable is available and reliable only for the last years of our analysis.

[5]There are no published studies on LMC and wages specific to Italy.Bassanini et al. (2024) investigate the Italian context without analyzing wages but focus on the conversion rate of temporary contracts. Pacelli and Passerini (2024) examine a similar but different topic, investigating the interplay between hiring subsidies, rent-sharing, concentration, and wages.

earnings and unitary wage, we also focus on inequality, since the literature on LMC and inequality is relatively scant (Rinz, 2022; Martins and Melo, 2024; Webber, 2015), although being an important issue from a policy point of view.

Capturing the dynamic effects of LMC is one of the main contributions of this paper. We employ the Local Projections methodology (Jordà, 2005) as a "natural bridge" from macro methods to applied microeconometrics (Dube et al., 2023; Jordà, 2023). Using local projections, we evaluate the impact of a LMC shock at time t on outcome variables from $t+1$ to $t+5$.

LMC may be endogenous to labor supply and demand shocks, which can simultaneously correlate with wages. To mitigate endogeneity concerns, we include in our econometric specification a comprehensive set of cell, industry-by-year, and LLM-by-year fixed effects, as well as we control for the lagged dynamics of the outcome variable. We also implement the standard approach in the literature (Azar et al., 2022; Bassanini et al., 2024, among others) by employing a leave-one-out instrumental variable (IV) strategy, which exploits shocks in concentration at the national industry level, excluding the LLM of interest: aggregated industry shocks in other labor markets are assumed to be exogenous to LLM conditions, provided we control for the full set of fixed effects and pre-shock values of the outcomes. We compute our instrumental variable by weighting it by the distance between LLMs to validate our IV approach further. This approach ensures that the instrument is essentially based on shocks occurring in more distant LLMs, thereby minimizing spillover effects across cells. We also conduct several robustness checks on the methodology and the derivation of the instrument.

Our results show that the impact of HHI is significantly stronger for annual earnings than for FTE wages and that the dynamics is crucial. In the first year following a LMC shock, the impacts on both measures are very similar, with elasticities around -2 to -3%, consistent with figures reported by Bassanini et al. (2024) for European countries. From the second year onward, elasticities for both FTE wages and earnings increase until the third year, after which they stabilize. However, the rise for earnings is considerably more pronounced: after five years, the HHI elasticity for earnings is near -10%, while for FTE wages, it is -4.5%. We investigate the mechanisms driving these differences, demonstrating that the more substantial impact on earnings can be attributed to HHI's negative effect on the employment-intensive margin, i.e., the reduction in worked weeks (-5.5%) and the increases in the share of temporary contracts and part-time by 17.5% and 6.6% respectively.

Moreover, we observe a positive effect of HHI on inequality, and also in this case the magnitude varies with the remuneration measure and the dynamics over time: the impact of HHI on an overall measure of inequality (MLD) is rather small and similar for both earnings and FTE wages when assessed one-year post-shock; afterward, the effect on earnings increases much more until the third year (up to a 16% increase), then stabilizes.

We also examine the impact of HHI on the different percentiles of earnings and wage distributions, computed at the cell level. Notably, the HHI impact is much more pronounced for unskilled workers (10th percentile), who thus emerge as the most vulnerable worker group to firms' monopsonistic power. The magnitude of this impact is remarkable: estimated elasticities from the second to the fifth year are around -30%. Median workers are also affected, with an elasticity of -10/15%, while high-skilled workers are the least affected (-5%). These findings align with results for the US case (Rinz, 2022), where the elasticity for unskilled workers is very high and close to -20%, and approaches zero for skilled workers. When investigating FTE wages, we still find a more substantial impact on the 10th percentile, although the magnitude is lower (around -10%), while the median and 90th percentiles remain unaffected.[6]

Our results show that doubling LMC explains around 32% of the standard deviation at the 10th percentile of earnings in a between cell dimension, and only 5% at the median. Furthermore, back-of-the-envelope calculations show that LMC is a crucial driver of the increase in inequality in Italy, since it explains around 15% of the increase in the inequality index p50/p10, the one that has increased the most in Italy in the period of analysis (Depalo and Lattanzio, 2025).

An original contribution of our paper is also to show that institutions, and specifically collective bargaining, play a role in affecting the LMC dynamic effects on remuneration and inequality trends, detected in the paper. Actually, we show that LMC shocks decrease the HHI of collective bargaining contracts as well as the share of the prevailing collective contract: in cells where LMC increases employers are more likely to move over time towards less representative collective contracts, i.e. not signed by the most representative unions and employers' associations, usually characterized by lower wages. While Martins and Melo (2024) provides an interesting heterogeneity analysis, showing that the LMC impact is higher where collective bargaining coverage is lower, our paper is the first, to the best of our knowledge, to show a direct effect of LMC on firms' choices of the adopted collective contract, in turn weakening labor market institutions.[7]

We also present two interesting heterogeneity analyses. First, we delve deeper into the differences between services and manufacturing. Also, in this case, the distinction between annual earnings and FTE wages is crucial: while the HHI impact on FTE wages does not significantly differ between the two sectors, substantial differences arise concerning earnings, with a much stronger and over-time increasing HHI impact in services, a sector characterized by a higher incidence of non-standard contracts, smaller firm size, weaker unions, and lower level of competition with respect to manufacturing, that is a tradable sector. Regarding earnings inequality, the HHI impact is much higher in services, with an elasticity of -30% for the 10th percentile.

Second, we explore the urban dimension of this phenomenon, a well-established feature when discussing LMC and monopsony (Hirsch et al., 2022; Luccioletti, 2022). We differentiate large cities (those with more than 100,000 inhabitants) from remote LLMs. The HHI impact is substantially stronger in remote LLMS, with an elasticity four times higher than in large cities. Interestingly, from the perspective of inequality, we find out that the lower concentration in cities relatively benefits medium- and high-skilled workers with respect to rural areas. In contrast, unskilled workers experience over time a penalty comparable to that observed in remote areas.

2 Data and the LMC index

Our analysis uses Italian administrative archives from INPS, which provide detailed information about the universe of private employees and firms, allowing us to compute labor market outcomes and concentration at the cell level between 2005 and 2018.[8] As mentioned, the cell of analysis is defined by combining NACE industry sections (NACE letters), 21 categories, and LLMs (*sistemi locali del lavoro*), 611 categories.

LLMs are identified with a data-driven approach by Istat, based on information about commut-

[6] Webber (2015), by using a different approach, derive findings similar to those of Rinz (2022) for the US.
[7] Benmelech et al. (2022) shows that in the US the LMC impact is lower where unions are stronger.
[8] We decided to stop before the pandemic to avoid peculiar features related to the associated economic crisis.

ing flows of individuals between municipalities for work reasons, collected in the population census, which occurs every ten years.[9] As for the industry classification, we rely on the 21 categories of the NACE Rev.2 classification since using finer categories would engender cells with a limited number of workers and firms.

We rely on the HHI, measured at the cell level, to measure LMC. The underlying assumption to compute the HHI at the cell level is that employees' mobility costs limit their job searches to a specific industry and LLM, as suggested by Manning and Petrongolo (2017) and Benmelech et al. (2022) among others.

The HHI index at the cell level j and at time t is computed as follows:

$$HHI_{j,t} = \sum_{f=1}^{N} sh^2_{f,j,t} \tag{1}$$

where $sh^2_{f,j,t}$ represents the squared employment share of firm f at the cell-year level.[10]

As for the evolution of the employment-weighted average HHI across Italian LLMs from 2005 to 2018, it increases by approximately 25%, particularly after 2009 (see Figure A1 in the annex for the associated trends, and also for the trends by sector and by urban dimension). When deepening sector differences, it comes out that services exhibit higher HHI values and a substantial increasing trend over time. In contrast, the manufacturing sector displays lower and rather stable HHI levels. As for the trends in the HHI between remote LLMs and large cities, remote areas have higher HHI values, especially after 2011, which points to greater and increasing LMC values with respect to cities.[11]

3 Empirical strategy

We employ the Local Projections (LPs) approach initially proposed by Jordà (2005) to capture the dynamic effects of LMC on the earnings distribution. LPs offer a flexible framework for estimating dynamic responses over different horizons and can be considered a "natural bridge" from macro methods to applied microeconometrics (Dube et al., 2023; Jordà, 2023). In this context, Dube et al. (2023) discussed various approaches to estimate dynamic effects with panel data: Local Projections Two-Way Fixed Effects, Local Projections Event Studies, and Local Projection Difference-in-Differences.

LMC is likely endogenous to labor supply and demand shocks. For instance, a demand shock may lead to wage variation and simultaneous changes in employer concentration (Bassanini et al., 2024), while concentration may vary due to productivity shocks, which correlate to wages too (Azar et al., 2022).

To mitigate these potential threats to identification, we rely on a widely employed approach in the concentration literature, the leave-one-out instrumental variable (IV) (Azar et al., 2022; Rinz,

[9] We use information from the 2011 population census, a median year in our analysis period.

[10] We focus on employment stocks, while some papers in the literature focus on flows using vacancy data (Azar et al., 2022). We cannot test the robustness of our results using flows since we do not have information on vacancies at the cell level for the period of analysis.

[11] To define large cities we select LLMs belonging to cities with more than 100,000 inhabitants, which capture 8.2% of units and 53.8% of employment.

2022; Bassanini et al., 2024; Marinescu et al., 2021). We instrument the HHI using the employment-weighted average of the HHI for each LLM-year combination computed across all other LLMs within the same industry.[12] This instrument captures variations in market concentration at the national level, which are unlikely to be influenced by endogenous changes within a specific LLM. Moreover, to further validate the exogeneity of our instrumental variable, we take into account a potential drawback of leave-one-out instruments, that is, aggregate industry-level shocks, such as productivity shocks, may be correlated across geographical areas and directly affect labor market outcomes, in addition to their indirect effect through local concentration. This could be primarily due to potential spillover effects on LLM outcomes derived from shocks that occur in nearby LLMs. Especially in metropolitan areas, shocks at the local level might affect surrounding LLMs and, in turn, affect national trends. To address this issue, we compute the instrumental variable in our baseline estimates by taking the average HHI across all other LLMs in the same industry using the square root of the distance between LLMs as an additional weight: the instrument is essentially based on shocks occurring in more distant LLMs, thereby minimizing endogeneity deriving from spillover effects across LLMs.

More formally, our IV is calculated using the following formulation:

$$log\left(\overline{HHI}_{it}^{-a}\right) = \log\left(\frac{\sum_{z\neq a} HHI_{zit} \cdot Emp_{zit} \cdot \sqrt{Dist}_{zi}}{\sum_{z\neq a} Emp_{zit} \cdot \sqrt{Dist}_{zi}}\right) \tag{2}$$

Hence, for each specific LLM a, we take the log of the employment-distance-weighted average HHI calculated using information on the HHI of each LLM $z \neq a$ in the same industry i, to estimate the dynamic effect of HHI on labor market outcomes over different horizons h (i.e., from 1 to 5 years after an exogenous shock in concentration) using the following equation:

$$y_{j,t+h} = \alpha + \beta_h \log \mathrm{HHI}_{j,t} + \sum_{l=0}^{1} \rho_l y_{j,t-l} + \delta_j + \omega_{i,t} + \tau_{a,t} + \epsilon_{j,t+h} \tag{3}$$

where $y_{j,t+h}$ is a labor market outcomes observed in cell j at time $t+h$: log mean annual earnings, log mean FTE weekly wages, log P90, P50, and P10 of earnings and wages, MLD of earnings and wages, worked weeks, the share of full time and part-time employees. Our model involves a comprehensive set of fixed effects: cell fixed effects δ_j, industry-by-year ($\omega_{i,t}$) and LLM-by-year (($\tau_{a,t}$)) fixed effects, that can simultaneously influence LMC and remuneration variables. Additionally, as is common in the LPs environment, we consider autoregressive components (i.e., $\sum_{l=0}^{1} \rho_l y_{j,t-l}$) to capture the past dynamics of a labor market outcome and account for potential pre-existing trends that might bias our results.

By incorporating the lagged values of the outcome variable on the right-hand side of Equation 3, we aim at accounting for potential autocorrelation within the data. As known, the Nickell bias poses a concern in cross-sectional fixed effects estimates when an autoregressive component is considered and the time dimension is constrained (Nickell, 1981). The fixed effects estimator is inherently

[12] Other papers use a slightly different leave-one-out instrument, the average log of the inverse of the number of firms operating in all other LLMs in the same industry. We do not pursue this alternative approach since the first stage statistic is sometimes below 10 for some horizon periods.

biased, with a bias of order $(1/T)$, arising from the estimation of (N) nuisance parameters with (NT) observations. Although GMM approaches can address this bias, they often encounter issues related to instability and the proliferation of instruments (Roodman, 2009). Consequently, we adopt the debiased fixed effects estimator proposed by Chen et al. (2019), which offers a robust solution using a sample-splitting technique.

4 Results

4.1 LMC remuneration effects

Panel (a) of Figure 1 refers to the impact of an HHI shock at time t on earnings and FTE wages in periods from *t+1* and *t+5*. Since variables are in logs, coefficients are elasticities.[13]

By confirming the relevance of the two main contributions of this paper, this figure points out that, in a highly regulated labor market, the difference between remuneration measures matters, mainly when considered from a dynamic perspective. More specifically, at time *t+1*, the coefficients associated with earnings and FTE wages are very close to each other, around 2- 3%, a figure that is consistent with what has been found by Bassanini et al. (2024) for European countries. Afterward, the elasticities increase for both variables until *t+3* and then remain stable. However, increases are much more pronounced for annual earnings: after five years, the HHI elasticity for earnings is almost -10%, while for FTE wages, it is around -4.5%. It is interesting to note that after the first year our estimates are close to those derived for Europe (Bassanini et al., 2024), while in the medium run estimates get closer to the US case (Azar et al., 2022).

We also investigate the channels underpinning the differences in the LMC impact on earnings and FTE wages, focusing on the employment-intensive margin. Panel (b) of Figure 1 clearly shows that the HHI shock at t entails a reduction over time in the number of worked weeks (both worked weeks or FTE worked weeks). In this case, the dependent variable is not in logarithm; hence, coefficients cannot be interpreted as elasticities. Being the baseline value of worked weeks in 2005 equal to 35.8, after five years, the 2 weeks reduction in worked weeks amounts to -5.5%, a non-negligible effect.

Additional standard proxies for the employment-intensive margin are the shares of fixed-term and part-time contracts in the cell. Panel (c) of Figure 1 supports the intuition that an HHI shock entails an increase in both contract types. Being the baseline value of around 17% for fixed-term and 18% for part-time in 2005, the increase after five years in fixed-term and part-time associated with a doubling LMC is around 3 p.p. and 1.2 p.p. (17.5% and 6.6%), respectively.

4.2 LMC inequality effects

Inequality is the second major dimension investigated in the paper. Panel (a) of Figure 2 focuses on an overall measure of inequality, i.e., the MLD. It confirms that the choice of the remuneration variable matters, especially when considered from a dynamic perspective. While in the first year after the LMC shock the HHI impact is close to zero for both earnings and FTE wages, from the

[13] Regressions are employment-weighted; standard errors clustered at the cell level. Further, in Figure 1, the Kleibergen-Paap tests are well beyond the value of 20, i.e., around 24 in panel (a), 23 in panel (b), and 20-23 in panel (c). Also for the following figures the values of Kleibergen-Paap tests are greater than 20.

second to the fifth year the impact on annual earnings increases much more than the one on FTE wages. Since the baseline value of MLD for earnings was 0.40 in 2005, doubling LMC increases MLD by around 0.06-0.07 in the third to fifth year after the shock, i.e. around 16%. For the impact of MLD on FTE wages, the HHI impact amounts to 10%, since its baseline value in 2005 is 0.10 and the HHI coefficient is equal to 0.01 from the second year onward.[14]

We then analyze different parts of the earnings and wage distribution, considering different percentiles (in logs): the 10th, the median, and the 90th percentile. Panel (b) of Figure 2 includes estimates of the HHI impact on annual earnings, while panel (c) refers to FTE wages. Both panels show that elasticities are much higher for unskilled workers at the 10th percentile for both remuneration measures. Nonetheless, the impact is much more substantial for earnings, where the associated elasticity is around -30% from the third year, while for FTE wages is around -10%. As for skilled workers, the 90th percentile is the least exposed to HHI shocks since impacts are always much smaller, even with respect to the median worker.

Therefore, our paper contributes to the literature confirming this stronger impact for unskilled workers, with respect to the upper tail of the distribution.[15]

Using elasticities (computed after five years from the shock) and standard deviations of the variable of interest, we can claim that LMC is a crucial driver of the dynamics of inequality in Italy. Actually, doubling LMC explains around 32% of the standard deviation in the 10th percentile of earnings in a between cell dimension, and only 5% of the median, confirming that monopsony plays a role mainly for unskilled workers.[16] Furthermore, since in Italy the increase in earnings inequality has been proved to be driven by the lower tail of the earning distribution, i.e., by the dynamics of the inequality index p50/p10 (Depalo and Lattanzio, 2025), we derive a back-of-the-envelope calculation to evaluate how much the change in HHI over the period 2005-2018 can explain the change in the p50/p10 index. Using estimated coefficients and variations over time of the HHI index and of the outcome variables, we find that almost 15% of the increase in the p50/p10 earnings dynamics can be attributed to the overtime change in HHI. LMC is then a key driver of inequalities in the labor market.[17]

4.3 Institutions matter: the impact of LMC on firms' strategies for collective bargaining

The dynamic and increasing effect of LMC on remuneration levels and inequality is one of the findings of the paper. To investigate the associated mechanisms, we focus on labor market institutions

[14]One might wonder whether the increase in inequality is related to a within or between firm dimension. To address this issue, we decompose the MLD index into the two dimensions of interest and carry out our baseline regressions separately. It emerges that the increase in earnings inequality occurs in both dimensions. Results are reported in Figure A2.

[15]This evidence contributes to the literature on the heterogeneous impact of monopsony on workers with different skill levels. Some studies argued that LMC could have a more significant effect on skilled jobs (Dodini et al., 2024; Muehlemann et al., 2013), because of specific human capital losses. Additionally, the demand for skilled jobs may be more concentrated, not all firms offer such positions. On the other hand, skilled workers might be more difficult to replace due to their specialized skills, which could increase their bargaining power relative to the firm. Furthermore, beliefs about outside options have been shown to be often strongly underestimated, particularly by low-skilled workers (Jäger et al., 2024).

[16]Similar findings apply for FTE wages, where doubling LMC explains 27% of the 10th percentile and only 9% for the median.

[17]For the FTE wages, the change in HHI can explain a lower but still non-negligible part of it, around 8%.

and, in particular, on the collective bargaining system. We implement the same empirical strategy used so far, using as dependent variable two proxies for the strength of the collective bargaining system at the local level: i) log HHI of the different collective contracts used by firms in a cell; ii) the share of workers in the collective contract with the highest incidence in the cell. A reduction over time of these two proxies entails a fall in the share of collective contracts signed by the most representative unions and employers' association, in favor of less representative contracts, usually associated with lower wages. Hence, in cells where LMC increases, firms might choose over time to adopt a more convenient collective contract, i.e. a collective contract associated to a different sector or a so-called "pirate" collective contracts signed by unions and employers' associations that do not represent any collective interest.

Results reported in Figure 3 clearly show that a LMC shock reduces the two proxies for the strength of the collective bargaining system at the local level. As for the HHI of the collective contracts, the estimated elasticity increases up to 0.2 after 3 years and then it stabilizes: doubling concentration in LMC reduces by 20% the concentration of collective contracts. Using the second proxy, the share of the prevailing collective contract, confirms this finding, with a negative and increasing elasticity until the third year, up to 0.06, and then remaining constant.

While there is evidence that the LMC effect can be heterogeneous with respect to the unions local strenght and to the local coverage of the collective agreement system, respectively by (Benmelech et al., 2022) and (Martins and Melo, 2024), we do claim this is the first paper investigating the role of LMC in directly affecting firms' strategy adoption of collective contracts.

4.4 Heterogeneity

We also investigate breakdowns for two interesting dimensions of the analysis, i.e. manufacturing versus services and cities versus remote areas.

Panel (a) and (b) in Figure 4 point out that, for earnings, the HHI impact is much stronger in services than in manufacturing, while, for FTE wages, the differences are negligible. As for earnings inequalities (panel (c)), the differences across percentiles are impressive in services: after 3-5 years, the elasticities are around -25/30% for unskilled workers at the 10th percentile, while no impact is detected for skilled workers. For FTE wages in services, differences across percentiles are negligible (panel (d)) since elasticities are all close to zero. This evidence suggests that monopsony power is much stronger in services, mainly when considering earnings from a dynamic perspective. This finding can be explained by the fact that services are characterized by lower competition levels, with respect to manufacturing, and also by weaker unions, smaller average firm size, and higher share of non-standard contracts. The differences between services and manufacturing are related to the mediating factors already identified for the baseline estimates, i.e., the employment-intensive margin: in services the HHI impact negatively affects worked weeks and positively affects the share of part-time and temporary contracts, while in manufacturing elasticities are very close to zero (see Figure A3).

The second interesting breakdown concerns the differences between urban, i.e., large cities and remote LLMs. Panel (a) and (b) of Figure 5 clearly show that for both earnings and FTE wages, the HHI impact is stronger and increasing over time for remote LLMs. As for earnings, elasticities in remote LLMs are around -8/10% after the third year and around -4/6% from the third year when FTE wages are considered. In cities, instead, elasticities are often close to zero, non statistically significant, and not increasing over time.[18] When considering earnings inequality, the impact is still stronger in remote areas, where all percentiles are negatively affected from the second year, with a stronger impact for unskilled and median workers. In cities, elasticities are much closer to zero, except for unskilled workers at the 10th percentile, where the elasticity equals -10%. This result is consistent with the literature (Manning and Petrongolo, 2017; Hirsch et al., 2022; Luccioletti, 2022): monopsony power in remote LLMs is stronger than in more competitive cities. Still, our findings clearly show that LMC strongly hits unskilled workers, no matter whether they work in remote LLMs or cities.[19]

4.5 Robustness checks

We carry out several robustness checks. First, we provide results using the standard instrumental variable approach used in the literature where the leave-one-out instrument is computed without distance weighting (Azar et al., 2022; Bassanini et al., 2024): results are very close in magnitude (slightly lower) with respect to the baseline ones (Figures A5 and A6 in appendix.

Second, our baseline estimates are based on aggregated data at the cell level (LLM and industry). We propose a two-step estimation procedure, a standard tool in the urban economics literature (Combes et al., 2008), to better control for compositional differences across cells and residual endogeneity issues. In the first stage, we regress the remuneration variable on cell fixed effects (interacted with year) and worker and firm characteristics, while in the second stage, the estimated cell fixed effects are regressed on LMC. Our results (see Figure A7 in appendix) are consistent with the baseline ones, both in the case where in the first stage we include only observed characteristics (gender, age, age squared, occupational dummies) and in the case where we also include individual fixed effects exploiting the longitudinal dimension of the microdata. We can conclude that compositional differences in observable and unobservable characteristics across cells do not play a major role in the estimations.

Third, our findings might be biased since we do not control for productivity trends at the firm level, a possible confounding factor. To address it, we derive additional control variables by exploiting a subsample of firms and workers for which balance sheet variables are available (i.e., for capital companies).[20] We compute at the cell level the following control variables: fixed assets, labor productivity, labor cost, production value, operating revenues, and value-added. Enriching our baseline specifications by adding these balance sheet control variables, results are very much in line with the baseline ones (Figure A8 and Figure A9), both for magnitude and trends over time.[21]

[18] Figure A4 provides additional information on the mediating channels, suggesting that in remote areas, with respect to cities, there is a stronger HHI impact on worked weeks and part-time contracts, even if differences are smaller than those observed between services and manufacturing.

[19] We have also derived similar effects between males and females, and a stronger impact for workers aged below 40. Results are available upon request.

[20] We use the CERVED archive, available in the Visitinps program for the years 2005-2018

[21] We also compute an additional robustness checks without using the debiased fixed effects estimator. Results are consistent and available on request.

5 Conclusion

By adopting a dynamic approach using local projections, we demonstrate that the estimated effect of LMC is stronger than that identified using static methods, and more pronounced for earnings than unitary wages, due to LCM's impact on the intensive employment margin (worked weeks, fixed-term and part-time contracts).

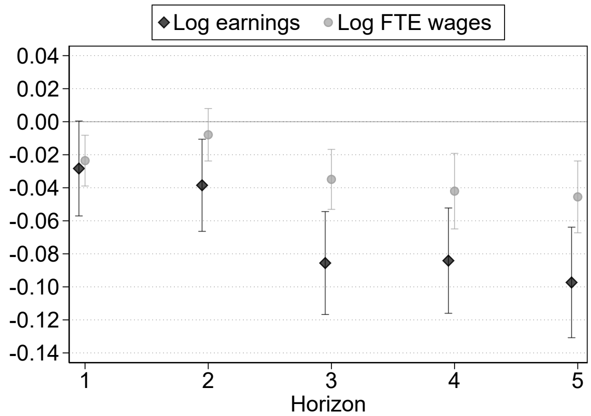
A similar pattern is observed for inequality. When considering percentiles, the LMC effect is relatively stronger for unskilled workers. Back-of-the-envelope calculations show that labor market concentration explains 14.5% of the increase in inequality in the lower part of the Italian earnings distribution.

We also point out that LMC directy affect the functioning of labor market institutions, specifically collective bargaining. This represents a mediating factor for the increasing dynamic impact of LMC on remumeration levels and inequality, that has to be taken into account when a regulated labor market is considered.

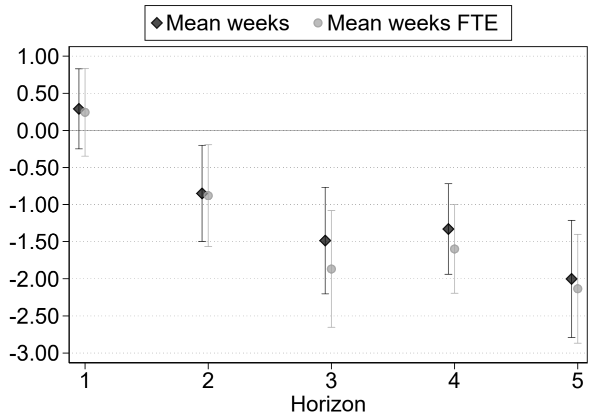
Overall, our results have significant policy implications. First and foremost, we demonstrate that estimating the LMC effect on contemporaneous outcomes rather than using a dynamic setting leads to a significant underestimation of the LMC impact. This issue is even more pronounced when considering earnings rather than FTE wages. Second, for a European country, we confirm that LMC increases inequality, mainly hampering unskilled workers. Third, labor market institutions, i.e. collective bargaining, is a crucial mediating factor for LMC effects.

Figures

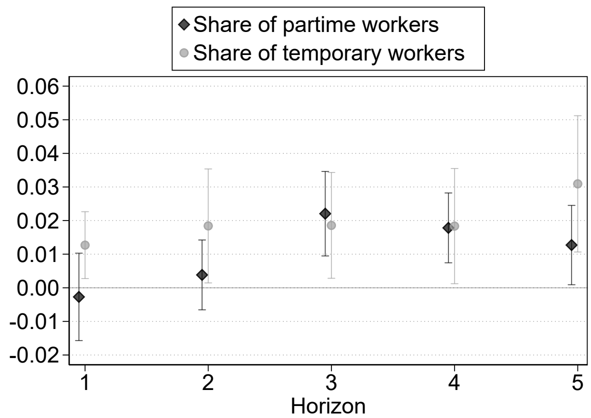
Figure 1: The effect of log HHI: main results



(a) The effect of HHI on log earnings and log FTE wages



(b) The effect of log HHI on the number of annual worked weeks

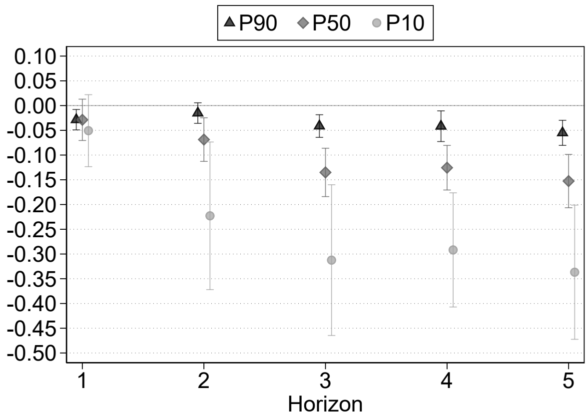


(c) The effect of log HHI on contractual arrangements

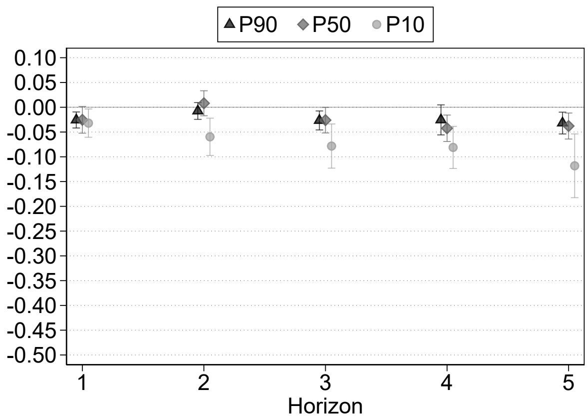
Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.

Figure 2: The effect of log HHI on inequality

(a) The effect of log HHI on inequality



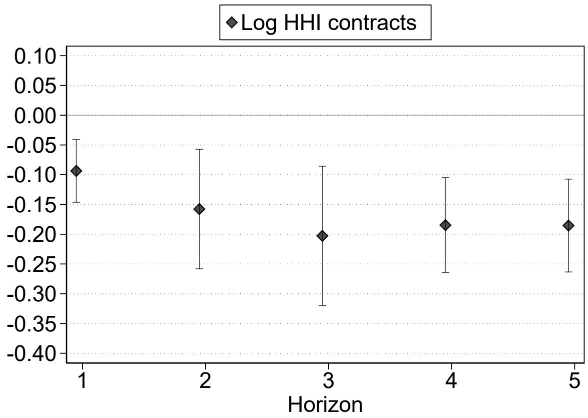
(b) The effect of log HHI along the earnings distribution



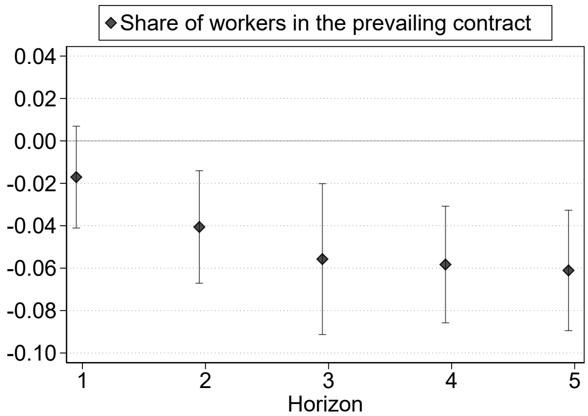
(c) The effect of log HHI along the wage distribution

Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.

Figure 3: The effect of log HHI on collective bargaining



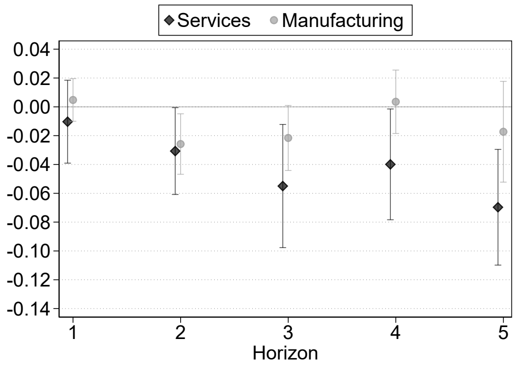
(a) The effect of log HHI on log HHI of collective contracts



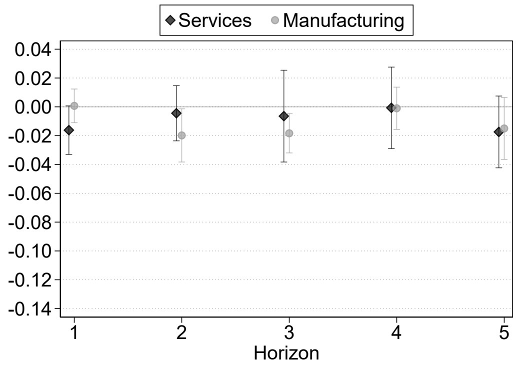
(b) The effect of log HHI on the share of the most representative collective contract

Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.

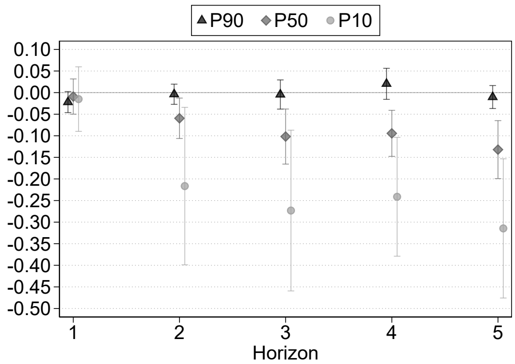
Figure 4: Heterogeneity: Manufacturing and Services



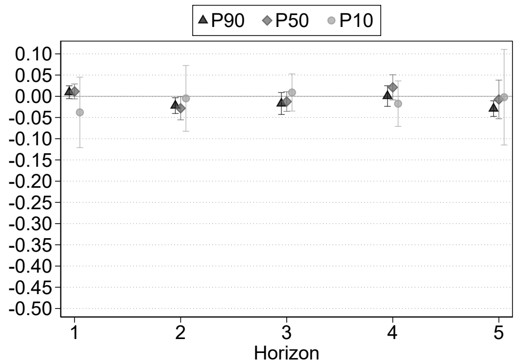
(a) The effect of log HHI on log earnings



(b) The effect of log HHI on log FTE wages



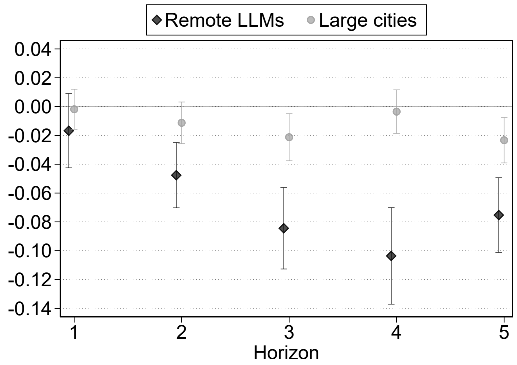
(c) The effect of log HHI along the earnings distribution in services



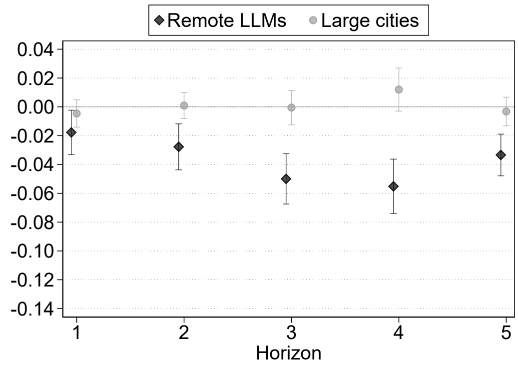
(d) The effect of log HHI along the earnings distribution in manufacturing

Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.

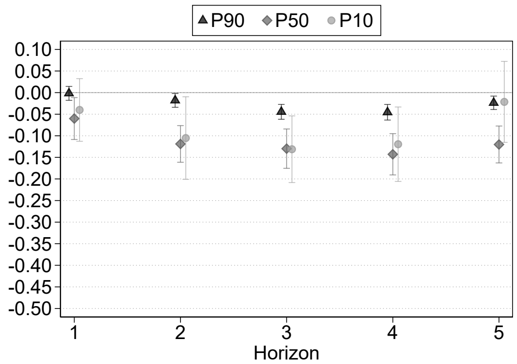
Figure 5: Heterogeneity: large cities and remote LLMs



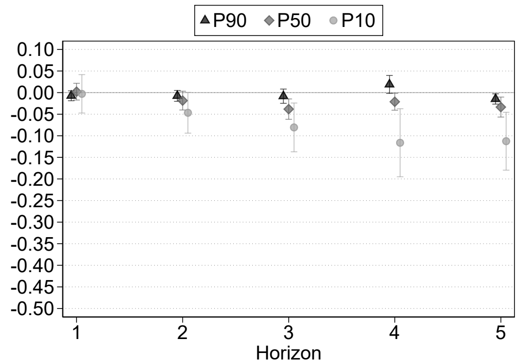
(a) The effect of log HHI on log earnings



(b) The effect of log HHI on log FTE wages



(c) The effect of log HHI along the earnings distribution in remote LLMs



(d) The effect of HHI along the earnings distribution in large cities

Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.

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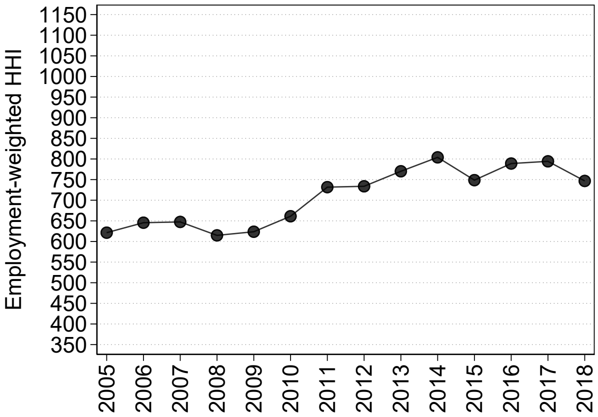
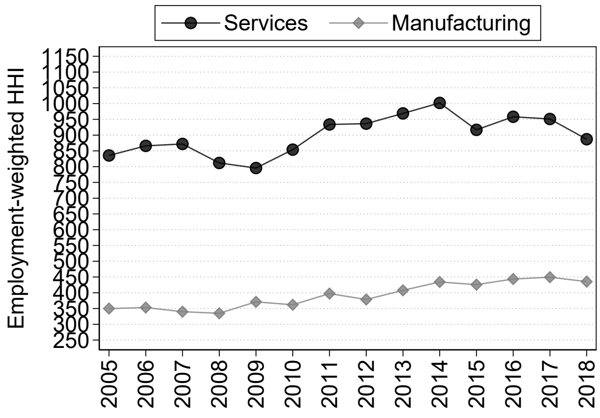
Online Appendix

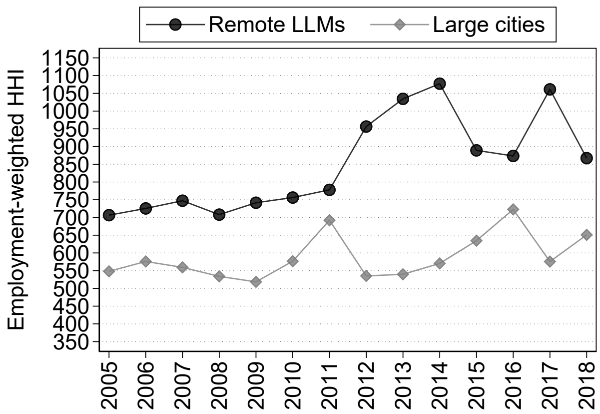
Figure A1: The evolution of the employment-weighted average HHI in Italy from 2005 to 2018



(a) HHI in all LLMs



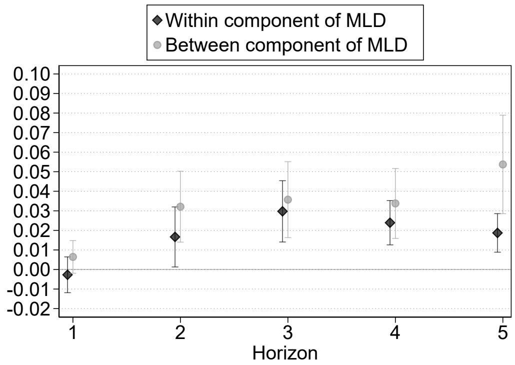
(b) HHI in services and manufacturing



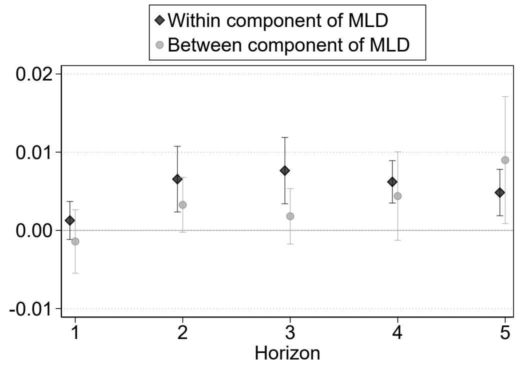
(c) HHI in remote LLMs and large cities

Notes: When computing the HHI, firms' employment shares are multiplied 100, and hence the HHI index ranges from 1 to 10000, as standard. Authors' elaborations on administrative archives from INPS.

Figure A2: Additional results: the effect of log HHI on between and within inequality



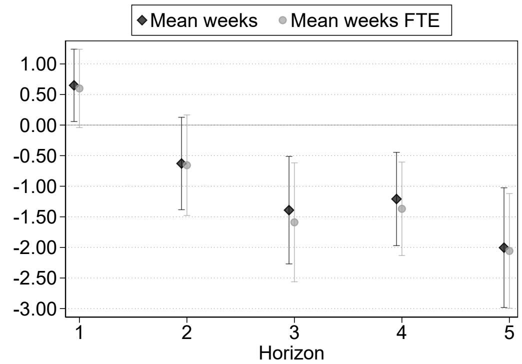
(a) The effect of log HHI on within and between earnings inequality



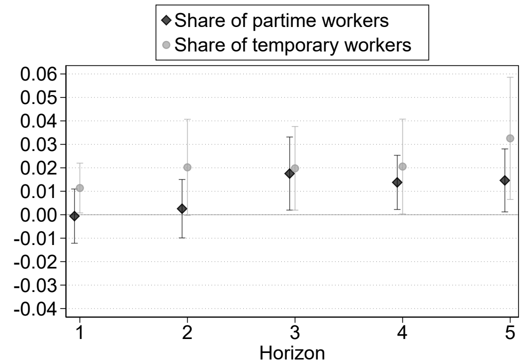
(b) The effect of log HHI on within and between wage inequality

Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.

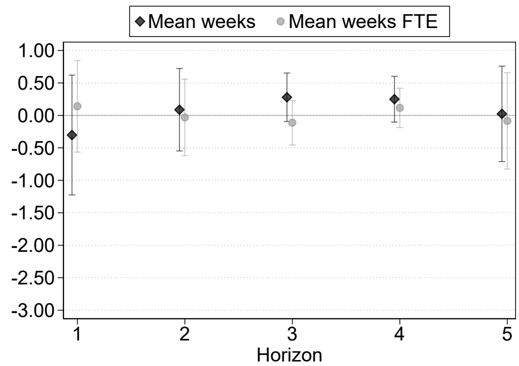
Figure A3: Additional heterogeneity: industry and services



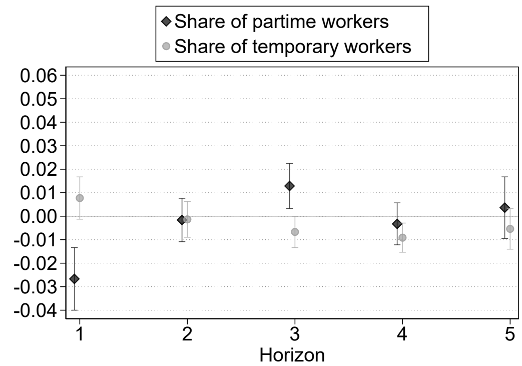
(a) The effect of log HHI on the number of annual worked weeks in services



(b) The effect of log HHI on the number of annual worked weeks in manufacturing



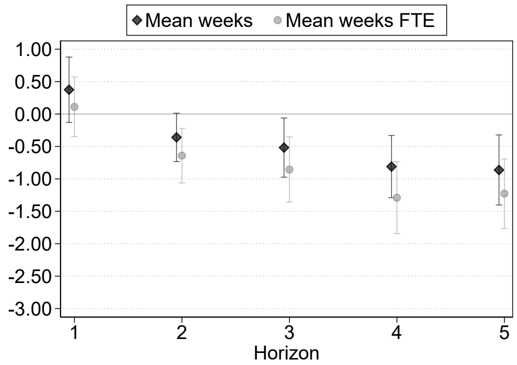
(c) The effect of log HHI on contractual arrangements in services



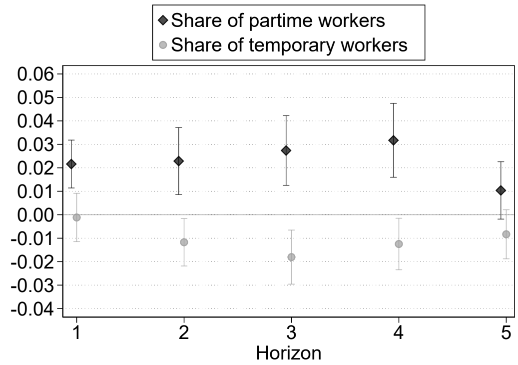
(d) The effect of log HHI on contractual arrangements in manufacturing

Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.

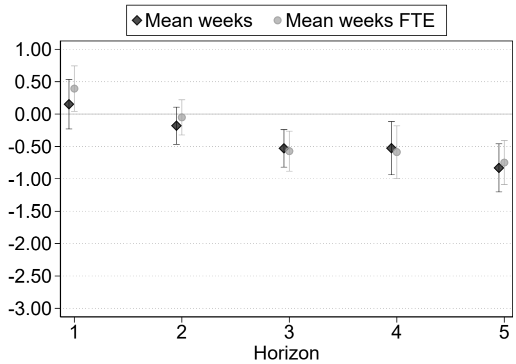
Figure A4: Additional heterogeneous results: large cities and remote LLMs



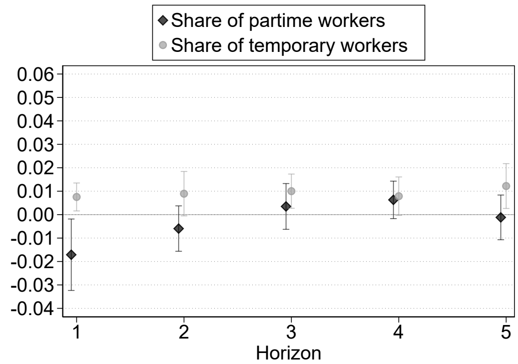
(a) The effect of log HHI on the number of annual worked weeks in remote LLMs



(b) The effect of log HHI on the number of annual worked weeks in large cities



(c) The effect of log HHI on contractual arrangements in remote LLMs

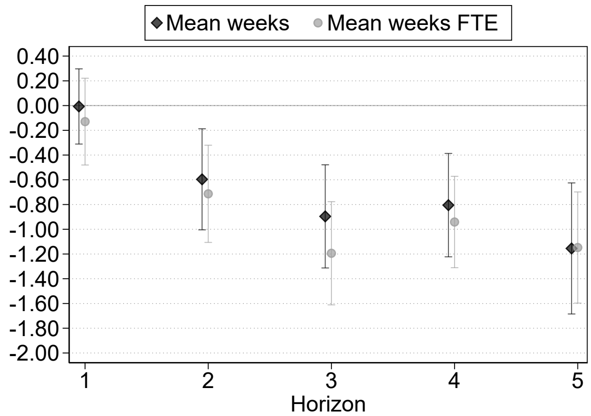


(d) The effect of log HHI on contractual arrangements in large cities

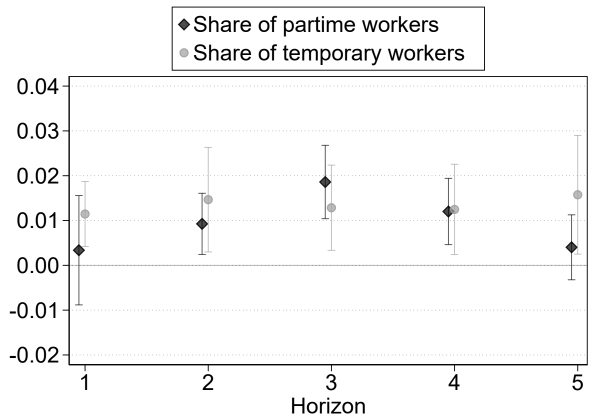
Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level. Cities with more than 100,000 inhabitants are the following (ordered by size): Roma, Milano, Napoli, Torino, Palermo, Genova, Bologna, Firenze, Bari, Catania, Verona, Venezia, Messina, Padova, Trieste, Parma, Brescia, Prato, Taranto, Modena, Reggio Calabria, Reggio Emilia, Perugia, Ravenna, Livorno, Rimini, Cagliari, Foggia, Ferrara, Latina, Salerno, Giugliano in Campania, Monza, Sassari, Bergamo, Pescara, Trento, Forlì, Siracusa, Vicenza, Terni, Bolzano, Piacenza, Novara..

Figure A5: The effect of log HHI: standard leave-one-out IV

(a) The effect of log HHI on log earnings and log FTE wages



(b) The effect of log HHI on the number of annual worked weeks

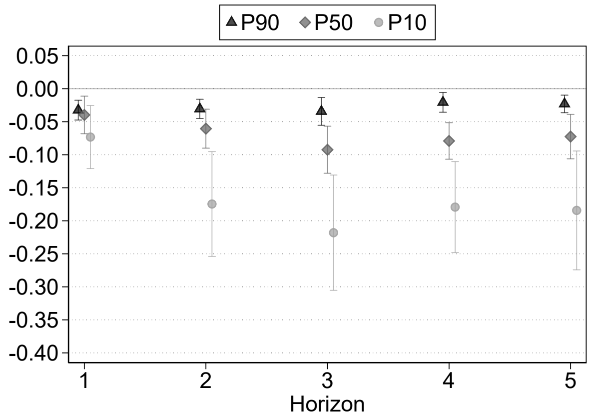


(c) The effect of log HHI on contractual arrangements

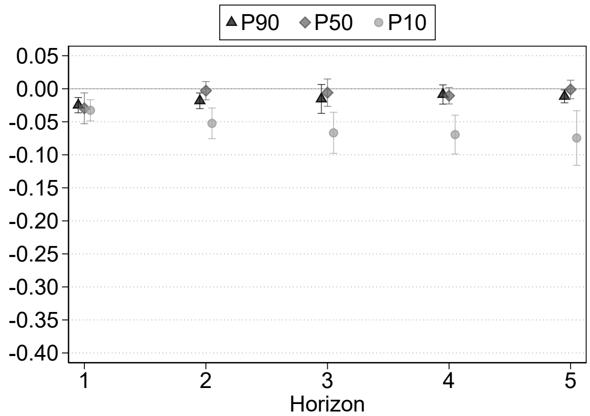
Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.

Figure A6: The effect of log HHI on inequality: standard leave-one-out IV

(a) The effect of log HHI on inequality



(b) The effect of log HHI along the earnings distribution

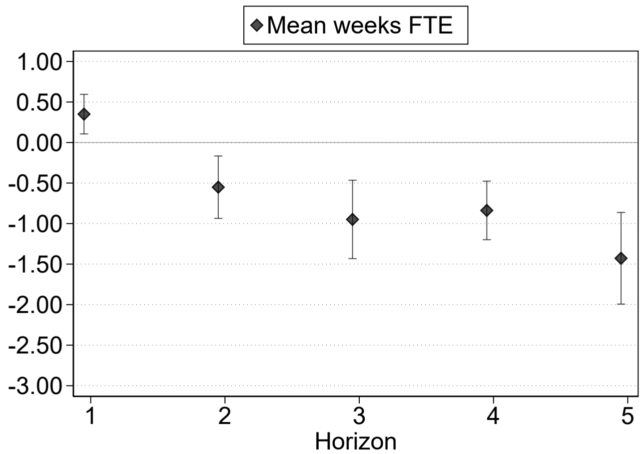


(c) The effect of log HHI along the wage distribution

Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.

Figure A7: The effect of log HHI: two-step procedure

(a) The effect of log HHI on log earnings and log FTE wages

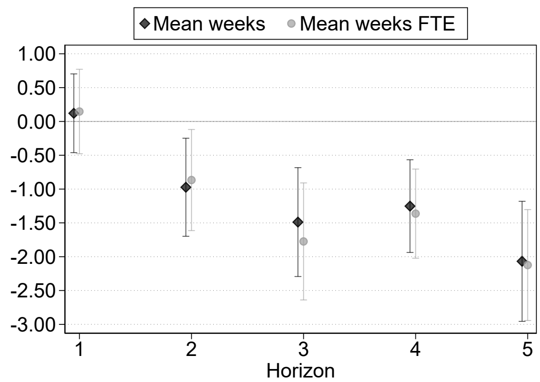


(b) The effect of log HHI on the number of annual worked weeks

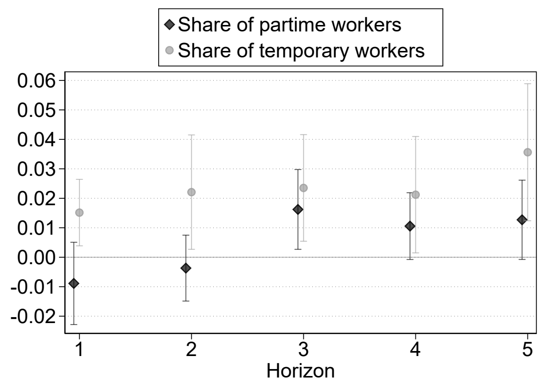
Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.

Figure A8: The effect of log HHI: controlling for balance sheet information

(a) The effect of log HHI on log earnings and log FTE wages



(b) The effect of log HHI on the number of annual worked weeks

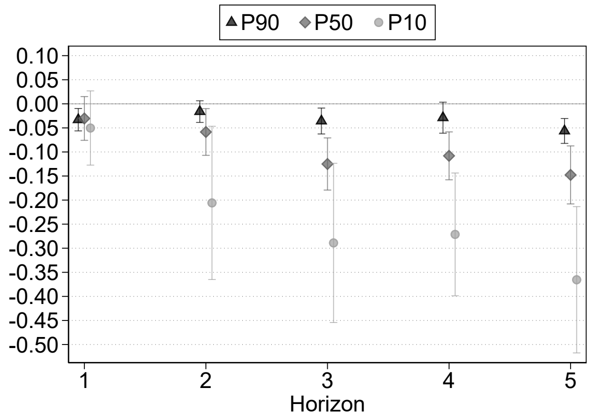


(c) The effect of log HHI on contractual arrangements

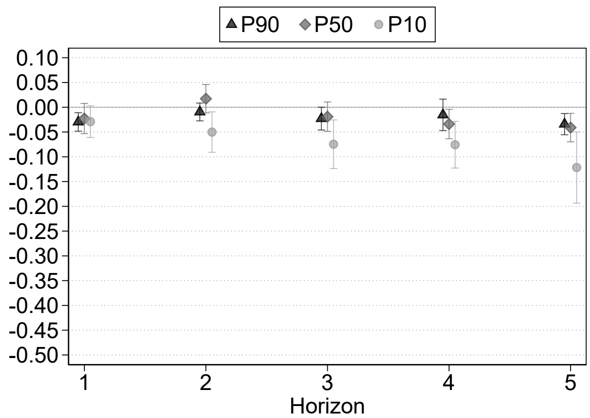
Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.

Figure A9: The effect of log HHI on inequality: controlling for balance sheet information

(a) The effect of log HHI on inequality



(b) The effect of log HHI along the earnings distribution



(c) The effect of log HHI along the wage distribution

Notes: LPs estimates are obtained using an IV approach and the debiased fixed effects method with 90% confidence intervals. Regressions are employment-weighted. Standard errors are clustered at the local labor market level.