Remote Work and Labor Market Power*

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Abstract

This paper examines the causal impact of the post-pandemic transition to remote work on labor market power, connecting to an extensive literature which highlights distaste for commuting as a key source of rent extraction for local employers. Our analysis combines three sources of microdata: (i) millions of job vacancy postings to derive an index of remote work using a frontier large language model; (ii) worker-level administrative records on the workplace and occupational group; and (iii) firm-level production data to estimate wage markdowns. Exploiting the heterogeneity in shifts to remote work across occupations — instrumented with shifts observed abroad — and the heterogeneity in occupation mixes across local labor markets, we implement a shift-share design and identify a substantial reduction in employer rents. Our counterfactual analysis quantifies the impact of the 2019-2023 transition to remote work in one-fifth of the deviation from perfect competition.

Keywords: work from home, monopsony, wage markdowns, job vacancies, shift share

JEL Codes: J31, J42, J63, R23, R32

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1 Introduction

Following Manning (2003), an important theoretical and empirical literature has emphasized that labor markets are largely monopsonistic and firms are typically able to set wages below the competitive level.[1] Monopsony power is often explained in terms of competition with limited substitutability between differentiated employers, arising from the idiosyncratic taste for different workplaces (Card et al., 2018). Chief among these sources of horizontal differentiation is location proximity, as workers dislike commuting costs and times (Manning & Petrongolo, 2024). This mechanism shields local employers from competition, allowing them to exert market power, especially in less connected areas. Considering the key role of commuting for monopsony power, a natural question is whether the unprecedented adoption of remote work, following the COVID-19 pandemic, has produced sizable changes in labor market competition.

Remote work arrangements have indeed persisted long after the forcing event subsided (Hansen et al., 2023).[2] The persistence of work-from-home (WFH) reflects both the value workers place on flexibility (Cullen et al., 2025; Mas & Pallais, 2017), as well as the benefits of relaxing geographic constraints and expanding the feasible set of jobs a worker might be willing to accept (Akan et al., 2025; Manning & Petrongolo, 2017). If the diffusion of remote work enlarges the set of appealing matches, then firms must compete for workers in a broader market, which could raise the elasticity of labor supply they face, and consequently, reduce the wedge betweem the marginal revenue product of labor (MRPL) and labor costs per worker.[3] At the same time, WFH represents a job amenity over which workers may have idiosyncratic preferences.[4] Heterogeneity in its adoption may generate further horizontal differentiation across employers, reducing competition. Thus, we need empirical guidance to infer which of the two mechanisms — a declining relevance of the geographical differentiation vs a novel amenity increasing differentiation — dominates.

We look at the relationship between WFH and monopsony power in Italy, combining three complementary data sources. First, we measure the diffusion of WFH using millions of job

[1] Examples include Azar et al. (2020), Dube et al. (2020), Bassier et al. (2022), Berger et al. (2022), Deb et al. (2022), Lamadon et al. (2022), Yeh et al. (2022), Goolsbee and Syverson (2023), Kroft et al. (2025). See Card (2022) for a summary and discussion.

[2] For the United States, Barrero et al. (2023) document that working from home remains a large share of paid workdays in the post-pandemic period and argue that this persistence reflects durable changes in technology, managerial practices, and worker preferences. Cross-country evidence on persistence appears in Zarate et al. (2025).

[3] Under static profit maximization, the percentage difference between MRPL and labor costs per worker equals the elasticity of the inverse labor supply.

[4] Consider, for instance, differences in housing conditions across workers.

vacancy postings, analysing the posting text with frontier large language model (LLM) processing methods and classifying whether jobs offer fully remote or hybrid arrangements. These measures are then aggregated by occupational group and year, to obtain occupation-specific WFH shifts that occurred during the pandemic. Second, we gain access to administrative records on worker-level characteristics to construct the pre-pandemic employment shares of each occupation across local labor markets, defined as interactions of commuting zones and industries. Third, we measure monopsony power at the firm-level by performing a parametric estimation of MRPL from the financial statements of Italian corporations, from which we derive net wage markdowns — henceforth markdowns — defined as percentage differences between MRPL and labor costs per worker. Markdowns are then aggregated by cell and year, to obtain time differences in the departure from perfect competition across local labor markets.

The 2019–2023 variations in aggregate markdowns constitute our dependent variable. Our empirical strategy exploits heterogeneity in the post-pandemic diffusion of remote work across local labor markets from two sources of variation: (i) the diverse capacity to carry out tasks remotely across occupations and (ii) the diverse occupation mix across commuting zones and industries. We construct a shift-share index of exposure to remote work by interacting the local occupational shares in 2019 with the national occupation-specific WFH shifts that occurred between 2019 and 2023.

A legitimate concern is that national shifts in WFH may be correlated at the occupation-level with other contemporaneous shocks. To address this potential source of endogeneity, we leverage the idea that the diffusion of remote work is partly driven by technology and task content transcending national boundaries. We process job postings from the United States with the same LLM applied to Italian data and instrument WFH shifts in Italy with WFH shifts observed in the US. A further advantage in this IV strategy lies in the superior accuracy of measurement based on US data due to sample size, which is larger by an order of magnitude. Additional identification issues are dealt with by specifying control variables and standard errors in accordance with the most recent guidance on the econometrics of shift-shares (Borusyak et al., 2025).

Our core finding is that WFH increases competition in the labor market reducing aggregate markdowns. The inferred impact is substantial in magnitude and robust to several specifications. An increase of one interquantile range in the WFH index lowers the aggregate markdown by nearly 6 basis points. Furthermore, using the same strategy we find a substantial effect on wages, which increase by 4%, consistent with a more competitive labor market. The counterfactual analysis considers scenarios with different diffusion of remote work. According to our estimates, without the WFH shifts occurring between 2019 and 2023, the country-level markdown in 2023 would be approximately one fifth higher, 0.36 instead of 0.29. Comparing the same industries across different commuting zones, our results reveal that, under the WFH shifts observed in major cities such as Rome or Milan, the aggregate markdown would be 0.26 or 0.25, respectively — a further drop by nearly one tenth.

Market-level results are then corroborated by tests at the firm-level and worker-level, confirming the negative effect on markdowns and the positive effect on wages. Worker-level analysis allows us to uncover an additional element in the mechanism. We document that exposure to WFH leads to a higher probability of mismatch in the commuting zones of the worker's residence and workplace, supporting the hypothesis of a pro-competitive effect due to an expansion of geographical constraints.

Related literature. Our work contributes to two literatures that have largely developed in parallel: research on labor market power and research on remote work. Growing evidence using a variety of approaches has established the presence of non-trivial employer power in labor markets. For instance, Bassier et al. (2022) use a matched event study to measure the elasticity of employer-employee separations to the wage, from which they obtain a net markdown of 0.24 in their preferred specification. Yeh et al. (2022) estimate plant-level production functions across US manufacturing and derive an average net markdown of 0.53, with an upward trend since 2002. Deb et al. (2022) instrument labor demand shocks with time-series variation in taxes and find a range spanning between 0.32 and 0.53, with a more muted time trend. Berger et al. (2022) develop and structurally estimate a model of oligopsonistic competition, obtaining an aggregate net markdown equal to 0.39, which generates a 21% output loss through resource misallocation.

Furthermore, monopsony power has been shown to explain several features of the labor markets, such as the elusive effect of minimum wages on employment (Dustmann et al., 2021; Manning, 2021), between-firm inequality in wages (Card et al., 2018) falling labor shares (Mertens & Mottironi, 2025) or urban wage premia (Hirsch et al., 2022). Regarding the roots of imperfect competition, recent research has emphasised the role of concentration in hiring flows (Azar et al., 2020, 2022), collusion against workers (Delabastita & Rubens, 2025), non-compete agreements (Alves et al., 2024; Boeri et al., 2025), search frictions (Berger et al., 2024; Burdett & Mortensen, 1998), and commuting distance (Datta, 2024; Manning & Petrongolo, 2024). This paper speaks to the latter factor, providing novel evidence that, by softening the need to commute — along either the extensive or intensive margin, in fully remote or hybrid arrangements respectively — the diffusion of remote work can increase competition in labor markets.

In parallel, an extensive body of research documents that remote work is persistent, its feasibility varies sharply across tasks, and its adoption differs across places (Althoff et al., 2022; Barrero et al., 2023; Dingel & Neiman, 2020). A central theme is that remote work is a non-wage amenity with heterogeneous valuations (Mas & Pallais, 2017; Song & Gao, 2018). Remote work also has organisational and productivity consequences that vary across settings and interact with selection, coordination, and collaboration mechanisms (Bloom et al., 2015; Emanuel & Harrington, 2024; Gibbs et al., 2023; Yang et al., 2022). Recent work has also considered its impact on worker mobility (Liu & Su, 2025), migration (Bick et al., 2024), and commuting (Monte et al., 2023).

Our analysis extends this literature by uncovering an overlooked channel, contributing to a broader understanding of the labor market effects of flexible work arrangements. The welfare-enhancing effects of remote work may not be limited to the direct effect on workers who experience greater flexibility. By enlarging the size of labor markets, remote work can change the spatial mobility and power dynamics between workers and firms, improving competition. These findings bear significant implications for policy, as the adoption of remote work, possibly combined with the supply of remote working locations to those who have limited work opportunities at home, could be encouraged as a tool to discipline monopsony power, mitigating unequal labor market opportunities across space and improving overall market allocation.

Outline. The remainder of this paper is organised as follows. Section 2 illustrates the diverse data sources employed in this project. Section 3 outlines our measurement methodology, including novel LLM tools for parsing remote work arrangements from job ads and markdown estimation from financial statements. Section 4 provides the details of our research design and how it relates to the recent literature on shift-share instruments. Section 5 reports the results of the 2SLS estimation and the counterfactual exercise. Section 6 concludes.

2 Data

2.1 Job postings

Our analysis employs over 20 million online job vacancy postings from Italy and nearly 200 million from the United States, collected during the period 2018–2024. Italian job postings cover all NUTS2 regions as well all two-digit ISCO occupations but the military. This database is produced by Lightcast, a company specialised in labor market analytics, successor brand of Burning Glass Technologies. Lightcast collects vacancy advertisements from a large set of online job boards and employer career pages, and then converts the unstructured content into a harmonised statistical dataset through a pipeline that includes de-duplication, entity resolution, and automated coding of occupations, industries, and locations (Lightcast, 2022).

Table 2.1 reports the number of online job vacancy postings for which we could retrieve reliable information on the ISCO classification, before and after the pandemics, i.e. the two periods considered in the empirical strategy discussed in Section 4. The US database shows a substantially larger sample size, which implies more accurate estimates. This advantage leads us instrumenting our index of WFH exposure based on Italian postings with the same index computed using the US database (see Section 4). The yearly count of postings in the full sample is reported in Appendix A.

Table 2.1: COUNT OF LLM-CLASSIFIED JOB POSTINGS

Year	Italy	United States
2019	1,097,174	28,140,958
2023	3,511,278	32,322,852

Note: This table reports the sample size of job postings for which we could retrieve reliable information on the ISCO classification, by year and country. Source of the raw data: Lightcast.

Although online postings are not equivalent to the full universe of vacancies in the economy, they provide uniquely timely and text-rich signals of labor demand and advertised job attributes, which is precisely the dimension we exploit in constructing vacancy-based measures of remote work.

2.2 Social security records

Our analysis requires to combine the occupation-level measure of 2019–2023 variations in remote work adoption with the 2019 employment share of each occupational group (three-digit ISCO) across Italian local labor markets, which we define as interactions of commuting zones (‘Sistemi Locali del Lavoro’, from ISTAT) and two-digit industries (NACE rev. 2).

Because this disaggregation is not present in publicly available datasets, we get access to Italian social security records through the VisitINPS program. These administrative data include information on worker-level characteristics such as the occupational group, education, working days, workplace location, and the employer's industry.[5] In particular, we merge two datasets: (i) UniLav, which collects 'compulsory communications' on the beginning, extension, transformation, and conclusion of employment contracts — including, crucially, information on the specific occupation held by the employee as well as the education level — and (ii) Uniemens, which provides yearly information on remuneration, working days, workplace location and industry for all employees.[6]

The resulting database is a cross-section of employer-employee-location matches active in 2019. For job relationships that appear as active in Uniemens but do not show a corresponding communication in UniLav, we impute occupational groups using the most recent compulsory communication made for the same worker by another employer. Our methodology classifies the occupational group of nearly 90% of private sector workers with an active record in 2019. Furthermore, the availability of information on working days allows us to derive the employment shares in full-time equivalent (FTE) units, taking into account potential heterogeneity in job discontinuity and part-time employment across occupations. Table 2.3 shows the summary statistics of the resulting database. Table 2.3 lists the three most frequent occupations, industries, and commuting zones.

Table 2.2: Worker-level summary statistics

Individual characteristic	Share (FTE)
Female	38.24%
Foreign citizen	14.03%
Under 30 year old	18.39%
Over 50 year old	27.19%
College graduate	14.19%
Employed in a high-skill job	22.15%
Employed in manufacturing	26.54%
Employed in the South	20.33%

Note: This table reports summary statistics from the 2019 sample of the social security records, merging Uniemens and UniLav datasets. Each observation is an employer-employee-location match, for a total of 15,970,571 matches. Values are computed using FTE units as weights. The weighted average of FTE units is 0.802. Source of the raw data: VisitINPS.

[5] Further details are available at https://www.inps.it/it/it/dati-e-bilanci/attivit--di-ricerca/programma-visitinps-scholars.html.

[6] The same data are used by INPS to compute social security contributions.

Table 2.3: MOST FREQUENT OCCUPATIONS, INDUSTRIES, AND CZS

Classification	Rank	Denomination	Share (FTE)
Occupation (ISCO)	1st	*General office clerks*	9.49%
Occupation (ISCO)	2nd	*Shop salepersons*	7.97%
Occupation (ISCO)	3rd	*Waiters and bartenders*	3.74%
Industry (NACE)	1st	*Retail trade*	8.94%
Industry (NACE)	2nd	*Food and beverage*	5.88%
Industry (NACE)	3rd	*Wholesale trade*	4.99%
Commuting zone (ISTAT)	1st	*Milan*	11.55%
Commuting zone (ISTAT)	2nd	*Rome*	7.54%
Commuting zone (ISTAT)	3rd	*Turin*	3.54%

Note: This table reports the three most common three-digit occupational groups (ISCO), two-digit industries (NACE), and commuting zones (Sistemi Locali del Lavoro, from ISTAT) in the 2019 sample of the social security records. Source of the raw data: VisitINPS.

2.3 Financial statements

To perform our estimations, we use financial statements of Italian corporations from the Orbis database (AIDA), covering the near-universe of incorporated companies in 2015–2023. Table 2.4 reports summary statistics for the full sample of firms with at least one employee.

Table 2.4: FIRM-LEVEL SUMMARY STATISTICS

	Median	Mean	SD	Obs.
Employment	5	17.9	235.2	4,828,357
Value added per employee	44.17	65.71	323.81	4,828,357
Labor costs per employee	25.56	28.34	92.32	4,828,357
Capital per employee	8.86	107.8	1,211.62	4,828,357

Note: This table reports the median, mean, standard deviation, and number of observations for firms with at least one empoloyee, based on the full 2015-2023 sample, before implementing the data cleaning routine. Monetary values are expressed in thousands of constant Euros (2020). Source of the raw data: AIDA.

Average employment per firm is above the value observed in the universe, partly because we exclude firms with no employee and partly because our firm-level database only includes incorporated companies. As for most papers in the related literature, the reason for choosing this sample is that unincorporated companies are not legally obliged to produce a statutory balance sheet, which is the key source of information for the variables used in our estimations.

Nevertheless, our database has a large coverage of micro firms, as shown by a median employment equal to five. Value added is defined by subtracting raw materials (net of changes in the corresponding inventory), purchased goods for resale, and intermediate services from the total value of production. Our sample includes firms with negative value added, which amounts to nearly 5%. Notice that value added is slightly less than twice as large as labor costs per employee, in line with aggregate statistics reported by ISTAT, the source of official statistics in Italy. Capital is defined as tangible fixed assets, net of the stock held for sale.

3 Measurement

3.1 Remote work

Methodology. Our primary use of the job postings is to measure the prevalence of remote and hybrid arrangements by occupational group, based on the textual content of each observation. The Lightcast database does not directly include structured information on the use of remote work, so we extend the methodology of Hansen et al. (2023) and apply an LLM to extract this feature and classify each job posting.

The exercise is carried out in three steps: first, we identify which postings contain any information at all about remote or hybrid work arrangements; second, focusing on the positive cases from the previous step, we identify the actual proposal of remote work, being careful to distinctly tag cases in which remote work is mentioned by being explicitly disallowed; finally, we evaluate the performance of the algorithm using a sample of 2,000 hand-classified postings.[7] Further details on our strategy and its validation — including a comparison with the assessments of occupation-specific remotability implemented at the beginning of the pandemic by Basso et al. (2020) — are available in Appendix A.

The results of our performance assessment are reported in Table 3.1. The F-score pooling the two years of interest is nearly 96%, showing high consistency between LLM-based and human-based classifications. Auditing points to Type 1 errors largely exceeding Type 2 errors in 2019, based on a subsample that equally represents remote and non-remote arrangements. This difference in the two types of errors implies a vastly superior performance in the population estimates as there are significantly fewer remote arrangements in 2019.

To derive the shift-share index of remote work adoption at the market-level, after classifying job postings by the availability of remote work we compute the occupation-specific shifts in the share of WFH jobs occurred during the pandemic. Such 2019-2023 WFH shifts (ΔS_o, with

[7] Our manual classification is available in the replication package.

Table 3.1: LLM PERFORMANCE

Metric	LLM classification	2019	2023	Pooled
Recall	WFH = 0	100%	99.6%	99.8%
Precision	WFH = 1	88%	96.4%	92.2%
F-score	Harmonic mean	93.6%	98%	95.8%

Note: Table 3.1 reports the performance metrics of our LLM algorithm, based on human auditing of a stratified subsample, i.e. manual classification of 1,000 postings, equally distributed by LLM classification and year. Recall (Precision) reports the percentage of observations in which the negative (positive) LLM classification is confirmed. The F-score is the harmonic mean of Recall and Precision. Source of the raw data: Lightcast.

o denoting a three-digit occupational group) are then combined with 2019 shares of workers in the corresponding occupation ($L_{o,c}$, in FTE units) within each labor market c, which we define as the interaction of a commuting zone and a two-digit industry. The resulting shift-share index (ΔWFH_c) constitutes the key regressor in our baseline specification.

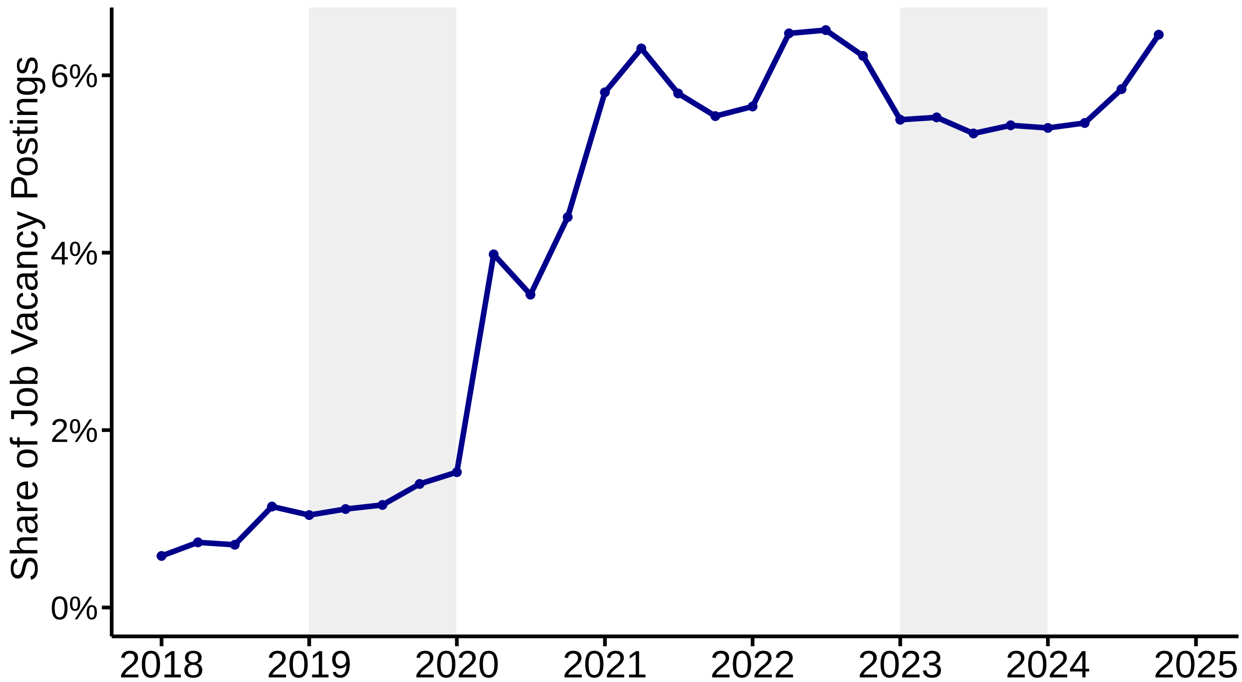
$$\Delta WFH_c \equiv \frac{\sum_o \Delta S_o L_{o,c}}{\sum_o L_{o,c}} \tag{3.1}$$

Descriptives. The rapid rise in remote work practices is now a well-documented fact across the developed world. We provide additional evidence that Italy, one of the earliest countries to be hit by the pandemic, has also experienced a substantial rise in the share of job ads explicitly offering such practices. Figure 3.1 reports the share of job postings offering remote work arrangements by quarter. As our measure is a lower bound for WFH and is confined to job posting on platforms, it should not come as a surprise the fact that the Italian Labor Force Survey points to a larger share of jobs offering WFH arrangements (see Appendix A.1). The trend displayed by our estimates is in line with LFS data: we observe a mild upward trend in 2018–2019, a rapid burst in 2020–2021, and fluctuations around a flat trend afterwards.[8]

Figure 3.2 documents this diffusion across terciles of occupational groups based on the degree of WFH adoption. The 'low WFH' occupations see almost no rise in such arrangements, whereas the 'high WFH' occupations see an almost six-fold increase since the onset of COVID-19. Teaching and ICT professionals are observed at the top of the WFH list. The lowest level of remote work offers is found in food-preparation and construction workers. In our main

[8] This magnitude also aligns with measures from other countries reported by Hansen et al. (2023).

Figure 3.1: WFH DIFFUSION IN ITALY

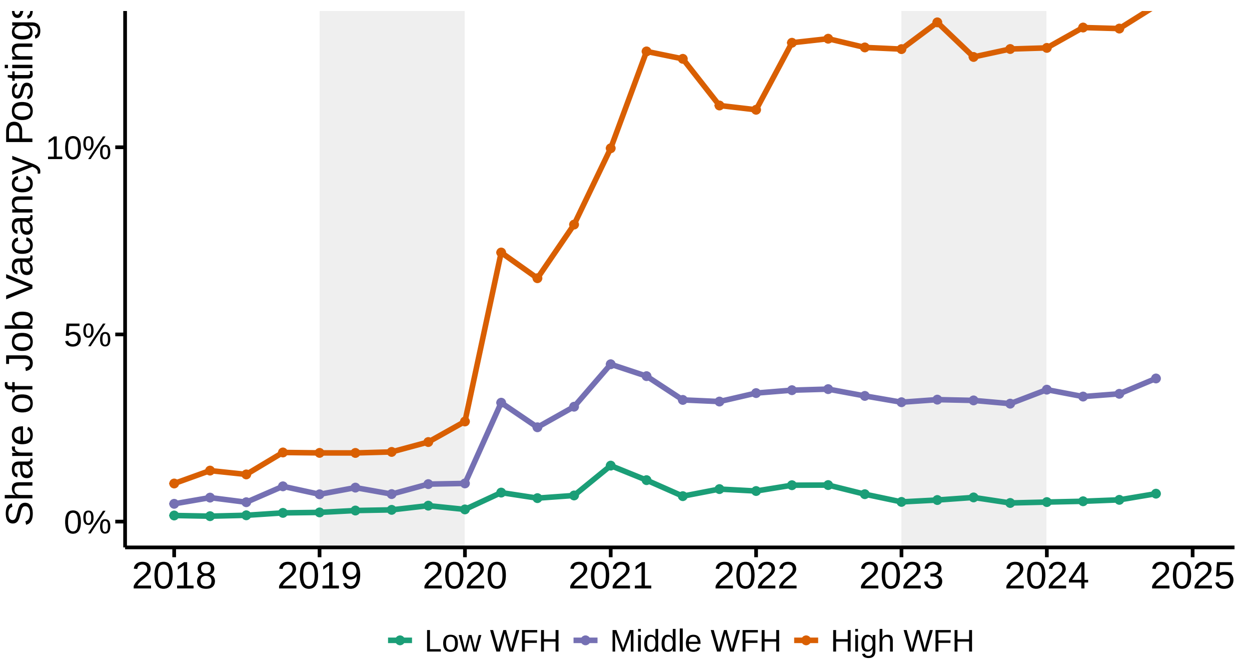


Note: This figure reports the share of online job vacancy postings explicitly offering remote arrangements by quarter. The sample includes 13,616,201 observations in total, where both an occupation code was present and raw textual description allowed for a classification of remote work using our LLM classification algorithm. Quarters in 2019 and 2023 are shaded as these subsets are used in our econometric application. Source of the raw data: Lightcast.

empirical exercise, we exploit this variation between occupational groups to define exposure to the rise of remote working across Italian local labor markets.

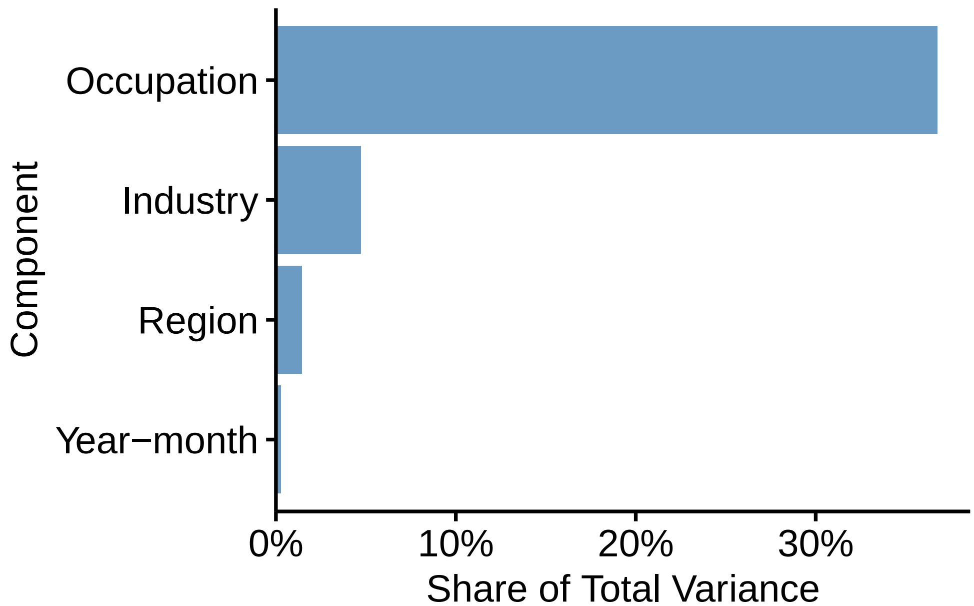
To ensure that our main empirical design exploiting occupational variation is sensible, we conduct a variance decomposition exercise using alternative dimensions of the job vacancy posting, namely regions, industries, and periods. We run a fixed-effects regression with these dimensions along with the occupational groups. Figure 3.3 reports the variance that each dimension explains, showing that occupation is by far the dominant source of variation in remote work opportunities. We see that the job ads occupation explains 38% of total variation, whereas industry and region have less explanatory power after conditioning on the occupation.

Figure 3.2: WFH HETEROGENEITY ACROSS OCCUPATIONS



Note: This figure reports the share of online job vacancy postings explicitly offering remote arrangements, broken into three equally-sized occupational groups, by quarter. The low, middle, and high WFH groups are defined using the share of job postings offering remote arrangements in 2023, split into terciles of two-digit ISCO occupations. The sample includes 13,616,201 observations in total, where both an occupation code was present and raw textual description allowed for a classification of remote work using our LLM classification algorithm. Quarters in 2019 and 2023 are shaded as these subsets are used in our econometric application. Source of the raw data: Lightcast.

Figure 3.3: WFH VARIANCE DECOMPOSITION



Note: This figure reports the variance decomposition of remote work calculated using fixed effects for (i) two-digit ISCO occupations, (ii) NUTS-2 regions, (iii) ISIC letters, and (iv) year-months from January 2022 to December 2024. Regression is fit across 281,482 cells defined using the interaction of these four dimensions. Each cell is weighted by the count of postings. Source of the raw data: Lightcast.

3.2 Labor market power

Methodology. We measure the degree of labor market power of firm f in period t by estimating its wage markdown ($\gamma_{f,t}$), defined as the percentage difference between its marginal revenue product of labor ($MRPL_{f,t}$) and labor costs per worker ($w_{f,t}$). Markdowns are commonly used to assess competition in labor markets as their theoretical value is null under perfect competition — one if expressed in gross terms (i.e. $1+\gamma_{f,t}$) — but can be higher with monopsony power and lower in the presence of strong unions.[9] By simply decomposing $MRPL_{f,t}$ into the revenue elasticity of labor times revenues per worker, markdowns can be expressed in terms of such elasticity ($\varepsilon^{R,L}_{f,t}$), revenues ($R_{f,t}$), and labor costs ($w_{f,t}L_{f,t}$).[10]

$$\gamma_{f,t} \equiv \frac{MRPL_{f,t} - w_{f,t}}{w_{f,t}} = \frac{\varepsilon^{R,L}_{f,t} R_{f,t} - w_{f,t}L_{f,t}}{w_{f,t}L_{f,t}} \tag{3.2}$$

Revenues and labor costs are directly observable in financial statements, whereas the revenue elasticity of labor requires a parametric estimation. We implement the latter by estimating revenue functions with a translog specification in capital, labor, and intermediate inputs, denoted by $F_i(k_{f,t}, l_{f,t}, m_{f,t})$, using small letters for logarithmic transformations and subscript i for a four-digit industry, the level at which the estimation is performed.[11] The form of the firm-level revenue function is shown in Equation 3.3, denoting the parameter interacted with factor x as $\alpha_{i,x}$ and decomposing the residual into a persistent revenue shock ($\omega_{f,t}$) and a measurement error ($\epsilon_{f,t}$).[12]

$$\begin{aligned} r_{f\in i,t} &= F_i(k_{ft}, l_{ft}, m_{ft}) + \omega_{ft} + \epsilon_{ft} \\ &= \alpha_{i,1} + \alpha_{i,k}k_{f,t} + \alpha_{i,l}l_{f,t} + \alpha_{i,m}m_{f,t} + \alpha_{i,k^2}k^2_{f,t} + \alpha_{i,l^2}l^2_{f,t} + \alpha_{i,m^2}m^2_{f,t} \\ &\quad + \alpha_{i,kl}k_{f,t}l_{f,t} + \alpha_{i,km}k_{f,t}m_{f,t} + \alpha_{i,lm}l_{f,t}m_{f,t} + \omega_{f,t} + \epsilon_{f,t} \end{aligned} \tag{3.3}$$

To deal with the endogeneity arising from the correlation between revenue shocks and the input demand, we adapt the 'control function approach' of Ackerberg et al. (2015) — typically employed for production function estimation — to the case of revenue functions.[13] This

[9] As discussed in footnote 3, there is a direct relationship between markdowns and the labor supply elasticity.

[10] By definition, $MRPL_{f,t} \equiv \frac{\partial R_{f,t}}{\partial L_{f,t}} = \varepsilon^{R,L}_{f,t}\frac{R_{f,t}}{L_{f,t}}$.

[11] Translog specifications approximate any twice continuously differentiable function up to second order, allowing nonlinear relationships and heterogeneity in the revenue elasticities across firms and periods.

[12] In standard production function applications, there is physical output — rather than revenues — on the left-hand side, and $\omega_{f,t}$ corresponds to the persistent productivity process (e.g. Olley & Pakes, 1996). Instead, in our framework, $\omega_{f,t}$ is not limited to the supply side but also includes revenue shocks coming from the product demand.

[13] Applications of the 'control function approach' to revenue function estimation can be found in Petrin and Sivadasan (2013), Hashemi et al. (2022), and Mottironi (2024).

methodology requires to purge the measurement error before estimating the parameters. In the first step, the demand for intermediate inputs is inverted to express the persistent shock, $\omega_{f,t}$, as a function of current input usage (hence the term 'control function'). As a result, we can purge $\epsilon_{f,t}$ by simply projecting revenues on a high-order polynomial combination of inputs, which leads to a prediction of $\phi_{f\in i,t} \equiv F_i(k_{f,t}, l_{f,t}, m_{f,t}) + \omega_{f,t}$. In the second step, $\omega_{f,t}$ is assumed to follow a first-order Markov chain, i.e. $\omega_{f,t} = g_i(\omega_{f,t-1}) + \eta_{f,t}$. Under this assumption, $\phi_{f,t}$ can be expressed in the following way.

$$\phi_{f\in i,t} = F_i(k_{f,t}, l_{f,t}, m_{f,t}) + g_i\left(\phi_{f,t-1} - F_i(k_{f,t-1}, l_{f,t-1}, m_{f,t-1})\right) + \eta_{f,t} \tag{3.4}$$

By approximating $g_i(.)$ with a polynomial in its argument, it is possible to estimate the parameters of $F_i(.)$ using the lags of the inputs (as well as their translog interactions) and $\phi_{f,t-1}$ — estimated in the first step — as they are all orthogonal to $\eta_{f,t}$, the innovation term of the persistent process.[14] From the estimated parameters we obtain the revenue elasticity of labor, which can vary across firms and years with input quantities, reflecting both firm size and relative input usage.

$$\varepsilon^{R,L}_{f\in i,t} = \alpha_{i,l} + 2\alpha_{i,l^2} l_{f,t} + \alpha_{i,kl} k_{f,t} + \alpha_{i,lm} m_{f,t} \tag{3.5}$$

Finally, we insert our estimation of Equation 3.5 in the firm-level markdown estimator defined in Equation 3.2.

For robustness, we derive an alternative measure based on output elasticities, following Yeh et al. (2022). Unlike revenue elasticities, output elasticities do not capture the elasticity of product prices to input usage. Therefore, the wedge between the output elasticity and the labor share includes the price markup. To isolate the wage markdown, the approach of YMH derives the markup from the same wedge but using intermediate inputs, under the assumption that the latter are traded in perfectly competitive markets — an unnecessary assumption in our preferred revenue-based methodology.[15] Further details are discussed in Appendix B.

Firm-level markdowns are averaged using labor costs as weights, to obtain aggregate markdowns as ratios of the market-level MRPL to market-level labor costs, in the spirit of Edmond et al. (2023). We denote the aggregate markdown as $\Gamma_{c,t}$ and use this measure to

[14] Further details on the theoretical assumptions and practical implementation of our approach to revenue function estimation are discussed in Appendix B.

[15] An additional difference concerns the market-level aggregation. YMH derive the aggregate MRPL by estimating production functions at a broader level (two-digit instead of four-digit industries) and combining these translog parameters with the market-level input usage.

define the market-specific index capturing variations in labor market power occurred during the pandemic (ΔLMP_c, the dependent variable of our baseline specification).[16]

$$\Gamma_{c,t} \equiv \frac{\sum_{f \in c} \gamma_{f,t} w_{f,t} L_{f,t}}{\sum_{f \in c} w_{f,t} L_{f,t}} = \frac{MRPL_{c,t} - w_{c,t}}{w_{c,t}} \tag{3.6}$$

$$\Delta LMP_c \equiv \Gamma_{c,2023} - \Gamma_{c,2019} \tag{3.7}$$

Descriptives. Table 3.2 reports summary statistics of firm-level and market-level markdowns in 2019 and 2023, the two periods considered in our main research design. Means and medians range between 0.14 and 0.43, an interval consistent with the measures provided by the literature on monopsony power (see Section 1).

At the market-level, markdown has substantially risen from 2019 to 2023, and this increase is not attributable to outliers as medians increase more than averages. One of the most likely drivers of this change lies in the limited capacity of workers, at least in the short run or medium run, to counterbalance inflationary bursts with equal adjustments in nominal wages.[17] This argument has solid empirical and theoretical evidence, from Shiller (1996) to more recent contributions (Afrouzi et al., 2024; Stantcheva, 2024). Italian collective bargaining institutions allow for forward-looking adjustments to inflation and collective agreements are typically signed with long delays, preventing adjustments in the period between two collective agreements. Limited mobility across jobs is another factor as workers locked into old contracts have limited options to renegotiate individually their wage. This drop in compensation may last for months or even years, especially if workers have little power in wage bargaining (Mengano, 2025; Stansbury & Summers, 2020).[18]

It is worth noting that the average time change in markdowns is not per se an object of study for our analysis, as we are only interested in how these changes correlate with WFH across local labor markets. Our results are not necessarily affected by aggregate trends or shocks operating at the national level. A source of concern may instead arise from the uneven relevance of this mechanism across labor markets. We believe that our large set of controls, illustrated in Section 4, can effectively attenuate this issue.

[16] The second equality in Equation 3.6 uses $MRPL_{c,t} \equiv \frac{\sum_{f \in c} MRPL_{f,t} L_{f,t}}{\sum_{f \in c} L_{f,t}}$ and $w_{c,t} \equiv \frac{\sum_{f \in c} w_{f,t} L_{f,t}}{\sum_{f \in c} L_{f,t}}$.

[17] In 2022, the Italian CPI exceeded 8% for the first time since 1986, and Italy is the EU country with the largest fall in real wages since the inflation upsurge of August 2021 (OECD, 2025).

[18] Through the lenses of our hypothesis, the availability of remote work may increase the boundaries of labor markets and facilitate job-to-job transitions, which has been shown to play a key role in helping workers to keep up with inflation bursts (Afrouzi et al., 2024)

Table 3.2: (Net) Markdowns

Aggregation	Year	Median	Mean	SD	Obs.
Firm-level ($\gamma_{f,t}$)	2019	0.14	0.43	1.05	493,437
Firm-level ($\gamma_{f,t}$)	2023	0.19	0.4	0.84	507,468
Market-level ($\Gamma_{f,t}$)	2019	0.17	0.3	0.7	27,179
Market-level ($\Gamma_{f,t}$)	2023	0.25	0.36	0.62	27,478

Note: This table reports the median, mean, standard deviation, and number of observations of our markdown estimates in 2019 and 2023, the two periods considered in the research design. Net markdowns are defined as the percentage difference between MRPL and labor costs per worker. Firm-level estimates are mapped into market-level estimates using labor costs as weights. Labor markets are defined as interactions of commuting zones and two-digit industries. Source of the raw data: AIDA.

4 Identification

The scope of our research design is to estimate the general equilibrium effect of market-level variations in WFH adoption on market-level variations in labor market power. In our analysis, we define labor markets c as interactions of commuting zones and two-digit industries, for a total of nearly 23,000 cells.

The baseline specification is as follows:

$$\Delta LMP_c = \beta_1 + \beta_{\Delta WFH}\, \Delta WFH_c + \beta_X X_c + u_c \tag{4.1}$$

ΔLMP_c and ΔWFH_c denote the 2019-2023 variations in labor market power and WFH adoption, respectively. As discussed in Section 3, labor market power is measured by aggregating firm-level wage markdowns, whereas the WFH index is derived as a shift share index, combining occupation-specific WFH shifts with the predetermined occupation shares.

The recent econometric literature highlights that identification in shift-share research designs requires an assumption of exogeneity either in the shares or the shifts (Borusyak et al., 2025), conditional on control variables. Accordingly, we select controls in X_c that allow us to claim the exogeneity of the shifts, i.e. conditional on controls, shifters ΔS_o can be considered as good as randomly assigned. To net out potential confounding factors, the set of controls include the 2019 values of following market-level variables: (i) share of high-skilled workers; (ii) share of college-educated workers; (iii) average age of workers; (iv) aggregate value added per worker (in logs); (v) aggregate labor costs per worker (in logs); (vi) number of workers per firm (in logs); (vii) number of workers in FTE units (in logs); (viii) lag of the dependent variable (i.e. the 2015–2019 variation in the aggregate markdown).

The share of high-skilled workers is defined using the first three categories of the one-digit ISCO classification (i.e. 1. Managers; 2. Professionals; and 3. Technicians and associate professionals). As our claim on the exogeneity of the shifts is conditional on controls, WFH shifters need to be as good as randomly assigned only within the same skill level. By including this control variable, we ensure that the identification exploits within-skill heterogeneity in WFH rather than the heterogeneity between high-skilled and low-skilled workers, potentially correlated with unobserved shocks.

The other six control variables do not have a direct correspondence with the occupation classification, but are included to make local labor markets comparable and net out confounding factors correlated with other market characteristics. We control for between-market heterogeneity in education, age, productivity, wages, firm size, and market size. Finally, the lag of the dependent variable accounts for time persistence or regression to mean.

Even after conditioning on this large set of controls, there might be unobserved occupation-specific shocks at the national level contaminating our identification. To prevent these unobservables from distorting our estimates, we follow Autor et al. (2013) and instrument our shift-share regressor with a related shift-share index, in which WFH shifters are measured using job vacancy postings from the United States rather than Italy.

$$\Delta WFH_c = \zeta_1 + \zeta_{IV}\, \Delta WFH_c^{US} + \zeta_X X_c + v_c \tag{4.2}$$

An additional issue highlighted by the econometric literature on shift-share designs concerns the estimation of standard errors. Adão et al. (2019) and Borusyak et al. (2025) argue that, when standard errors have a shift-share structure, typical tests involving heteroskedasticity-robust or clustered standard errors may lead to severe over-rejection of the null hypothesis. Intuitively, local labor markets with similar occupational shares are exposed to similar WFH shifts and will likely have similar residuals. Thus, multiple observations may bear little additional information on the underlying shocks although the 'traditional' standard errors mechanically fall in sample size. To account for this issue, we follow the methodology of Adão et al. (2019) — henceforth AKM — which derive an estimator of standard errors that is asymptotically valid under any correlation structure of the residuals across markets, provided that occupation-level shifters are uncorrelated.

Finally, we face a practical issue in dealing with observations lacking a critical mass to be considered as labor markets in a meaningful way. Especially in rural areas, the interaction of a commuting zone (CZ) and a two-digit industry may consist in a negligible number of workers. While acknowledging that any artificial threshold is hard to justify per se, we decide to set 15 workers as the the minimum threshold for our baseline estimation, and then test the robustness of our results under two extreme alternatives: (i) no threshold, which implies including *markets* with less than a single FTE worker; and (ii) a 1,500 threshold, larger than the baseline by two orders of magnitude. The baseline threshold corresponds to a sample size of 16,993 observations, roughly three-fourth of the 22,833 observations considered under no threshold, whereas the 1,500 threshold leads us to only consider the 835 largest markets.

5 Results

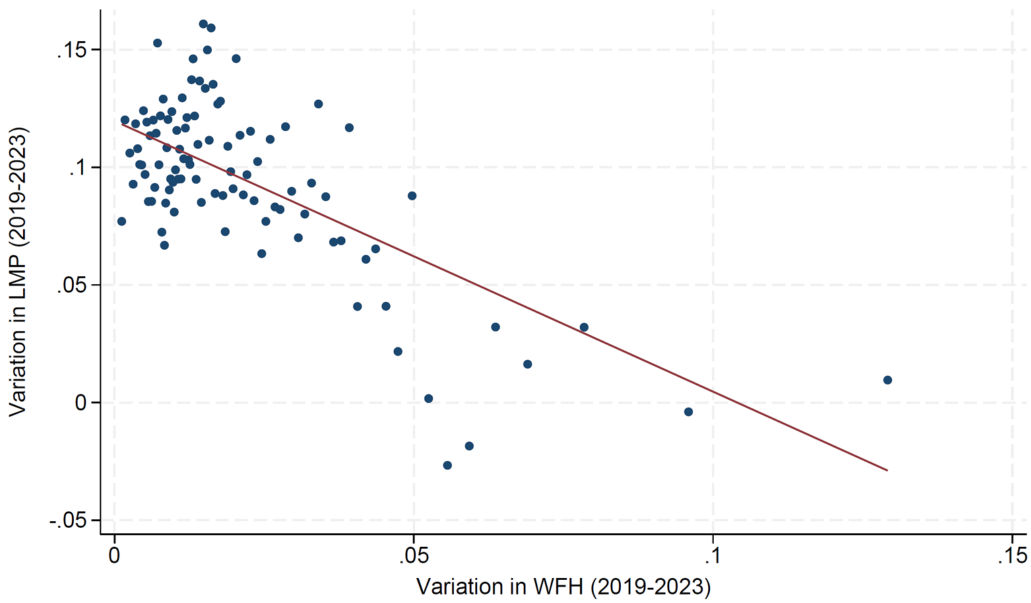
This Section presents the main empirical findings on the association between the diffusion of remote work and labor market power. We begin by illustrating the market-level empirical relationship visually. We then turn to regression analysis, reporting the results of the baseline specification under OLS and 2SLS estimators, with both heteroskedasticity-robust and AKM shift-share standard errors. These results are corroborated by a test of pre-trends as well as variety of alternative specifications. To better interpret the estimated magnitude, we conduct a counterfactual analysis under different scenarios of WFH diffusion. Finally, we deepen the analysis by running additional tests at the firm-level and worker-level, including the effect of WFH exposure on geographic mobility.

5.1 Market-level

Graphical results. Figure 5.1 displays the unconditional correlation between time differences in labor market power (LMP) and time differences in work-from-home (WFH), revealing a clear negative association between the two variables. This binned scatter plot represents the raw relationship, equivalent to an OLS regression without controls. Each of the 100 dots represents nearly 200 local labor markets.

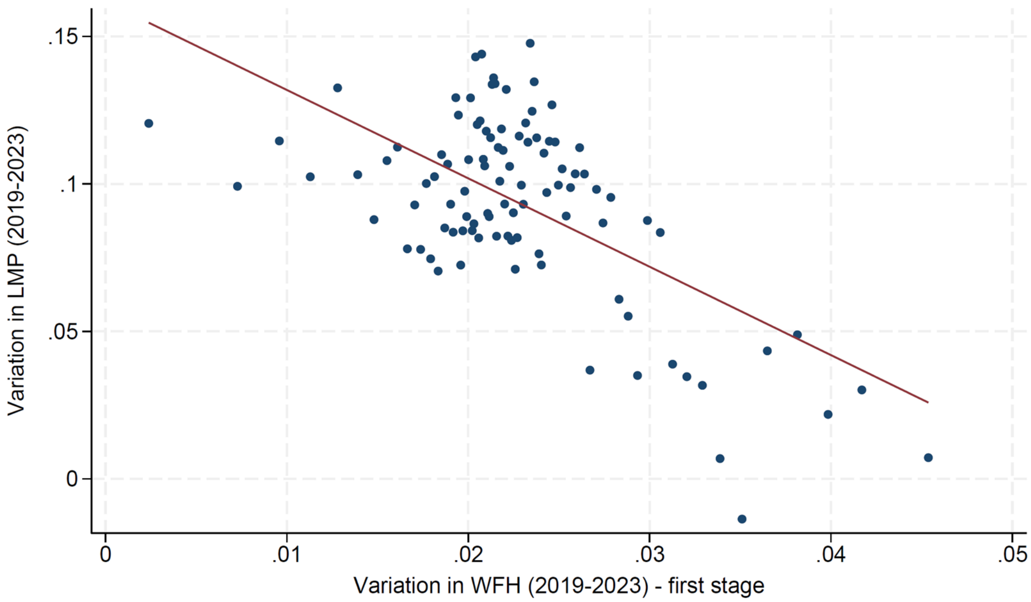
To account for endogeneity, we include a set of controls and instrument WFH shifts in Italy with WFH shifts in the US. Figure 5.2 visualizes our baseline specification. It plots the variation in LMP against the variation in WFH instrumented by the first stage, residualized on the full set of controls discussed in Section 4. The negative slope confirms that the relationship holds when we isolate the exogenous variation in the adoption of remote work.

Figure 5.1: Labor market power and WFH — unconditional correlation



Note: This figure shows a binned scatter plot with variations in labor market power (Equation 3.7) versus variations in work from home (Equation 3.1) at the market-level. Sources of the raw data: Lightcast, VisitINPS, and AIDA.

Figure 5.2: Labor market power and WFH — baseline



Note: This figure shows a binned scatter plot with variations in labor market power (Equation 3.7) versus variations in work from home (Equation 3.1) at the market-level. Both variables are residualised against the full set of controls, and WFH variations are instrumented using shifts from the US (see Section 4). Sources of the raw data: Lightcast, VisitINPS, and AIDA.

Regression tables. The equation to estimate is 5.3. Table 5.1 presents the OLS results as well as both stages of the 2SLS for our baseline specification, using heteroskedasticity-robust standard errors (Columns 1-3) and AKM shift-share standard errors (Columns 4-6).

OLS coefficients (-1.22, in Columns 1 and 4) are substantially lower than 2SLS coefficient (-3.01, in Columns 3 and 6). A possible reason lies in the superior signal-to-noise ratio in the instrument, due to the vastly larger sample of US job postings compared to Italian job postings, offsetting the attenuation bias induced by measurement error in the regressor. Alternatively, dependent and independent variables may co-move with occupation-specific shocks at the country-level, suffering from an omitted variable bias which is net out using WFH shifts from the US.[19] Predictably, heteroskedastic standard errors (Columns 1-3) are notably lower than AKM standard errors (Columns 4-6). Similarily, the F-Stat of the first stage is almost two-orders of magnitude lower in the AKM case compared to the heteroskedastic case (941.81 in Column 5 and 10.79 in Column 2). Nevertheless, coefficients remain highly significant under this more conservative specification, in the OLS case (Column 4) as well as both stages of the 2SLS (Columns 5 and 6).

Column 6 represents our baseline specification. We find that an increase in WFH exposure causes a significant reduction in labor market power. The coefficient is -3.01, which implies a -0.06 drop in the aggregate markdown for one interquantile range in WFH variations.[20]

We then test the role of pre-trends by replacing the 2019-2023 variation in labor market power with its lag (2015-2019) as the dependent variable. For an accurate comparison, we replicate the baseline removing the lag of the dependant from the set of control variables, and then substitute the dependent with its lag. Column 1 of Table 5.2 shows that removing the lag from the set of controls has negligible effects, as the coefficient remains significant at 1% and its point estimate (-2.98) is very similar to the baseline (-3.01 in Column 6 of Table 5.1). Crucially, switching the dependent variable with its lag (from Column 1 to Column 2 of Table 5.2) leads to a null result, with the point estimate reduced by nearly 95%, from -2.98 to -0.16, and the p-value increased from $<1\%$ to $>80\%$.

Our findings are validated by a large set of robustness checks. Table 5.3 provides the results — first-stage F-Stat and second-stage key coefficient — across six alternative specifications, using 2SLS and AKM standard errors. Column 1 replaces our revenue-based measure of labor market power with the production-based approach of Yeh et al. (2022), showing a very similar

[19]For instance, lower real wages and higher wage markdowns due to outdated collective contracts (as discussed in subsection 3.2) may induce employers to offer remote arrangements in order to attract more workers.

[20]Using the standard deviation instead of the interquantile range leads to similar results. We report the quantification based on the interquantile range for two reasons: (i) the regressor is highly skewed and (ii) the interquantile range is unaffected by winsorization in the regressors.

Table 5.1: Baseline specification

	(1) ΔLMP	(2) ΔWFH	(3) ΔLMP	(4) ΔLMP	(5) ΔWFH	(6) ΔLMP
ΔWFH	-1.22***		-3.01***	-1.22**		-3.01***
	(0.12)		(0.27)	(0.49)		(0.99)
ΔWFH^{US} (IV)		0.35***			0.35***	
		(0.01)			(0.11)	
I stage F-Stat		941.81			10.79	
Method	OLS	2SLS (I)	2SLS (II)	OLS	2SLS (I)	2SLS (II)
Standard errors	Heterosk.	Heterosk.	Heterosk.	AKM	AKM	AKM
LMP measure	Revenues	Revenues	Revenues	Revenues	Revenues	Revenues
Controls	Full set	Full set	Full set	Full set	Full set	Full set
Weighting	None	None	None	None	None	None
Minimum FTE	15	15	15	15	15	15
Unit	CZ-industry	CZ-industry	CZ-industry	CZ-industry	CZ-industry	CZ-industry
Observations	16,993	16,993	16,993	16,993	16,993	16,993

Note: ***p<0.01, **p<0.05, *p<0.1. This table reports the OLS results (Columns 1 and 4), as well as the first stage (Columns 2 and 5) and second stage (Column 3 and 6), of the estimation of Equation 5.3. Heteroskedasticity-robust standard errors (Columns 1-3) and AKM shift-share standard errors (Columns 4-6) are reported in parentheses. Each observation is the interaction of a commuting zone and a 2-digit industry. Sample restricted to a minimum of 15 FTE workers. The full set of controls includes: (i) share of high-skilled workers; (ii) share of college-educated workers; (iii) average age of workers; (iv) aggregate value added per worker (in logs); (v) aggregate labor costs per worker (in logs); (vi) number of workers per firm (in logs); (vii) number of workers in FTE units (in logs); and (viii) lag of the dependent variable (i.e. the 2015–2019 variation in the aggregate markdown). All variables are winsorized at the top and bottom 1%. Sources of the raw data: Lightcast, VisitINPS, AIDA.

point estimate (-3.03, from the -3.01 baseline in Column 6 of Table 5.1). Similarly, results do not change substantially in Column 2 (-3.06), in which the set of controls is reduced from eight variables to three (i.e. share of high-skilled workers, aggregate labor costs per worker in logs, and number of workers per firm in logs). Column 3 reports the results in a weighted estimation, using the geometric mean of FTE labor in 2019 and 2023 as weights, which slightly reduces the magnitude (-2.71).[21] In Columns 4 and 5, we make *extreme* manipulations to the threshold of minimum FTE to be considered as a labor market. In Column 4, we remove the threshold including every cell, even those made of one or less FTE workers, and thus increasing the number of observations from 16,993 to 22,833. In Column 5, we increase the threshold by two orders of magnitude, from 15 to 1,500 FTE units, reducing the sample

[21]We prefer the unweighted specification because our hypothesis concerns a general equilibrium effect taking place at the market-level rather than a worker-level mechanism; thus, we view each labor market as an equally relevant unit of observation for our tests.

Table 5.2: Test of pre-trends

	(1) ΔLMP	(2) $\Delta LMP_{2015-2019}$
ΔWFH	-2.98***	-0.16
	(0.96)	(0.67)
I stage F-Stat	10.79	10.79
Method	2SLS (II)	2SLS (II)
Standard errors	AKM	AKM
LMP measure	Revenues	Revenues
Controls	Full set \lag	Full set \lag
Weighting	None	None
Minimum FTE	15	15
Unit	CZ-industry	CZ-industry
Observations	16,993	16,993

Note: ***p<0.01, **p<0.05, *p<0.1. This table reports the second stage, as well as the F-stat of the first stage, of the 2SLS estimation of Equation 5.3, using the contemporaneous variation of the dependent variable (2019-2023 in Column 1) and using its lag (2015-2019 in Column 2). AKM shift-share standard errors are reported in parentheses. Each observation is the interaction of a commuting zone and a 2-digit industry. Sample restricted to a minimum of 15 FTE workers. The full set of controls includes: (i) share of high-skilled workers; (ii) share of college-educated workers; (iii) average age of workers; (iv) aggregate value added per worker (in logs); (v) aggregate labor costs per worker (in logs); (vi) number of workers per firm (in logs); and (vii) number of workers in FTE units (in logs). All variables are winsorized at the top and bottom 1%. Sources of the raw data: Lightcast, VisitINPS, AIDA.

to the 835 largest labor markets. The magnitude increases when we include tiny markets and decreases when we restrict to the largest ones, whilst remaining in a relatively confined range (between -3.47 in Column 4 and -2.11 in Column 5).

Finally, we directly test the effect on wages, specifically on the 2019-2023 growth in labor costs per worker. Although labor market competition is only one of several potential channels through which WFH may affect wages, our hypothesis is consistent with the positive effect on wages that emerges from the data (a coefficient of 2.07 in Column 6). This result is informative in two dimensions: first, it supports our hypothesis of a pro-competitive impact of the transition to remote work without relying on markdown estimation; second, it documents that the negative impact on wage markdowns is not dominated by opposite forces. For instance, if workers appreciate to have a remote option, the WFH transition may induce an extra labor supply in remotable occupations, leading to relatively lower wages. This channel could indeed moderate the pay rise induced by greater labor market competition, but our evidence documents that it does not revert it, as the more exposed markets experience a relatively higher wage growth in the period under consideration.

Table 5.3: ALTERNATIVE SPECIFICATIONS

	(1) ΔLMP	(2) ΔLMP	(3) ΔLMP	(4) ΔLMP	(5) ΔLMP	(6) $\Delta\%W$
ΔWFH	-3.03*	-3.06***	-2.71**	-3.47***	-2.11**	2.07**
	(1.76)	(0.99)	(1.12)	(1.09)	(0.85)	(0.93)
I stage F-Stat	10.81	10.12	10.53	10.64	10.79	11.12
Method	2SLS (II)	2SLS (II)	2SLS (II)	2SLS (II)	2SLS (II)	2SLS (II)
Standard errors	AKM	AKM	AKM	AKM	AKM	AKM
LMP measure	Production	Revenues	Revenues	Revenues	Revenues	Revenues
Controls	Full set	Subset	Full set	Full set	Full set	Full set
Weighting	None	None	FTE (gm)	None	None	None
Minimum FTE	15	15	15	0	1,500	15
Unit	CZ-industry	CZ-industry	CZ-industry	CZ-industry	CZ-industry	CZ-industry
Observations	16,993	16,993	16,993	22,833	835	16,993

Note: ***p<0.01, **p<0.05, *p<0.1. This table reports the second stage of the 2SLS estimation of Equation 5.3, as well as the F-stat of the first stage, under a set of alternative specifications. AKM shift-share standard errors are reported in parentheses. Each observation is the interaction of a commuting zone and a 2-digit industry. Sample restricted to a minimum of 15 FTE workers, except fro Columns (4) and (5). The full set of controls includes: (i) share of high-skilled workers; (ii) share of college-educated workers; (iii) average age of workers; (iv) aggregate value added per worker (in logs); (v) aggregate labor costs per worker (in logs); (vi) number of workers per firm (in logs); (vii) number of workers in FTE units (in logs); and (viii) lag of the dependent variable (i.e. the 2015–2019 variation in the aggregate markdown). All variables are winsorized at the top and bottom 1%. Sources of the raw data: Lightcast, VisitINPS, AIDA.

Counterfactual analysis. The coefficient estimated in the baseline specification -3.01, which implies a -0.06 drop in the aggregate markdown for one interquantile range in WFH variations. To provide a more intuitive interpretation of this magnitude, in Table 5.4 we consider the level of labor market power in 2023 — a country-level measure derived by weighting market-level markdowns with market-level labor costs — against three counterfactual scenarios. First, using the point estimate of our baseline specification, for each local labor market we derive the aggregate markdown that would have emerged if the 2019–2023 WFH shifts never occurred. According to our estimates, the country-level markdown would be 0.36 instead of the realised 0.29, a rise by nearly one fifth from the realised value.

We then use the superior transition to remote work taking place in large cities as a potential benchmark for a wider transition. To simulate a more realistic counterfactual, we have to first net out WFH differences between commuting zones stemming from differences in their industry composition, as the higher WFH rates in large cities may depend on their greater specialization in industries whose associated tasks are instrinsically more remotable.[22] For this purpose, we project the observed WFH shifts of local labor market c — defined as the interaction of commuting zone j and industry i — on commuting zone and industry fixed effects.

$$\Delta WFH_{i,j} = \theta_1 + \theta_i + \theta_j + \upsilon_{i,j} \tag{5.1}$$

Albeit most of the heterogeneity in WFH shifts come from heterogeneity between industries, which we take as given, commuting zones still explain a non-negligible component. We use the fixed effects of Rome and Milan as a WFH benchmark for other commuting zones. The counterfactual WFH shifts are thus computed at the market-level by substituting θ_j with θ_{Rome} and θ_{Milan}. The results in Table 5.4 reveal that, under the benchmark of Rome or Milan, the country-level markdown would be 0.26 or 0.25 respectively, a drop by approximately one tenth from the 0.29 realized value.

Table 5.4: Counterfactual analysis

Scenario	WFH transition (2019-2023)	Aggregate markdown (2023)
Observed data	$\Delta WFH_{i,j}$	0.29
No transition	0	0.36
Rome as benchmark	$\Delta WFH_{i,j} - \theta_j + \theta_{Rome}$	0.26
Milan as benchmark	$\Delta WFH_{i,j} - \theta_j + \theta_{Milan}$	0.25

Note: This table simulates the country-level markdown under three scenarios: no WFH shift occurred between 2019 and 2023; each labor market experiencing the WFH shift that occurred in the same industry in Rome; each labor market experiencing the WFH shift that occurred in the same industry in Milan. Counterfactuals are derived using the coefficient estimated in our baseline specification (i.e. Column 6 of Table 5.1). Sources of the raw data: Lightcast, VisitINPS, AIDA.

5.2 Firm-level

Although a market-level specification is the most natural setting to test the general equilibrium effect considered in this paper, we complement our findings with further evidence derived at

[22] In the thought experiment of this exercise, we consider how labor market power would have evolved if industries across all commuting zones transitioned to remote work by the amount observed in the same industries in large cities.

a narrower level — firm-level in this Subsection and worker-level in the next Subsection — taking full advantage of the richness of our data.

Equation 5.3 is now expressed at the firm-level: the dependent variable is the 2019-2023 variation in the firm's markdown (or labor costs per worker, in a robustness exercise). The key regressor and the instrument are built analogously to our market-level procedure: occupation-specific WFH shifts (from Italian data in the regressor and from US data in the IV) are combined with the 2019 employment shares of each occupational group. The fundamental distinction is that we are now using the firm-level — rather than market-level — employment shares. The set of controls includes: (i) share of high-skilled workers; (ii) share of college-educated workers; (iii) average age of workers; (iv) value added per worker (in logs); (v) labor costs per worker (in logs); (vi) number of workers in FTE units (in logs); (vii) the lag of dependent variable, i.e. the 2015-2019 variation in the firm's markdown (or labor costs per worker).

A key difference, and perhaps limitation, in the firm-level setting is that we are forced to restrict the sample to firms that have been active between 2015 and 2023. An additional difference is that observations cannot be considered as equally representative of their own general equilibrium effect, thus in this case we opt for a weighted specification, using the geometric mean of FTE workers in 2019 and 2023 as weights, with no minimum FTE threshold.

Table 5.5 provides the first-stage F-Stat and second-stage key coefficient of such specifications. Columns 1 and 2 replicate the firm-level equivalent the market-level baseline, with heteroskedasticity-robust and AKM shift-share standard errors, respectively. Column 3 and 4 test alternative dependent variables, with AKM standard errors: in Column 3 we consider the alternative measure of wage markdowns (Yeh et al., 2022), and in Column 4 we test the effect on wage growth.

In all instances, results are significant and go in the same direction as in the market-level analysis. We do not interpret these findings as a proof that market-level and firm-level *treatments* generate comparable mechanisms. In fact, its shift-share structure makes the regressor an imperfect proxy of the firm's decision in isolation: despite being defined at the firm-level, by attributing an occupation-based treatment to each firm, the regressor still recovers spillovers induced by WFH adoption in competitors with a comparable occupation mix.

Firm-level regressions may then be better interpreted as tests of the same market-level mechanism with more specific controls and an alternative market definition, which in this case depends on the firm's occupation mix rather than commuting zone and industry. Our

Table 5.5: Firm-level tests

	(1) ΔLMP	(2) ΔLMP	(3) ΔLMP	(4) $\Delta \%W$
ΔWFH	-1.23***	-1.23***	-1.66***	0.94*
	(0.14)	(0.29)	(0.38)	(0.54)
I stage F-Stat	1462.88	43.27	43.28	43.50
Method	2SLS (II)	2SLS (II)	2SLS (II)	2SLS (II)
Standard errors	Heterosk.	AKM	AKM	AKM
LMP measure	Revenues	Revenues	Production	Revenues
Controls	Full set	Full set	Full set	Full set
Weighting	FTE (gm)	FTE (gm)	FTE (gm)	FTE (gm)
Minimum FTE	0	0	0	0
Unit	Firm	Firm	Firm	Firm
Observations	234,127	234,127	234,127	234,127

Note: ***p<0.01, **p<0.05, *p<0.1. Columns 1-3 (Column 4) report the second stage of the 2SLS estimation of the impact of WFH on labor market power (wage growth), as well as the F-stat of the first stage. Heteroskedasticity-robust standard errors (Column 1) and AKM shift-share standard errors (Columns 2-4) are reported in parentheses. Each observation is a firm. The full set of controls includes: (i) share of high-skilled workers; (ii) share of college-educated workers; (iii) average age of workers; (iv) aggregate value added per worker (in logs); (v) aggregate labor costs per worker (in logs); (vi) number of workers in FTE units (in logs); and (vii) lag of the dependent variable (i.e. the 2015–2019 variation in the firm's markdown). All variables are winsorized at the top and bottom 1%. Sources of the raw data: Lightcast, VisitINPS, AIDA.

results document that firms whose workers are more exposed to the WFH shock exhibit lower variations in wage markdowns. We remain agnostic on whether this effect depends on the actual firm's decision or on the decisions of other firms competing for workers in the same occupational groups.

5.3 Worker-level

This Subsection examines the worker-level impact of remote work on two dimensions: wage growth and geographic mobility. For the latter, we consider whether the commuting zone where the worker has residence corresponds to the commuting zone of its workplace, and how the probability of such mismatch has evolved between 2019 and 2023 across workers with different levels of WFH exposure. In this Subsection we do not test the effect on markdowns as they are defined at the firm-level (and through aggregation, at the market-level).

The combination of the worker's occupational group with the corresponding occupation-specific WFH shift constitutes the key regressor in this setting, thus there is no need for the shift-share aggregations used in market-level and firm-level regressions. Because standard errors do not have a shift-share structure, our worker-level tests are implemented using standard errors clustered at the occupation-level, the primary source of heterogeneity in WFH adoption (see Figure 3.3). As with previous specifications, such WFH shifts are measured using Italian job postings for the endogenous regressor and US job postings for the instrument.

The following two equations represent the estimations implemented is this Subsection. Each observation is a worker a belonging to an occupation o in 2019. $y_{a\in o}$ is the dependent variable, which could either be the 2019-2023 wage growth or a dummy capturing geographic mobility in 2023, equal to one in case of a mismatch between the commuting zones of the worker's residence and workplace. S_o and S_o^{US} are the occupation-specific WFH shifts, measured using Italian and US data respectively. B_a is a vector of worker-level controls.

$$y_{a\in o} = \lambda_1 + \lambda_S S_o + \lambda_B B_a + \iota_a \tag{5.2}$$

$$S_o = \mu_1 + \mu_{IV} S_o^{US} + \mu_B B_a + \xi_a \tag{5.3}$$

Table 5.6 shows the worker-level effect of WFH exposure on wage growth, which is positive and significant at any level of confidence. All Columns include market fixed effects, with labor markets defined as interactions of commuting zones and two-digit industries as in the main analysis. Columns 1 and 3 pool all workers, whereas Columns 2 and 4 only consider those who changed employer between 2019 and 2023. In Columns 3 and 4 we incorporate additional worker-level controls: skills, education, sex, nationality, age, and the lag of the dependent variable. The key coefficient ranges between 0.48 and 0.81, which corresponds to a +1.6-2.7% in wage growth for an interquantile range in the 2019-2023 WFH shift. This magnitude is lower than what we find in the market-level specifications (i.e. a coefficient of 2.07 in Column 6 of Table 5.3, which corresponds to a +4% in wage growth). A possible reason for this discrepancy is that the impact of remote work unfolds not only through the worker-level WFH exposure in isolation, but also through the market-level exposure due to general equilibrium spillovers.

Finally, we investigate the impact of WFH exposure on geographic mobility, an aspect that we could not test under market-level and firm-level specifications. All Columns in Table 5.7 incorporate market fixed effects as well as the lag of the dependent variable as a control. Columns 2 and 4 only consider those who changed employer between 2019 and 2023.

Table 5.6: Worker-level — wages

	(1) $\Delta\%W$	(2) $\Delta\%W$	(3) $\Delta\%W$	(4) $\Delta\%W$
ΔWFH	0.67***	0.81***	0.48***	0.52***
	(0.1)	(0.13)	(0.14)	(0.13)
I stage F-Stat	55.13	53.11	26.58	27.57
Method	2SLS (II)	2SLS (II)	2SLS (II)	2SLS (II)
Standard errors	Clustered	Clustered	Clustered	Clustered
Fixed effects	CZ # industry	CZ # industry	CZ # industry	CZ # industry
Individual controls	No	No	Yes	Yes
Weighting	FTE (gm)	FTE (gm)	FTE (gm)	FTE (gm)
Unit	Worker	Worker	Worker	Worker
Sample	All	Switchers	All	Switchers
Observations	9.87 mln	4.65 mln	7.02 mln	2.88 mln

Note: ***p<0.01, **p<0.05, *p<0.1. This table reports the second stage of the 2SLS estimation, as well as the F-stat of the first stage, of the impact of WFH exposure (measured as the 2019-2023 WFH shifts in the worker's 2019 occupation) on wage growth (2019-2023). The IV uses WFH shifts measured from US data. Occupation-clustered standard errors (ISCO three-digit) are reported in parentheses. Each observation is a worker, weighted by the geometric mean of the worker's FTE units in 2019 and 2023. Columns 1 and 3 pool all workers whereas Columns 2 and 4 only include those who switched employer between 2019 and 2023. All Columns include fixed effects based on the interaction of a commuting zone and two-digit industry. Columns 3 and 4 also include the following individual controls: (i) skill level (dummy); (ii) college degree (dummy); (iii) female sex (dummy); (iv) foreign nationality (dummy); (v) age; (vi) age squared; and (vii) lag of the dependent variable (i.e. wage growth in 2015-2019). All variables are winsorized at the top and bottom 1%. Sources of the raw data: Lightcast, VisitINPS.

In Columns 3 and 4 we include additional individual controls. Coefficients range between 0.17 and 0.55, which corresponds to a +0.6-1.8% increase in the probability of a mismatch of commuting zones between the residence and workplace in 2023 for an interquantile range in WFH shifts, conditioning on having this mismatch in 2019.

Table 5.7: Worker-level — geographic mobility

	(1) CZ mismatch	(2) CZ mismatch	(3) CZ mismatch	(4) CZ mismatch
ΔWFH	0.31***	0.55***	0.17***	0.25**
	(0.07)	(0.12)	(0.06)	(0.1)
I stage F-Stat	55.05	53.03	25.83	26.56
Method	2SLS (II)	2SLS (II)	2SLS (II)	2SLS (II)
Standard errors	Clustered	Clustered	Clustered	Clustered
Fixed effects	CZ # industry	CZ # industry	CZ # industry	CZ # industry
Individual controls	Lag	Lag	Full set	Full set
Weighting	FTE (gm)	FTE (gm)	FTE (gm)	FTE (gm)
Unit	Worker	Worker	Worker	Worker
Sample	All	Switchers	All	Switchers
Observations	9.87 mln	4.65 mln	9.87 mln	4.65 mln

Note: ***p<0.01, **p<0.05, *p<0.1. This table reports the second stage of the 2SLS estimation, as well as the F-stat of the first stage, of the impact of WFH exposure (measured as the 2019-2023 WFH shifts in the worker's 2019 occupation) on geographic mobility (measured as the probability of a commuting zone mismatch between the worker's residence and workplace in 2023). The IV uses WFH shifts measured from US data. Occupation-clustered standard errors (ISCO three-digit) are reported in parentheses. Each observation is a worker, weighted by the geometric mean of the worker's FTE units in 2019 and 2023. Columns 1 and 3 pool all workers whereas Columns 2 and 4 only include those who switched employer between 2019 and 2023. All Columns include fixed effects based on the interaction of a commuting zone and two-digit industry, as well as the lag of the dependent variable (i.e. CZ mismatch in 2019) as a control. Columns 3 and 4 also include the following individual controls: (i) skill level (dummy); (ii) college degree (dummy); (iii) female sex (dummy); (iv) foreign nationality (dummy); (v) age; and (vi) age squared.. All variables are winsorized at the top and bottom 1%. Sources of the raw data: Lightcast, VisitINPS.

6 Conclusion

This paper provides novel evidence on an overlooked consequence of the transition to remote work, connecting to an extensive literature that identifies distaste for commuting as a primary source of rent extraction by local employers.

Our analysis combines three sources of microdata: (i) millions of job vacancy postings to measure the WFH transition at the occupation-level using a frontier LLM; (ii) worker-level administrative records on the workplace location and occupational group, which we use to map occupation-level WFH shifts into a market-level index; and (iii) firm-level production data to estimate wage markdowns and infer time changes in the degree of competition across local labor markets.

Exploiting heterogeneity in shifts to remote work across occupations — instrumented with contemporaneous shifts observed abroad — and heterogeneity in occupational shares across commuting zones and industries, we construct a shift-share IV to infer causal effects. Our evidence shows that work from home has substantially attenuated the 2019–2023 increase in wage markdowns, which we observe in the data and attribute to the 2022–2023 inflationary surge. Absent the transition to remote work over this period, local labor markets would have experienced, on average, a one-fifth larger departure from perfect competition.

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Online Appendix

A Further remarks on measuring remote work

The unit of observation in the Lightcast data is an online job posting (or, more precisely, a de-duplicated advertisement record). Each record includes the job title and the full job description text as scraped from the source website, alongside a set of structured fields produced by Lightcast. In our Italian extract, coverage begins in 2018 and runs through 2024, spanning the pre-pandemic period, the rapid adoption of emergency remote work during 2020, and the subsequent stabilisation of hybrid arrangements. The dataset includes postings from thousands of distinct online sources — job boards as well as employer websites — which is important in Italy where recruiting channels are fragmented and differ across sectors and regions (Lightcast, 2022). Table A.1 reports the number of online job vacancy postings by year.

Table A.1: Count of Online Job Vacancy Postings

Year	Postings	Occupations	Regions	Firms	Sources
2018	1,218,007	40	22	40,266	198
2019	1,724,453	40	22	69,880	253
2020	1,863,369	40	22	102,310	327
2021	2,593,521	40	22	135,553	381
2022	3,388,474	41	22	172,220	1,890
2023	5,026,268	41	22	174,605	2,300
2024	4,427,934	41	22	168,821	2,255
Total	20,242,026	41	22	575,988	3,407

Note: This table reports the number of online job vacancy postings by year. Occupations are defined using the two-digit ISCO classification. Regions correspond to the NUTS-2 regional classification. Firms are unique employer name strings, constructed from cleaned identifiers. Job-board sources correspond to distinct platforms or career sites. Source of the raw data: Lightcast.

A central challenge with online vacancy data is that the same job opportunity can appear multiple times and on multiple platforms, either because employers cross-post an ad across job boards, or because intermediaries syndicate ads. Lightcast addresses through a proprietary de-duplication procedure that attempts to identify and collapse duplicate ads into a single record, using information in job titles, descriptions, employers, and locations (Lightcast, 2022). In addition, Lightcast performs entity resolution on employer names, which is crucial in practice because the same firm may appear under different spellings, legal forms, or language variants across sources. These steps are a key reason that job-posting datasets such as Lightcast/Burning Glass have become widely used in empirical research on labor demand, where scale and standardisation are essential (Cammeraat & Squicciarini, 2021; Carnevale et al., 2014).

Beyond cleaning and de-duplication, Lightcast enriches postings with harmonised classifications. The pipeline assigns occupation codes and industry codes to postings using the text and any available structured information, enabling aggregation at standard taxonomies — for Europe, commonly ISCO for occupations and NACE for industries (Lightcast, 2022). Locations are geocoded so that postings can be aggregated to municipalities, provinces, regions, or other functional geographies. This geographic structure is central for our application, because we map postings into local labor markets and study the uneven diffusion of remote work across space. Finally, Lightcast extracts additional features from job description text, including skill requirements and credentials, producing structured indicators that can be used either directly as outcomes or as controls in empirical designs (Lightcast, 2022). In our application, we primarily use the raw text and the harmonised occupation field.

The Lightcast data do not provide a consistently populated, structured indicator of remote or hybrid status for Italy over our full sample window, which is why we classify remote/hybrid arrangements directly from the posting text. This approach follows a broader methodological trend in job-posting research, which increasingly relies on modern NLP methods to extract job attributes from text while preserving transparency and validating performance against human labels. Table A.2 shows the prompt template used for the classification remote arrangements, whereas Table A.3 reports examples of classifications.

Table A.2: Prompt Template for the LLM Classification

Component	Description
Overall role	System message: the model is instructed to act as an expert assistant analysing Italian job postings to identify remote or hybrid work options.
Step 1: Key words mentioned	Determine whether the posting explicitly mentions remote work (e.g. working from home or a mix of home and office). The variable remote_hybrid_mentioned is coded 'Y' if any remote term appears anywhere in the text (including negative contexts such as 'no smart working') and 'N' otherwise.
Step 2: Offering type	Classify whether the posting explicitly offers or rules out remote work. The variable offering_type takes value 'P' if the text explicitly offers remote work, 'N' if it explicitly disallows remote work, and 'U' if there is no explicit offer or denial.
Step 3: Exact arrangement	Classify the work arrangement based only on explicit phrasing in the text. The variable work_arrangement_exact takes value 'Hybrid' for mixed office/home arrangements, 'Fully Remote' for entirely remote arrangements, and 'U' if the arrangement is not explicitly stated.
Step 4: Contextual arrangement	For postings with offering_type == 'P', classify the arrangement based on the broader context of the ad. The variable work_arrangement_contextual takes value 'Hybrid' or 'Fully Remote' based on the model's best guess. For postings with offering_type not equal to 'P', the model may respond 'U'.
Step 5: Supporting phrase	Extract the exact phrase or short sentence (approximately 3–10 words) from the original posting that most directly supports the classification of the remote offering. This text is stored in extracted_supporting_phrase and preserves the original language and spelling. It is set to 'null' if no relevant phrase exists.
Step 6: Confidence score	Return a numeric confidence_score between 0.0 (no confidence) and 1.0 (fully confident) capturing how certain the model is about the classification for a given posting.

Continued on next page

Table A.2 continued from previous page

Component	Description
Example of keywords	The prompt lists Italian and English keywords that should trigger remote_hybrid_mentioned, including for example: 'lavoro da remoto', 'smart working', 'telelavoro', 'lavoro a distanza', 'lavoro agile', 'ibrido', 'da casa', 'home office', 'remote work', and 'WFH'. The prompt is clear that this list is not exhaustive.
Disambiguation notes	The prompt instructs the model to ignore uses of 'ibrido' that clearly refer to schedules or shifts (e.g. 'orario ibrido') rather than work location, to treat even negative references such as 'no smart working' as remote_hybrid_mentioned = 'Y', and to base classifications strictly on the text of the job title and description.

Note: This table documents the LLM prompt template used to classify remote and hybrid work options in Italian vacancy postings. The system message specifies that the model acts as an expert assistant and the user message contains the job title and full description. The model returns a structured JSON object with fields remote_hybrid_mentioned, offering_type, work_arrangement_exact, work_arrangement_contextual, extracted_supporting_phrase, and confidence_score, as described in the table. The full Python implementation, including the exact system prompt and JSON schema, is provided in the replication code.

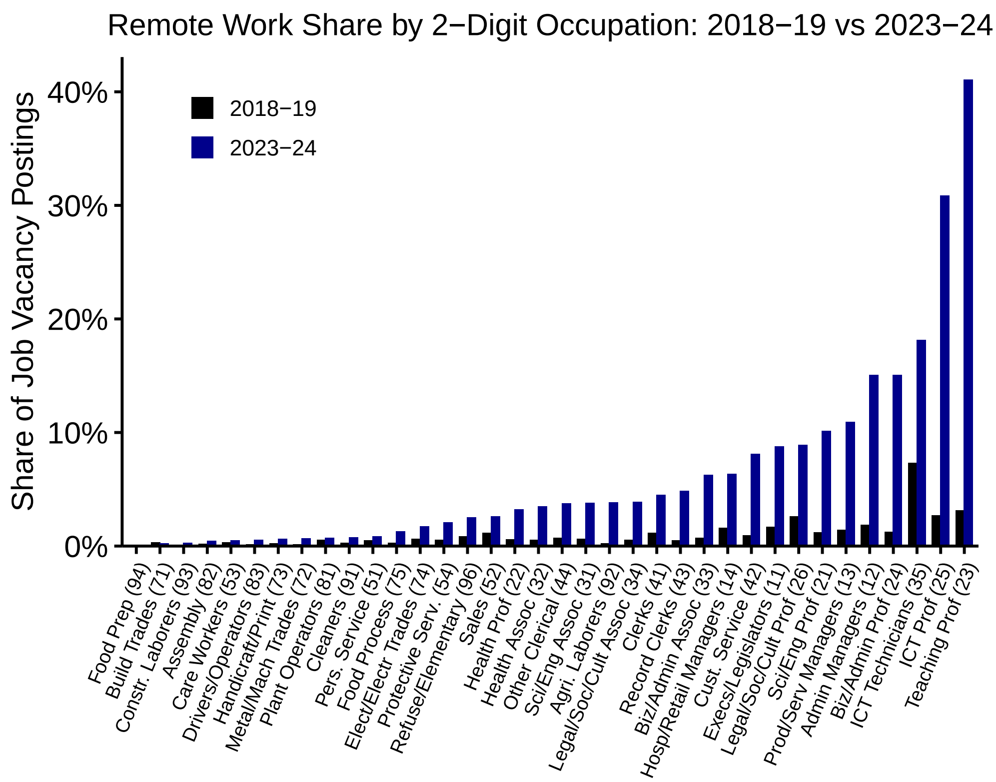
Finally, Figure A.1 documents the relative intensity of postings offering remote work across each sub-major occupation from the ISCO classification. In our main empirical exercise, we exploit this variation across occupations to define exposure to the rise of remote working across Italian local labor markets, aggregated using employment share across each occupation. We see teaching professionals, such as university teaching professionals, at the top of the list, along with ICT professionals. The lowest level of new job opportunities offering remote work are found in food-preparation and building and construction occupations.

Table A.3: Examples of Remote Classifications

Supporting phrase from the Job Ad	Remote type
Lavorare in Full – Remote	Fully Remote
Lavoro agile al 100% or Posizione completely da remoto	Fully Remote
Remote role in Southern Europe	Fully Remote
Work from anywhere	Fully Remote
Flexible work from home policy (3 days in office, 2 days at home)	Hybrid
modalità di lavoro ibrida (3 giorni in sede e 2 giorni in smart working)	Hybrid
Lavora da casa a Firenze e riporta due giorni al mese presso i nostri uffici	Hybrid
Sono previsti 2 giorni a settimana di smart-working	Hybrid
Contratto di lavoro full time in sede (no smart working)	Disallowed
Full remote is not allowed	Disallowed
Modalita' di lavoro: ON SITE 5/5	Disallowed
Smart-Working: NO	Disallowed
Non saranno prese in consider candidature da remoto	Disallowed

Note: This table reports examples of classifications drawn from Italian job postings, labelled by a LLM, with the supporting phrase representing the text that most directly supports the assigned assignment. 'Remote Type' indicates the type of arrangement mentioned in the phrase: Fully Remote, Hybrid, or Disallowed.

Figure A.1: Share of Job Postings Offering Remote Work by Occupation



Note: This figure shows the share of job vacancy postings explicitly offering remote work arrangements by two-digit ISCO occupation. The occupation code is in brackets and the label for each is our own short descriptive title. Solid black lines report the share for 2018-19 and solid blue bars report the share for 2023-24. Remote offers are identified using the textual content of each job posting, by applying our LLM classification algorithm. Source of the raw data: Lightcast.

A.1 Comparison of Labour Force Survey (LFS) responses to text-based measures of remote work arrangements

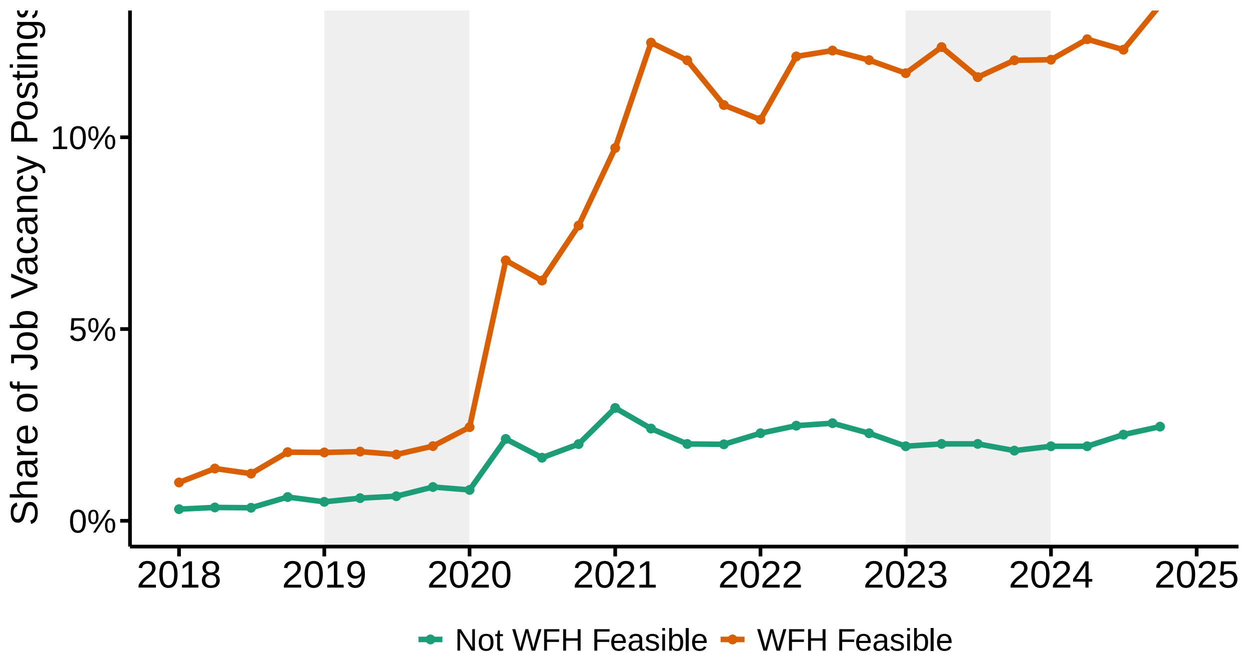
Official survey-based measures of remote work provide a statistically representative measure of the stock of workers engaging in remote work, which is quite complimentary to our vacancy based measure of the flow of new hires. Each measure have advantages and draw-backs. The main advantage of our approach is the sheer scale of job vacancy postings from which to extract our WFH signal, especially for granular occuaption groups which may not be well covered in survey samples. The vacancy-based approach also emphasises forward-looking commitments by employers to offer the amenity in perpetuity, whereas the stock of workers engaged in remote work is likely to be more volatile, for example during periods of closures and 'lockdowns'. Indeed, we see in Figure **??** that ISTAT's Labor Force Survey (LFS) which collects information on remote work practices. They allow for respondents to select 'no WFH', 'sometimes WFH', and 'usually WFH'. We see that 'sometimes' work from home has a similar dynamics to our vacancy-based measure, rising during the pandemic and sustaining at it's peak there-after. The pattern for the share of employees who 'usually' work from home has a much higher peak during the COVID-19 lockdows, declines thereafter, and reaches a much lower level in the years since the pandemic. This evidence is largely aligned with our interpretation of our vacancy-based measure as predominantly capturing hybrid work arrangements i.e. those who work 1-3 days a week at home, a finding supported by other survey based measures Barrero et al. (2021).

Figure A.2: Share of Dependent Employees with WFH or Hybrid jobs

A.2 Comparison of feasibility classifications to text-based measures of remote work arrangements

A number of studies have sought to measure remote work based on the task-content of occupations (Basso et al., 2020; Dingel & Neiman, 2020). These expert assessments of 'WFH feasibility' provide a binary classification of occupations for which remote work is feasible. Despite these large methodological differences, we show in Figure A.3 that the share of vacancies offering remote work are very well explained by the classification of Italian occupational groups by (Basso et al., 2020), implemented at the beginning of the pandemic-induced transition to remote work. The set of occupations these authors classify as not WFH feasible shows almost no increase in the share of WFH postings post-pandemic, whereas the share of job ads offering remote work for those occupations grouped as 'WFH feasible' grew by a factor of five.

Figure A.3: Rising Share of Remote-work Postings since Pandemic is well predicted by 'WFH Feasibility' classification



Note: This figure reports the share of online job vacancy postings explicitly offering remote arrangements, broken into two groups of occupations, by quarter. The groupings come from (Basso et al., 2020)), who reviewed the task-content of ISCO 3-digit occupations to assess whether work is feasible for remote work or not feasible. The sample includes 13,616,201 observations in total, where both an occupation code was present and raw textual description allowed for a classification of remote work using our LLM classification algorithm. Quarters in 2019 and 2023 are shaded as these subsets are used in our econometric application. Source of the raw data: Lightcast.

B Further remarks on measuring labor market power

Practical notes. Our data cleaning routine for the financial variables consists of trimming observations in the top and bottom 1% of the labor share of revenues and the ratios of capital to labor and intermediates to labor. Percentiles used for this procedure are computed separately for different groups of firms based on their broad industry (NACE letters) and size class (<10 employees; 10–249 employees; 250+ employees).

For revenue function estimation, revenues are deflated using the Harmonized Index of Consumer Prices (HICP), from Eurostat. For production function estimation, we obtain quasi-physical quantities of output we use industry-specific gross output deflators from ISTAT. To obtain quasi-physical quantities of capital and intermediate inputs for revenue function estimation, we use input-specific industry-specific deflators from ISTAT.

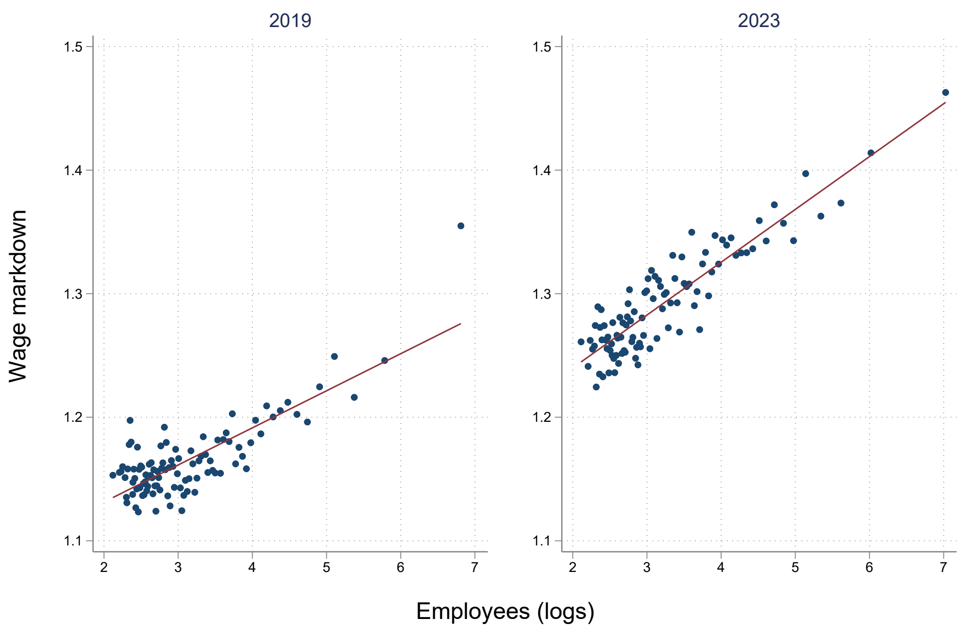
Revenue functions and production functions are estimated using firm-level data from 2015–19. Data are available up to 2023, but information in 2020–22 may not provide an accurate representation of the production process due to the COVID-19 shock as well as the related government interventions. Time-invatiant industry-specific translog parameters (see subsection 3.2 for the details) are thus estimated from 2015–19 data and then used to derive firm-level wage markdowns in the two periods of interest: 2019 and 2023.

For our preferred approach (revenue-based), translog estimations are performed at the four-digit industry level. The aggregation approach of YMH requires the estimation to be run at the same level as the aggregation. Thus, translog elasticities are estimated at the two-digit industry level. This constraint constitutes an additional reason to opt for weight-based aggregation, as the two-digit industry level might be too broad considering the large technology differences between industries.

Top and bottom 2.5% of firm-level markdowns are winsorized before market-level aggregation.

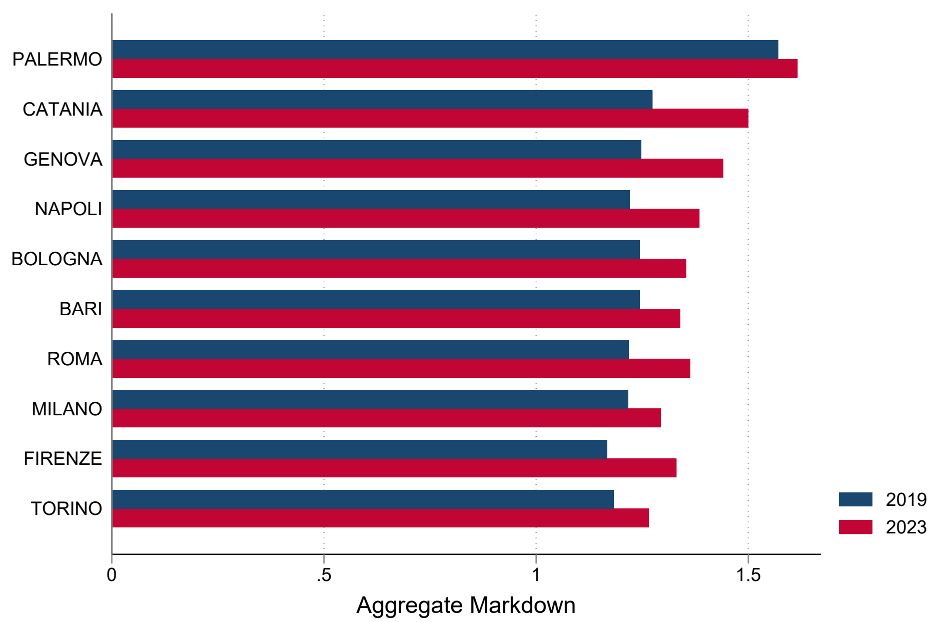
Descriptive results. Figure B.1 shows the positive firm-level relationship between wage markdowns and firm size, conditioning on a commuting zone (local labor market) fixed effect. Figure B.2 reports aggregate markdowns in the commuting zones containing the ten Italian cities with largest population.

Figure B.1: Markdowns and Firm Size



Note: This figure shows binned scatter plots with markdowns against employment at the firm-level for firms with at least 10 employees. The two panels report separate results for the two years considered in the research design. Each dot represents approximately 4,498 firms in the left panel and 3,349 firms in the panel on the right. Source of the raw data: AIDA.

Figure B.2: Markdowns Across Cities



Note: This figure reports the aggregate markdown in 2019 and 2023, the two periods considered in our research design, for a selection of commuting zones including the ten cities with largest population in Italy. Source of the raw data: AIDA.