The Geography of Remote Workers and Firm Productivity: Evidence from Matched Employer-Employee Data

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Abstract

The rise of work from home (WFH) has profoundly reshaped commuting patterns and work dynamics across the globe. Using matched employer-employee data on the whole universe of French workers, we study the effect of post-pandemic changes in workers' commuting patterns on firm-level outcomes. We find that the average French firm saw an 8% increase in employee commute distances compared to the pre-pandemic period. This shift was primarily driven by incumbent firms hiring individuals who live further away, and was especially notable in occupations with high WFH potential. In the aftermath of the pandemic, firms with larger increases in commute distances exhibited gains in value-added, productivity and hours worked. Overall, our findings highlight the positive impacts of the pandemic-induced shift towards remote working on firms.

Keywords: Work-from-home; Commuting; Firms; Workers; Productivity; Wages
JEL: J61, J24, R30, D24

1 Introduction

The unprecedented measures taken to contain the spread of COVID-19 forced firms to shift from in-person to remote working to avoid shutting down their activities. This forced adoption of remote work has necessitated significant investments in complementary IT technologies (Calvino, Criscuolo, & Ughi, 2024; Gathmann et al., 2023) and has profoundly altered both workers' and employers' perceptions and attitudes towards remote working practices (Barrero, Bloom, & Davis, 2023). Consequently, the adoption rate of work from home (WFH) practices has now stabilised at levels approximately twice those seen pre-pandemic, both in the US Barrero, Bloom, and Davis, 2023 and across European countries Crescenzi, Martino, and Rigo, 2023b.

Firms are currently grappling with the decision of whether to permanently retain remote work policies or require workers to return to the office.[1] Central to this decision is the impact of remote work on firm productivity. While there is a burgeoning body of research on the individual-level effects of remote work post-pandemic, aggregated firm-level effects remain scarce due to the lack of comprehensive data on WFH. On one hand, remote working can enhance job satisfaction and retention (Angelici & Profeta, 2024; Bloom, Han, & Liang, 2024; Choudhury et al., 2024). On the other hand, it may introduce challenges by increasing communication costs (Bao et al., 2022; Gibbs, Mengel, & Siemroth, 2022) and hindering workers' promotion rates and career trajectories (Emanuel & Harrington, 2021; Emanuel, Harrington, & Pallais, 2023), potentially offsetting these gains.

This paper examines one of the most dramatic consequences of the rise in homeworking, namely the sudden decline in co-agglomeration forces that traditionally bound workers and firms to the same geographical location. WFH practices can substantially lower the opportunity cost of commuting, which, in turn, may influence individuals' preferences concerning the optimal distance from the office. This reduction in commuting costs can expand the size

[1] A notable example is Amazon, which recently mandated its employees to return to the office five days a week (link.

of local labour markets surrounding firms, significantly influencing their hiring strategies. With reduced commuting concerns, workers have access to a broader range of potential employers, enhancing their job search scope. Conversely, firms can attract and screen a wider pool of candidates. Consequently, the WFH-driven expansion in market size is poised to facilitate more optimal employment matches, potentially boosting firm productivity(Dauth et al., 2022).

In this study, we exploit matched employer-employee data on the universe of French workers to measure the geographical distance between each establishment and its employees (*hereafter* home-work distance). We quantify that in 2022 an average French firm experienced an increase of 8% in the commuting distance of their employees compared to 2019. Using a difference-in-differences framework and an instrumental variable approach, we explore to what extent these changes in commute distance impacted firm-level outcomes. Our working hypothesis is that the enlargement of local labour markets should enhance firms' productivity and performance thanks to better employer-employee matches. We find causal evidence supporting this conjecture: firms with larger increases in their labour pool post-pandemic exhibited sizable gains in value-added, productivity and hours worked. Our identification strategy relies on novels firm-level instruments based on firms' pre-pandemic occupational composition. In particular, we introduce two new instruments for firms' changes in commuting patterns: i) the firm's WFH potential, calculated as the weighted average of employees' teleworkability (based on the methodology developed by Dingel and Neiman, 2020); and, 2) a shift-share measure of exposure to the rise in WFH, computed by weighting occupational changes in WFH adoption (from the Labour Force Survey) by the firm's occupational composition.

Thanks to the granularity of our worker-level data, we investigate how the COVID-19 pandemic has expanded the labour pool of French firms. This analysis exploits the COVID-19 shock as a quasi-natural experiment and the different suitability of workers' occupations to WFH (hereafter *WFH potential*). Our measure of WFH potential, calculated based on the methodology developed by Dingel and Neiman, 2020), is highly collinear with the actual use of WFH retrieved from the *Labour Force Survey*. Our results indicate that, in the post-pandemic period, workers with a higher WFH potential reside farther away from their employers in 2021, but not in the first pandemic year, 2020. This rise in commute distance is primarily driven by the locational decisions of new hires. In contrast, the commute distances for incumbent workers remained relatively unchanged, exhibiting a statistically significant reduction in 2020. This stability among existing employees may be attributed to more entrenched life arrangements such as homeownership or family commitments, which deter relocation in the short term. We also find evidence that remote working has reduced the gender commuting gap, with women experiencing a larger increase in home-work distance in 2021.

Lastly, our analysis explores how these changes have affected the geography of workers. Our results show that the observed increase in commuting distances is partly due to workers relocating to more affordable and peripheral areas. This pattern points to a substantial post-pandemic realignment in the labour market. Supporting theoretical insights from the literature (Gupta et al., 2022; Rosenthal, Strange, & Urrego, 2022), we find that the reduction in commuting costs has allowed workers to exchange longer work-home distances for reduced living costs and potentially better local amenities. Overall, this trend has led to an expansion of firms' local labour markets. By diminishing traditional geographical constraints, such as distance, gender discrimination, and housing rigidity, the labour market now enables employers and employees to optimize their matches within a much broader geographical scope. This evolution reflects a significant adaptation in labor market dynamics, providing both employers and employees the opportunity to find the optimal match within a wider geographical space.

Contribution to the literature. This study contributes to the rapidly growing literature on the pandemic-induced shift to WFH on firms. Contrary to recent studies focused on specific firms and contexts (Angelici & Profeta, 2024; Bao et al., 2022; Bloom, Han, & Liang, 2024; Choudhury et al., 2024; Emanuel & Harrington, 2021; Emanuel, Harrington, & Pallais, 2023; Gibbs, Mengel, & Siemroth, 2022), our analysis provides firm-level evidence across the entire universe of French firms. Our findings regarding the positive effects of increased commute distances on firms' productivity align with Kwan, Matthies, and Yuskavage, 2023, that use IP traffic data to determine whether employees were working from home or the office. Our results also resonate with insights from randomised control trials (Bloom, Han, & Liang, 2022; Bloom et al., 2015; Choudhury et al., 2022). Significantly, this study is the first to explore the post-pandemic expansion of local labor markets and its implications for firms, offering new insights into how geographic flexibility impacts organizational productivity.

Our study adds to a growing body of research on the implications of WFH practices on the transition towards a new spatial equilibrium. Existing literature, using real estate data, has documented the rapid flattening of the rent gradients in numerous cities around the world. A trend largely driven by the relocation of workers away from expensive urban centres (Althoff et al., 2022; Bergeaud et al., 2023; Coven, Gupta, & Yao, 2021; De Fraja, Matheson, & Rockey, 2021; Delventhal, Kwon, & Parkhomenko, 2022; Gupta et al., 2022; Liu & Su, 2021; Ramani & Bloom, 2021; Rosenthal, Strange, & Urrego, 2022). Our results align with this pattern, providing for the first time evidence for an entire nation. Additionally, other studies have examined changes in home-to-work distances, documenting reductions in commuting patterns fostered by WFH, in the United States (Monte, Porcher, & Rossi-Hansberg, 2023), using cell phone data, and Germany, (Coskun et al., 2024), using a representative sample of matched employer-employee data. We contribute to this literature by examining the impact of these changes in commute distances for the universe of French firms.

The rest of the paper is structured as follows. In Section 2, we present the datasets used in the analysis. In section 3, we provide some descriptive evidence on the aggregate changes in home-work distance. In Section 4 we exploit worker-level data to identify some of the underlying mechanisms. In Section 5, we study the effect of the pandemic-induced changes in commuting patterns on firm-level outcomes. Finally, section 6 concludes and draws some relevant policy implications.

2 Data

To investigate the effects of changes in commute distance on firms, we combine administrative data sources on firms and workers. These data cover the universe of private firms and workers established in France. France offers an interesting institutional setting to study the implications of WFH on companies and their employees. First, France is a large advanced economy, characterised by a rich industry composition, and a complex geography. From this perspective, it represents an ideal case study to investigate how WFH practices can reshape the location and firms and workers across urban and rural areas. Second, in France, the prevalence of hybrid and fully remote work surged remarkably, with nearly 35% of jobs adopting these flexible work arrangements in 2022, a significant increase from 21% in 2019 (Crescenzi, Martino, & Rigo, 2023b).

2.1 Firm-level Data

Fichier Approaché des Résultats d'Esane (FARE). The dataset includes tax fillings by firms for the corporate income taxes, providing the complete balance sheets of firms, including information on total sales, number of employees for the universe of French firms, as well as information on location, industry, and date of opening and closure of all firms in the data. When merging with the worker-level data, we aggregate establishments at their respective firms. The main cleaning step is to exclude companies that consist solely of a single employee to maintain focus on a business model where companies offer designated office spaces for their staff. In 2019, our final dataset covers 616,284 individual firms (see Table 1), accounting for over 90% of gross total output recorded in the economy.

Répertoire Sirene. The Répertoire Sirene is a national directory of companies and their establishments (business register), managed by the National Institute of Statistics and Economic Studies (INSEE, 2021b). It offers detailed information on the precise locations of each establishment operating in France during the study period.

La Base tous salariés (BTS-Postes or DADS-Postes). La Base Tous Salariés (INSEE, 2021a) is a matched employer-employee dataset encompassing the entire population of private sector workers in France (on average 28,000,000 workers per year), with the exception of individual employers and extraterritorial activities (division 99 of the NAF rev. 2). From the various versions provided by INSEE, we utilize DADS Poste (Fichiers Régionaux des Postes), which offers data at the individual job spell level. The data include information on gross annual earnings[2], number of paid hours[3], the start and end dates of the pay period, employment condition (full-time or part-time), occupation (at the 4-digit level), municipality of residence, gender and year of birth. Each worker in the dataset is associated with an establishment identifier, and if the same employee works in two different establishments during the same year, only the main job is included in our analysis.

In terms of data cleaning, we restrain the sample to people employed for at least 9 months, to limit the impact of workers with spells of unemployment or inactivity[4]. Furthermore, we keep only workers between the ages of 20 and 70, and we drop workers residing abroad while working in France (*frontaliers*) and seasonal workers. We winsorise the hourly wage to be higher than 80% of the legal minimum hourly wage for the corresponding year, and lower than 1,000 euro. As shown in Table 1, in 2019 our final dataset covers over 9 million individual workers.

[2]The variable includes: base salary, premiums, overtimes, reimbursements, severance benefits, amounts paid by third parties, actions and stock-options, holiday pay

[3]We trim the raw variable so that no worker works more than 1820 hours a year (equivalent to a full-time job in France) for each firm.

[4]Previous studies have documented that the total annual number of hours worked (as well as the duration in days) is not entirely reliable for workers with a discontinuous employment history.

Table 1: Summary Statistics (2019)

Variable	Source	Obs. (Nb)	Mean	Sd	p25	p50	p75
			Firm-level				
N. of workers	DADS	616,284	20	417	3	5	10
Paid Hours	DADS	616,284	37,028	759,738	4,887	8,914	19,025
Value Added	FARE	616,284	1,600,000	39,000,000	135,246	276,317	631,903
Distance	DADS/FARE	616,284	25	597,151	6	11	20
Hourly Wage	DADS	616,284	17	106,861	12	15	19
WFH potential	DADS	616,284	0.27	0.26	0.07	0.17	0.44
			Worker-level				
Age	DADS	9,391,866	41	12	31	40	50
Distance	DADS/FARE	9,391,866	31	92	4	10	21
Hourly Wage	DADS	9,391,866	20	17	13	16	22
Incumbent	DADS	9,391,866	0.73	0.44	0	1	1
Males	DADS	9,391,866	0.63	0.48	0	1	1
Paid Hours	DADS	9,391,866	1,495	540	1,158	1,806	1,820
WFH potential	DADS	9,391,866	0.28	0.34	0.01	0.12	0.67
Urban resident	DADS	9,391,866	0.69	0.46	0.00	1.00	1.00

The table reports summary statistics for firms and workers units used in the analysis. All variables are euros except for those involving working hours and distance.

2.2 Commute Distance

Commute distance is calculated by the geographical distance[5] in km between each plant's exact location[6] and their employees' *commune* of residence. French communes correspond to small/medium size municipalities or single arrondissements (suburban areas) of the largest cities (Paris, Lyon and Marseille). France is composed of around 36,000 communes and in 2015 the average municipality hosted 2,975 residents and covered an area of 7.28 km^2.

2.3 Task Content and WFH Potential

Following Dingel and Neiman, 2020, we develop an index that classifies occupations on the basis of their suitability for remote work, given the activities and tasks performed by workers. This information is retrieved from the Occupational Information Network (O*NET) for the

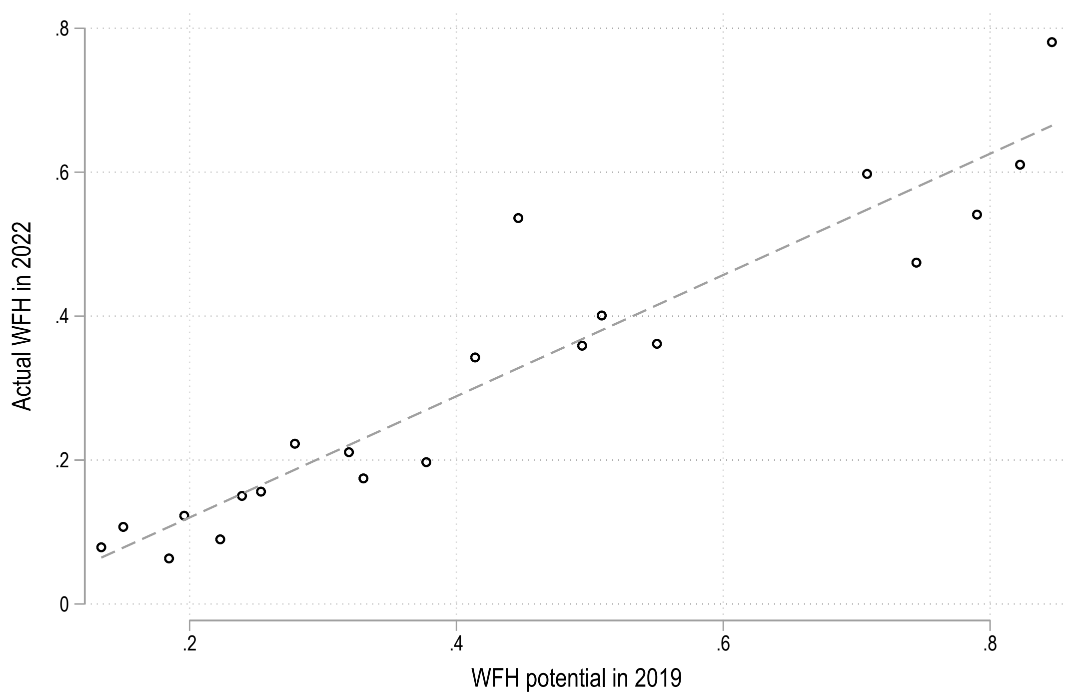
[5]We calculate the haversine distance, which is the shortest distance over the earth's surface, between the approximate home location and the office location for each employee.

[6]We have the exact coordinate of each plant for the whole population of French firms

United States. To link this measure of WFH to the French data, we use a crosswalk from the International Standard Classification of Occupations to the French "Professions et catégories socioprofessionnelles" (PCS) taken from Le Barbanchon and Rizzotti, 2020.

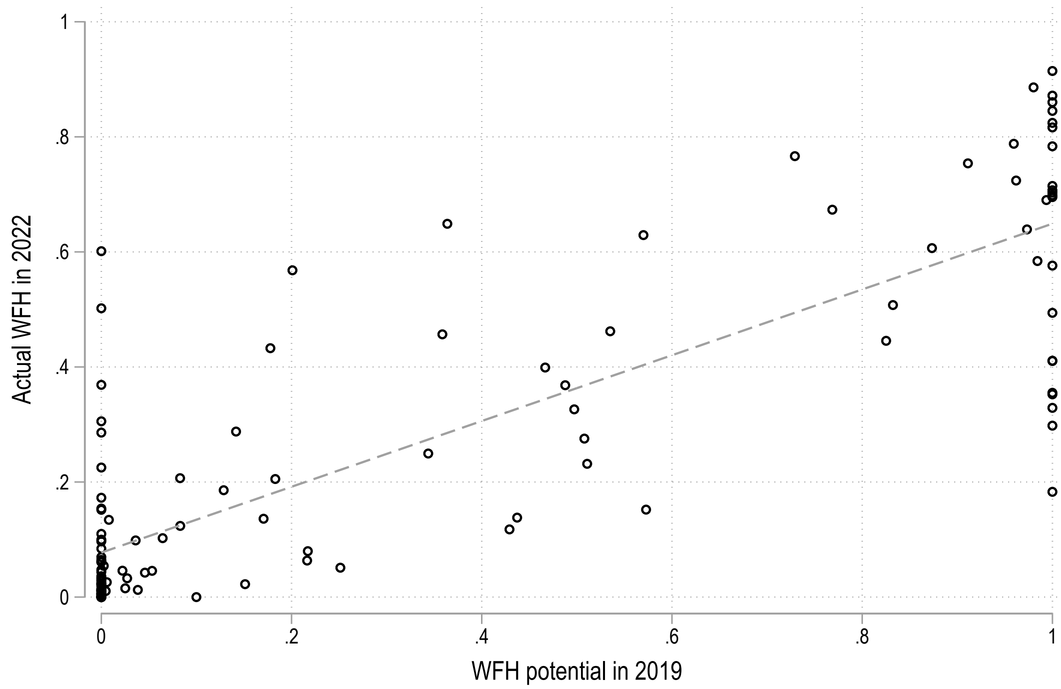
To check the validity of our index, we examine its correlation with the actual adoption of WFH across occupations, industries and French NUTS-3 regions. Our measures of the actual adoption of WFH is retrieved from the *Labour Force Survey*, as done in Crescenzi, Martino, and Rigo, 2023b. We find a strong positive correlation between our measure of WFH potential and the actual use of WFH. The correlation is remarkably high (at 94%) across NACE 1-digit industries and lower at 84% across ISCO 3-digit occupations. Figure 1 and Figure 2 show the correlation between the average use of WFH and the estimated WFH potential for each 1-digit industry and 3-digit occupations, respectively.

Figure 1: Actual versus potential WFH, by NACE 1-digit industries



Notes: The values of the actual use of WFH at the level of industrial main groups (1-digit code of the NACE rev. 2 classification) are taken from Crescenzi, Martino, and Rigo, 2023a. Our measure of WFH potential is based on the teleworkability of workers' occupations following Dingel and Neiman, 2020.

Figure 2: Actual versus potential WFH, by ISCO 3-digit occupations



Notes: The values of the actual use of WFH at the level of occupations (3-digit code of the ISCO 2008 classification) are taken from Crescenzi, Martino, and Rigo, 2023a. Our measure of WFH potential is based on the teleworkability of workers' occupations following Dingel and Neiman, 2020.

3 Descriptive Statistics

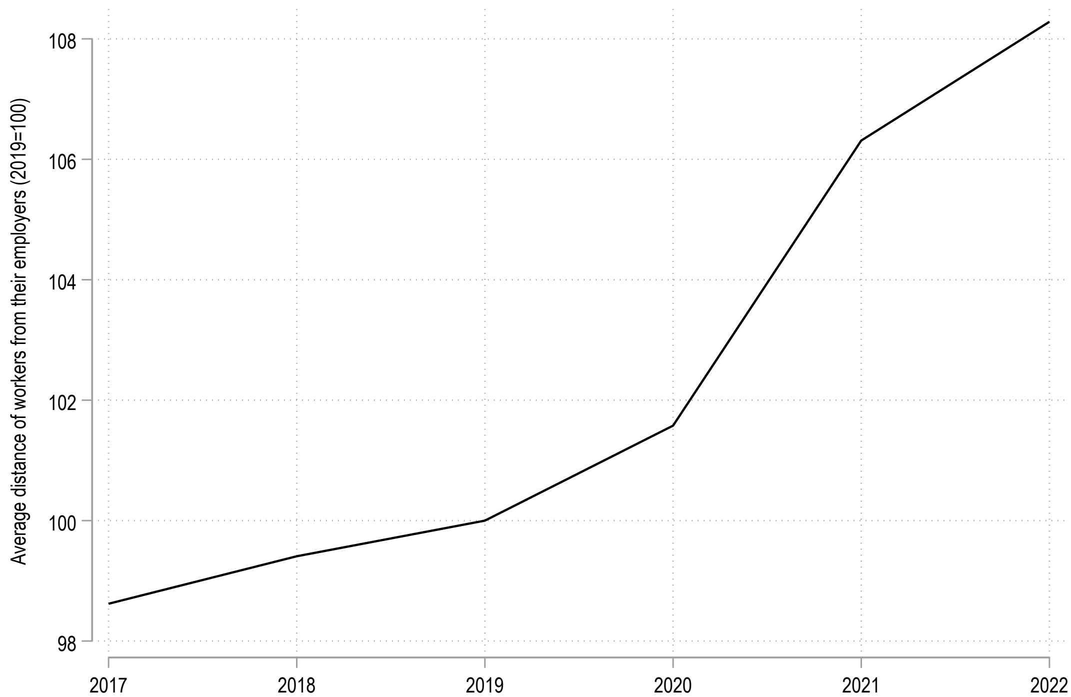
This section explores the broader spatial consequences of the pandemic-induced transition to remote work, focusing on how these changes have reshaped commuting patterns. We document the shifts in home-work distances both before and after the COVID-19 outbreak, across different worker groups such as new hires, incumbent employees, and men and women. By examining these trends, we describe the underlying dynamics that drive these changes.

3.1 Aggregate Trends

First, we examine aggregate employees' responses to the new opportunities offered by the increased availability of flexible work arrangements.

Figure 3 illustrates that, since the pandemic onset, the average distance between employees and their workplace has increased rapidly, arguably due to the growing acceptance of WFH practices. Although there was a secular trend of increasing work-home distances already before the pandemic, the data show a distinct acceleration between 2019 and 2022. In three years, the average commute distance increased by over 8%. This evident discontinuity hides even more profound changes in home-work distance that characterised specific segments of the labour force.

Figure 3: Average distance between employees and their employers (2019 = 100)



While the pandemic shock affected the whole economy, it is reasonable to expect a certain degree of heterogeneity across sectors and industries with respect to the adoption of WFH practices. As shown in Figure 4, workers in occupations characterised by high WFH potential[7] recorded a particularly sharp change in home-to-work distance. Between 2019 and 2022, these workers recorded an 18% increase in average home-work distance.

[7]Workers with high WFH potential are defined as those employees in an occupation in the top 10% of the WFH potential distribution.

Figure 4: Average distance between high-WFH potential employees and their employers (2019 = 100)

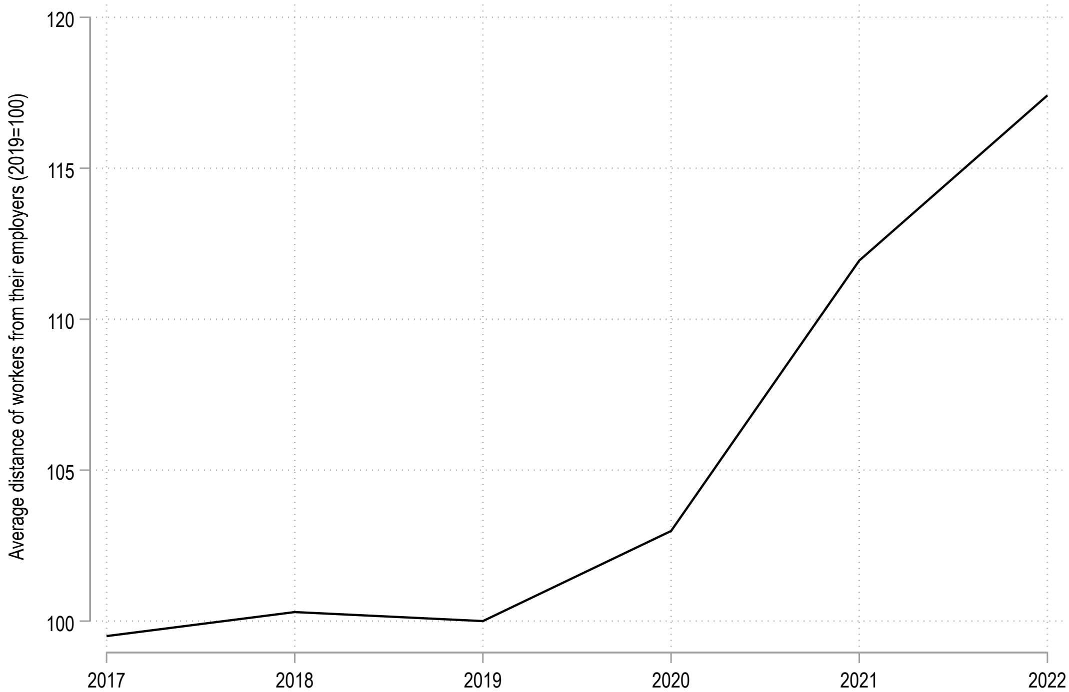
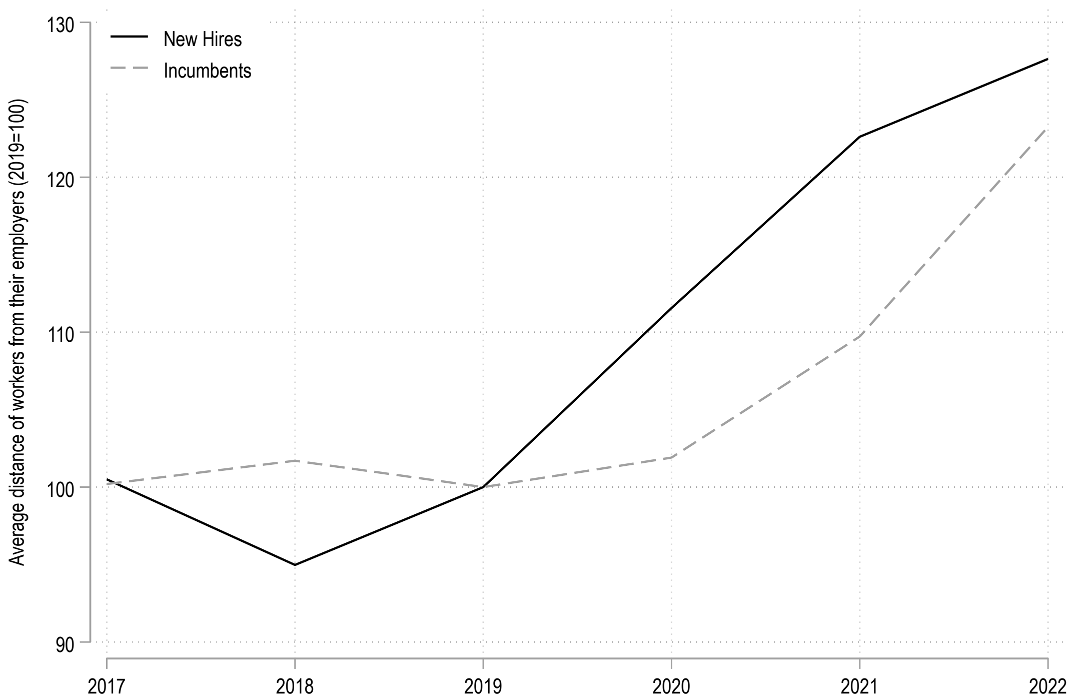


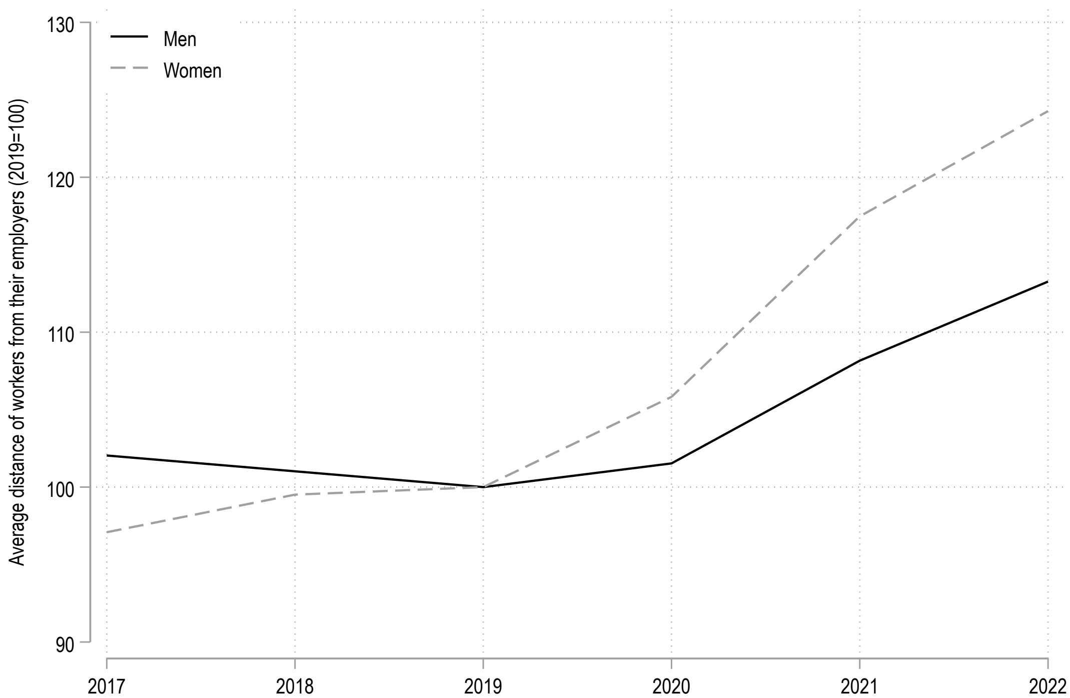
Figure 5 shows that the increase in home-work distance for workers with high WFH potential is initially larger for new hires. This finding aligns with the expansion of local labour markets for firms, highlighting the broader geographic scope within which companies are recruiting. This trend is particularly significant considering that new hires account for roughly 15% of the workforce in the 2017-2022 period. Notably, in 2021 and 2022, the home-work distance for incumbent workers began to increase more substantially, indicating a gradual alignment with the trends observed among new hires. This pattern suggests that incumbents, who may have more entrenched life arrangements such as homeownership or family commitments, are slower to relocate due to these factors but are increasingly adapting to remote working.

Figure 5: Average distance between high-WFH potential employees and their employers (2017 = 100), new hires versus incumbents workers



Recent literature has highlighted a significant gender disparity in commuting distances, corroborating the well-documented observation that women typically operate within tighter labour markets (Le Barbanchon, Rathelot, & Roulet, 2021). From this perspective, it is interesting to observe that women recorded a larger increase in home-work distance than men (see Figure 6). This evidence suggests that the pandemic may have altered the fundamental patterns of gender-specific commuting behaviours. The increase in remote work opportunities created by the pandemic may have provided women with the flexibility to extend their geographic job search, potentially reducing previous constraints.

Figure 6: Average distance between high-WFH potential employees and their employers (2019 = 100), men vs. women

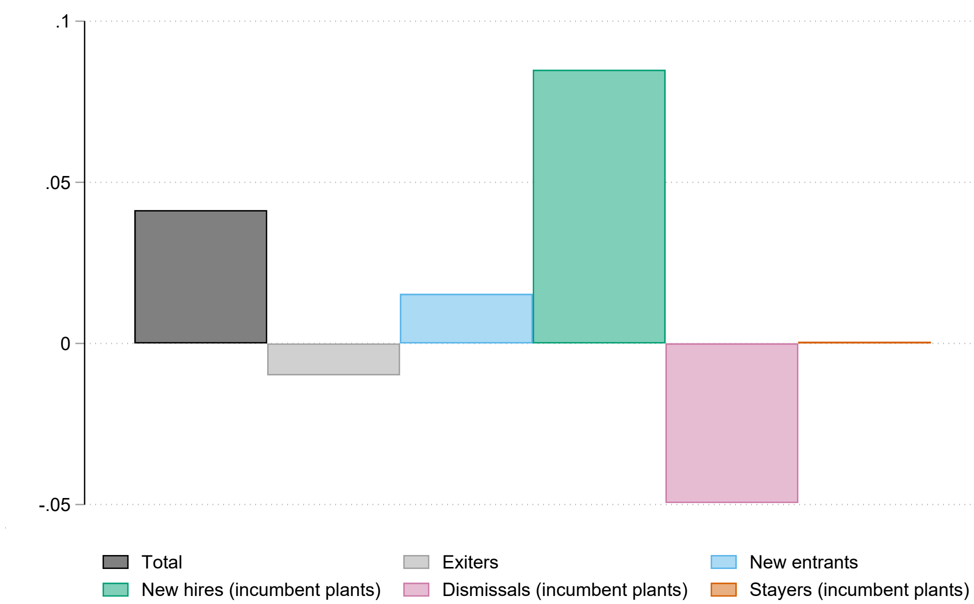


3.2 Drivers and Spatial Implications

In the previous section, we provided evidence about the sharp increase in commuting distance that took place in the aftermath of the pandemic. We now propose a simple decomposition to identify what dynamics drove the aggregate pattern and shed light on the actual mechanisms in place. The decomposition is presented in Annex E.

Figure 7 separately identifies the contribution of incumbent plants, exiters, and new entrants, as well as the role of different types of workers within incumbent plants (namely, new hires, stayers, and those dismissed). As expected, the increase in commute distance is predominantly driven by new hires in incumbent plants and new entrants. Figure A.1 in the Appendix compares changes in commuting patterns between 2021 and 2019 with those in the 2019-2017 period, showing a clear discontinuity between the two periods.

Figure 7: Decomposition of the % change in commute distance, 2019-2021

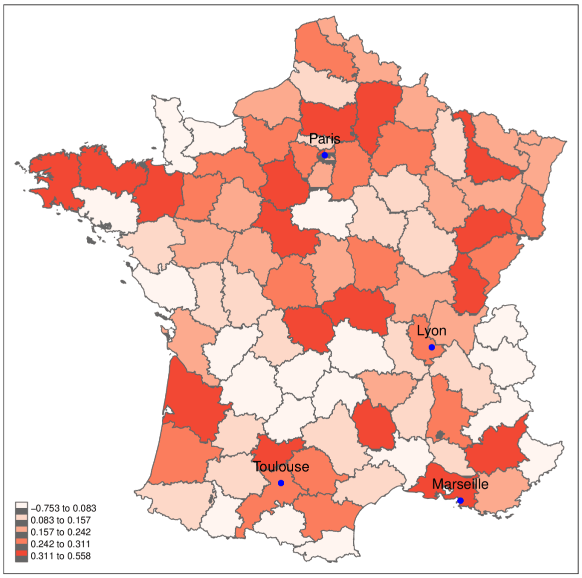


Lastly, we explore the implications of the rise in remote work practices on the geography of workers. In Figure 8, we investigate the heterogeneity in the evolution of commuting patterns across different French *départements*.[8] The change in home-work distance is found to be primarily driven by plants located in large urban areas. We analyse the median change in the commuting distance by Department of residence and work. In 2019, 82.7% of workers worked in a different commune from the one where they lived. This share remained substantially stable in 2022. However, over this period, France recorded a significant increase in the average distance between office and residence. Behind this overall pattern, we can identify two complementary patterns. On one hand, workers that in 2021 were employed in larger urban areas experienced the larger median change in commuting distance (Figure 8a). On the other hand, the larger median change in home-to-work distance was experienced by workers who lived far from main urban areas (Figure 8b). Taken together, these two dynamics suggest that plants located in the largest urban areas (which generally face higher

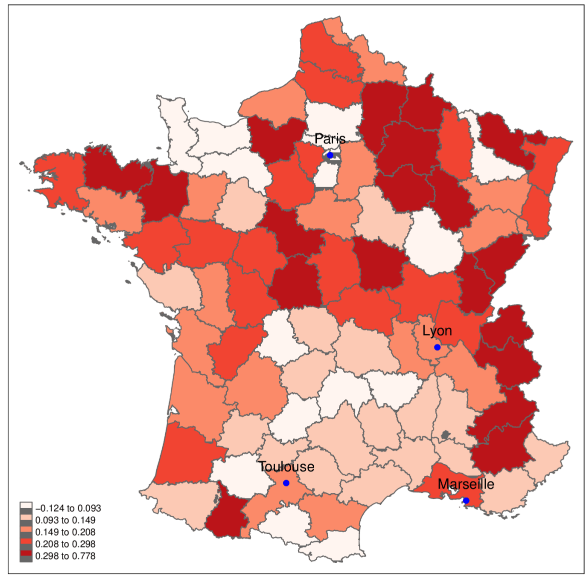
[8] In France, there are 101 départements, 96 are included in our analysis as part of metropolitan France (the mainland and Corsica), and 5 are excluded as overseas departments (Guadeloupe, Martinique, French Guiana, Réunion, and Mayotte).

rents and pay higher wages) managed to increase their share of employees living in more affordable peri-urban and rural areas.

Figure 8: Median change in commuting distance, 2019-2021



(a) Department of work



(b) Department of residence

4 The Impact of Remote Work on Home-work Distance

We have shown that the aggregate change is mostly driven by new hires and women in large urban areas. In this section, we provide more robust evidence validating these conclusions and exploit the worker-level data to investigate the underlying mechanisms[9]. Why do these new hires tend to live further away from the office? Why is this trend particularly relevant in large urban areas?

4.1 Econometric Framework

To explore the factors driving the macro-trend identified in the previous section, we separately analyse changes in commuting distance, housing markets, and urban areas. Our specification takes the following form:

$$log(Y_{koit}) = \sum_{t=2020}^{2021} \beta_t(WHFpotential_o \times Year_t) + X_k\gamma + \lambda_i + \theta_{jt} + \psi_{mt} + \eta_o + \varepsilon_{koit}$$

where $log(Y_{koit})$ indicates the work-home distance, the home-work rent differential or the home-work density ratio recorded by worker k employed by plant i in year t. X_k represents worker-level control variables, including age, job tenure, and gender. $WHFpotential_o$ refers to the occupation-level WFH index based on Dingel and Neiman, 2020. The terms λ_i, θ_{jt}, ψ_{mt}, and η_o represent plant, industry-year, municipality-year, and occupation fixed effects, respectively. To shed further light on the mechanisms at play, we estimate this model separately for new hires, incumbents, males, and females.

We estimate this specification for every year between 2017 and 2022. β_t is our vector of coefficients of interest, showing the interaction terms between the variable $WHFpotential_o$ and year dummies. These interaction terms capture the changing effect of WFH potential on

[9]Due to data limitations, the analysis will focus on the period 2019-2021.

distance relative to the pre-pandemic period (2017-2019). In Figure A.4, we plot the event study coefficients relative to the year 2019 (the omitted reference category). The figure reveals that the trend was substantially stable in the three years before the pandemic.

4.2 Empirical Evidence

The results are presented in Table 2. In Panel (A), we examine the relationship between work-from-home potential and individual commuting distance. Workers with higher work-from-home potential show a small but significant increase in average commuting distance following the pandemic. Consistent with the descriptive evidence provided earlier, columns (2) and (3) demonstrate that this effect is primarily driven by new hires. The estimates in columns (4) and (5) suggest that the effect is more pronounced for women. This evidence indicates that the pandemic may have altered gender-specific commuting patterns. Women, who traditionally tend to commute less due to the 'double burden' are likely to benefit the most from the flexibility guaranteed by new remote working practices (Arntz, Ben Yahmed, & Berlingieri, 2020).

In Panel (B), we replicate the analysis focusing on home-work rent differentials (i.e. the difference between the average house price in the municipality of residence and municipality of work). While we observe a negative relationship across all groups, the effect is again primarily driven by new hires and females. These findings align with recent applications of the monocentric city model, which predict a flattening of the rent gradient following reductions in commuting costs and changes in housing preferences due to the pandemic. Finally, we analyse changes in home-to-work density differentials. The estimates in Panel (C) suggest a significant shift towards less dense areas. Once again, the effect is mostly driven by new hires, with gender appearing to play a less significant role. These results confirm that the observed increase in commuting distance partly reflects a relocation towards peripheral areas.

Overall, this analysis shows that, from the onset of the pandemic, the economy has progressively migrated towards a new spatial equilibrium. Consistently with the theoretical literature (Gupta et al., 2022; Rosenthal, Strange, & Urrego, 2022), the reduction in commuting costs allowed workers to trade higher home-work distances for savings in rents and potentially an improvement in local amenities.

Table 2: Worker-level Analysis

	(1) All	(2) New Hires	(3) Incumbents	(4) Males	(5) Females
Panel A: Log distance					
WFH potential x Year == 2020	0.000147	0.0215***	-0.00415**	0.00001	0.00217
	(0.00119)	(0.00654)	(0.00162)	(0.00131)	(0.00143)
WFH potential x Year == 2021	0.00672***	0.0596***	-0.00321	0.00615***	0.0103***
	(0.00209)	(0.0114)	(0.00197)	(0.00212)	(0.00251)
Observations	44,206,924	10,908,983	33,262,645	27,933,080	16,255,006
R-squared	0.332	0.347	0.344	0.353	0.36
Panel B: Log home-work rent differential					
WFH potential x Year == 2020	-0.00006	-0.001*	-0.00034**	-0.00005	-0.00217
	(0.00015)	(0.00062)	(0.00165)	(0.0002)	(0.00143)
WFH potential x Year == 2021	-0.00102***	-0.0020***	-0.00275	-0.0009***	-0.0103***
	(0.0002)	(0.00067)	(0.00198)	(0.00028)	(0.00251)
Observations	40,601,063	9,988,372	30,578,210	25,672,635	14,910,144
R-squared	0.384	0.39	0.392	0.396	0.416
Panel C: Log home-work density differential					
WFH potential x Year == 2020	-0.0011	-0.0091**	0.0020	-0.0009	-0.00115
	(0.0013)	(0.0042)	(0.0015)	(0.0018)	(0.0013)
WFH potential x Year == 2021	-0.0083***	-0.0174***	-0.00269	-0.0087***	-0.0071***
	(0.0017)	(0.0035)	(0.00244)	(0.0020)	(0.0025)
Observations	44,134,393	10,889,343	32,209,712	27,886,645	16,228,916
R-squared	0.381	0.387	0.388	0.398	0.402
Occupation FE	✓	✓	✓	✓	✓
Municipality x Year FE	✓	✓	✓	✓	✓
4-digit indutry x Year FE	✓	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓	✓
Worker-level control variables	✓	✓	✓	✓	✓

Notes: The data is a balanced panel at the worker-plant-year level. Worker, municipality×year and 4-digit industry×year fixed effects are included in all regressions. The workers' age, tenure in the job and gender in 2017 are added as controls. Standard errors are clustered at the worker level. *** p<0.01, ** p<0.05, * p<0.1.

5 The impact of changes in commute distance on firms

So far, we described key mechanisms behind the aggregate pandemic-induced changes in commuting patterns. Now we turn our attention to the implications of such changes in LLMs for French firms. In this section, we present several novel facts on the impact of WFH on French firms by leveraging changes in commute distance before and after the COVID-19 pandemic. We focus on the effects of WFH adoption on value-added, productivity, hourly wage and hours worked. Section 5.1 outlines our econometric framework, Section 5.2 reports our main estimates, followed by a discussion in Section 5.3 on the robustness of the results.

5.1 Econometric framework

To study the impact of changes in commute distance on firms, we implement a difference-in-differences estimation strategy and an event study approach. Contrary to the first part of the paper, we aggregate our variables at the firm level because we don't have information at the plant level on firms' performance. Let Y_{it} denote one of our four dependent variables (gross value added, total factor productivity, the hourly wage and hours worked) for firm i in year t. Then, our difference-in-differences estimation equation is:

$$log(Y_{it}) = \sum_{t=2017;t\neq 2019}^{2021} \beta_t(log(distance_{it}) \times Year_t) + \gamma(X_i^{2017} \times Post_t) + \delta_i + \theta_{jt} + \psi_{mt} + \varepsilon_{it} \quad (1)$$

where $log(distance_{it})$ indicates the log of the average home-work distance for firm i in year t. δ_i are firm fixed effects, θ_{jt} are 4-digit industry-by-year fixed effects and ψ_{mt} are municipality-by-year fixed effects. Note that there are about 36,000 municipalities and 603 4-digit industries. We also include a vector of firm-level control variables, X_i^{2017}, including the log of number of employees, the log of value added per employee and age. All these variables are recorded in 2017, but we estimate time-varying coefficients γ to allow for pre- and post-pandemic trends in X_i^{2017}. We include these controls and fixed effects to mitigate the issue that firms increasing their home-work distances have underlying characteristics that are different and may therefore be on different trends. All regressions are weighted by the number of employees in the firm in 2017, as a result, firms not operating in 2017 are excluded from our analysis.

One potential concern is that changes in firms' home-work distance can be endogenous, for example, because it correlates with other technological investments. Our estimates might also be affected by reverse causation. Firms may choose to change their labour pool according to their productivity or other business fundamentals. To address this concern, we instrument firm commuting patterns with the degree of teleworkability recorded in 2019. Our index of WFH potential, for a firm i, is calculated as the weighted average of the WFH index, h_o, for occupation o, across all employees in firm i:

$$WFHPotential_i = \sum_o \frac{E_{oi,2017}}{E_{i,2017}} \times h_o \tag{2}$$

where $E_{o,i}$ is the number of employees in occupation o for firm i in year 2019, E_i is the total number of employees in firm i in year 2019, and h_o is the occupational level WFH index based on Dingel and Neiman, 2020.

Alternatively, we instrument the changes in commute distance, $log(distance_i)$, with a shift-share measure of WFH adoption computed using aggregate trends in WFH adoption (calculated from the Labour Force Survey) and the pre-sample occupational composition measured at the firm-level:

$$WFHShiftShare_i = \sum_o \frac{E_{oi,2019}}{E_{i,2019}} \cdot \Delta WFH_o^{EU} \tag{3}$$

where ΔWFH_o^{EU} is the change in the share of employees in occupation o who worked from home between 2019 and either 2020 or 2021. This **shift** is based on the adoption of WFH in 11 EU countries with a similar level of GDP per capita to France. $\frac{L_{oi,2019}}{L_i,2019}$ is the **share** of occupation o workers in firm i. The time variation in this instrument only stems from the variation in the (unexpected) rise in WFH across a selection of European countries (excluding

France) and cannot be influenced by French firms' business decisions. Additionally, firm-level weights are fixed at their value in the pre-pandemic year 2019, so they are not influenced by any endogenous post-pandemic variation in firms' hiring. This is quite similar to a standard shift-share or "Bartik" (Bartik, 1991) setting in which aggregate shocks are combined with measures of shock exposure.

5.2 Empirical Evidence

Baseline results. Table 3 presents our baseline firm-level results. The estimates indicate that firms recording larger changes in home-work distance reported a higher increase in value added and hours worked, whereas the effect for TFP and Hourly Wages is significant only in 2020. In particular, the coefficients indicate that a one-standard-deviation increase in average distance is associated with a 3.1% increase in valued added and 3.5% increase in hours worked. The coefficients from the pre-pandemic period suggest that there is no systematic relationship between firms' LLMs and the pre-lockdown trends in Y_{it}, with the exception of hourly wages. This evidence supports the presence of parallel trends, a crucial identifying assumption necessary for the validity of the difference-in-differences analysis strategy.

Table 3: Firm-level results for changes in home-work distance

VARIABLES	(1) log(GVA)	(2) log(TFP)	(3) log(Hourly wage)	(4) log(Hours worked)
log(Distance) × Year=2017	0.00137	-0.00254	-0.00343***	0.0104
	(0.00733)	(0.00192)	(0.000525)	(0.0101)
log(Distance) × Year=2018	0.00535	-0.00164	-4.42e-05	0.0117
	(0.00820)	(0.00197)	(0.000316)	(0.0113)
log(Distance) × Year=2020	0.0268*	0.00647*	0.00170**	0.0269
	(0.0110)	(0.00283)	(0.000563)	(0.0129)
log(Distance) × Year=2021	0.0315**	0.00609	0.000292	0.0351**
	(0.0111)	(0.00333)	(0.000658)	(0.0122)
Observations	1,972,068	1,972,068	1,972,068	1,972,068
R-squared	0.996	0.965	0.977	0.998
Firm-level control variables × Year	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓
4-digit industry fixed effects × Year	✓	✓	✓	✓
Municipality fixed effects × Year	✓	✓	✓	✓

Notes: The data is a balanced panel at the firm-year level. Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. TFP is estimated based on Wooldridge (2009)'s method using output (value added), number of employees and capital (total fixed assets). Standard errors are clustered at the firm and year level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

2SLS results. In this section, we implement an instrumental variable (IV) approach using firms' WFH potential in 2019 and exposure to WFH adoption in the 2019-2021 period as instruments for the pandemic-induced changes in their local labour markets. To reassure us regarding the relevance of our instruments, Figure C.1 and Table D.2 in the Appendix shows that a higher WFH potential or WFH exposure is a strong predictor of changes in commute distance after the pandemic onset.

The estimates reported in Table 4 indicate a sizable positive effect of an increase in commuting distance on firms' value-added and TFP. In column 1, for example, a one standard deviation increase in home-work distance is associated with a 13.5% increase in value added and a 10.6% increase in TFP in 2021. Instead, the coefficients for hourly wages and hours worked have a smaller magnitude and are not significant in 2021. Table 5, which exploits the exposure to the post-pandemic adoption in WFH, confirms these main findings for value added and TFP. However, in this case, we also record a positive and significant effect on hours worked. Overall, these results suggest that pandemic-induced changes in home-work distance may have favoured firms characterised by a higher work-from-home potential.

Table 4: Firm-level results for changes in commute distance, 2SLS estimates, WFH potential

VARIABLES	(1) log(GVA)	(2) log(TFP)	(3) log(Hourly wage)	(4) log(Hours worked)
log(Distance) × Year=2020	0.163***	0.111**	0.0305**	0.0443*
	(0.0267)	(0.0292)	(0.00840)	(0.0195)
log(Distance) × Year=2021	0.135***	0.106**	0.00415	0.0357
	(0.0271)	(0.0290)	(0.00825)	(0.0196)
Observations	1,971,001	1,971,001	1,971,001	1,971,001
K-Papp F-stat	486.2	486.2	486.2	486.2
Firm-level control variables × Year	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓
4-digit industry fixed effects × Year	✓	✓	✓	✓
Municipality fixed effects × Year	✓	✓	✓	✓

Notes: The data is a balanced panel at the firm-year level. The firm-level average home-work distance is instrumented by firms' WFH potential in 2019 as defined by equation 2. TFP is estimated based on Wooldridge (2009) method using output (value added), number of employees and capital (total fixed assets). Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at the firm and year level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Firm-level results for changes in commute distance, 2SLS estimates, WFH shift-share

VARIABLES	(1) log(GVA)	(2) log(TFP)	(3) log(Hourly wage)	(4) log(Hours worked)
log(Distance) × Year=2020	0.225***	0.131**	0.0269**	0.0991***
	(0.0453)	(0.0349)	(0.00969)	(0.0146)
log(Distance) × Year=2021	0.197**	0.121**	0.00780	0.0880***
	(0.0457)	(0.0344)	(0.00950)	(0.0161)
Observations	1,970,916	1,970,916	1,970,916	1,970,916
K-Papp F-stat	318	318	318	318
Firm-level control variables × Year	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓
4-digit industry fixed effects × Year	✓	✓	✓	✓
Municipality fixed effects × Year	✓	✓	✓	✓

Notes: The data is a balanced panel at the firm-year level. The firm-level average home-work distance is instrumented by firms' WFH potential in 2019 as defined by equation 2. TFP is estimated based on Wooldridge (2009) method using output (value added), number of employees and capital (total fixed assets). Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at the firm and year level. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Robustness

In this section, we present several robustness checks by estimating a different econometric model and excluding industries that may be affected by the pandemic-induced decline in the demand for office spaces.

First differences results. We present first-differences estimates based on the following equation:

$$\Delta log(Y_i) = \beta \Delta log(distance_i) + \gamma(X_i^{2019} \times Post_t) + \theta_{jt} + \psi_{mt} + \varepsilon_i$$

where Δ denotes the change between 2020 or 2021 and 2019. Table D.5 and D.1 shows results consistent with our baseline findings. We also instrument the change in home-work distance using our measures of WFH potential and WFH post-pandemic exposure. In practice, in the first stage, we regress our instruments on the firm's growth rate in home-work distance between 2021 or 2020 and 2019. In the second stage, we regress the growth rate of the outcome variable on the predicted growth rate of home-work distance. The 2SLS results confirm our conclusions (as shown in Table D.3 and D.4). Firms which increased their commute distance during and after the pandemic crisis experienced higher growth rates, though hourly wages were lower than prior to the pandemic.[10] Lastly, the first-stage results, reported in Table D.2, are precisely estimated, and the Kleibergen-Paap F-statistic is always higher than 10 for the WFH potential while slightly lower than 10 for the WFH shift-share instrument.

Accounting for the declining demand for space. The rapid diffusion of remote working practices has significantly depressed the demand for office space in the most expensive real estate markets. The high vacancy rate recorded in the city centres has been followed by a general slowdown in post-Covid construction in the most teleworkable counties (Bergeaud et al., 2023). While this dynamic does not directly affect our analysis, it is possible that part of our results could be driven by sectors which recorded the largest decline in tangible assets. In Figure A.5, we show the difference between the tangible asset growth recorded over the periods 2017-2019 and 2019-2021. While many sectors recorded a slowdown, only two industries - admin and professional services - recorded a large decline. Tangible assets in these sectors consist in large part of real-estate assets, often located in large urban areas. Hence, the aggregate pattern was likely influenced by the office space price dynamics.

We address this concern by replicating the main analyses, excluding these two sectors. In Table D.8, we replicate the analysis presented in Table 3. The estimates are very similar to the one obtained using the whole sample: firms recording larger changes in home-work distance reported a higher increase in value added and hours worked, while the effect for TFP and Hourly Wages is significant only in 2020. In Table D.9 we replicate the analysis presented in Table 4. The results are broadly in line with the ones obtained using the

[10] The results for the 2020-2019 period are reported in the Appendix (see Table D.6 and D.7), yielding qualitatively similar conclusions.

full sample, but in this case, we notice a non-negligible decrease in the magnitude of the coefficients. In Table D.10, we re-estimate the model presented in Table D.1. Once again, the results are confirmed, but in this case the magnitude is even higher than the one recorded in the baseline analysis. Overall, the exclusion of admin and professional services does not significantly affect our findings.

6 Conclusions

In this paper, we use employer-employee data on the universe of French private sector workers to document a set of stylized facts about post-pandemic changes in commuting patterns and their impact on firms. We observe a significant increase in commute distances beginning at the onset of the COVID-19 crisis, which persisted through 2021. This change was predominantly driven by new hires in occupations with a higher potential for remote work. Notably, the effect was particularly pronounced for women, indicating a potential shift in gender-specific commuting behaviours due to the pandemic.

We then examine the impact of remote work on firm productivity measures. Employing an identification strategy based on each firm's pre-pandemic potential for WFH adoption, we find that increased instrumented commute distances are associated with higher firm productivity growth. Lastly, we investigate the wage effects of increased commuting distances. Our preliminary results suggest that the COVID-19-induced rise in home-to-office distances has a positive effect on wages.

Overall, our preliminary results indicate that the new WFH practices are creating lasting impacts on firm management strategies, commuting patterns, and ultimately on the spatial distribution of economic activities.

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APPENDIX

A Additional Figures

Figure A.1: Decomposition of the % change in commute distance, 2021-2019 minus 2019-2017

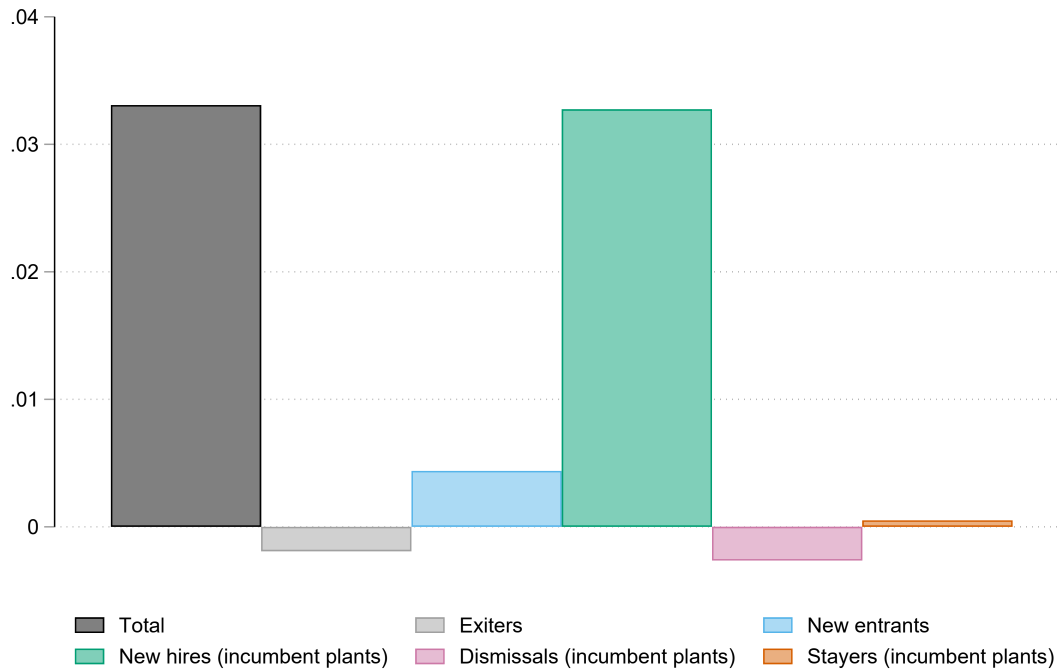


Figure A.2: % change in commute distance across NACE 1-digit industries, 2019-2021

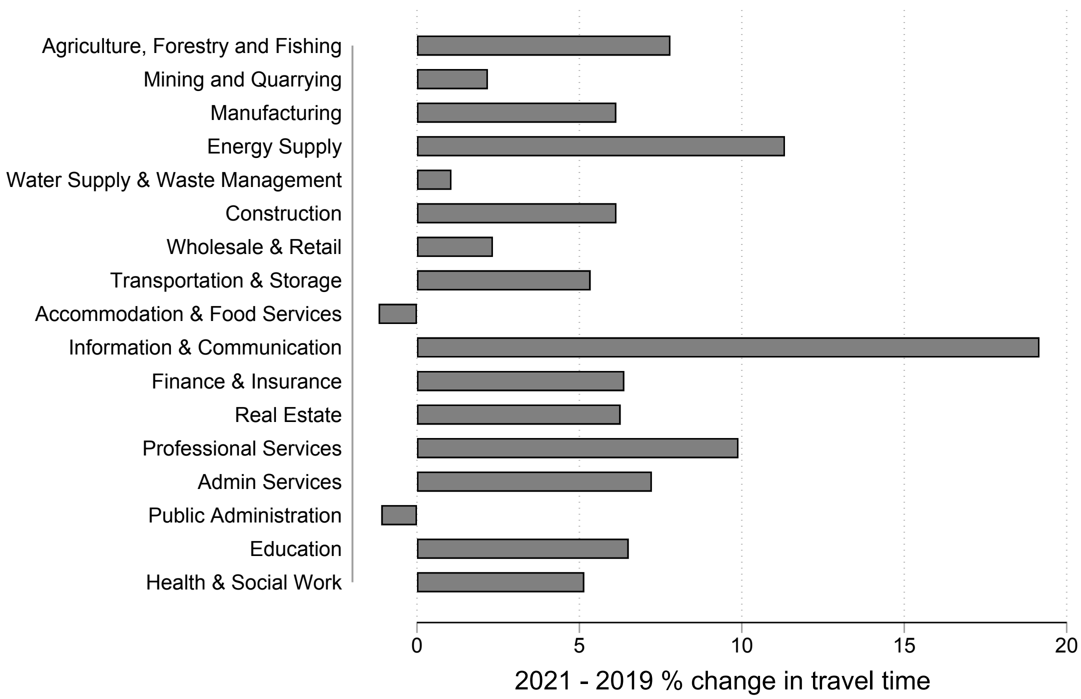


Figure A.3: % change in commute distance across 2-digit occupations, 2019-2021

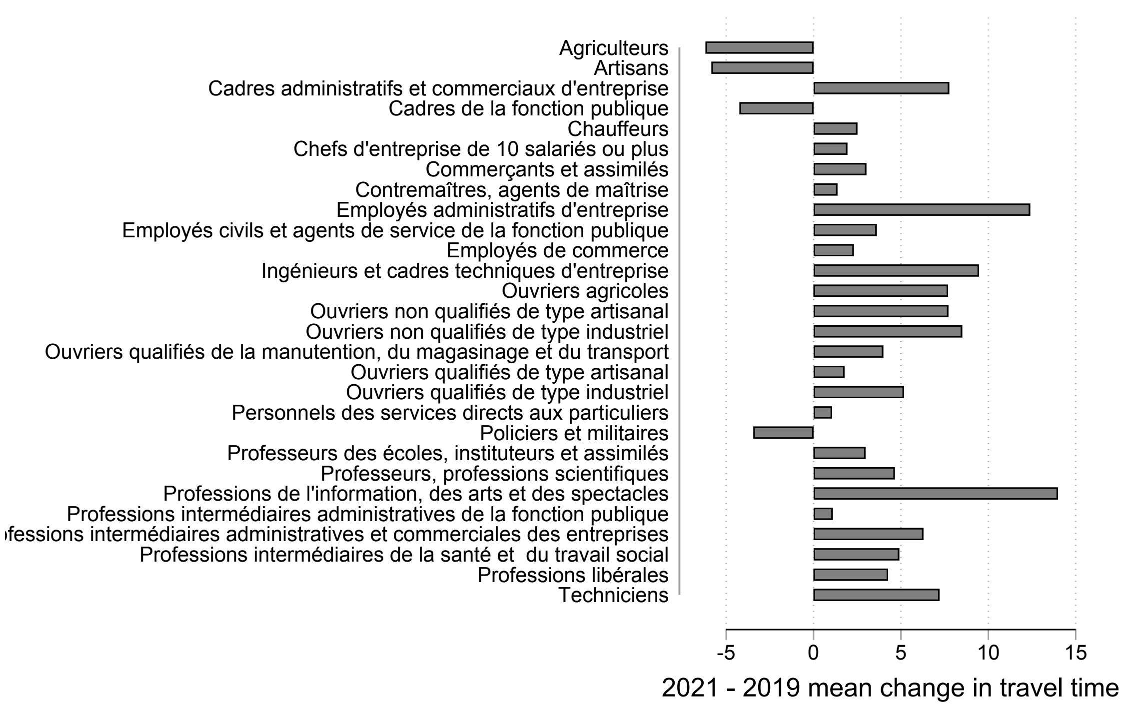
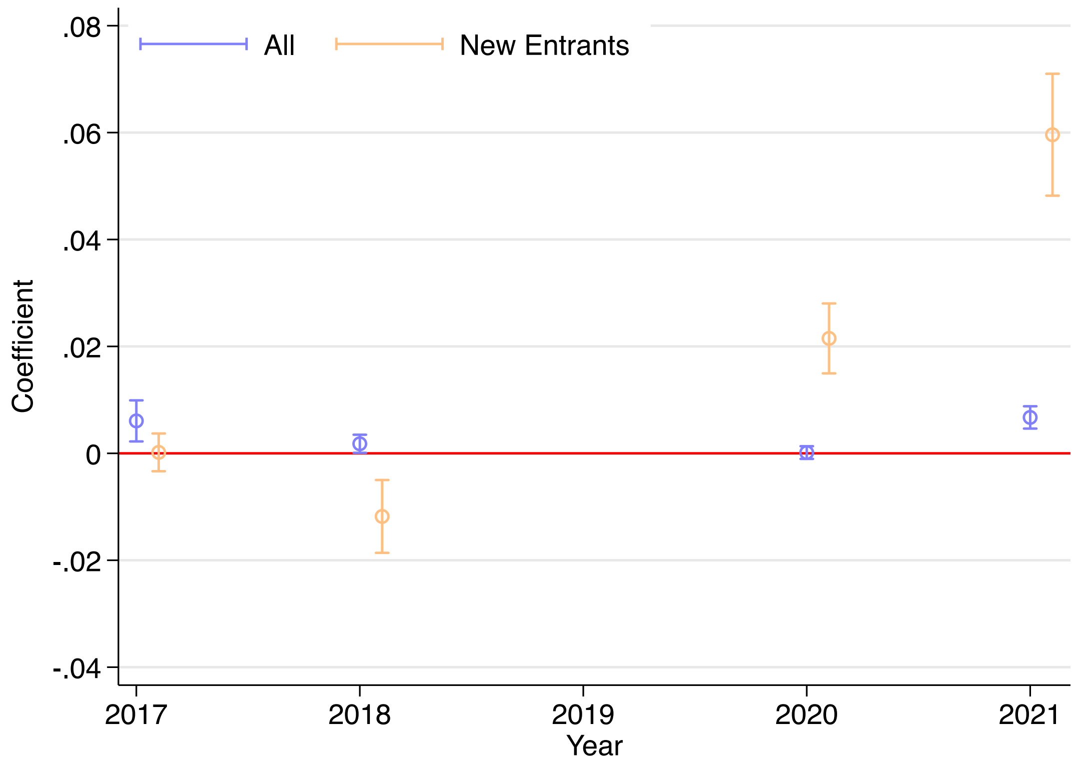


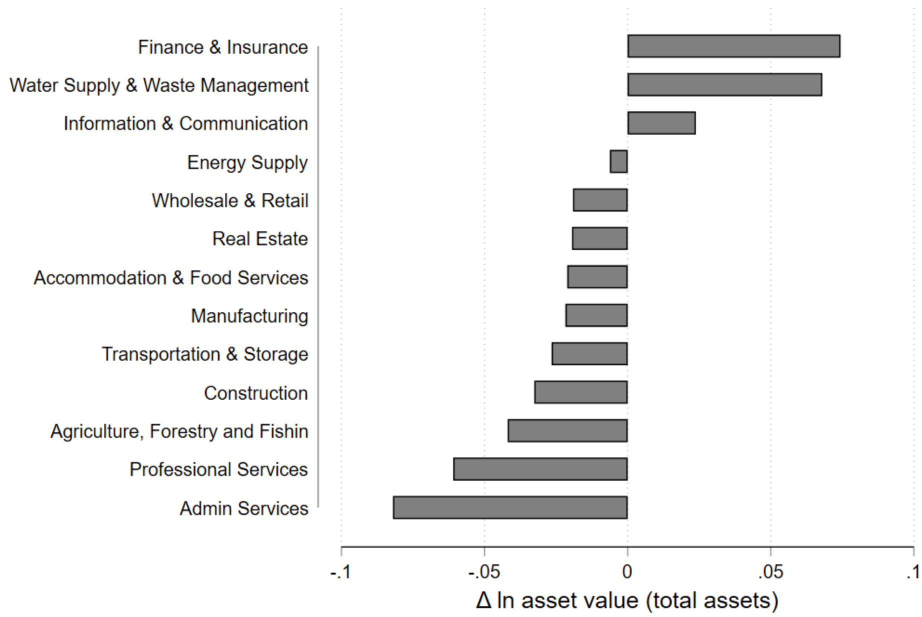
Figure A.4: WFH home-work distance



Notes: ...

A.1 Excluding professional and admin services

Figure A.5: log change in tangible assets' growth (2021-2019 vs 2019-2017)



B Additional Tables

Table B.1: Firm-level first-stage results for changes in commute distance, 2019-2021, 2SLS estimates

	(1)	(2)
	ln Distance	
	2020	2021
WFH potential#Year=2020	0.25***	-0.0061*
	(0.0068)	(0.0046)
WFH potential#Year=2021	-0.0045*	0.2539***
	(0.0033)	(0.0069)
Observations	1,970,991	1,970,991
F stat	1297.45	1315.27
KP Wald rk F stat	486	
Firm-level control variables x Year	✓	✓
4-digit industry fixed effects x Year	✓	✓
Municipality fixed effects x Year	✓	✓

Notes: The data is a balanced panel at the firm-year level. The main explanatory variable is the WFH potential in 2019 as defined by equation 2. Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at 4-digit industry×year level. *** p<0.01, ** p<0.05, * p<0.1.

C Event study

In this section, we test for the relevance of our firm-level instruments by conducting an event study analysis through the estimation of the following difference-in-difference specification:

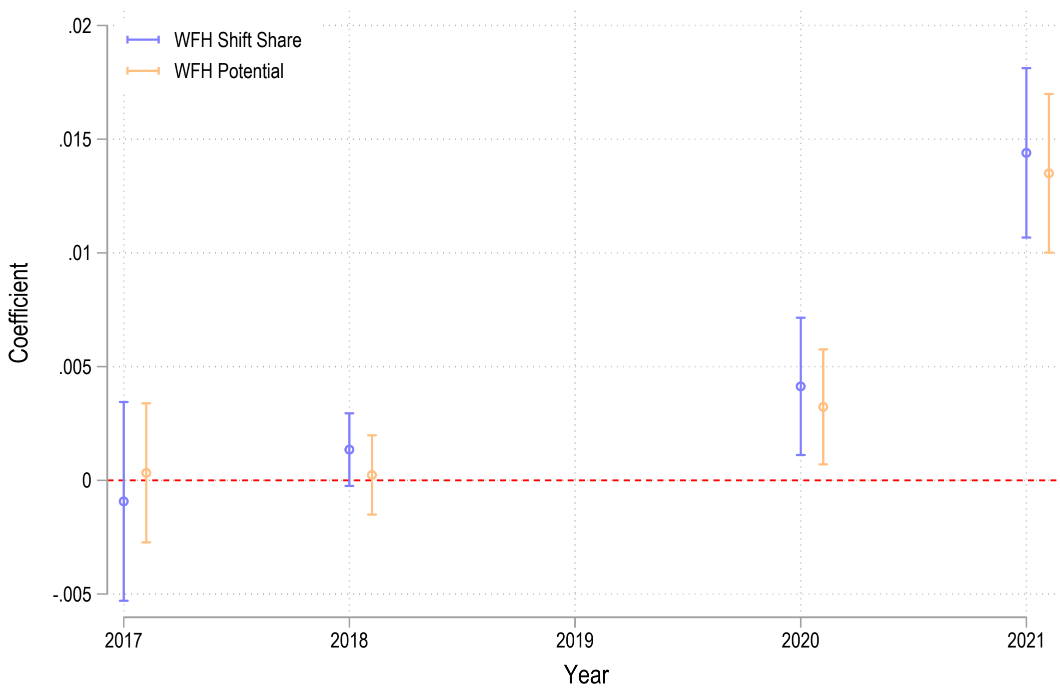
$$log(Distance_{it}) = \sum_{t=2020}^{2021} \beta_t(WFH_i^{IV} \times Year_t) + (X_i^{2017} \times Post_t) + \delta_i + \theta_{jt} + \psi_{mt} + \varepsilon_{it};$$

where $Distance_{it}$ represents the mean home-work distance (in km) of employees of firm i in year t. The variable WFH_i^{IV} denotes firm's i: WFH potential (in year 2019) or WFH shift-share, defined in Section 5.1. $Post_t$ is set to 1 for the years 2020 and 2021, delineating the post-pandemic period. Additionally, the vector X_i^{2019} includes the firm's log number of employees, age and log value added per employee in 2017, which could influence both the feasibility and impact of WFH arrangements. To control for unobserved heterogeneity, firm, 4-digit industry×year and municipality×year fixed effects denoted as δ_i, θ_{jt} and ψ_{mt}

respectively, are included, ensuring that the analysis accounts for unobserved time-invariant characteristics of each firm and common industry, municipality and time trends.

Figure C.1 shows that our instruments are significantly correlated with firms' post-pandemic changes in home-work distance. Importantly, the event study graph shows the lack of any pre-pandemic trend. This evidence indicates that before the year 2020, we did not observe any systematic correlation between our instruments and the firms' average home-work distance.

Figure C.1: WFH instruments and home-work distance



Notes: The data is a balanced panel of firms. Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at the firm and year level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

D Robustness

D.1 First differences Analysis (2019-2021)

Table D.1: Firm-level results for changes in commute distance, 2019-2021, FD-OLS estimates

VARIABLES	(1) Δ log(GVA)	(2) Δ log(TFP)	(3) Δ log(Hourly wage)	(4) Δ log(Hours worked)
Δ log(Distance)	0.0470***	0.00717***	-0.000972	0.0611***
	(0.00640)	(0.00233)	(0.000652)	(0.00854)
Observations	541,452	500,819	556,475	556,477
R-squared	0.276	0.266	0.092	0.205
Firm-level control variables	✓	✓	✓	✓
4-digit industry fixed effects	✓	✓	✓	✓
Municipality fixed effects	✓	✓	✓	✓

Notes: The data is a balanced panel of firms. TFP is estimated based on Wooldridge (2009) method using output (value added), number of employees and capital (total fixed assets). Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at the firm and year level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.2: Firm-level first-stage results for changes in commute distance, 2019-2021, FD-IV estimates

	(1) Δlog(Distance)	(2) Δlog(Distance)
WFH potential	0.0215***	
	(0.00559)	
WFH shift-share		0.0326***
		(0.00809)
Observations	568,364	568,364
R-squared	0.054	0.054
Firm-level control variables × Year	✓	✓
4-digit industry fixed effects × Year	✓	✓
Municipality fixed effects × Year	✓	✓

Notes: The data is at the firm level. Changes in commute distance is instrumented by firms' WFH potential in 2019 as defined by equation 2. TFP is estimated based on Wooldridge (2009) method using output (value added), number of employees and capital (total fixed assets). 4-digit industry×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at 4-digit industry×year level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.3: Firm-level results for changes in commute distance, 2019-2021, FD-IV estimates, WFH potential

VARIABLES	(1) Δ log(GVA)	(2) Δ log(TFP)	(3) Δ log(Hourly wage)	(4) Δ log(Hours worked)
Δ log(Distance)	3.887***	2.442**	-0.207**	2.134***
	(1.397)	(1.004)	(0.101)	(0.713)
Observations	541,452	500,819	556,475	556,477
K-Papp F-stat	13.2	11.1	13.3	13.3
Firm-level control variables	✓	✓	✓	✓
4-digit industry fixed effects	✓	✓	✓	✓
Municipality fixed effects	✓	✓	✓	✓

Notes: The data is a balanced panel of firms. Changes in home-work distance is instrumented by firms' WFH potential in 2019 as defined by equation 2. TFP is estimated based on Wooldridge (2009) method using output (value added), number of employees and capital (total fixed assets). Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at the firm and year level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.4: Firm-level results for changes in commute distance, 2019-2021, FD-IV estimates, WFH shift-share

	(1) Δ log(GVA)	(2) Δ log(TFP)	(3) Δ log(Hourly wage)	(4) Δ log(Hours worked)
Δ log(Distance)	4.488**	2.565*	-0.281*	2.645**
	(2.052)	(1.334)	(0.158)	(1.133)
Observations	541,427	500,797	556,448	556,450
K-Papp F-stat	8.2	6.8	8.7	8.7
Firm-level control variables	✓	✓	✓	✓
4-digit industry fixed effects	✓	✓	✓	✓
Municipality fixed effects	✓	✓	✓	✓

Notes: The data is a balanced panel of firms. Changes in home-work distance is instrumented by firms' WFH potential in 2019 as defined by equation 2. TFP is estimated based on Wooldridge (2009) method using output (value added), number of employees and capital (total fixed assets). Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at the firm and year level. *** p<0.01, ** p<0.05, * p<0.1.

D.2 First differences Analysis (2019-2020)

Table D.5: Firm-level results for changes in commute distance, 2019-2020, FD-OLS estimates

	(1)	(2)	(3)	(4)
	Δ log(GVA)	Δ log(TFP)	Δ log(Hourly wage)	Δ log(Hours worked)
Δ log(Distance)	0.0258***	0.000439	-0.000308	0.0380***
	(0.00453)	(0.00225)	(0.000482)	(0.00491)
Observations	589,732	542,840	603,394	603,396
R-squared	0.348	0.358	0.098	0.237
Firm-level control variables	✓	✓	✓	✓
4-digit industry fixed effects	✓	✓	✓	✓
Municipality fixed effects	✓	✓	✓	✓

Notes: The data is at the firm level. TFP is estimated based on Wooldridge (2009) method using output (value added), number of employees and capital (total fixed assets). 4-digit industry×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at 4-digit industry×year level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.6: Firm-level results for changes in commute distance, 2019-2020, FD-IV estimates, WFH potential

	(1)	(2)	(3)	(4)
	Δ log(GVA)	Δ log(TFP)	Δ log(Hourly wage)	Δ log(Hours worked)
Δ log(Distance)	4.522**	2.614*	0.191*	3.009*
	(2.197)	(1.422)	(0.101)	(1.561)
Observations	589,732	542,840	603,394	603,396
K-Papp F-stat	5.3	5.2	4.1	4.1
Firm-level control variables	✓	✓	✓	✓
4-digit industry fixed effects	✓	✓	✓	✓
Municipality fixed effects	✓	✓	✓	✓

Notes: The data is a balanced panel of firms. Changes in home-work distance is instrumented by firms' WFH potential in 2019 as defined by equation 2. TFP is estimated based on Wooldridge (2009) method using output (value added), number of employees and capital (total fixed assets). Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at the firm and year level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.7: Firm-level results for changes in commute distance, 2019-2020, FD-IV estimates, WFH shift-share

	(1) Δ log(GVA)	(2) Δ log(TFP)	(3) Δ log(Hourly wage)	(4) Δ log(Hours worked)
Δ log(Distance)	5.147	2.718	-0.0290	3.710
	(3.243)	(1.782)	(0.119)	(2.630)
Observations	589,701	542,814	603,361	603,363
K-Papp F-stat	3.3	3.6	2.5	2.5
Firm-level control variables	✓	✓	✓	✓
4-digit industry fixed effects	✓	✓	✓	✓
Municipality fixed effects	✓	✓	✓	✓

Notes: The data is a balanced panel of firms. Changes in home-work distance is instrumented by firms' WFH potential in 2019 as defined by equation 2. TFP is estimated based on Wooldridge (2009) method using output (value added), number of employees and capital (total fixed assets). Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at the firm and year level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.8: Firm-level results for changes in home-work distance (excluding professional/admin services)

VARIABLES	(1) log(GVA)	(2) log(TFP)	(3) log(Hourly wage)	(4) log(Hours worked)
log(Distance) × Year=2017	0.00232	-0.00336	-0.00277**	0.0122
	(0.00659)	(0.00217)	(0.000618)	(0.00965)
log(Distance) × Year=2018	0.00455	-0.00366	-0.000146	0.0135
	(0.00720)	(0.00203)	(0.000594)	(0.0105)
log(Distance) × Year=2020	0.0291**	0.00787*	0.00179	0.0290*
	(0.0103)	(0.00320)	(0.000857)	(0.0121)
log(Distance) × Year=2021	0.0312**	0.00652	-6.94e-05	0.0362**
	(0.0106)	(0.00360)	(0.000938)	(0.0116)
Observations	1,700,737	1,700,737	1,700,737	1,700,737
R-squared	0.996	0.961	0.975	0.998
Firm-level control variables × Year	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓
4-digit industry fixed effects × Year	✓	✓	✓	✓
Municipality fixed effects × Year	✓	✓	✓	✓

Notes: The data is a balanced panel at the firm-year level. Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. TFP is estimated based on Wooldridge (2009)'s method using output (value added), number of employees and capital (total fixed assets). Standard errors are clustered at the firm and year level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.9: Firm-level results for changes in commute distance, 2SLS estimates, WFH potential (excluding professional/admin services)

VARIABLES	(1) log(GVA)	(2) log(TFP)	(3) log(Hourly wage)	(4) log(Hours worked)
log(Distance) × Year=2020	0.118**	0.0830**	0.0253**	0.0247
	(0.0263)	(0.0275)	(0.00734)	(0.0139)
log(Distance) × Year=2021	0.104**	0.0875**	0.00515	0.0179
	(0.0275)	(0.0282)	(0.00742)	(0.0137)
Observations	1,698,956	1,698,956	1,698,956	1,698,956
K-Papp F-stat	822.8000000000001	822.8	822.8	822.8
Firm-level control variables × Year	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓
4-digit industry fixed effects × Year	✓	✓	✓	✓
Municipality fixed effects × Year	✓	✓	✓	✓

Notes: The data is a balanced panel at the firm-year level. Changes in home-work distance is instrumented by firms' WFH potential in 2019 as defined by equation 2. TFP is estimated based on Wooldridge (2009) method using output (value added), number of employees and capital (total fixed assets). Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at the firm and year level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.10: Firm-level results for changes in commute distance, 2019-2021, FD-IV estimates, WFH potential (excluding professional/admin services)

VARIABLES	(1) Δ log(GVA)	(2) Δ log(TFP)	(3) Δ log(Hourly wage)	(4) Δ log(Hours worked)
Δ log(Distance)	5.412***	3.561***	-0.319**	2.563***
	(1.615)	(1.241)	(0.149)	(0.808)
Observations	443,181	418,285	455,431	455,431
K-Papp F-stat	11.9	9.1	12.6	12.6
Firm-level control variables	✓	✓	✓	✓
4-digit industry fixed effects	✓	✓	✓	✓
Municipality fixed effects	✓	✓	✓	✓

textitNotes: The data is a balanced panel of firms. Changes in home-work distance is instrumented by firms' WFH potential in 2019 as defined by equation 2. TFP is estimated based on Wooldridge (2009) method using output (value added), number of employees and capital (total fixed assets). Firm, 4-digit industry×year and municipality×year fixed effects are included in all regressions. The log of number of employees, age and the log value added per employee in 2019 are added as controls. Standard errors are clustered at the firm and year level. *** p<0.01, ** p<0.05, * p<0.1.

E Decomposition

In this section, we analyse the main components that drive the year-by-year change in distance recorded in the economy. First of all, the aggregate commuting pattern can be driven by entry-exit dynamics involving plants characterised by different average work-to-home spatial patterns or by changes in the local labour market of surviving plants.
The aggregate percentage change in distance recorded in the economy, $\Delta\overline{d_t}$, can thus be decomposed in three different components: the contribution of plants exiting the market between $t-1$ and t, $\Delta\overline{X^{ex}}$, the contribution of new entrants, $\Delta\overline{X^{ne}}$, and the variation driven by changes in the average work-to-home distance recorded by incumbent plants, $\Delta\overline{X^{inc}}$.

$$\Delta\overline{d_t} = \Delta\overline{X^{ex}} + \Delta\overline{X^{ne}} + \Delta\overline{X^{inc}}$$

$$\Delta\overline{X^{ex}} = \left(\frac{N^{ex}_{t-1}}{N_t}\right)\left(1 - \frac{d^{ex}_{t-1}}{d_{t-1}}\right)$$

$$\Delta\overline{X^{ne}} = \left(\frac{N^{ne}_{t}}{N_t}\right)\left(\frac{d^{ne}_{t}}{d_{t-1}} - 1\right)$$

$$\Delta\overline{X^{inc}} = \left(\frac{N^{inc}_{t}}{N_t}\right)\left(\frac{d^{inc}_{t}}{d_{t-1}} - 1\right) + \left(\frac{N^{inc}_{t-1}}{N_t}\right)\left(\frac{d^{inc}_{t-1}}{d_{t-1}} - 1\right)$$

In turn, the changes in the average work-home distance recorded by incumbent plants can be decomposed in the entry/exit dynamic of workers living at different distances from the firms and in the contribution of workers changing residence over the period.
The aggregate percentage change in distance recorded by incumbent plants, $\Delta\overline{X^{inc}}$, can thus be decomposed in three different components: the contribution of workers dismissed between $t-1$ and t, $\Delta\overline{X^{dis}}$, the contribution of new hires, $\Delta\overline{X^{nh}}$, and the variation driven by changes in the average work-home distance recorded by incumbent workers, $\Delta\overline{X^{incw}}$.

$$\Delta\overline{X^{inc}} = \Delta\overline{X^{dis}} + \Delta\overline{X^{nh}} + \Delta\overline{X^{incw}}$$

$$\Delta\overline{X^{dis}} = \left(\frac{N^{dis}_{t-1}}{N_t}\right)\left(1 - \frac{d^{dis}_{t-1}}{d_{t-1}}\right)$$

$$\Delta\overline{X^{nh}} = \left(\frac{N^{nh}_{t}}{N_t}\right)\left(\frac{d^{nh}_{t}}{d_{t-1}} - 1\right)$$

$$\Delta\overline{X^{incw}} = \Delta\overline{X^{inc}_t} - \Delta\overline{X^{dis}} - \Delta\overline{X^{nh}}$$