Working From Home and the Centrality Premium

Implications for Business Districts

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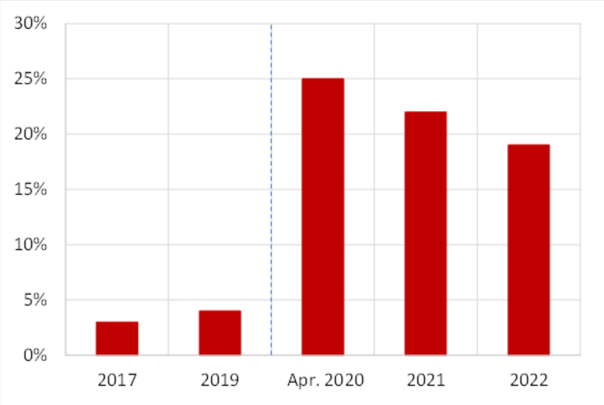
1. Motivation
2. Contribution
3. Data and methodology
4. Results
5. Appendix

Large and persistent rise of WFH induced by the pandemic

Figure 1: Employees working from home in France

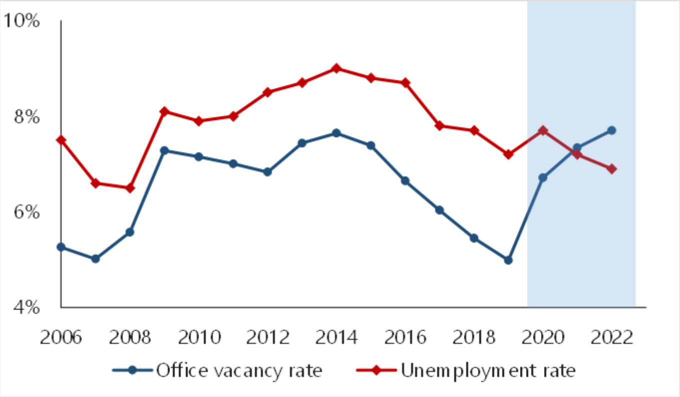


Notes: This figure plots the share of employees regularly working from in France. Sources: DARES, INSEE

E-Commerce

Recent divergence between office and labour markets

Figure 2: Office occupier market vs labour market in the Paris region



Notes: This figure plots the aggregate office vacancy rate, defined as the ratio of office vacant space to office stock, and the unemployment rate, both in the Paris region. Sources: BNP Paribas Real Estate, INSEE.

Major potential implications

- Negative effect for office owners through a reduced demand...
  'WFH and the Office Real Estate Apocalypse' (Gupta et al., 2022)
- ... and for financial stability and investment through the collateral channel (Chaney et al., 2012, AER)
- Negative effect for consumption services located in business districts (Gokan et al., 2022)

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Research Question

- Main question:

How has the large-scale deployment of WFH affected business districts?

- Through two dimensions:

1. the effect of WFH on office property (rental) markets
$\rightarrow$ **office vacancy**

2. its consequences on local consumption services (retail, restaurants)
$\rightarrow$ **employment**, **business number**

This paper in a nutshell

Methodology:

- build a WFH exposure indicator at the municipality level
- implement a **diff-in-diff** taking advantage of the pandemic as a natural experiment for WFH

At the municipality level, a one standard deviation increase in WFH exposure yields, compared to pre-Covid:

- an **increase in office vacancy** by about 15%
- the effect of WFH exposure on office vacancy is stronger (i) further from the city center (ii) in areas with longer commuting distances (iii) with respect fo firm size

$\rightarrow$ **preference for the fundamentals offered by centrality**

- a **decline in retail employment** and **businesses** by 3% and 2%

Data

Main sources

- Teleworkability index at the occupation level (Dingel and Neiman, 2020)
- Office vacancy and stock at the municipality level (BNP Paribas Real Estate and ORIE, 2011-2022)
- Employment by occupation (PCS29) in France (INSEE, 2019)
- Employment by sector in France (URSSAF, 2011-2022)

Sample

- Annual frequency from 2011 to 2022
- Balanced panel data
- for the 'office' regression: 268 municipalities representative of the regional office markets
(accounting for 90% of employment in Île-de-France)

'WFH-Occupation'

I develop and test the effect of a **WFH indicator**:

- At the municipality level
- Throughout the Paris region

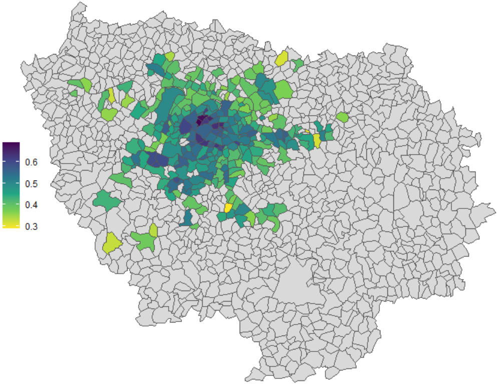
First, I build the **'WFH-Occupation'** indicator by

- Using Dingel and Neiman (2020) teleworkability index for each occupation according to the US O-Net/SOC classification...

  (Unteleworkable=0, Teleworkable=1)

- ... and a crosswalk from the ISCO classification of occupations to the french PCS following Le Barbanchon and Rizzotti (2020) similarly to Bergeaud et al. (2023)
- Combining this index with the weight of each occupation category (PCS 29) at the municipality level in France Chart PCS

Figure 3: Estimated WFH(-Occupation) exposure in the Paris area



Notes: This figure maps WFH exposure at the workplace municipality throughout the 268 municipalities representative of the office market in the Paris Metropolitan Area, according to the estimated 'WFH-Occupation' indicator. If the indicator equals 0 (1), it means that no one (everyone) can theoretically telework.

Gradient

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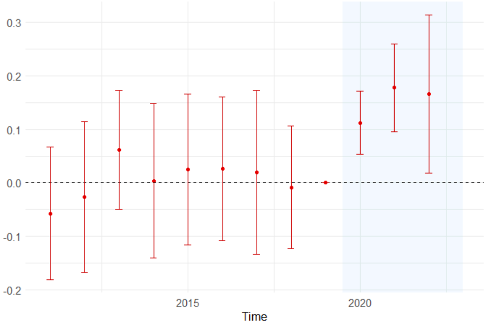
$$vacancy_{it} = \exp(\alpha_i + \gamma_t + \sum_t \beta_t WFH_i + \log(stock_{it}) + Urate_t \times \log(dens_i)) + \epsilon_{it} \quad (2)$$

Figure 5: Effect of WFH(-Occupation) exposure on office vacancy



Notes: This figure plots the point estimates of β_t from model (2) and the 95% confidence interval, for different values of t ranging from 2011 to 2022, where the dependent variable is the municipal office vacancy, and the treatment is 'WFH-Occupation'. The event study is estimated by Poisson pseudo-maximum-likelihood. Standard errors are clustered at the municipality level.

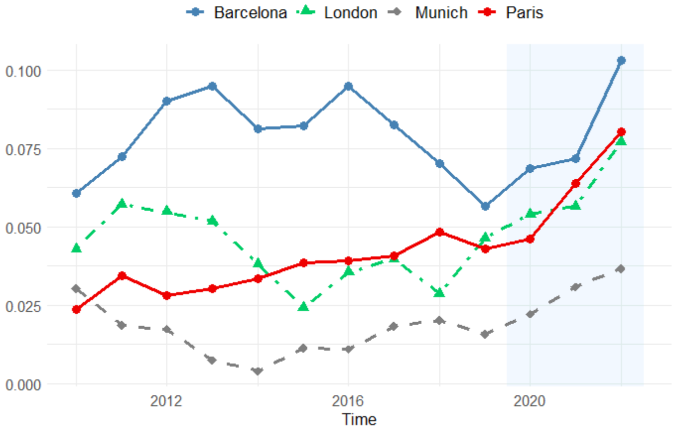
from 2006

Table 2: Effect of WFH-Occupation on office vacancy

	Vacancy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WFH-Occupation × Post	0.153**	0.256***	0.162*	0.010	0.010	0.214**	0.069	0.067
	(0.054)	(0.059)	(0.081)	(0.059)	(0.052)	(0.072)	(0.062)	(0.064)
WFH-Occupation × Post × dmean-log(*distance*)		0.185***					0.242***	0.242***
		(0.052)					(0.054)	(0.047)
WFH-Occupation × Post × dmean-log($density_{2019}$)			−0.049					
			(0.040)					
WFH-Occupation × Post × dmean-log($commuting_{2019}$)				0.449**			0.573***	
				(0.142)			(0.158)	
WFH-Occupation × Post × dmean-log($firmsize_{2019}$)					0.142**			0.157**
					(0.055)			(0.058)
WFH-Occupation × Post × dmean-log($connection_{2019}$)						−0.033		
						(0.026)		
Post × dmean-log(*distance*)		−0.369**					−0.507***	−0.557***
		(0.121)					(0.124)	(0.112)
...								
log(*Stock*)	0.955***	0.886***	0.899***	0.967***	0.921***	0.944***	0.886***	0.826***
	(0.209)	(0.195)	(0.205)	(0.210)	(0.205)	(0.204)	(0.193)	(0.191)
URate× log($density_{2019}$)	0.091**	0.098***	0.121***	0.086**	0.078**	0.096***	0.095***	0.101***
	(0.030)	(0.024)	(0.024)	(0.030)	(0.026)	(0.028)	(0.024)	(0.023)
Municipality and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	3072	3072	3072	3072	3072	3072	3072	3072
Pseudo R^2	0.936	0.938	0.936	0.936	0.937	0.936	0.939	0.939

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$. This table presents the estimates from the diff-in-diff, where the dependent variable is the municipal office vacancy expressed in square metres, and the treatment variable is 'WFH-Occupation'. All regressions are estimated by Poisson pseudo-maximum-likelihood. Standard errors are clustered at the municipality level.

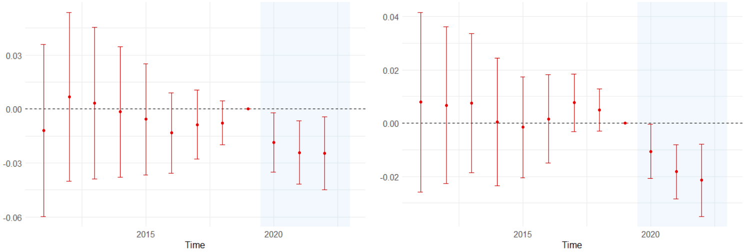
Figure 6: Vacancy rate: gap between peripheral areas and CBDs



Notes: This figure plots the end-of-year office vacancy rate gaps between peripheral areas and CBDs in the metropolitan areas of Barcelona, Munich, Paris and London, from 2010 to 2022. Source: BNP Paribas Real Estate

$$retail_{it} = \exp(\alpha_i + \gamma_t + \sum_t \beta_t WFH_i + \delta hotelshare_i \times \log(hotelnights_t) + X_{it}\lambda) + \epsilon_{it} \quad (3)$$

Figure 7: Effect of WFH-Occupation on the retail industry



(a) Employment (b) Business number

Notes: This figure plots the point estimates of β_t from model (3) and the 95% confidence interval, for different values of t ranging from 2011 to 2022. The dependent variable is the municipal employee or business number in the retail sector. The treatment is 'WFH-Occupation'. The event study is estimated by Poisson pseudo-maximum-likelihood. Standard errors are clustered at the municipality level.

Hotel Nights Sub-Sectors

Table 3: Effect of WFH-Occupation on retail employment

	Retail employment							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WFH-Occupation × Post	-0.035^{**}	-0.029^{*}	-0.044^{***}	-0.042	-0.007	-0.004	-0.026	-0.027
	(0.012)	(0.013)	(0.012)	(0.030)	(0.028)	(0.020)	(0.018)	(0.025)
WFH-Occupation × Post × dmean-log(*distance*)			-0.008					
			(0.008)					
WFH-Occupation × Post × dmean-log($density_{2019}$)				0.003				
				(0.006)				
WFH-Occupation × Post × dmean-log($commuting_{2019}$)					-0.009			
					(0.011)			
WFH-Occupation × Post × dmean-log($firmsize_{2019}$)						$-0.031^{\cdot}$		
						(0.017)		
WFH-Occupation × Post × dmean-log($connection_{2019}$)							-0.000	
							(0.004)	
WFH-Occupation-Resi × Post								-0.002
								(0.018)
Post × dmean-log(*distance*)			0.032					
			(0.046)					
...								
log(*hotelnights*)× log($hotelshare_{2019}$)		1.556^{*}	1.842^{**}	1.572^{*}	1.567^{*}	1.748^{**}	1.491^{*}	1.545^{*}
		(0.623)	(0.599)	(0.644)	(0.614)	(0.597)	(0.644)	(0.611)
Trend × log($density_{2019}$)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Urate× log($density_{2019}$)	-0.001	-0.000	0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Municipality and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	11928	11928	11928	11928	11904	11844	11928	11928
Pseudo R^2	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.991

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$. All regressions are estimated by Poisson pseudo-maximum-likelihood. Standard errors are clustered at the municipality level.

Conclusion

- WFH has already led to a perceptible **rise in office vacancy**, indicating that firms, especially the large ones, have already started to incorporate telework into their property strategies.

- In this new environment, firms seem to maintain a strong **preference for the fundamentals offered by central locations**

→ local amenities and prestige are key parameters for productivity
→ downsizing makes central areas more affordable
→ early signals about the long-term consequences of WFH on cities

- WFH exposure yields a notable **decrease in local retail sector employment and business numbers**, underscoring the broad economic implications of teleworking.

Further implications

- Office downsizing combined with the centrality premium tends to **increase spatial disparities** between business districts at the expense of suburban areas, which in turn affects local CRE and labor markets, amenities and public finances.
- The spillover effects on LCS and therefore local amenities may further exacerbate these disparities.
- It emphasizes the need to **(i) to account for the heightened vacancy risk when pricing offices** located in deserted peripheral business districts, and (ii) raises the issue of the **revitalisation** of these areas.

Thank you !

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Literature

WFH and cities: an empirical study on firms' spatial decisions and LCS, demonstrating a centrality premium phenomenon

- Safirova (2002, JUE), Rhee (2008, JUE), Behrens et al. (2021)
- Delventhal et al. (2022, JUE), Brueckner et al. (2023, AEJ), Breuillé et al. (2022), Gupta et al. (2023, JFE), Ramani and Bloom (2021)

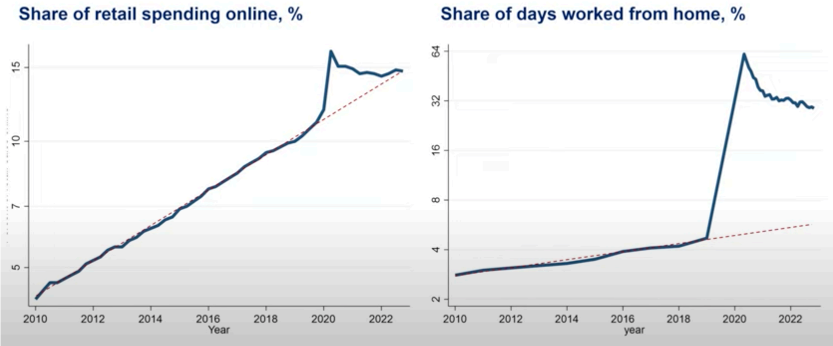
Covid 19, WFH, and corporate real estate: a local analysis demonstrating causality, shedding light on LCS

- Gupta et al. (2022), Bergeaud et al. (2023, RSUE)
- Milcheva and Xie (2022), Hoesli and Malle (2021, JERES), Ling et al. (2020, RAPS)

Measuring WFH: provides intra-city estimations of WFH

- Dingel and Neiman (2020, JPubE), Bartik et al. (2020), Mongey et al. (2021, JEIneq)
- Milcheva and Xie (2022), Gupta et al. (2022)

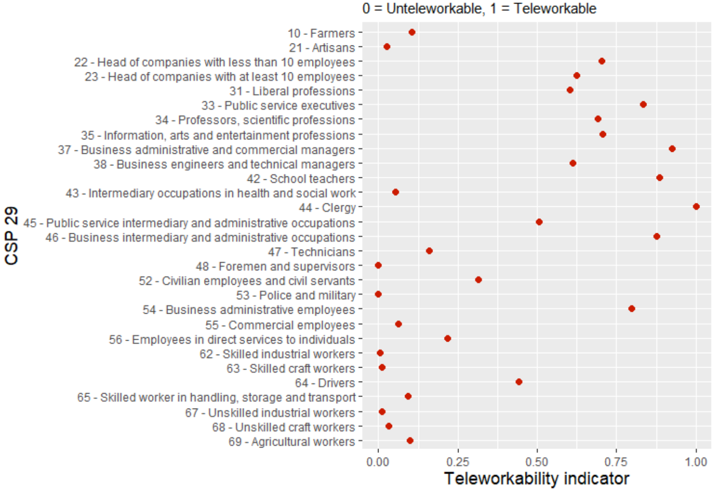
WFH vs E-Commerce in the US



Source: "Does Working From Home have a Future?" Nick Bloom (2022)

France

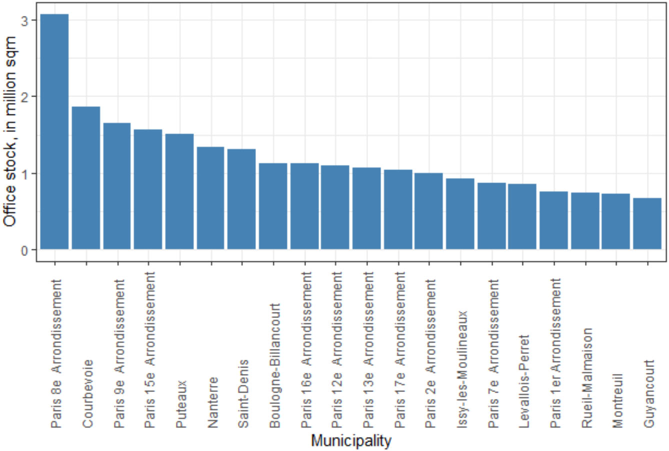
Figure 8: Teleworkability index by occupation in France



Notes: This figure plots the Dingel and Neiman (2020)' s teleworkability index applied to the french 2-digit PCS occupation groups.

WFH-Occupation

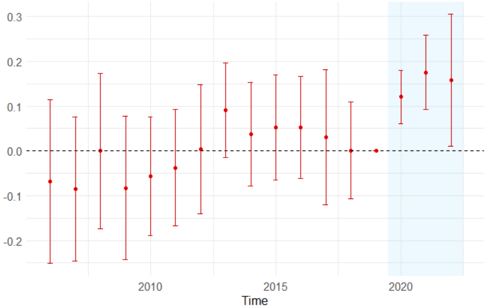
Figure 9: Top 20 office markets in the Paris metropolitan area



Notes: This figure plots the office stock, measured in million sqm, for the top 20 municipalities in the Paris region, in 2019.

$$vacancy_{it} = \exp(\alpha_i + \gamma_t + \sum_t \beta_t WFH_i + \log(stock_{it}) + Urate_t \times \log(dens_i)) + \epsilon_{it} \quad (4)$$

Figure 10: Effect of WFH(-Occupation) exposure on office vacancy

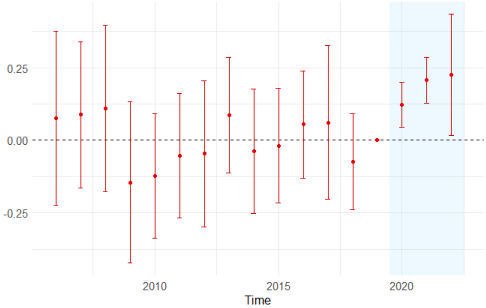


Notes: This figure plots the point estimates of β_t from model (1) and the 95% confidence interval, for different values of t ranging from 2006 to 2022, where the dependent variable is the municipal office vacancy expressed in square metres, and the treatment variable is 'WFH-Occupation'. The event study is estimated by Poisson pseudo-maximum-likelihood. Standard errors are clustered at the municipality level.

Weighted | from 2011 | WFH-Sector | Log transfo

$$vacancy_{it} = \exp(\alpha_i + \gamma_t + \sum_t \beta_t WFH_i + \log(stock_{it}) + Urate_t \times \log(dens_i)) + \epsilon_{it} \quad (5)$$

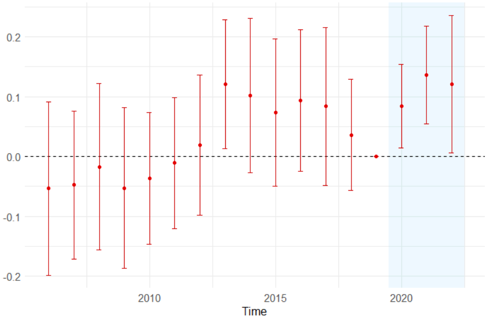
Figure 11: Effect of WFH(-Occupation) exposure on office vacancy



Notes: This figure plots the point estimates of β_t from model (3) and the 95% confidence interval, for different values of t ranging from 2006 to 2022, where the dependent variable is the municipal office vacancy, and the treatment is 'WFH-Occupation'. The event study is estimated by Poisson pseudo-maximum-likelihood and is weighted by the 2019 municipal office stock. Standard errors are clustered at the municipality level. Unweighted

$$\textit{vacancy}_{it} = \exp(\alpha_i + \gamma_t + \sum_t \beta_t \textit{WFH}_i + \log(\textit{stock}_{it}) + \textit{Urate}_t \times \log(\textit{dens}_i)) + \epsilon_{it} \quad (6)$$

Figure 12: Effect of WFH(-Sector) exposure on office vacancy



Notes: This figure plots the point estimates of β_t from model (4) and the 95% confidence interval, for different values of t ranging from 2006 to 2022, where the dependent variable is the municipal office vacancy, and the treatment is 'WFH-Sector'. The event study is estimated by Poisson pseudo-maximum-likelihood. Standard errors are clustered at the municipality level. Unweighted

'WFH-Sector'

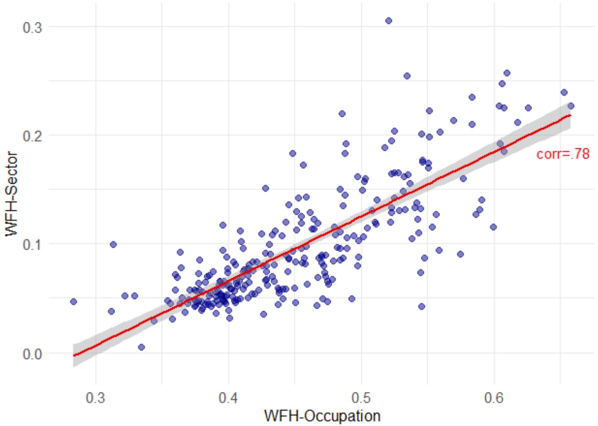
As a robustness check, I build an alternative **'WFH-sector'** indicator, combining

- For each sector j (NACE38), the **share of employees WFH at least one day in a reference week** μ_j at the french national level during the pandemic from the following equation (source: Dares, from April 2020 to March 2022)

$$WFH_{jt} = \mu_j + \nu_t + \epsilon_{jt} \tag{1}$$

- The **sectoral composition of employment** at the workplace at the municipality level in 2019 (source: Urssaf)

Figure 4: Correlation between the two WFH indicators



Notes: Scatter plot of WFH-Occupation versus WFH-Sector. The fitted line indicates a positive linear relationship.

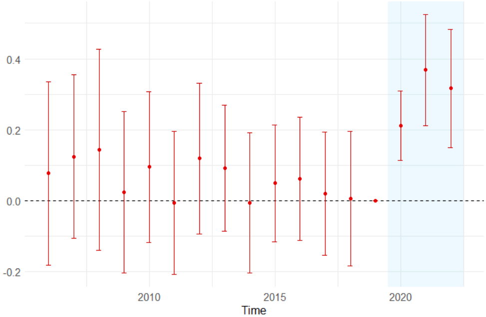
Table 1: Summary statistics

Variable	Unit	N	Min	Q1	Median	Mean	Q3	Max	SD
WFH-Occupation	teleworkable=1	268	0.284	0.398	0.441	0.452	0.498	0.657	0.070
WFH-Sector	% of employees	268	0.031	0.057	0.081	0.098	0.126	0.304	0.050
Vacancy rate	% of stock	268	0	0	0.020	0.047	0.0650	0.963	0.0853
Office stock	sqm	268	259	23,261	53,988	189,474	185,555	3,074,471	351,703
Employment	units	268	99	2985	6,382	16,125	15,443	215,608	25,913
Employment density	thousands/sqm	268	0.016	0.545	1.063	3.679	2.718	95.964	8.916
Distance to center	km	268	0	9.95	15.59	17.35	23.37	51.11	9.88
Median commuting distance	km	268	0	4.52	6.72	6.90	8.99	20.41	3.01
Rail connection density	units/ha	268	0	0	0.23	0.75	0.70	10.37	1.50
WFH-Occupation	teleworkable=1	1,020	0.068	0.344	0.392	0.395	0.444	0.674	0.11
WFH-Sector	% of employees	1,020	-0.036	0.033	0.053	0.065	0.082	0.491	0.06
Retail employment	units	1,020	0	0	7	291	142	15,708	987
Restaurant employment	units	1,020	0	0	5	213	81	12,899	868
Retail businesses	units	1,020	0	0	2	36	18	1,394	124
Restaurant businesses	units	1,020	0	0	1	27	13	1,178	103
Area	ha	1,020	10	477	769	937	1,187	17,241	794
Employment	units	1,020	0	24	178	3,790	1,796	215,608	13,457
Employment density	thousands/sqm	1,020	0	0.000	0.000	0.832	0.283	95.964	4.324

Notes: This table first presents basic summary statistics for the 268 municipalities representative of the office market the Paris metropolitan area for 2019. The second part of the table presents summary statistics for the sample on local consumption services.

$$\log(vacancy_{it}+1) = \alpha_i + \gamma_t + \sum_t \beta_t WFH_i + \log(stock_{it}) + Urate_t \times \log(dens_i) + \epsilon_{it} \quad (7)$$

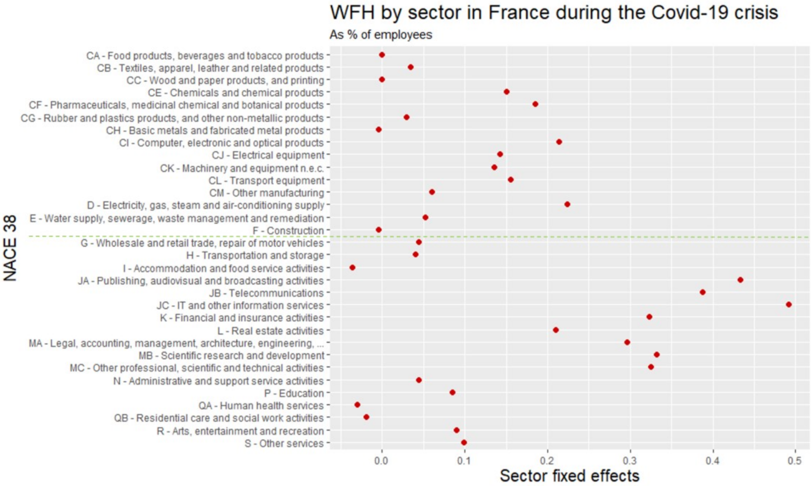
Figure 13: Effect of WFH(-Occupation) exposure on office vacancy



Notes: This figure plots the point estimates of β_t from model (4) and the 95% confidence interval, for different values of t ranging from 2011 to 2022, where the dependent variable is the log-transformation of municipal office vacancy expressed in square metres, and the treatment variable is 'WFH-Occupation'. The event study is estimated by OLS and is weighted by the 2019 office stock. Standard errors are clustered at the municipality level.

Unweighted

Heterogeneous WFH intensity across sectors



Gradients

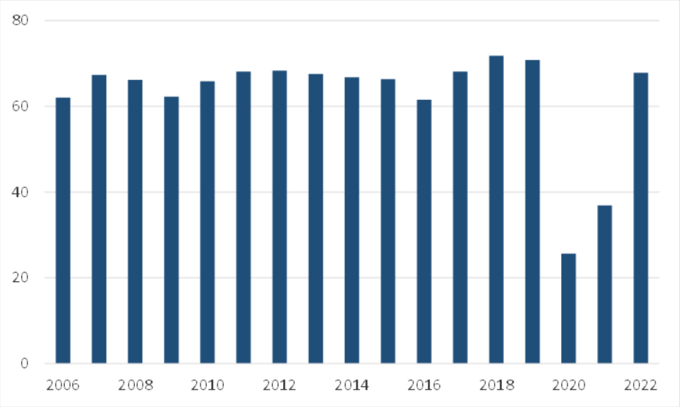
Table 4: Distance to center gradients

	log(*rent*)	log(*density*)		log(*connection*)		WFH-Occupation		WFH-Sector	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(*distance*)	-0.35^{***}	-0.04^{***}		-0.39^{***}		-0.04^{***}	-0.06^{***}	-0.02^{***}	-0.02^{***}
	(0.03)	(0.00)		(0.02)		(0.00)	(0.00)	(0.00)	(0.00)
Intercept	6.13^{***}	0.83^{***}		1.42^{***}		0.60^{***}	0.58^{***}	0.32^{***}	0.31^{***}
	0.08	(0.04)		(0.04)		(0.03)	(0.01)	(0.03)	(0.02)
'Office' sub-sample	Yes	Yes	No	Yes	No	Yes	No	Yes	No
R^2	0.44	0.24		0.48	0.16	0.24	0.17	0.15	0.09
Num. obs.	153	268	1,020	268	1,020	268	1,020	268	1,020

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$. This table presents the estimates from the linear regressions performed at the municipality level of the average office rent, job density, rail connection density, and both WFH exposure indicators (WFH-Occupation and WFH-Sector) on the natural logarithm of the euclidian distance to the center, for 2019 and both the office sub-sample and the entire metropolitan area (i.e. region). The average office rent, which measures the rent per sqm on new office leases, is available for only 153 municipalities in 2019.

Map

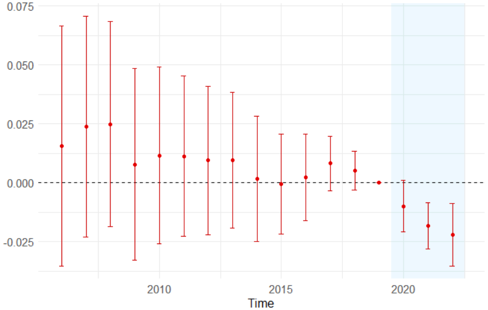
Figure 14: Hotel nights spent in hotels in the Paris region



Notes: This figure plots the annual total number of hotel nights spent in hotels and similar accommodations in the Paris region, expressed in millions, from 2006 to 2022. Source: Eurostat Employment

$$retailB_{it} = \exp(\alpha_i + \gamma_t + \sum_t \beta_t WFH_i + \delta hotelshare_i \times \log(hotelnights_t) + X_{it}\lambda) + \epsilon_{it} \quad (8)$$

Figure 15: Effect of WFH-Occupation on retail business number

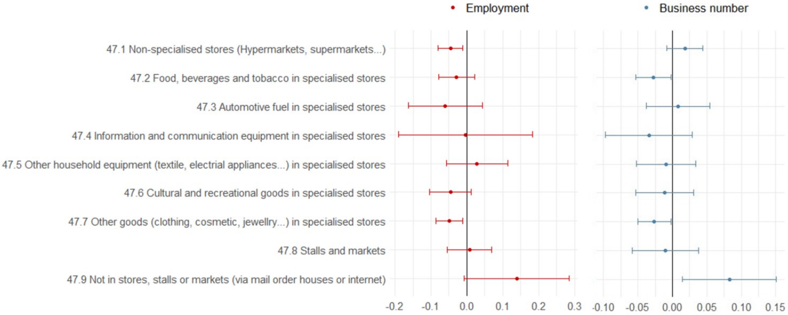


Notes: This figure plots the point estimates of β_t from model (7) and the 95% confidence interval, for different values of t ranging from 2006 to 2022, where the dependent variable is the municipal number of businesses in the retail sector, and the treatment variable is 'WFH-Occupation'. The event study is estimated by Poisson pseudo-maximum-likelihood. Standard errors are clustered at the municipality level.

Retail

$$retail_{it} = \exp(\alpha_i + \gamma_t + \beta Post \times WFH_i + \delta hotelshare_i \times \log(hotelnights_t) + X_{it}\lambda) + \epsilon_{it} \quad (9)$$

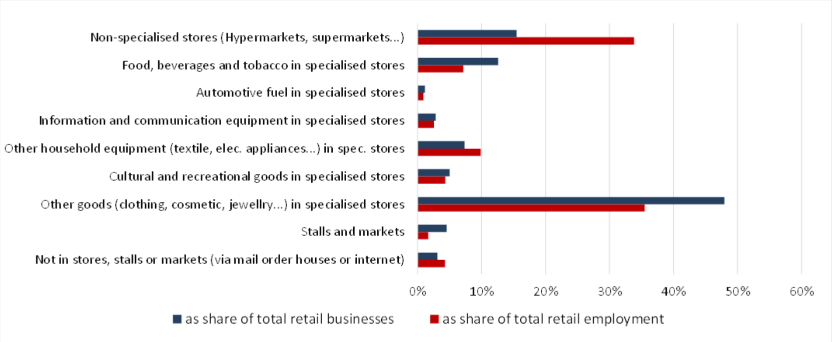
Figure 16: Effect of WFH-Occupation on the retail sector



Notes: This figure plots the point estimates of β from model (3) and the 95% confidence interval, where the dependent variable is on the municipal number of employees and the number of businesses in the retail sector respectively on the left and the right plot, and the treatment variable is 'WFH-Occupation'. The regression is estimated by Poisson pseudo-maximum-likelihood. Standard errors are clustered at the municipality level.

Desc Stats 1 Retail

Figure 17: Retail sub-sectors in the Paris region

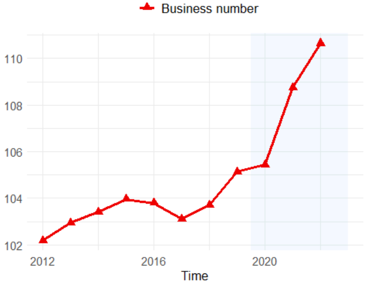


Notes: This figure plots the share of each retail sub-sectors in terms of employment and number of businesses in 2019 in the Paris region

DiD Sub-Sectors1

Figure 18: Employment and business number in Paris

(a)



(b)

Notes: Figure (a) plots the end-of-year number of employees (in units) per occupied office space (in sqm) in Paris while figure (b) plots the number of businesses (in thousands) in Paris, from 2012 to 2022. The data is restricted to services, which are usually the main office occupiers, and therefore excludes the restaurant, retail and hotel sectors.