Working From Home and the Centrality Premium

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EEA-ESEM

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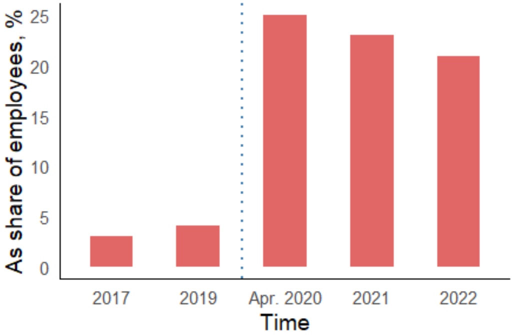
Large and persistent rise of WFH induced by the pandemic

Figure: Employees working from home in France



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

Motivation

Many studies on the effect of remote work on household migration and housing markets
→ **donut effect**

- Delventhal et al. (2022, JUE), Brueckner et al. (2023, AEJ), Gupta et al. (2023, JFE)

Few papers have highlighted the negative impact of telework on office markets
→ **office downsizing**

- Gupta et al. (2022), Bergeaud et al. (2023 | RSUE)

Little is known about the impact of WFH on firm behaviour within cities

- Delventhal et al. (2022, JUE): firms' **centralization** phenomenon
- Rosenthal et al. (2022, JUE): the pandemic has **weakened the appeal** of urban centers

Research Question

- Main question:

How has the large-scale deployment of WFH affected business districts?
→ **intracity effects**

- Through two dimensions:

1. the effect of WFH on **office markets** : reflecting **firms' location choice**
→ office vacancy | investment and prices
2. its consequences on **local consumption services** : **ripple effects**
→ employment | number of businesses

Contribution

1) Spatial consequences of WFH within cities

- donut effect on households + ambiguous effect on firms + indirect effect on LCS

Brueckner et al. (2023, AEJ), Gupta et al. (2023, JFE) , Ramani and Bloom (2021), Delventhal et al. (2022, JUE), Rosenthal et al. (2022, JUE), Althoff et al. (2022, RSUE), Gokan et al. (2023)

- **1st empirical study** on the intracity effect of WFH on firms' behaviour
- Novel way to **identify** the impact of telework on local consumption services

2) Impact of Covid and WFH on Commercial Real Estate markets

- Negative effect on office markets and REITs' stock performance

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

- **1st empirical evidence in Europe** at a fine spatial granularity

This paper in a nutshell

Methodology:

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

A one std deviation $\nearrow$ in WFH exposure yields, compared to pre-Covid:

- an $\nearrow$ **in office vacancy** by 15%
- stronger in areas (i) further from the city center, (ii) with longer commuting distances (iii) with larger firms
  $\rightarrow$ firms use downsizing to relocate to the best locations
  $\rightarrow$ large firms + longer commuting = more WFH
- a $\searrow$ **in office prices and investment** by 3% and 25%
  $\rightarrow$ anticipation of enduring changes in the office market
- a $\searrow$ **in retail employment and businesses** by 1.5%
  $\rightarrow$ wide-reaching effects of WFH

Data

Main sources

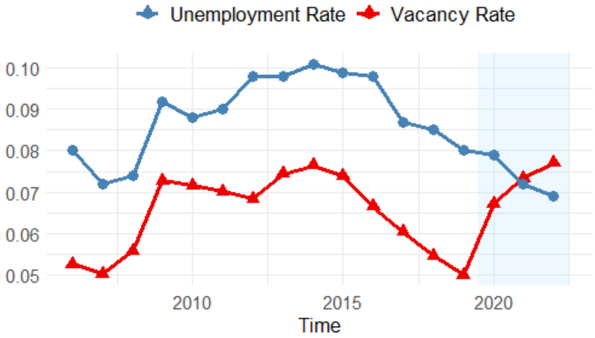
- Office vacancy and stock| BNP Paribas Real Estate and ORIE
- Office sales and prices | DV3F (Cerema)
- Employment by occupation in France | INSEE
- Employment by sector in France | URSSAF

Sample

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

Recent divergence between office and labour markets

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



Notes: This figure plots the aggregate office vacancy rate and the unemployment rate in the Paris region. Sources: BNP Paribas Real Estate, INSEE.

Measuring WFH

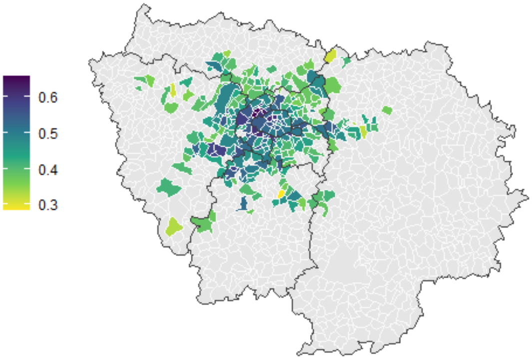
I develop and test the effect of a **WFH indicator**:

- At the municipality level
- Throughout the Paris region

I build the **'WFH-Occupation'** indicator

- 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: Estimated WFH exposure in the Paris area

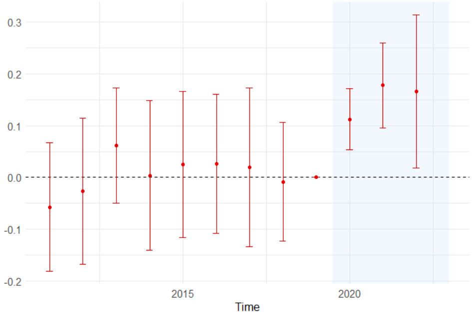


Notes: This figure maps WFH exposure at the workplace municipality throughout the 268 municipalities representative of the office market in the Paris Metropolitan Area. If the indicator equals 0 (1), no one (everyone) can theoretically telework.

Gradient CompStat

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

Figure: Effect of WFH exposure on office vacancy



Notes: Point estimates of β_t from model (1) and the 95% confidence interval. Dependent variable: office vacancy. Treatment: 'WFH-Occupation'. Estimated by Poisson pseudo-maximum-likelihood. Standard errors clustered at the municipality level.

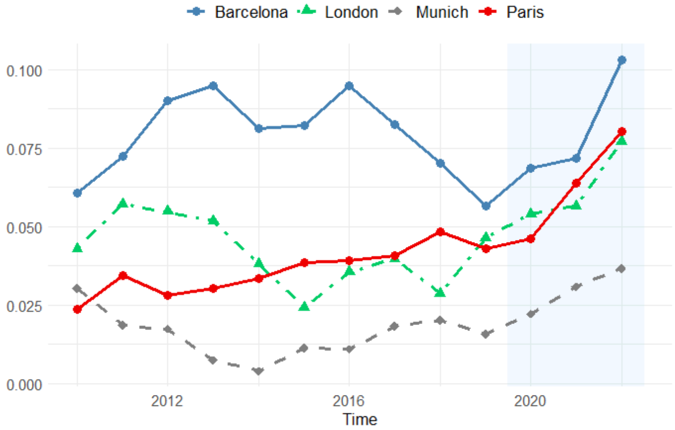
DiD table - vacancy

Table: Non-linear Effect of WFH on office vacancy

	Vacancy				
	(1)	(2)	(3)	(4)	(5)
WFH-Occupation × Post	0.230***	0.002	0.000	0.060	0.042
	(0.058)	(0.058)	(0.051)	(0.060)	(0.061)
WFH-Occupation × Post × log(*distance*)	0.167**			0.218***	0.236***
	(0.054)			(0.056)	(0.050)
WFH-Occupation × Post × log($commuting_{2019}$)		0.432**		0.514**	
		(0.140)		(0.157)	
WFH-Occupation × Post × log($firmsize_{2019}$)			0.138**		0.159**
			(0.053)		(0.058)
Post × log(*distance*)	−0.319**			−0.439***	−0.531***
	(0.123)			(0.125)	(0.115)
Post × log($commuting_{2019}$)		−0.195		−0.016	
		(0.178)		(0.177)	
Post × log($firmsize_{2019}$)			−0.008		0.103
			(0.108)		(0.102)
log(*Stock*)	0.898***	0.964***	0.922***	0.893***	0.838***
	(0.197)	(0.212)	(0.206)	(0.196)	(0.194)
Urate× log($density_{2019}$)	0.085***	0.078**	0.072**	0.082***	0.092***
	(0.024)	(0.030)	(0.026)	(0.024)	(0.023)
Municipality and year fixed effects	✓	✓	✓	✓	✓
Num. obs.	3216	3216	3216	3216	3216
Pseudo R^2	0.938	0.936	0.937	0.939	0.939

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$. Estimates from the diff-in-diff. Dependent variable: office vacancy. Treatment variable: 'WFH-Occupation'. Estimated by PPML. Standard errors clustered at the municipality level.

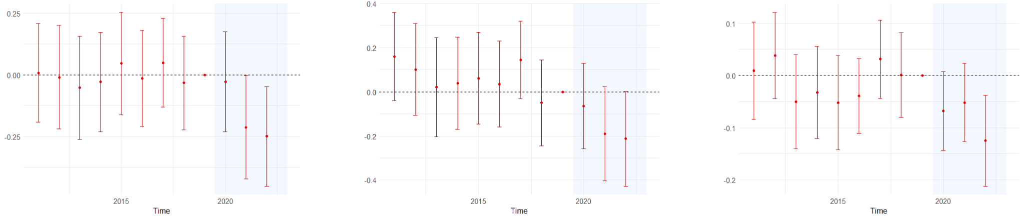
Figure: Vacancy rate: gap between peripheral areas and CBDs



Notes: 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

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

Figure: Marginal effect of WFH on office investment



(a) Value (b) Volume (c) Number of transactions

Notes: Point estimates of β_t and the 95% confidence interval. Dependent variable: municipality-evel office investment (a) value, (b) volume, (c) number of transactions. Treatment variable is 'WFH-Occupation'. Estimated by PPML. Standard errors clustered at the municipality level.

Estimate the effect of WFH on office prices: a linear regression at the transaction level

- A **hedonic price model**

$$\log(\text{price/sqm}_{jtm}) = \alpha_{tm} + \gamma WFH_i + \beta Post_{tm} \times WFH_i + \theta Post_{tm} + Z_{jtm}\delta + \mu_{jtm} \quad (3)$$

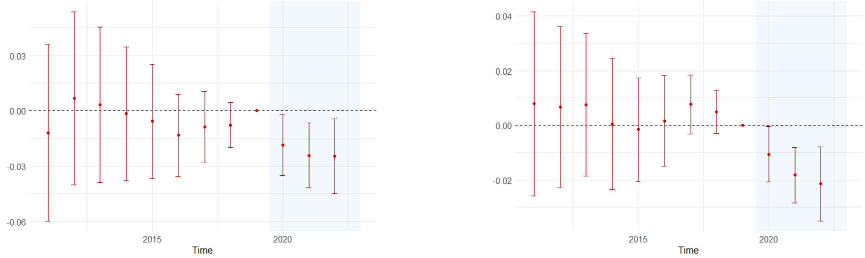
i: municip./neighbor., j: transaction, t: year, m: month.

	log(*price*/*sqm*)	
	(1)	(2)
WFH	0.138***	0.138***
	(0.006)	(0.006)
WFH × *Post*	−0.020*	
	(0.010)	
WFH ×2020		0.003
		(0.013)
WFH ×2021		−0.031*
		(0.013)
WFH ×2022		−0.032*
		(0.015)
Post	0.078	0.055
	(0.117)	(0.117)
log(distance.to.center)	−0.317***	−0.316***
	(0.013)	(0.013)
log(*sqm*)	−0.298***	−0.298***
	(0.004)	(0.004)
log(*land*.*area*)	0.080***	0.080***
	(0.002)	(0.002)
log(*distance*.*closest*.*station*)	−0.071***	−0.071***
	(0.007)	(0.007)
log(*number*.*stations*.800*m*.*radius* + 1)	0.156***	0.156***
	(0.008)	(0.008)
sale in state of future completion	0.366***	0.305***
	(0.079)	(0.059)
...		
Year-Month fixed effects ✓	✓	✓
Num. obs.	26,932	26,932
R^2	0.549	0.550

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$. Std errors clustered at the municipality/neighborhood level.

$$retail_{it} = \exp(\alpha_i + \gamma_t + \sum_t \beta_t WFH_i + \delta hotelshare_i \times \log(hotelnights_t) + X_{it}\lambda) + \epsilon_{it} \quad (4)$$

Figure: Effect of WFH-Occupation on the retail industry



(a) Employment (b) Number of businesses

Notes: Point estimates of β_t from model (2) and the 95%. Dependent variable: Number of employees or businesses in the retail sector. Treatment is 'WFH-Occupation'. Estimated by Poisson pseudo-maximum-likelihood. Standard errors clustered at the municipality level.

DiD table - retail Sub-Sectors

Robustness Checks

Already done

- Alternative WFH exposure indicator WFH-Sector
- Alternative estimations ext-period log-transfo ext-sample
- Check for biases due to sectoral specialization bartik
- Ensure robustness to the choice of the reference year
- Test the effect of WFH exposure at the place of residence on LCS CorrMat
- Account for the differential impact on LCS depending on the employment-population ratio

Next steps

- Update to 2023
- SUTVA / spatial autocorrelation
- Parallel trends test | Rambachan and Roth (2023, ReStud)
- Consolidate results on investment and prices

Conclusion

- WFH has already led to a significant **rise in office vacancy**, more pronounced further from the city center → Companies use office downsizing as a **cost-effective strategy to relocate to central locations** | labor and customer market access
- The higher propensity of **large firms** to embrace teleworking + the encouragement to WFH by **longer commuting distances** → **heterogeneous impact** on office space demand across business districts
- Investment patterns have also adjusted, with a **decrease in investment and prices** in areas most exposed to WFH → anticipation of enduring changes
- WFH exposure yields a notable **decrease in local retail sector** employment and number of businesses → underscores the broad economic implications of teleworking

Policy Implications

- Strategic shift towards premium locations creating a novel form of office vacancy → **emerging mismatch** between the current office supply and the evolving demand
- **Exacerbated spatial disparities** at the expense of suburban areas, affecting local CRE and labor markets, amenities and public finances → raises the needs of a **strategic revitalization** of these suburban districts.
- Important risk for CRE investors due to the emergence of **stranded assets** → potential spillovers through the **collateral channel** (Chaney et al., 2012, AER)
- Ambiguous effect of WFH on **agglomeration effects** → firms centralization vs reduction in face-to-face interactions

Thank you !

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Literature (1/3): WFH and Urban Structure: Spatial Consequences

WFH creates a **donut effect** by making the city expand and reducing home price gradients as households migrate to the suburbs

- Safirova (2002, JUE), Rhee (2008, JUE), Behrens et al. (2024, RSUE)
- Delventhal et al. (2022, JUE), Brueckner et al. (2023, AEJ), Gupta et al. (2023, JFE)

No empirical evidence on the consequences of WFH on firm behaviour within cities

- Delventhal et al. (2022, JUE): firms' **centralization** phenomenon
- Rosenthal et al. (2022, JUE): the pandemic has weakened the appeal of urban centers
- Althoff et al. (2022, RSUE): consumer spending declined most in locations exposed to WFH

My contribution:

- **1st empirical study** on the intracity effect of WFH on firms' location choice
- Novel way to **identify** the impact of telework on LCS - controlling for local exposure to **tourism**

Literature (2/3): WFH and Commercial RE: Financial Implications

The pandemic and remote working have a **negative impact on office** properties

- Vacancy, rents, prices (Gupta et al., 2022; Bergeaud et al., 2023 | RSUE)
- REITs' stock performance (Milcheva and Xie, 2022; Hoesli and Malle, 2021 | JERES; Ling et al., 2020 | RAPS)

My contribution:

- Offer the first empirical evidence **in Europe**, at a **fine spatial granularity**
- Leverage the most recent data to **provide early indications of market adjustments post-pandemic**

Literature (3/3): Measuring WFH

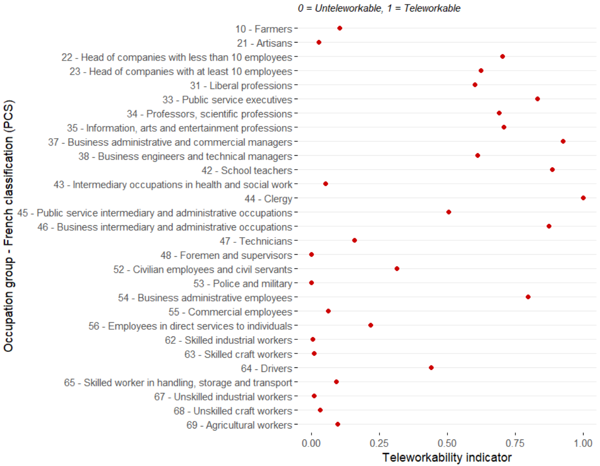
WFH predominantly characterizes the skilled jobs, and is therefore heterogeneous across industries and geographies

- National surveys (Dingel and Neiman, 2020 | JPubE; Bartik et al., 2020; Mongey et al., 2021 | JEIneq)
- Job posting data and webscraping (Milcheva and Xie, 2022; Gupta et al., 2022)

My contribution

- A **municipality-level estimation** of WFH exposure in France
- Shedding light on **multifaceted dimensions**, including commute distances and firm size, that influence local teleworking intensity

Figure: Teleworkability index by occupation in France



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Gradients

Table: Distance to center gradients

	log(*rent*)	log(*density*)	log(*connection*)	WFH-Occupation
	(1)	(2)	(3)	(4)
log(*distance*)	-0.35^{***}	-0.04^{***}	-0.04^{***}	-0.02^{***}
	(0.03)	(0.00)	(0.00)	(0.00)
Intercept	6.13^{***}	0.83^{***}	0.60^{***}	0.32^{***}
	0.08	(0.04)	(0.03)	(0.03)
'Office' sub-sample	Yes	Yes	Yes	Yes
R^2	0.44	0.24	0.24	0.15
Num. obs.	153	268	268	268

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$. Estimates from the linear regressions performed at the municipality level. Dependent variables: average office rent, job density, rail connection density, and WFH exposure. Covariate: natural logarithm of the euclidian distance to the center. The average office rent, which measures the rent per sqm on new office leases, is available for only 153 municipalities in 2019.

Map

Table: Correlation matrices

	A: Municipality characteristics					
	WFH-Occ.	log(*dist.*)	log($dens._{2019}$)	log($comm._{2019}$)	log($firms._{2019}$)	log($conn._{2019}$)
WFH-Occupation	1					
log(*distance*)	-0.50	1				
log($density_{2019}$)	0.62	-0.69	1			
log($commuting_{2019}$)	0.183	0.06	0.18	1		
log($firmsize_{2019}$)	0.33	0.06	0.32	0.57	1	
log($connection_{2019}$)	0.41	-0.65	0.64	0.01	-0.08	1

	B: WFH indicators			
	WFH-Occ.	WFH-Occ.-LCS	WFH-Occ.-Resi	WFH-Sector
WFH-Occupation	1			
WFH-Occupation-LCS	0.99	1		
WFH-Occupation-Resi	0.95	0.75	1	
WFH-Sector	0.78	0.77	0.74	1

Notes: This table presents two matrices composed of the correlation coefficients for each pair of variables: (A) for the main municipality characteristics and (B) the WFH indicators.

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Table: Comparative summary statistics

Variable	Unit	Mean (<Median WFH)	Mean (>Median WFH)	T-Test
WFH-Occupation	teleworkable = 1	0.395	0.510	***
Vacancy rate	% of stock	0.027	0.067	***
Stock	sqm	46,914	332,034	***
Employment	units	6,213	26,036	***
Employment density	thousand/sqm	9.41	63.66	***
Retail employment	units	675	1,664	***
Retail businesses	units	72	219	***
Distance to center	km	21.5	13.2	***
Median commuting distance	km	6.2	7.6	***
Rail connection density	units/ha	0.26	1.23	***
Average firm size	employees/business	12.3	17.7	***

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$. Presents the mean values of indicators for subsets of the sample divided at the median level of the WFH indicator. T-Test' column provides p-values significance for the comparison of means across these two subsets.

'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)

$$WFH_{jt} = \mu_j + \nu_t + \epsilon_{jt} \tag{5}$$

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

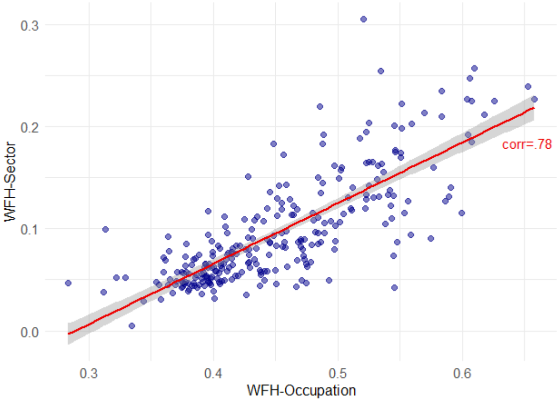
Table: Effect of WFH on office vacancy

	Vacancy			
	(1)	(2)	(3)	(4)
WFH-Occupation × Post	0.081	0.152^{**}	0.143^{**}	
	(0.057)	(0.056)	(0.053)	
WFH-Occupation × 2020				0.105^{*}
				(0.051)
WFH-Occupation × 2021				0.172^{**}
				(0.058)
WFH-Occupation × 2022				0.157^{*}
				(0.078)
Urate× $\log(density_{2019})$		0.071^{*}	0.083^{**}	0.086^{**}
		(0.031)	(0.030)	(0.030)
$\log(Stock)$			0.952^{***}	0.949^{***}
			(0.210)	(0.211)
Municipality and year fixed effects	✓	✓	✓	✓
Num. obs.	3216	3216	3216	3216
Pseudo R^2	0.932	0.933	0.936	0.936

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$. Estimates from the diff-in-diff. Dependent variable: office vacancy. Treatment variable: 'WFH-Occupation'. Estimated by PPML. Standard errors clustered at the municipality level.

event study - vacancy

Figure: Correlation between the two WFH indicators



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

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Figure: WFH by sector in France during the Covid-19 crisis

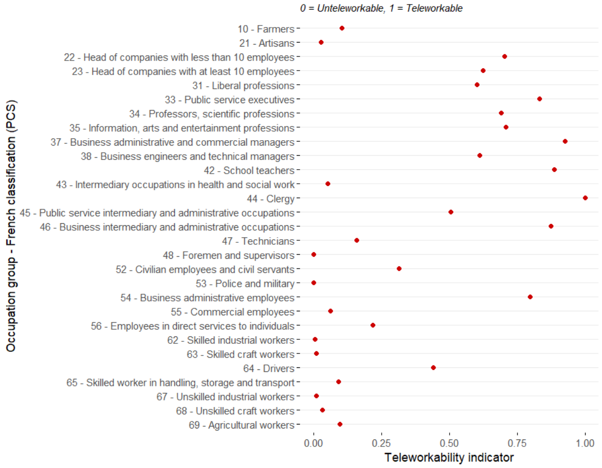

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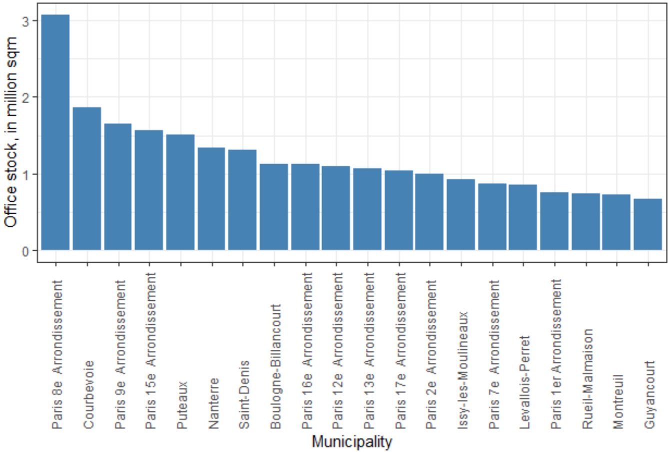
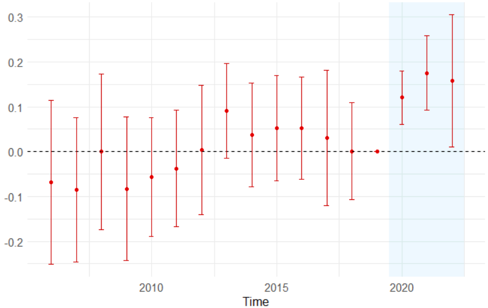
Figure: Top 20 office markets in the Paris metropolitan area



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

$$vacancy_{it} = \exp(\alpha_i + \gamma_t + \sum_t \beta_t WFH_i + \log(stock_{it}) + Urate_t \times \log(dens_i)) + \epsilon_{it} \quad (6)$$

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



Notes: Estimates of β_t from model and 95% confidence interval. Dependent variable: office vacancy. Treatment variable: 'WFH-Occupation'. Estimated by PPML. Standard errors clustered at the municipality level.

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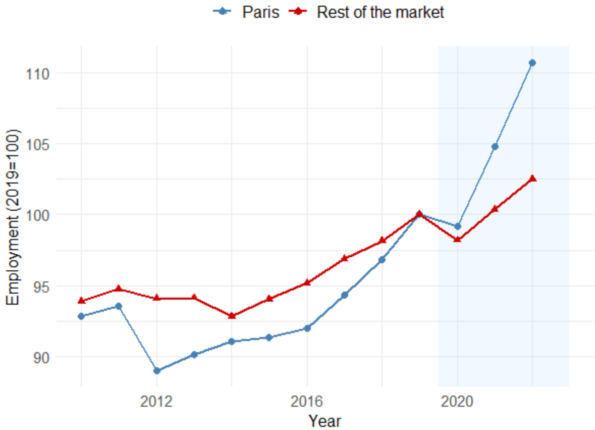
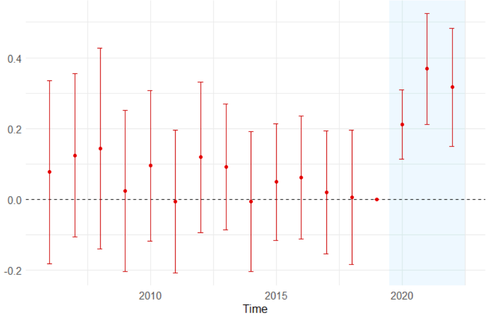
Figure: Employment in the Paris metropolitan area



Notes: End-of-year employment in the Paris metropolitan area, by comparing Paris and the suburbs, from 2010 to 2022. Source: URSSAF

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

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



Notes: Estimates of β_t and 95% confidence interval. Dependent variable: log-transformation of the municipalility-level office vacancy. Treatment variable: 'WFH-Occupation'. Estimated by OLS and is weighted by the 2019 office stock. Standard errors clustered at the municipality level. Back

Table: Effect of WFH-Occupation on the Retail Industry

	Employment			Number of businesses		
	(1)	(2)	(3)	(4)	(5)	(6)
WFH-Occupation × Post	−0.014	−0.024*	−0.018·	−0.016**	−0.017**	−0.014*
	(0.009)	(0.009)	(0.010)	(0.006)	(0.006)	(0.006)
Trend × log($density_{2019}$)		0.002	0.002*		0.001	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Urate× log($density_{2019}$)		0.000	0.002		0.004*	0.005**
		(0.003)	(0.003)		(0.002)	(0.002)
log($hotelnights$)× $hotelshare_{2019}$			2.060**			1.188**
			(0.711)			(0.395)
Municipality and year fixed effects	✓	✓	✓	✓	✓	✓
Num. obs.	3216	3216	3216	3216	3216	3216
Pseudo R^2	0.989	0.989	0.989	0.972	0.972	0.972

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$. Estimates from the diff-in-diff. Dependent variable: employment and number of businesses in the retail industry. Treatment variable: 'WFH-Occupation'. Estimated by PPML. Standard errors clustered at the municipality level.

event study - retail Hotel Nights

Table: Effect of WFH-Occupation on the Retail Industry - Extended Sample

	Employment			Business number		
	(1)	(2)	(3)	(4)	(5)	(6)
WFH-Occupation × Post	-0.023^{*}	-0.035^{**}	-0.029^{*}	-0.025^{***}	-0.028^{***}	-0.024^{***}
	(0.011)	(0.012)	(0.013)	(0.007)	(0.007)	(0.007)
Trend × $\log(density_{2019})$		0.001	0.001		$0.001^{\cdot}$	0.001^{*}
		(0.001)	(0.001)		(0.001)	(0.001)
Urate× $\log(density_{2019})$		-0.001	-0.000		0.004^{***}	0.005^{***}
		(0.002)	(0.002)		(0.001)	(0.001)
$\log(hotelnights)$× hotelshare_{2019}			1.556^{*}			0.797^{*}
			(0.623)			(0.327)
Municipality and year fixed effects	✓	✓	✓	✓	✓	✓
Num. obs.	11952	11928	11928	12060	12036	12036
Pseudo R^2	0.991	0.991	0.991	0.971	0.971	0.971

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$. Estimates from the diff-in-diff. Dependent variable: employment and number of businesses in the retail industry. Treatment variable: 'WFH-Occupation'. Estimated by PPML. Standard errors clustered at the municipality level.

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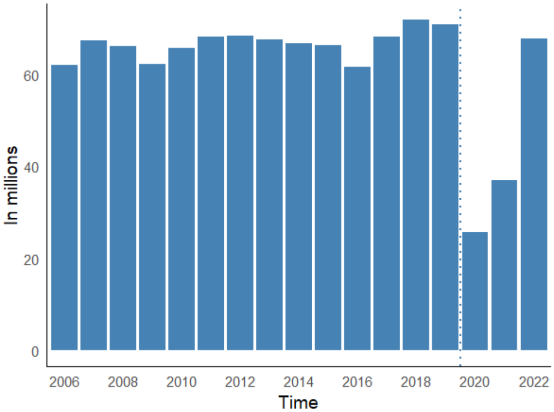
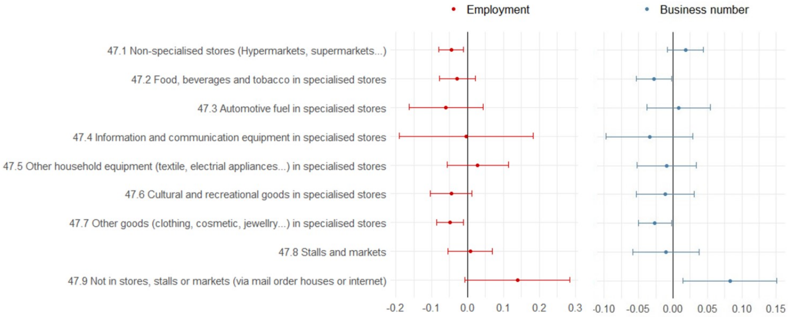
Figure: Hotel nights spent in hotels in the Paris region



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 Back

$$retail_{it} = \exp(\alpha_i + \gamma_t + \beta\, Post \times WFH_i + \delta\, hotelshare_i \times \log(hotelnights_t) + X_{it}\lambda) + \epsilon_{it} \quad (8)$$

Figure: Effect of WFH-Occupation on the retail sector



Notes: Point estimates of β. Dependent variable: number of employees and the number of businesses in the retail sector respectively. Treatment variable: 'WFH-Occupation'. Estimated by Poisson pseudo-maximum-likelihood. Standard errors are clustered at the municipality level.

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$$\text{Bartik}_{it} = \sum_j \left(\frac{\text{Employment}_{ij,base}}{\sum_k \text{Employment}_{ik,base}} \right) \times \text{Growth Rate}_{j,t} \quad (9)$$

$\text{Employment}_{ij,base}$: employment in sector j for municipality i in the baseline year; $\sum_k \text{Employment}_{ik,base}$: totals employment i at the baseline, and $\text{Growth Rate}_{j,t}$ is the national growth rate for sector j at time t.

Table: Effect of WFH on Bartik instruments

	$\log(Bartik_{38})$		$\log(Bartik_{88})$	
	(1)	(2)	(3)	(4)
WFH-Occupation × Post	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.003)
Urate× $\log(density_{2019})$		0.000		0.000
		(0.000)		(0.000)
Municipality and year fixed effects	✓	✓	✓	✓
Num. obs.	3216	3216	3216	3216
R^2	0.999	0.999	0.999	0.999

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$. Dependent variable: natural logarithm of Bartik sectoral instruments. Treatment variable: 'WFH-Occupation'. Estimated by OLS. Standard errors clustered at the municipality level.

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