Working From Home and Corporate Real Estate*

Antonin Bergeaud Jean-Benoît Eyméoud
Thomas Garcia Dorian Henricot

February 2023

Abstract

We examine how corporate real estate market participants adjust to the take-off of teleworking. We develop an index for the exposure of counties to teleworking in France by combining teleworking capacity with incentives and frictions to its deployment. We find that the valuation of offices declined more in areas more exposed to telecommuting, a pattern that we do not observe for retail assets. In addition, we show that telecommuting increases vacancy, decreases construction, while transaction volumes are not affected. It implies that the drop in price is due to a shift in demand for space. In addition, our result suggests that market participants are expecting the shift to teleworking to durably affect the demand for office space.

JEL classification: G11, G14, G23, J60, R33
Keywords: corporate real estate, commercial real estate, teleworking

*Addresses: Bergeaud: HEC Paris, CEP-LSE and CEPR; Eymeoud: Banque de France and LIEPP Sciences Po Paris; Garcia: Banque de France and European Central Bank; Henricot: Banque de France and Sciences Po Paris. This research has benefited from the support of the real estate and finance network (REFINE) and more precisely from data provided by the IEIF. We are indebted to Laure Arcizet for exceptional research assistance. We also thank Kevin Beaubrun-Diant, Jean Boissinot, Guillaume Chapelle, Gilbert Cette, Stéphanie Galiègue, Blaise Heurteux, Maxime Ponsart, Helene Tanguy, Alain Trannoy, Morgan Ubeda and Etienne Wasmer. The views expressed herein do not necessarily represent the views of the Banque de France or the European Central Bank.

1 Introduction

One of the most persistent consequences of the Covid-19 pandemic on the organization of work is probably the dramatic take-off of teleworking. This type of work arrangement was relatively uncommon before 2020 in France as only 3% of the workforce worked from home at least once a week in 2017 (Hallépée and Mauroux, 2019). Forced by circumstances, employers and employees had to implement new ways of working remotely to limit physical interactions during the acute stages of the outbreak. This experience has helped to eliminate some prejudices about the feasibility of telework and to establish a more appropriate legal framework, but also to convince companies to invest more in computer equipment and to adapt their management practices. For this reason, teleworking has already become a standard practice for many workers and is likely to stick in the future. For instance, Barrero et al. (2021) estimate that one out of five workdays will now be spent working from home in the US for 50% of the working population.

Many of the potential long-run macroeconomic effects of an increase in telecommuting have been the subject of recent studies. Scholars have been interested in analyzing its effect on productivity (OECD, 2020; Criscuolo et al., 2021; Barrero et al., 2021; Gibbs et al., 2021; Bergeaud et al., 2021), on labor market reallocation (Eyméoud et al., 2021), on digitalization (Consolo et al., 2021), or on urbanization (De Fraja et al., 2020). In this paper, we exploit the important structural change represented by Covid-19 to analyze the effect of telecommuting on commercial real estate in France, taking advantage of the availability of exceptionally granular data on building permits, on prices and on the valuation of assets held by real estate investment funds. Our work is distinguishable from existing literature for two main reasons. First, while some articles consider the response of corporate real estate to the pandemics,[1] none of these studies try to disentangle the direct effect of lockdowns and other containment measures (short-term responses) from the more structural effect of telecommuting.

Second, unlike the majority of the literature, our paper does not focus on the United States but on a continental European country, namely France. European urban plan-

[1] Rosenthal et al. (2022) show that the commercial real estate distance gradient for rents has declined in denser cities, in line with the observations made for residential real estate. Xie and Milcheva (2020) and Ling et al. (2020) study the correlation between exposure to the Covid-19 pandemic, and commercial real estate prices through the lens of Real Estate Investment Trust (REIT) stock returns. Hoesli and Malle (2021) provide a different picture by also studying the impact on sectoral price indices. Milcheva (2021) focuses on the differences between REIT performance in Asia and in the US during the ongoing pandemic.

ning is very different from that of the United States, and urban spaces are much less discriminated by uses (residential, commercial, office, etc.). In addition, the use of telecommuting is lower in Europe than in the United States (Aksoy et al., 2022). Finally, office prices are typically more volatile in the US than in France leading to a stronger impact of the Covid crisis in the US: -3.6% in the US and +0.8% in France over the period 2019-2021. While less salient, this stronger reaction in the US is also noticeable on the increase in vacancy rates which has increased by 5.2pp in the US against 3.9pp in France.[2] For these reasons, one might expect real estate to react differently in Europe. For example, Schulz et al. (2022) uses a survey and finds that telecommuters in Scotland are not overwhelmingly willing to relocate in contrast to what is documented in the US.

To measure telecommuting, our empirical analysis relies on the construction of a county-level index for the propensity of teleworking in France.[3] We build on Dingel and Neiman (2020)'s assessment of the "teleworkability" of each occupation, and apply it to local labor markets in France. It provides us with a measure of teleworking capacity by county which we then augment with information on local incentives and frictions to teleworking to assess the *actual* propensity to telework. This index turns out to allow for more precise estimations of the effect of telecommuting than previous proxies such as Dingel and Neiman (2020)'s famous indicator. It also correlates well with actual measures of teleworking.

We then provide quantitative evidence that working from home is already factored in by market participants as of end-2021. In particular, the valuation of offices has declined more in the most teleworkable areas compared to other real-estate assets. We then turn to potential drivers of this relative decline. We show that vacancy rates have increased more after 2020 in areas more exposed to teleworking, again only for offices. This implies that firms have already been able to revise their demand for office space downwards in the most teleworkable areas. A back-of-the-envelope calculation suggests that the observed price decline would be consistent with a prolonged contraction of demand for space. Construction of new offices also halted in areas most exposed to teleworking, and still remains below a no-pandemic counterfactual. This reinforces the argument that a durable drop in demand for office space driven by a larger deployment of teleworking is behind declining prices. Finally, we examine

[2]These numbers come from MSCI, see Section 2.1.

[3]Throughout, we call county a French *département*. There are 94 *départements* in mainland France (excluding Corsica) with an average population of about 700,000 inhabitants in 2019.

transaction volumes and show that they have evolved similarly across areas, suggesting that the relative drop in prices cannot be attributed to a drop in market liquidity in these areas.

Teleworking is a recent phenomenon, we thus contribute to the nascent literature on the measurement of teleworking. Using occupation level data and employment composition, Dingel and Neiman (2020) estimate that 37% of American jobs could switch to full teleworking with heterogeneity across sectors, skill level, and space (Sostero et al., 2020 find a similar share in Europe). Gottlieb et al. (2020) and Hensvik et al. (2020) provide some detailed results by occupation and estimate that while over 75% of managers could work from home, this share can also be null for specific jobs like motor vehicle operators. Brynjolfsson et al. (2020) report that 34% of American workers declare that they used to commute and now telework (as of April 2020). Finally, Baker (2020) and Mongey and Weinberg (2020) identify the types of occupation that cannot be done at home and their geographical distribution, enabling the characterization of counties that are likely to be strongly impacted by the intensification of teleworking. In this paper, we propose a measure of the local exposure to teleworking that not only captures the theoretical potential for teleworking, but also accounts for incentives and frictions to better apprehend the actual level of teleworking.

We also contribute to document how the take-up of telecommuting is likely to reshape the organization of cities with important consequences for all industries. Althoff et al. (2022) provide early evidence for this mechanism in the US and conjecture that big cities might shrink in size unless they adapt. Similarly, Ramani and Bloom (2021) examine migration patterns within and between U.S. cities and find a shift from centers to suburban cores within the same area. A stream of recent papers has proposed theoretical models to better understand how telecommuting could affect the fortune of cities. For example, Behrens et al. (2021) present a framework where firms trade-off between on-site workers benefiting from knowledge spillovers and home-based workers reducing office space consumption. They show that profit-maximizing firms implement a partial working from home strategy which ultimately results in a decline in the demand for corporate real estate and a downward effect on prices. A similar result is found by Davis et al. (2021) in a model focusing specifically on the effects of telework on the structure of cities.

What should then be the impact on real estate prices? Delventhal et al. (2021) and Gupta et al. (2021) model the expected impact of teleworking on urban geography, and predict increases in periphery real estate prices associated with declines in city cores. Empirically, their predictions are echoed in Liu and Su (2021) who observe a reduced demand for density driven by a lower need of living near jobs. Most of these studies focus on residential real estate. Indeed, if people are fleeing dense urban centers (see for example Nathan and Overman, 2020; Chareyron et al., 2022), one would expect residential real estate prices to adjust quickly. By contrast, our study focuses on commercial real estate.

Understanding the response of corporate real estate dynamics to a structural change in work organization, such as telecommuting, is of great macroeconomic importance. First, real estate is an important asset class for firms and serves multiple functions either as a productive asset or as collateral for raising external finance (Chaney et al., 2012; Fougère et al., 2019). It is also an important source of friction that limits capital adjustments and employment dynamics of firms (Bergeaud and Ray, 2021). Second, it constitutes a central class of assets in financial markets, and any imbalance in this sector can put financial stability at risk. Bank commercial real estate exposures have for instance been identified as the primary source of bank fragility in the 2008 crisis (Cole and White, 2012; Antoniades, 2021). Finally, commercial and residential real estate compete for land which gives rise to strong interactions between both markets (Gyourko, 2009; Davis et al., 2021; Ferrière and Henricot, 2021). Corporate real estate market participants are directly exposed to the consequences of the generalization of teleworking. Studying how they adapt to this new paradigm not only gives us a better understanding of how real estate markets operate, but it also allows us to assess to what extent this shift is likely to be permanent. As office users seek to adjust their demand for space to the new normal, office owners may experience an increase in vacancy rates, and downward pressure on office rents. Developers may also incur losses as prospective new tenants become scarce. While the development of new projects may stall and mitigate the price decline, the completion of projects designed prior to the shock may struggle to meet a faded demand. All this should ultimately result in a decline in real estate asset prices, with the adjustment of construction helping to stabilize expected revenues in the medium run. In any case, as prices are forward-looking, any price adjustment may hint at the permanence of the teleworking shock.

The remainder of this paper is organized as follows: section 2 presents our data and telework index. Section 3 presents our results and section 4 concludes.

2 Data

To measure corporate real estate market dynamics, we rely on four different data sources presented in section 2.1: i) county-level appraisal-based prices and rental market indicators, ii) asset-level appraisal-based prices of Real Estate Investment Funds' (REIF) non-financial holdings, iii) asset-level data on construction activity by sector and iv) asset-level transaction data to measure investment activity in volumes, and actual asset prices as a robustness to appraisal-based indicators. Section 2.2 presents how we construct our synthetic teleworking index, and assesses its external validity.

2.1 Measuring corporate real estate market dynamics

2.1.1 County-level prices and rental market indicators

To assess prices and current rental demand, we use yearly time series of French county-level indicators for commercial real estate (price and market rental value growth, vacancy rate) produced by MSCI, over 1998-2021. This dataset is based on a granular data collection by MSCI among its contributors and covers around 45% of the French market as of 2020 (€224B, MSCI, 2021). The perimeter is that of the commercial real estate market i.e., assets held and managed by professionals. Indicators are defined at the segment level (either "office" or "retail"). Descriptive statistics are presented in Table I.

TABLE I. Descriptive statistics of county-level stock indicators

	Indicator	Num. Obs.	Num. Dep.	Min.	Q1	Median	Mean	Q3	Max.
Office	Price (growth in %)	597	42	-21.49	-2.01	0.85	1.04	4.19	17.50
	Rent (growth in %)	494	38	-13.34	-0.99	0.07	0.56	2.04	25.59
	Vacancy rate (in %)	601	43	0.00	5.49	9.26	10.91	14.09	74.75
Retail	Price (growth in %)	1007	71	-25.86	-2.84	0.97	2.24	5.93	37.61
	Rent (growth in %)	767	68	-31.70	-1.99	0.12	0.53	2.63	86.97
	Vacancy rate (in %)	1033	73	0.00	1.34	4.53	6.11	8.64	44.63

Notes: Descriptive statistics on the variation of prices, rents and vacancy rates (all in %). Numb. Obs. is the number of observations, Numb. Dep. is the number of counties (*"département"*). Time period: 1998-2021. Source: MSCI.

The valuations reported to MSCI correspond to appraisal-based measures of prices. There are indeed two broad families of price indices: i) transaction-based measures and ii) appraisal-based measures. While the former relies on actual transactions, the latter is based on expert estimations. Each family has its own advantages. Transaction-based measures provide actual but non-representative price estimates, as real estate assets are infrequently traded. Samples may not be comparable from one period to the next. Issues of representativeness are exacerbated in times of stress, when transactions become less frequent and biased towards "prime" assets (BNP, 2020). By contrast, appraisal-based prices rely on estimations and can thus be subject to biases such as over-smoothing and lagging (Delfim and Hoesli, 2021). However, they rely on assets that represent a typically large share of the stock and that are comparable from one period to the other. In this paper, we rely mainly on appraisal-based prices as we focus on the stress episode of the Covid-19 pandemic. We check in Section 3.5 that our results are robust to using transaction-based indicators.

2.1.2 Real estate investment funds' asset-level data

We rely on a Banque de France regulatory reporting providing the appraisal-based valuation of all real estate assets owned by REIFs (*OPC Titres*). This dataset provides quarterly information on real estate assets of 426 French REIFs from June 2016 to December 2021. By the end of 2019, the total net asset of REIFs in our sample stood at €91B (more than two-thirds of the total capitalization of all French REIFs according to AMF, 2020). These funds can take two legal forms, SCPI (*Sociétés Civiles de Placement Immobilier* - real estate investment companies) or OPCI (*Organismes de Placement Collectif en Immobilier* - undertakings for collective investment in real estate).

We identify 17,161 distinct buildings in the dataset (9,263 as of end-2019) for which the valuation, the country, the county (for French buildings), and the segment or purpose (i.e., office, retail, industry, or residential) are all available. Their values add up to €64B at end-2019. Offices are worth half of the total and retail assets a quarter (see Table II for more details). In the remainder of the paper, we focus on buildings located in France which represent 97.9% of all buildings.

TABLE II. Real estate assets - descriptive statistics (end-2019)

		Industrial	Office	Residential	Retail	Other	Total
All assets	Volume (€B)	4.9	34.0	4.3	17.3	3.6	64.2
	Buildings (Num.)	496	2843	878	4664	382	9263
French assets	Volume (€B)	4.4	32.9	4.3	16.9	3.4	62.1
	Buildings (Num.)	440	2806	877	4573	374	9070

Notes: Real estate assets owned by French REIFs in our dataset by segment and location.

2.1.3 Construction data

For construction, we use administrative data on building permits. In France, developers planning greenfield projects or large asset transformations are legally bound to file for a building permit at the relevant municipality. The *Sitadel2* database provides comprehensive information on all building permits granted at the monthly frequency. This includes the characteristics of the buyers (legal classification, personal identifier), the type of activities that the building will serve (office, retail, warehouses...), its surface, and location. The database provides several dates, the date of administrative authorization, the date of construction commencement or project abandonment, and the date of completion of the project, at which compliance with the initial project is verified. We rely here on administrative authorizations which react first to economic shocks. Finally, we restrict our analysis to buildings that are not intended for the public sector, and start the analysis in 2014 when the data collection procedure was harmonized throughout the country.

2.1.4 Transactions data

We use tax data produced by the French Public Finances Directorate General (DGFiP) on the universe of transactions from 2010 to 2021.[4] Descriptive statistics are given in Table A2. This database allows us to measure transaction volumes, measured in number of transactions or total transacted square meters per unit of time and county. It also provides actual prices that we aggregate at the county level to verify the robustness of our analysis on appraisal-based prices.

2.2 Measuring teleworking

2.2.1 A synthetic index

In this section, we present our index of teleworking based on an innovative combination of occupational and environmental characteristics. The first level of assessment, the occupational characteristics, focuses only on the nature of the activity. It measures whether it is possible to work from home based on individual occupations and thus

[4]To illustrate its coverage, the database contains granular information on €12B of transacted offices in 2020 (approximately two-thirds of the total volume transacted, BNP, 2020).

captures the potential to work remotely. The second level of assessment, the environmental characteristics, evaluates if the environment favors or impairs teleworking. By combining both measures, our index aim at capturing the actual propensity to work from home.

To evaluate the ability to work remotely, we start from the seminal work of Dingel and Neiman (2020). In this recent paper, the authors use the detailed occupation characteristics from the O*NET database to estimate whether the task contents of each occupation can be done at home. To link this US nomenclature to a French one, we use their classification and a crosswalk from the International Standard Classification of Occupations to the French "Professions et catégories socioprofessionnelles" (PCS) taken from Le Barbanchon and Rizzotti (2020). This latter classification references about 300 different jobs. We then use the weight of each of these occupations based on workers' residence in every county to construct a measure between 0 (no one can telework in the county) and 1 (everyone can theoretically telework).[5] These weights are taken from the Labor Force Survey ("*Enquête Emploi*") as an average between 2014 and 2017. We take this first measure as an estimate of the maximal local potential of teleworking in the absence of any type of friction.

While this measure has been used extensively in the literature (see e.g. Mongey et al., 2021; Cajner et al., 2020), it only captures a predicted maximum number of workers that can work from home but does not take into account the potential frictions and incentives to actually resort to this type of work arrangement. For this reason, we complement it with different environmental characteristics that would influence the intensity of telework, on top of the occupational composition. Intuitively, we expect workers with young children, more connected to the internet, and with longer commutes to be more willing to work from home. Hence we use these three measures at the county level. First, we exploit the share of households that are connected to the optical fiber. This share is measured in 2019 and is taken from the French agency in charge of regulating telecommunications, ARCEP. Then, we use the share of high-skill workers with a child under 18, taken from the Labor Force Survey (on average between 2017 and 2018). Finally, we rely on the median travel time between the place of residence and the place of work, taken from the Observatoire des territoires. This measure is available for high-skill workers and for all workers. We use the former,

[5]Using administrative social security data (DADS) which reports the address of residence and work of each worker in France, we estimate that most workers work and have their residence in the same county (75% and 83% if we exclude Paris).

but using the latter would not alter our results.

As expected these variables are positively correlated with each other, but not perfectly as they capture different local characteristics that are *a priori* all relevant for the intensity of the use of teleworking (see Table III). They are also all correlated with population density, which we plot directly in Figure A1. While population density constitutes a direct incentive to teleworking (Liu and Su, 2021), it may also correlate with confounding factors such as the intensity of the pandemic. Thus, we will control for population density throughout our analysis and measure the effect of teleworking on top of density-driven effects.[6]

TABLE III. Correlation between the different measures of teleworking

	Dingel and Neiman (2020)	**Fiber**	**Share young children**	**Commuting Time**	**Density (log)**
Dingel and Neiman (2020)	1				
Fiber	0.6163	1			
Share young children	0.3762	0.3970	1		
Commuting Time	0.6487	0.6809	0.6371	1	
Density (log)	0.7872	0.7373	0.3955	0.7455	1

Notes: This table presents the correlation matrix between the different local measures that are expected to influence teleworking, the Dingel and Neiman (2020) indicator aggregated a the county (*"département"*) level and the logarithm of density (see Section 2.2 for more details). The correlations are calculated over 91 counties of mainland France (out of 94) for which they can be measured. Missing counties are *"département"* 05, 48 and 55. Observations are not weighted.

To compute our teleworking index, we combine all these measures using the following methodology. We use Principal Component Analysis (PCA) between the three local characteristics: commuting time, percentage of high-skill workers with children under 18, and share of households connected to the internet through the optical fiber. We then extract the first eigenvector that we scale to be constrained between 0 (less incentive to telework) and 1 (more incentive to telework) using an inverse logit transformation. This value is then multiplied by the Dingel and Neiman (2020) indicator. The results can be found in Table A1 in Appendix A and in Figure I.[7]

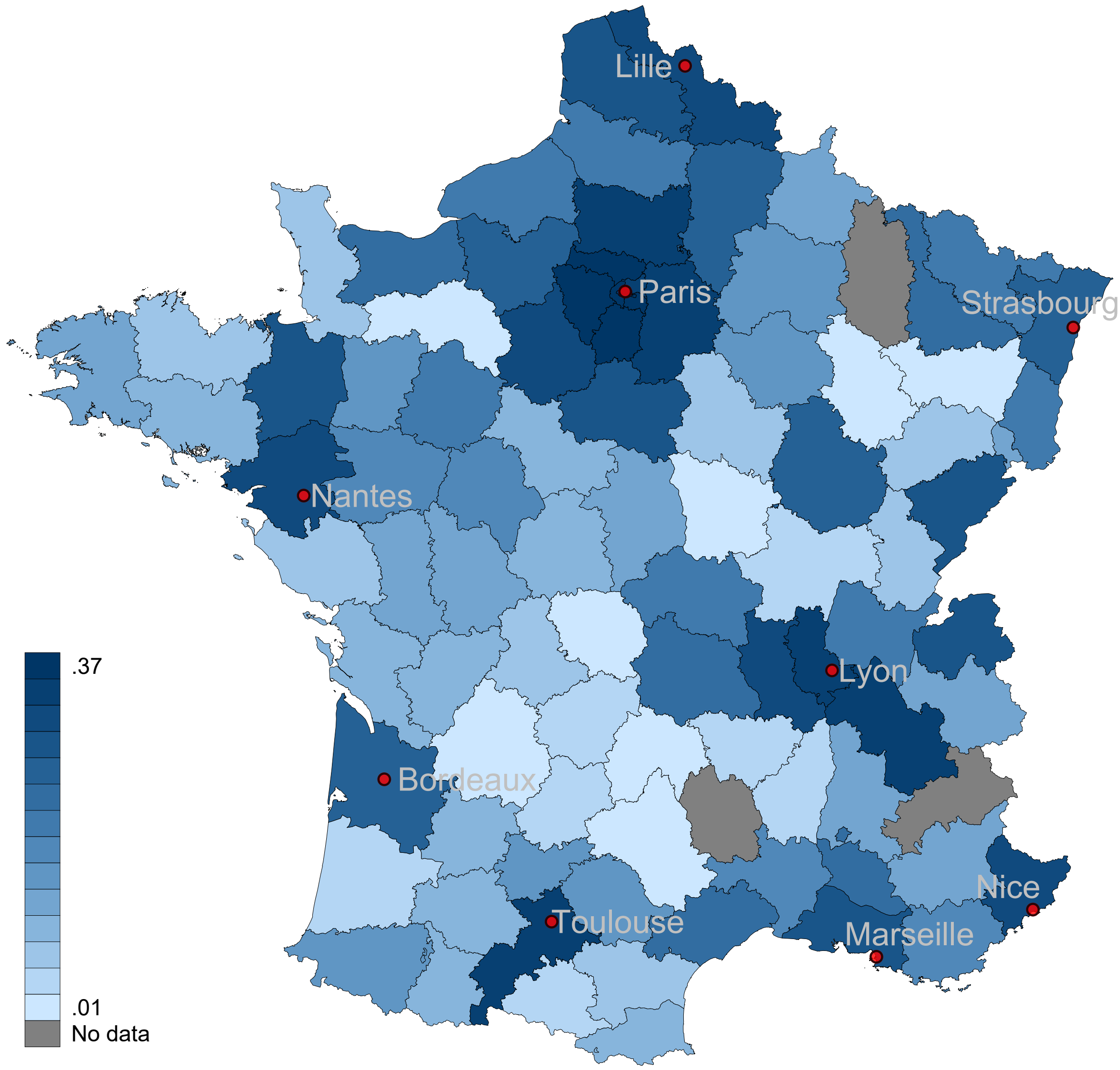
2.2.2 Index performance

Teleworking index and actual teleworking measures To assess the validity of this new index, we benchmark it against various actual measures of teleworking at the county level. The first such measure is taken from the wave 2021 of the "enquête

[6]Controlling for density reduces the predictive power of our measure of teleworking as part of the variance of teleworking comes from cross county variations in density while it is not clear whether density itself has a direct impact on real estate developments after the pandemics.

[7]Figure I confirms the intuition that the areas with the largest probability to telework are also the more densely populated and more urban counties. In Appendix A, we plot a similar map but for the residual of the teleworking index on the logarithm of density, see Figure A2.

FIGURE I. Telework index by county



Notes: This figure maps the telework index presented in Section 2.2.2. Three counties are excluded due to missing data (in grey). See Table A1 for more details.

sur la durée des équipements", an annual survey on how manufacturing firms use their production factors (see Gerardin et al., 2021). In 2021, a representative sample of 1,600 manufacturing firms was specifically asked to report the share of their workforce that was working from home at least one day a week, respectively in 2019 and in September 2020.[8] We use their responses and the weights of the survey to construct an aggregate share for each county. The second measure that we use comes from the Covid-19 Community Mobility Reports from Google. Based on mobile data, Google

[8]In September 2020, the largest Covid-related restrictions were completely lifted in France and most firms were fully functioning.

evaluates the variation in workplace occupancy at a detailed geographical level compared to a benchmark period on a daily basis. We take the average value by county in two specific periods, September 2020 and June 2021, during which there were no specific restrictions and obligations regarding working from home (see Figure A3 in Appendix A). Finally, we use the 2021 waves of the "Enquête Emploi" (Labor Force Survey) which includes a question about the number of days teleworked during each quarter. We exclude the first quarter which was still slightly impacted by pandemic-related containment measures and calculate the share of workers reporting at least one day a week worked at home.[9]

Based on these measures and our synthetic index for teleworking, we estimate the following simple cross-sectional model:

$$Y_c = \alpha + \beta T_c + \gamma \log(density_c) + \varepsilon_c \tag{1}$$

where Y_c is the actual measure of teleworking (from Google Mobility data, the manufacturing survey, or the labor force survey) and T_c is our proxy for teleworking. We also control for local density. Results are presented in Table IV and show that the estimate of β has the expected sign (negatively correlated with workplace occupancy and positively correlated with the share of teleworkers) and is always significantly different from 0.

TABLE IV. Teleworking at the county-level - regression results

	GM 2020	GM 2021	Manuf 2019	Manuf 2020	LFS	GM 2020	GM 2021	Manuf 2019	Manuf 2020	LFS
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
T_c	-33.260***	-40.563***	0.041*	0.154*	0.298**	-30.743***	-35.336***	0.042*	0.157*	0.279**
	(5.480)	(11.469)	(0.023)	(0.080)	(0.141)	(5.079)	(7.694)	(0.021)	(0.093)	(0.147)
Density (log)	-1.105***	-1.550**	0.001	0.003	0.035***	-1.464***	-2.266***	0.000	0.002	0.039***
	(0.366)	(0.743)	(0.001)	(0.004)	(0.009)	(0.343)	(0.443)	(0.001)	(0.005)	(0.008)
R^2	0.757	0.513	0.138	0.235	0.634	0.845	0.725	0.150	0.202	0.777
N	91	91	88	88	90	91	91	88	88	90

Notes: This table presents regression results from an estimation of Equation (1). Columns 1, 2, 6 and 7 use a measure of workplace occupancy from the Google Mobility (GM) data as a dependent variable, columns 3, 4, 8 and 9 use the share of teleworkers in manufacturing firms from Gerardin et al. (2021) and columns 5 and 10 use the share of teleworkers as reported by the labor force survey in 2021. Telework denotes the synthetic proxy for the potential for teleworking (see Section 2.2.2). Columns 6 to 10 use a weighted GLS with weights equal to the population in 2019. Other columns use the OLS estimator. Standard errors are corrected for heteroskedasticity. "*Département*" 2, 4 and 9 are excluded from the sample as there are no manufacturing firms surveyed. ***, ** and * respectively indicate p-values below 1, 5 and 10% for the Student test of the nullity of coefficients.

Teleworking index and occupational-level index Our new telecommuting index is highly correlated with the share of telecommuters predicted by the occupation-level results of Dingel and Neiman (2020) projected in each county using employment shares. As explained earlier, the rationale for this new measure is to deviate from the theoretical maximum value of telework intensity (which is what Dingel and

[9]We use the population weights provided by the survey to aggregate the number at the county level.

Neiman, 2020 measures) by using a number of county-specific incentives and limits to implement this arrangement. When the government implemented mandatory work-at-home during the peak of the pandemic, the number of teleworkers was closer to this maximum value. However, as these containment measures become more flexible, we believe that telecommuting intensity will be better predicted by our new index.

In Appendix B, we show that most of our results are robust to using only the index based on Dingel and Neiman (2020), but gain in precision as we add our different additional factors separately (see Section 3.5).

Finally, to show suggestive evidence that our index is explaining a larger share of the variance of teleworking over time, we proceed as follows. We take the occupancy rate of offices for each county from the Google Mobility data at the monthly frequency as a measure of the effective intensity of teleworking. We then look at the share of variance explained by our index by running a regression similar to the one presented in Table IV.[10] We do the same exercise but use the index based on Dingel and Neiman (2020) alone. The ratio of the corresponding R2 is reported in Figure A4 in the Appendix A each month from January 2021 to September 2022. This ratio is most of the time larger than 1 which means that the new index of teleworking explains a larger share of the variance of the occupancy rate of offices. The only exception is the first half of 2021 when working from home was still very much encouraged by the French authorities. This figure also shows that the ratio of R2 increases over time, in line with our prediction that the long-run intensity of teleworking should be better explained by a measure that includes the limits and frictions associated with working from home, on top of the occupational composition.

3 Empirical analysis

To assess the impact of teleworking on corporate real estate, we evaluate the differential impact of the Covid-19 crisis on corporate real estate depending on the propensity to telework. We first examine price dynamics using county-level and asset-level data. To understand the driving forces behind prices, we then study the rental market and focus mainly on its demand side—vacancy rates—but also on rent levels, both at the

[10]To compare counties over time, we add the occupancy rate of residential buildings as an additional control variable. Indeed, different counties experience different flows of people (holidays, migrations...) that could affect the occupancy rate of offices without being directly related to teleworking.

county level. Then, we turn to the supply side and focus on construction, before finally analyzing the evolution of liquidity conditions via transaction volumes.

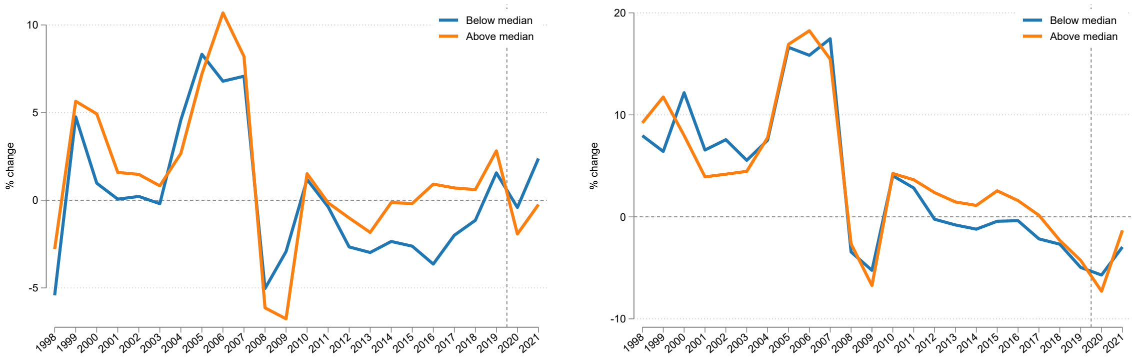
3.1 Asset valuations

3.1.1 County-level

We first analyze how county-level asset price indicators correlate with teleworking exposures. From a descriptive point of view, Figure II plots median office and retail price growths depending on counties' positions relative to the median teleworkability of counties with available office data. For offices, we notice a post-crisis price decline for counties with an above-median telework index only. For retail, both below and above median counties follow similar dynamics.

FIGURE II. Price growth and teleworking

(a) Median office price growth by county (b) Median retail price growth by county



Notes: Average value of the growth rate of price from MSCI respectively for counties below and above the yearly median in terms of the teleworking index. Only counties with available data on price are included in the calculation of the median.

To look at this question more formally, we estimate the following equation for county c and year t:

$$Y_{c,t} = \beta T_c * \mathbb{1}\left[t \geq 2020\right] + \gamma X_{c,t} + \nu_c + \mu_t + \varepsilon_{c,t} \quad (2)$$

where $\mathbb{1}\left[t \geq 2020\right]$ is a dummy taking value 1 in 2020 or 2021, T our teleworking index at the county level, $X_{c,t}$ a vector of county-specific characteristics that include the first difference of unemployment and the 2008 population density (in log) interacted with a time trend. Finally, ν_c and μ_t are respectively county and year fixed effects. The dependent variable, $Y_{c,t}$, is the growth rate of prices at the county level, taken directly from MSCI. We estimate the regression for the two separate subsamples of retail and offices.

TABLE V. Correlation between real estate markets and teleworking propensity

	Office			Retail		
	Price growth (1)	Vacancy rate (2)	Rent growth (3)	Price growth (4)	Vacancy rate (5)	Rent growth (6)
Telework index post 2020	-18.821***	28.333*	1.485	-16.076**	8.242	-2.290
	(5.860)	(16.781)	(4.673)	(6.564)	(6.590)	(5.735)
R^2	0.639	0.307	0.348	0.755	0.424	0.331
N	597	606	492	1032	1057	803

Notes: This table presents regression results from an estimation of Equation (2). Columns 1 to 3 use data for the office segment and columns 4 to 6 for the retail segment. Telework is our indicator of teleworking (see Section 2.2.2). OLS regression with robust standard errors. Not all counties are included due to missing information in MSCI (see Table I). Time period 1998-2021. All regressions include additive year and county (*"Département"*) fixed effects. $***$, $**$ and $*$ respectively indicate p-value below 1, 5 and 10% for the Student test of the nullity of coefficients.

Results are presented in Table V, columns 1 and 4, and show that prices declined more in the most teleworkable counties for both the retail and the office segments after the pandemic. The joint reduction in office and retail prices suggests that teleworking may not be the only channel at play. However, price differences may be difficult to detect in a small county-level panel. In the next section, we turn to asset-level data to control for additional confounding factors at the county-level using fixed effects and to better disentangle the relative dynamics of both segments. The robustness presented in Section 3.5 also shows that using transaction prices instead of appraisal values results in a significant price decline only for the office segment.[11]

3.1.2 Building-level

In this section, we leverage on the granular asset-level database drawn from REIF regulatory reporting. As explained in Section 2.1.2, it contains information on the valuation of buildings owned by real estate funds at a quarterly frequency. In line with the results presented in Section 3.3, we anticipate that funds will be more inclined to revise downwards the valuation of their real estate assets which are more impacted by a likely future increase in teleworking. These assets are office buildings that are located in counties more exposed to teleworking. We therefore estimate the following linear probability model:

$$D_{i,t} = \beta_t C_i T_{c(i)} + \delta X_{i,t} + \nu_{c(i),t} + \mu_i + \kappa_{j(i)} + t\gamma_{j(i),\tau(i)} + \varepsilon_{i,t} \tag{3}$$

[11] To give perspective to our study, we compare the dynamics of vacancy and price growth in the US and in France. The unconditional evolution between 2019 and 2021 in the US and in France is, respectively, +36.11% and +31.7% for vacancy and -3.59% and +0.82% for price. The raise in vacancy is thus similar in both countries but prices are more severely affected in the US in line with stronger reaction to previous crisis (2000s recession and great financial crisis).

where $D_{i,t}$ is equal to 1 if the valuation of building i has been revised downward during quarter t compared to quarters $t-1$. $c(i)$ and $j(i)$ respectively denote the county in which building i is located and the fund to which it belongs. C_i is a binary variable equal to 1 if the building is used for offices, $T_{c(i)}$ is our measure of local exposure to teleworking, and $X_{i,t}$ is a vector of control variables that include the total assets of funds $j(i)$, and the past 3 quarters of the building price (all taken in log). The various set of fixed effects is included to capture the direct effects of any local characteristics, variations, and trends ($\nu_{c(i),t}$), and the specificity of the fund ($\kappa_{j(i)}$) and of the building (μ_i). Finally, we have included a set of fund j interacted with the type of real-estate τ specific time trends ($t\gamma_{j(i),\tau(i)}$) in order to account for any inherent dynamics of a given REIF.

We are essentially interested in the evolution of β_t over time as it captures the additional probability of revising a value downwards for an office compared to other types of buildings during quarter t. We estimate the model using generalized least squares and allow for correlation in modeling residuals at the level of the treatment: within each county and real-estate segment.[12] The value and 95% confident intervals for each β_t are presented in Figure 3(a). In Figure 3(b), we take an alternative methodology and follow the approach of Ahlfeldt et al. (2018); Dustmann et al. (2022) who de-trend their coefficients using a pre-treament outcome trend. This corresponds to average changes in trends around the time of the pandemics. Similarly to Figure 3(a), the effect continues to be significant and concentrated around 2020q3.

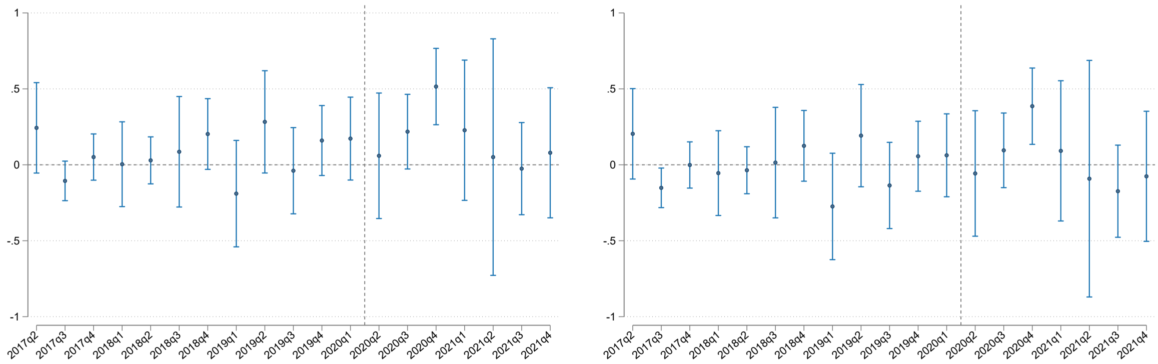
These results suggest that funds were indeed more likely to update negatively the valuation of their office buildings following the pandemic (in particular in 2020q3 and 2020q4), all the more when these buildings are located in areas that are more exposed to a large generalization of teleworking. Column 1 of Table B1 reports the values for the coefficients post and pre pandemics. The magnitude of the effect in 2020 (the sum of the coefficients from 2020q2 to 2020q4) suggests that a one standard deviation increase in the value of the teleworking index (0.072) increases the relative probability of the downward revision of a price by about 6.9 percentage points over the 4 quarters of 2020. This corresponds to a very large effect knowing that the unconditional observed probability of a downward revision of price was 5.8% prior to 2020.

Column 1 of Table B1 reports the average value of the coefficients for different periods.

[12] Table B1 in Appendix A show how our estimates vary with the level of clustering and across different variations in our main model.

FIGURE III. Marginal effect of teleworking on the probability to revise price downwards - Office

(a) Raw (b) Detrended



Notes: This figure plots the point estimate of β_t from model (3) for different values of t ranging from 2017q2 to 2021q4 as well as the confidence interval at 95%. These are obtained using a GLS estimation of model (3) allowing for correlation of the residuals within each county (*département*). Left-hand side panel plots the value of β_t and right-hand side panel plots their detrended values over the pre-treatrment period. Number of observations: 137,870.

The magnitude of the effect during the year following the pandemic (the sum of the coefficients from 2020q2 to 2021q1) suggests that a one standard deviation increase in the value of the teleworking index (0.072) increases the relative probability of the downward revision of a price by about 6.9 percentage points over the 4 quarters of 2020. This corresponds to a very large effect knowing that the unconditional observed probability of a downward revision of price was 5.8% prior to 2020.

One advantage of using data at the building level is that it allows us to look more precisely at differential effects across real estate segments within a county. As underlined before, it is likely that retail and office real estate developments remain highly correlated at the county level, above and beyond unemployment and density dynamics that we controlled for in county-level regressions. Here, the high dimensionality of the database allows us to control for county-time fixed effects and to estimate the reaction of offices compared to the other segments. In the next sections, we examine different channels that could explain why price declines have been stronger in the most teleworkable areas.

3.2 Rental market

The rental market can be impacted via rents and vacancy rates. Vacancy rates are expected to adjust quicker to an external shock, as rents come from a bargaining between landlord and prospective tenant that introduces frictions in the adjustment process (see for example Chau and Wong, 2016). As our study is based on early adjustments to the Covid-19 shock, the supply of space can be assumed constant, and we can attribute our results on rents and vacancy rates to changes in rental demand driven by teleworking.

From a descriptive point of view, we can compare the most teleworkable areas (above quantile 75%) and the others. The relative increase in vacancy rates between pre-crisis periods and post-crisis periods is equal to 4.6 percentage points (pp). To look at this question more formally, we use the model presented in Section 3.1.1 and use vacancy rate changes and rent growth as dependent variables.

Results are presented in Table V, columns 2, 3, 5 and 6. They suggest that office vacancy rates increased more in teleworkable areas after the pandemic, while the relative increase remains non significant in the retail segment. Rent growth rates on the other hand did not react which could be related to the relative rigidity of rent levels. Overall, these results show that some firms were already able to adjust their demand for space in response to an increase in telecommuting and suggest that telework is already settling in. Controlling for the change in unemployment as well as density-specific time trends alleviates the concern that our measure for T_c captures the relative economic shock that counties experienced due to their sectoral composition during the pandemic. This suggests that lower rental demand is a driver of the previously highlighted decrease in prices—consistent with the rise in teleworking.

Combining these results on prices with those on vacancy allows us to run a simple rule-of-thumb exercise to assess the consistency of their joint evolution. In particular, we are interested in assessing whether prices capture a short-term vacancy decrease or a longer one. As made explicit in Equation (4), we model asset prices P as 36-year Net Present Values (NPV) of a unit rent flow l growing at 2% annual growth rate g, with a vacancy rate v (8.4% in 2019), discounted using the historical average of income returns r (5.5% for offices).[13]

Assuming vacancy rates remain permanently at their 2019 level, this cash flow (P/l) would be priced at 18.2€. Based on our model presented in 3.2, a one standard deviation increase in teleworking (i.e., a 0.072 increase in the index) would translate into a 2.0 pp increase in vacancy rates and a price decline of 1.35%. The magnitude of the price reaction is consistent with a shock of 16 years (-1.34%). By contrast, a one-year shock to vacancies would lead to a price decrease of 0.1%. It thus seems that the price

[13]The service life of an office is based on BEA information. Based on MSCI data, the vacancy rate is the national vacancy rate for offices and average income return is the mean of national office income returns from 1998 to 2021.

adjustment already prices a durable increase in vacancy rates rather than a short-term pandemic-related effect.

$$P(v_t) = \sum_{t=1}^{36} \frac{l \times (1 - v_t) \times (1 + g)^t}{(1 + r)^t} \tag{4}$$

3.3 Construction

Has the decline in (expected) demand for office real estate led to a reduction in supply? The supply of real estate is rigid in the short-term as construction projects take time to deliver. However, in the longer run supply may adjust due to new constructions. We thus now focus on how teleworking affects construction after the pandemic. The dynamics of construction capture short-term as well as more structural changes. The construction sector has been no exception to the economic downturn observed with the outbreak of the virus and the implementation of health protection measures. After reaching an all-time high of 1,000,000 square meters of office space built in January 2020, office construction collapsed to 125,000 square meters of space built in April 2020, its lowest level on record. Office construction then slowly recovered without returning to pre-crisis levels, and was then impacted again by raw materials and labor shortage in 2022.

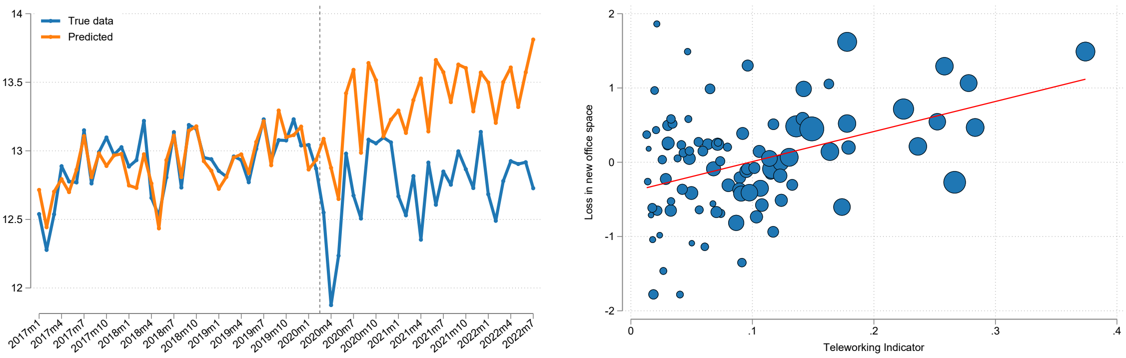
To measure the shortfall in office space built, we take advantage of the monthly frequency of *Sitadel2* construction data, and build a simple statistical model for the development of new office real estate before the pandemic, and capture in particular its cyclical dynamics. Office space construction is modeled as follows:

$$\log(\textit{office space built}_t) = \alpha + \beta t + m_t + \varepsilon_t \tag{5}$$

where $\textit{office space built}_t$ is office space built in period t, βt is a time trend, m_t a month fixed effect and ε_t the error term. We estimate this model at the country level over Jan. 2014 - Jan. 2020, and use the estimated coefficients to construct a counterfactual for office space construction. Figure 4(a) shows the evolution of actual office space built since 2017 (blue line), and its counterfactual (orange line). The dynamics of the data are accurately predicted by the model estimated up to the pandemic. The market is cyclical with the amount of space built almost doubling from one month to the next. Importantly, the gap between the orange and blue lines starting in March 2020 suggests that the flow of commercial property built still falls short of its counterfactual, despite a strong rebound after the first lockdown (from March 17^{th} to May 10^{th} 2020). The office stock shortfall is thus still trending up.

FIGURE IV. Correlation between office space construction and telework index

(a) Dynamics of office space construction (b) Loss in office building and telework index



Notes: This figure shows (a) time series of losses in office space building (seasonally adjusted and relative to trend as detailed in the text) between Jan. 2017 and July. 2022, and (b) the correlation between the loss of office space construction after the outbreak of the pandemic and the telework index at the department level.

To assess the relationship between exposure to teleworking and commercial property construction dynamics, we now turn to a county-level panel and estimate the following model over Jan. 2014 - Jan. 2020:

$$\log(\textit{office space built}_{c,t}) = \alpha + \beta_c t + X_{c,t} + m_c + \varepsilon_{c,t} \tag{6}$$

This model allows to control for county c specific and time-varying observable characteristics ($X_{c,t}$) that could be correlated with the development of new office spaces, on top of county and time-fixed effects. In particular, we control for the local unemployment rate[14] and the logarithm of the density in 2018 interacted with a time trend. In addition, we remove the average value of the dependent variable for each t in order to control for global effects.[15]

From this model, we predict the loss in construction. Formally, we measure the average gap between predicted and actual values (both taken in log) of new square meters of offices from May 2020 to July 2022. Figure 4(b) presents this county-level loss as a function of the teleworking index. We see that while the whole country underwent

[14]Unemployment at the county-level is taken from the Insee and is only available at the quarterly level, we create artificial monthly data using linear interpolation.

[15]One natural alternative would be to include time-fixed effects to the model. However, in the next step, we will predict and project the dependent variable using this model and for this reason, we prefer to use demeaned variables.

an important slowdown in terms of new construction, predicted losses are unevenly distributed over the territory and are positively correlated with the telework index defined in Section 2.2.2. We also present the cross-section regression coefficients of Equation (7) in Table VI (columns 1 and 2).

$$\log(\textit{office space built}_{c,t}) - \log(\widehat{\textit{office space built}}_{c,t}) = \beta T_c + \varepsilon_{c,t} \tag{7}$$

Alternatively, we build on Equation (6) to directly estimate the effect of being more exposed to teleworking after the pandemic. Formally, we add T_c interacted with $\mathbb{1}[t \geq 2020m5]$ (a dummy variable equal to 1 after May 2020). In addition, we directly include time-fixed effects to the model. The coefficient associated with $T_c * \mathbb{1}[t \geq 2020m5]$ therefore captures the additional variation in new construction associated with an increase in the teleworking index after the pandemic. We expect it to be negative.

Results are presented in column 3 of Table VI and show that, as expected, the estimate of the coefficient is significantly negative. Its magnitude (-2.79) indicates that a one standard deviation increase in the value of the teleworking index (0.072) corresponds to a decline in new office construction of about 20%. This decrease can be attributed to the current take-up of teleworking, as well as the anticipation of future teleworking.

TABLE VI. Impact of teleworking on county-level office and retail loss

	Office			Retail		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
T_c	3.629***	4.046***		2.435**	3.345***	
	(0.930)	(0.930)		(0.940)	(0.560)	
$T_c * \mathbb{1}[t \geq 2020m5]$			-2.790***			-1.225
			(0.955)			(0.779)
R^2	0.132	0.254	0.576	0.053	0.197	0.481
N	91	91	9,005	91	91	9,005

Notes: Columns 1, 2, 4 and 5 of this table present regression results of Equation (7). T_c is the synthetic index for the propensity to telework (see Section 2.2.2). Columns 1 and 4 use OLS estimators and columns 2 and 5 use a GLS with weights equal to the population as of 2019. Columns 3 and 6 estimate directly by OLS the following model $\log(\textit{office space built}_{c,t}) = \alpha + \beta T_c \mathbb{1}[t \geq 2020m5] + \beta_c t + X_{c,t} + m_c + \varepsilon_{c,t}$. In all cases, standard errors are corrected for heteroskedasticity. ***, ** and * respectively indicate p-value below 1, 5 and 10% for the Student test of the nullity of coefficients.

Next, we replicate the analysis for retail. Results are housed in columns 4 to 6 of Table VI. They are consistent with findings for offices, but slightly less precisely estimated and not significant for the panel estimation. We expect some level of correlation between the loss in new office spaces and the loss in new retail spaces due to local spillovers from the former to the latter. Indeed, the drop in office attendance should directly affect neighboring shops. More generally, real estate prices are strongly correlated within county which limits the possibility to disentangle effects across segments. However, the fact that the results are mainly not significant for retail suggests that what we are capturing in Table VI is mostly specific to offices.

We thus conclude that working from home negatively impacts office supply. First, it suggests that market participants expect the effect of teleworking to be durable, as construction projects take time to be delivered. Second, this effect constitutes a natural balancing forces that implicitly mitigates the drop in office prices.

3.4 Transaction volumes

Another channel that could explain the stronger devaluation of office assets in more teleworkable areas could be related to liquidity conditions. For instance, the Paris area is the most teleworkable, and is also the object of international capital flows which could have dried up during the Covid-19 period and led to stronger price contractions. We evaluate this channel by looking at whether transaction volumes declined more in the more teleworkable counties, replicating the specification of Equation (2). We use granular transaction data as described in Section 2.1.4 and measure transaction volumes alternatively by aggregating the total number of transactions, and the total number of transacted square meters per county-year. Results are housed in Table VII, and show that transaction volumes do not seem to have varied more in the most teleworkable areas, be it for office or retail assets. This suggests that liquidity conditions cannot account for the observed price patterns.

3.5 Robustness

Removing Paris Paris is by far the largest city in France. It is at the same time the densest county, the center of economic activities and the main recipient of foreign investments. Since the region also hosts some of the counties with the highest teleworking potential, any unobserved shock affecting Paris could spuriously be attributed to teleworking. For instance, high population density could have led to a stronger effect of containment measures. Alternatively, high exposure to international capital flows may have made Paris area prices more sensitive to the global retrenchment in the wake of the pandemic. We therefore present our main results on offices excluding Paris and its immediate suburbs (3 counties: Seine-Saint-Denis, Haut-de-Seine, and Val de Marne). Results are presented in Tables B4 and B5 and B6 respectively

TABLE VII. Correlation between the volume of transactions and teleworking propensity

	Office		Retail	
	Number	Surface	Number	Surface
	(1)	(2)	(3)	(4)
Telework index post 2020	0.395	0.162	-0.355	-2.345
	(0.375)	(0.759)	(0.359)	(1.682)
R^2	0.333	0.118	0.255	0.131
N	968	968	968	968

Notes: This table presents regression results from an estimation of Equation (2). Columns 1 to 2 use data for the office segment and columns 3 to 4 for the retail segment. Telework is our indicator of teleworking (see Section 2.2.2). OLS regression with robust standard errors. Data are taken from DV3F and cover the year 2011-2021. Columns 1 and 3 use the growth rate in the number of transactions and columns 2 and 4 use the growth rate in the total surface transacted. All regressions include additive year and county ("*Département*") fixed effects. $***$, $**$ and $*$ respectively indicate p-value below 1, 5 and 10% for the Student test of the nullity of coefficients.

and are qualitatively similar to our baseline models but with smaller coefficients in absolute values. This confirms that the Paris region is a significant contributor to our results, supporting the notion that its corporate real estate is more responsive to global shocks.

Using transaction data As explained in Section 2.1, appraisal data used in Sections 3.1.1 and 3.1.2 allow to track a stable and larger set of building over time, even in times of systemic stress. However, they are the product of market participants' estimations and may differ from actual transaction prices. To check that our results on prices are robust to using actual data, we use tax data produced by the French Public Finances Directorate General (DGFiP) on the universe of transactions from 2010 to 2021, as described in Section 2.1.4. We estimate for each county an average price per unit of surface. Results are presented in Table VIII. The results for price growth show a negative effect of teleworking only for offices - consistently with previous analyses.

Changing our index As explained in Section 2.2.2, our index builds upon the value based on the local (pre-pandemics) occupational composition and the data computed by Dingel and Neiman (2020). We augmented this index with an additional component based on three measures. In Tables B2 and B3 and in Figure B1, we show how our main results are impacted from using separately each of these three measures interacted with the index of Dingel and Neiman (2020). We do this by first standardizing each of the three factors so that the mean and standard deviation are respectively equal to 0 and 1. We then multiply the corresponding inverse logit transformation of this variable with the Dingel and Neiman (2020) index. These Tables show that such interaction systematically outperforms what is found by the use of the Dingel and Neiman (2020) index alone in terms of precision.

TABLE VIII. Correlation between real estate markets and teleworking propensity

	Office (1)	Retail (2)
Telework index post 2020	-1.058**	0.020
	(0.455)	(0.367)
R^2	0.054	0.047
N	968	968

Notes: This table replicates Table V (columns 1 and 4) but use a the yearly average weighted growth rate of price per square meter from transaction data.

4 Conclusion

The Covid-19 pandemic generated an unforeseen teleworking shock, which we examine in relation to its impact on corporate real estate. We begin by presenting evidence that office prices experienced a greater decline in areas with high potential levels of teleworkability, a trend that was not observed for retail properties. To shed light on this phenomenon, we delve into rental market data and discover that the crisis led to higher increases in vacancy rates in these areas which are highly teleworable. This suggests that companies with high teleworking rates have already released some office spaces soon after the pandemics started. Furthermore, we observe a slowdown in post-Covid construction in the most teleworable counties, which further indicates that market participants anticipate a long-term decrease in demand for corporate real estate. The reaction of construction serves as a natural counterbalance in the office space market, mitigating the downward pressure on prices through lower supply in the medium-term. Finally, we demonstrate that transaction volumes have evolved similarly across counties, further supporting the hypothesis that teleworking and its associated reduction in demand for space were the primary drivers of the decline in prices

The shift towards teleworking as a result of the Covid-19 pandemic has the potential to significantly impact the economy in various ways. In the short-term, the decline in corporate real estate prices and associated uncertainty may impede the capacity of firms to secure financing through the collateral channel. Additionally, the reduced demand for office spaces could cause imbalances on the supply-side of the market, which the market will need to absorb and adjust to. For example, a decrease in prices may result in higher Loan-to-Value ratios and thus increased credit risk for banks. On the longer-run, the increased vacancy rates in the commercial segment may eventually spill over to the residential real estate market, as both markets tend to be historically correlated. This could mitigate recent price increases in the residential real estate market. Additionally, urban areas that are more exposed to teleworking are often areas with high-value-added jobs and higher incomes, which also tend to have higher real estate prices. The impact of teleworking on real estate prices in these areas could therefore contribute to economic rebalancing by decreasing prices in areas where they are the highest, and potentially decreasing spatial inequalities between urban areas. Future developments now depend on whether market participants over-reacted, in a context of heightened uncertainty, or downplayed the future organization of labor.

References

Ahlfeldt, G. M., D. Roth, and T. Seidel (2018). The regional effects of germany's national minimum wage. *Economics Letters 172*, 127–130.

Aksoy, C. G., J. M. Barrero, N. Bloom, S. J. Davis, M. Dolls, and P. Zarate (2022). Working from home around the world. Technical Report w30446, National Bureau of Economic Research.

Althoff, L., F. Eckert, S. Ganapati, and C. Walsh (2022). The geography of remote work. *Regional Science and Urban Economics 93*, 103770.

AMF (2020). 2020 risk and market mapping *(cartographie 2020 des marchés et des risques)*. Technical report, AMF.

Antoniades, A. (2021). Commercial bank failures during the great recession: The real (estate) story. Available at SSRN 2325261.

Baker, M. G. (2020). Who cannot work from home? characterizing occupations facing increased risk during the covid-19 pandemic using 2018 bls data. *Medrxiv*.

Barrero, J. M., N. Bloom, and S. J. Davis (2021). Why working from home will stick. Technical Report w28731, National Bureau of Economic Research.

Behrens, K., S. Kichko, and J.-F. Thisse (2021). Working from home: Too much of a good thing? *Available at SSRN 3768910*.

Bergeaud, A., G. Cette, and S. Drapala (2021). Télétravail et productivité avant, pendant et après la crise. Mimeo Banque de France.

Bergeaud, A. and S. Ray (2021). Adjustment costs and factor demand: New evidence from firms' real estate. *The Economic Journal 131*(633), 70–100.

BNP (2020). At a glance q42020 - investment in france. BNP Real estate.

Brynjolfsson, E., J. J. Horton, A. Ozimek, D. Rock, G. Sharma, and H.-Y. TuYe (2020). Covid-19 and remote work: an early look at us data. Working Paper w27344, National Bureau of Economic Research.

Cajner, T., L. D. Crane, R. A. Decker, J. Grigsby, A. Hamins-Puertolas, E. Hurst, C. Kurz, and A. Yildirmaz (2020). The us labor market during the beginning of the pandemic recession. Technical Report w27159, National Bureau of Economic Research.

Chaney, T., D. Sraer, and D. Thesmar (2012). The collateral channel: How real estate shocks affect corporate investment. *American Economic Review 102*(6), 2381–2409.

Chareyron, S., C. Régnier, F. Sari, et al. (2022). Covid-19 and dynamics of residential property markets in france: An exploration. *Economie et Statistique/Economics and Statistics* (536-37), 75–93.

Chau, K. W. and S. K. Wong (2016). Information asymmetry and the rent and vacancy rate dynamics in the office market. *The Journal of Real Estate Finance and Economics 53*(2), 162–183.

Cole, R. A. and L. J. White (2012). Déjà vu all over again: The causes of us commercial bank failures this time around. *Journal of Financial Services Research 42*(1-2), 5–29.

Consolo, A., G. Cette, A. Bergeaud, V. Labhard, C. Osbat, S. Kosekova, S. Anyfantaki, G. Basso, H. Basso, E. Bobeica, and E. Ciapanna (2021, September). Digitalisation: channels, impacts and implications for monetary policy in the euro area. Occasional Paper Series 266, European Central Bank.

Criscuolo, C., P. Gal, T. Leidecker, F. Losma, and G. Nicoletti (2021). The role of telework for productivity during and post covid-19: results from an oecd survey among managers and workers. OECD.

Davis, J. S., K. X. Huang, and A. Sapci (2021). Land price dynamics and macroeconomic fluctuations with imperfect substitution in real estate markets. *Journal of Economic Dynamics and Control*, 104274.

Davis, M. A., A. C. Ghent, and J. M. Gregory (2021). The work-from-home technology boon and its consequences. Technical report, National Bureau of Economic Research.

De Fraja, G., J. Matheson, and J. Rockey (2020). Zoomshock: The geography and local labour market consequences of working from home. Available at SSRN 3752977.

Delfim, J.-C. and M. Hoesli (2021). Robust desmoothed real estate returns. *Real Estate Economics 49*(1), 75–105.

Delventhal, M. J., E. Kwon, and A. Parkhomenko (2021). Jue insight: How do cities change when we work from home? *Journal of Urban Economics*, 103331.

Dingel, J. I. and B. Neiman (2020). How many jobs can be done at home? *Journal of Public Economics 189*, 104235.

Dustmann, C., A. Lindner, U. Schönberg, M. Umkehrer, and P. Vom Berge (2022). Reallocation effects of the minimum wage. *The Quarterly Journal of Economics 137*(1), 267–328.

Eyméoud, J.-B., N. Petrosky-Nadeau, R. Santaeulàlia-Llopis, and E. Wasmer (2021). Labor reallocation and labor policy after covid-19. Mimeo.

Ferrière, T. and D. Henricot (2021). Corporate and residential real estate: what spillovers in the context of the health crisis? https://blocnotesdeleco.banque-france.fr/en/blog-entry/corporate-and-residential-real-estate-what-spillovers-context-health-crisis.

Fougère, D., R. Lecat, and S. Ray (2019). Real estate prices and corporate investment: theory and evidence of heterogeneous effects across firms. *Journal of Money, Credit and Banking 51*(6), 1503–1546.

Gerardin, M., P. Lesterquy, L. Baudry, S. Tarrieu, H. Dekoninck, F. Heurtebize, and J. Zory (2021). Capital operating times plummeted in 2020 amid the unprecedented use of teleworking. results of the survey conducted by the banque de france in september 2020. *Bulletin de la Banque de France* (235).

Gibbs, M., F. Mengel, and C. Siemroth (2021). Work from home & productivity: Evidence from personnel & analytics data on it professionals. *University of Chicago, Becker Friedman Institute for Economics Working Paper* (2021-56).

Gottlieb, C., J. Grobovsek, and M. Poschke (2020). Working from home across countries. *Covid Economics*.

Gupta, A., V. Mittal, J. Peeters, and S. Van Nieuwerburgh (2021). Flattening the curve: pandemic-induced revaluation of urban real estate. Technical report, National Bureau of Economic Research.

Gyourko, J. (2009). Understanding commercial real estate: Just how different from housing is it? nber working papers 14708.

Hallépée, S. and A. Mauroux (2019). Quels sont les salariés concernés par le télétravail? Technical Report 051, DARES ANALYSES.

Hensvik, L., T. Le Barbanchon, and R. Rathelot (2020). Which jobs are done from home? evidence from the american time use survey. Discussion Paper No. DP14611, CEPR.

Hoesli, M. and R. Malle (2021). Commercial real estate prices and covid-19. *Journal of European Real Estate Research*.

Le Barbanchon, T. and N. Rizzotti (2020). The task content of french jobs. Available at SSRN 3653262.

Ling, D. C., C. Wang, and T. Zhou (2020). A first look at the impact of covid-19 on commercial real estate prices: Asset-level evidence. *The Review of Asset Pricing Studies 10*(4), 669–704.

Liu, S. and Y. Su (2021). The impact of the covid-19 pandemic on the demand for density: Evidence from the us housing market. *Economics letters 207*, 110010.

Milcheva, S. (2021). Volatility and the cross-section of real estate equity returns during covid-19. *The Journal of Real Estate Finance and Economics*, 1–28.

Mongey, S., L. Pilossoph, and A. Weinberg (2021). Which workers bear the burden of social distancing? *The Journal of Economic Inequality 19*(3), 509–526.

Mongey, S. and A. Weinberg (2020). Characteristics of workers in low work-from-home and high personal-proximity occupations. *Becker Friedman Institute for Economic White Paper*.

MSCI (2021). Real estate market size 2020/21. MSCI.

Nathan, M. and H. Overman (2020). Will coronavirus cause a big city exodus? *Environment and Planning B: Urban Analytics and City Science 47*(9), 1537–1542.

OECD (2020). Productivity gains from teleworking in the post covid-19 era: How can public policies make it happen? Technical report, OECD publishing.

Ramani, A. and N. Bloom (2021). The donut effect of covid-19 on cities. Technical Report w28876, National Bureau of Economic Research.

Rosenthal, S. S., W. C. Strange, and J. A. Urrego (2022). Jue insight: Are city centers losing their appeal? commercial real estate, urban spatial structure, and covid-19. *Journal of Urban Economics 127*, 103381.

Schulz, R., V. Watson, and M. Wersing (2022). Teleworking and housing demand. Available at SSRN 4182936.

Sostero, M., S. Milasi, J. Hurley, E. Fernandez-Macias, and M. Bisello (2020). Teleworkability and the covid-19 crisis: a new digital divide? Technical Report 2020/05, JRC working papers series on labour, education and technology.

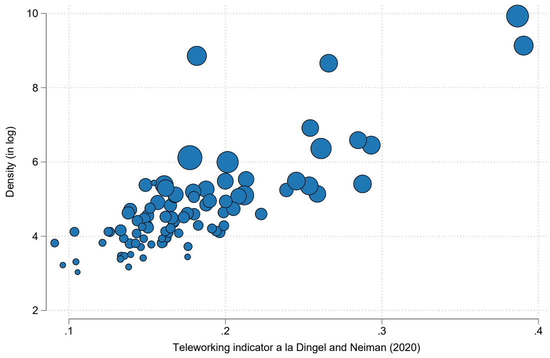
Xie, L. and S. Milcheva (2020). Proximity to covid-19 cases and reit equity returns. *Available at SSRN 3641268*.

APPENDIX

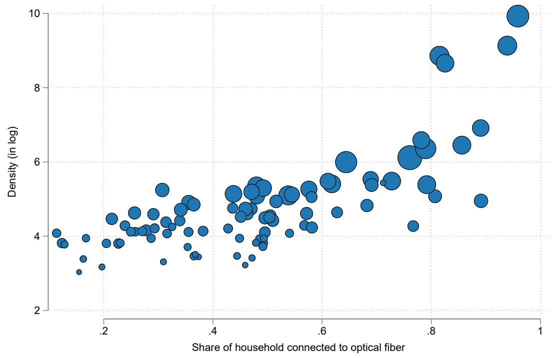
A Additional information on data

FIGURE A1. Correlation between the different measures of teleworking and population density

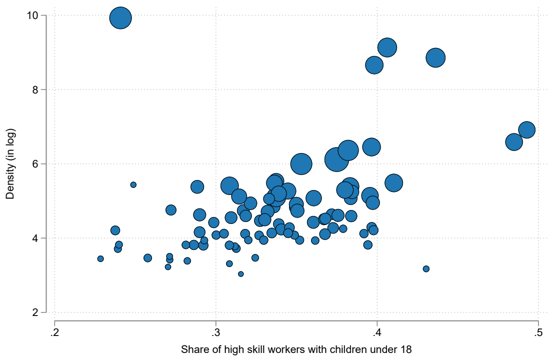
(a) Dingel and Neiman (2020) indicators



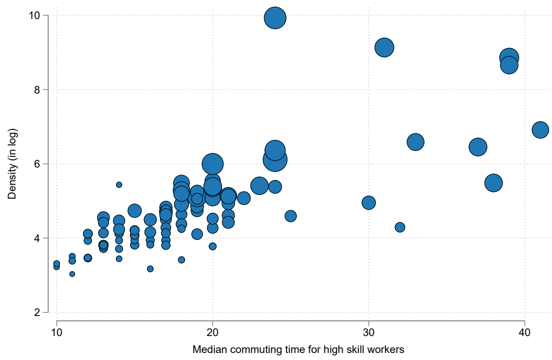
(b) Share of households connected to the optical fiber



(c) Share of high skill workers with children under 18

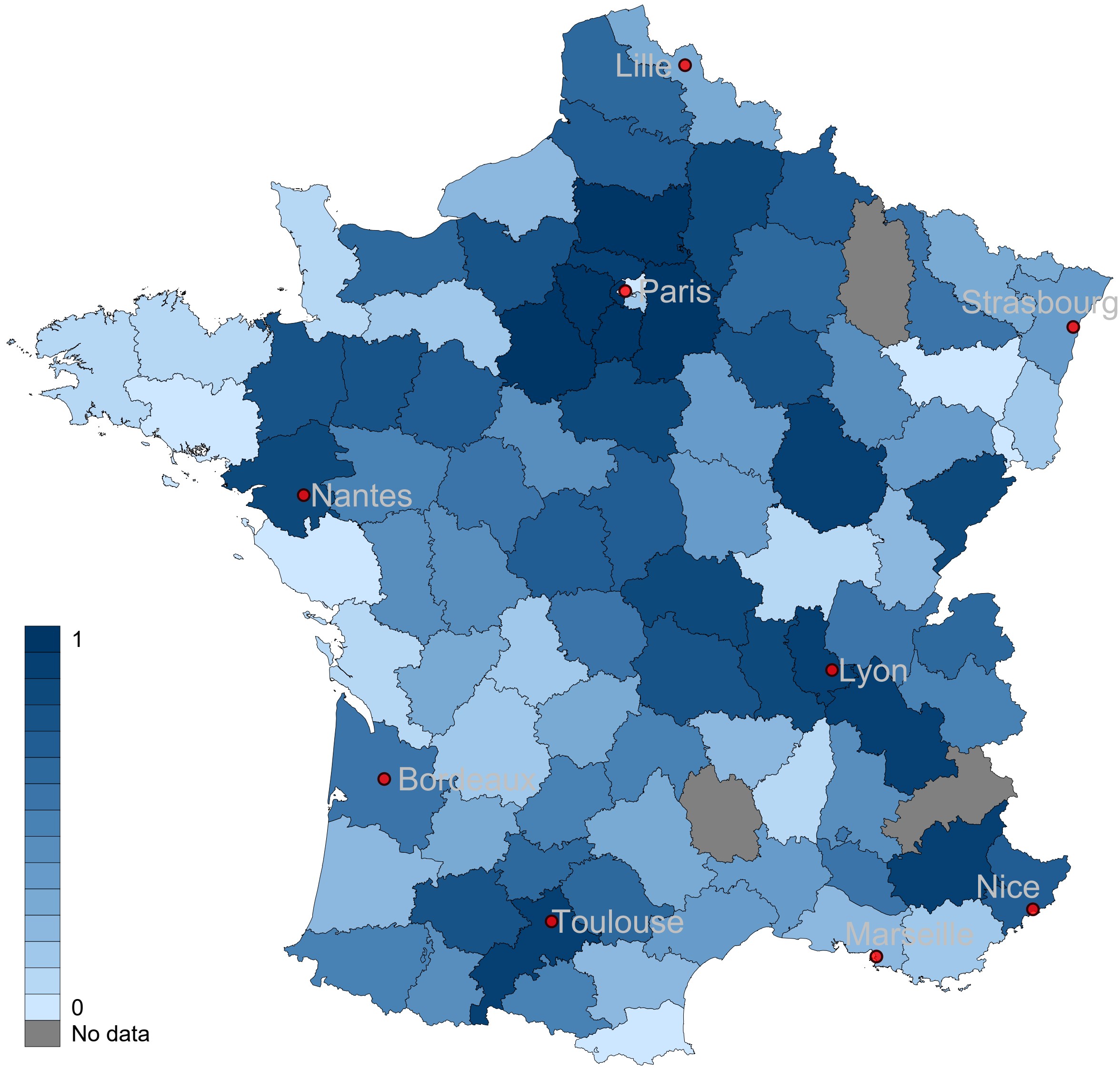


(d) Commuting time for high skill workers



Notes: These figures report the cross section between the logarithm of density at the "*département*" level (defined as the ratio of population in 2019 over area) and our different measures of teleworking presented in Section 2.2. Bins are proportional to population. Adjusted R squared are respectively equal to 0.597, 0.100, 0.052, 0.474.

FIGURE A2. Telework index by county controlling for population density



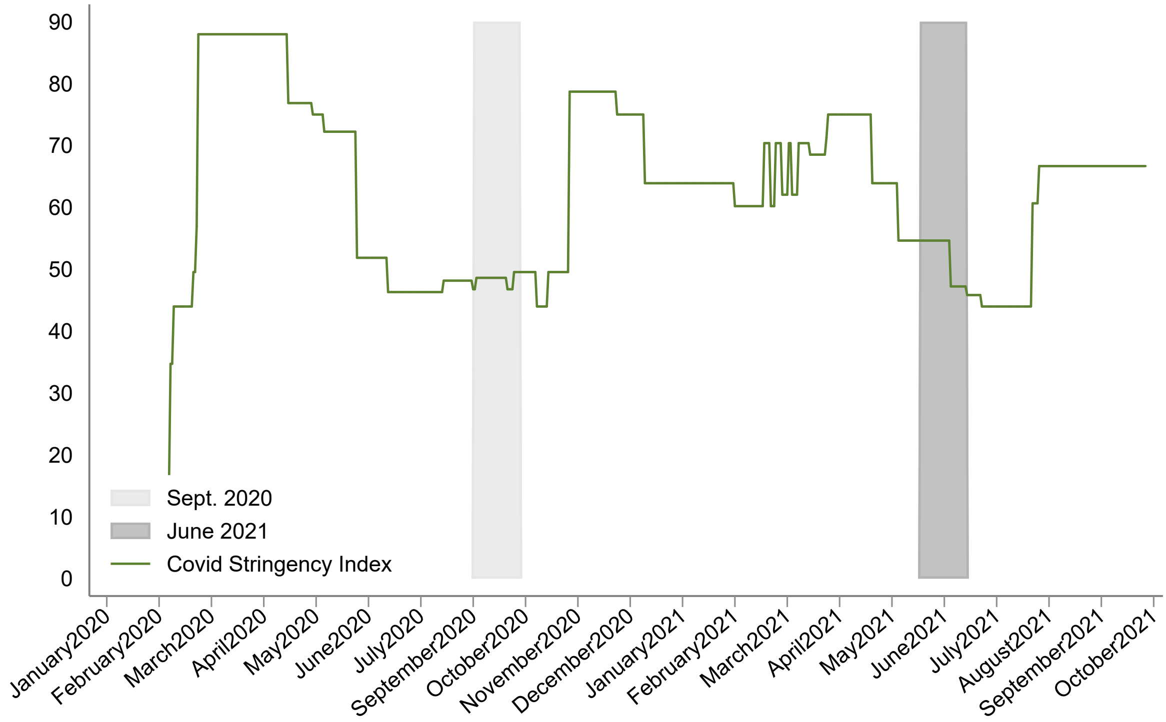
Notes: This figure maps the telework index presented in Section 2.2.2 once residualized on the log of density at the county-level. Three counties are excluded due to missing data. The residual has been standardized.

TABLE A1. Detailed county-level measures

Code	Name	Main city	Density	Telework index	Dingel and Neiman (2020)	Fiber	Children	Commuting Time
75	Paris	Paris	20,515	0.266	0.387	0.959	0.241	24
92	Hauts-de-Seine	Nanterre	9,255	0.374	0.391	0.939	0.406	31
93	Seine-St-Denis	Bobigny	7,025	0.178	0.182	0.815	0.436	39
94	Val-de-Marne	Créteil	5,762	0.258	0.266	0.825	0.398	39
95	Val-D'Oise	Pontoise	1,006	0.252	0.254	0.891	0.493	41
91	Essonne	Évry	726	0.278	0.285	0.782	0.485	33
78	Yvelines	Versailles	635	0.283	0.293	0.856	0.397	37
69	Rhône	Lyon	579	0.224	0.261	0.790	0.382	24
59	Nord	Lille	453	0.149	0.177	0.761	0.375	24
13	Bouches-du-Rhône	Marseille	402	0.136	0.201	0.644	0.353	20
6	Alpes-Maritimes	Nice	253	0.142	0.213	0.689	0.337	20
77	Seine-et-Marne	Melun	241	0.236	0.245	0.728	0.410	38
67	Bas-Rhin	Strasbourg	240	0.114	0.200	0.611	0.336	18
90	Territoire de Belfort	Belfort	230	0.050	0.154	0.712	0.249	14
31	Haute-Garonne	Toulouse	223	0.178	0.288	0.618	0.308	23
62	Pas-de-Calais	Arras	219	0.130	0.161	0.792	0.383	20
68	Haut-Rhin	Colmar	217	0.095	0.149	0.691	0.288	24
44	Loire-Atlantique	Nantes	212	0.164	0.254	0.480	0.383	20
76	Seine-Maritime	Rouen	200	0.098	0.162	0.492	0.380	18
34	Hérault	Montpellier	194	0.107	0.188	0.576	0.345	18
74	Haute-Savoie	Annecy	190	0.123	0.239	0.307	0.384	19
83	Var	Toulon	181	0.087	0.179	0.471	0.339	18
38	Isère	Grenoble	171	0.174	0.259	0.438	0.396	21
57	Moselle	Metz	167	0.091	0.168	0.545	0.314	21
33	Gironde	Bordeaux	164	0.116	0.212	0.538	0.337	19
35	Ille-et-Vilaine	Rennes	160	0.123	0.208	0.480	0.361	20
42	Loire	Saint-Étienne	160	0.141	0.168	0.807	0.384	22
84	Vaucluse	Avignon	157	0.102	0.180	0.581	0.333	19
60	Oise	Beauvais	142	0.179	0.190	0.891	0.397	30
54	Meurthe-et-Moselle	Nancy	139	0.108	0.200	0.516	0.321	21
29	Finistère	Quimper	136	0.068	0.157	0.356	0.350	18
30	Gard	Nîmes	128	0.080	0.188	0.365	0.336	19
14	Calvados	Caen	125	0.103	0.165	0.682	0.349	17
66	Pyrénées-Orientales	Perpignan	116	0.042	0.152	0.436	0.272	17
1	Ain	Bourg-en-Bresse	114	0.092	0.205	0.470	0.317	19
49	Maine-et-Loire	Angers	114	0.089	0.205	0.460	0.351	15
56	Morbihan	Vannes	111	0.050	0.139	0.341	0.332	17
25	Doubs	Besançon	104	0.133	0.199	0.627	0.372	18
85	Vendée	La Roche-sur-Yon	102	0.031	0.138	0.256	0.290	17
45	Loiret	Orléans	101	0.124	0.176	0.572	0.376	21
37	Indre-et-Loire	Tours	99	0.090	0.223	0.463	0.318	17
27	Eure	Évreux	99	0.115	0.180	0.291	0.384	25
17	Charente-Maritime	La Rochelle	95	0.048	0.150	0.505	0.309	13
80	Somme	Amiens	92	0.096	0.162	0.451	0.368	20
72	Sarthe	Le Mans	91	0.096	0.173	0.503	0.367	17
64	Pyrénées-Atlantiques	Pau	90	0.071	0.166	0.495	0.330	16
22	Côtes-d'Armor	Saint-Brieuc	87	0.033	0.148	0.215	0.327	14
63	Puy-de-Dôme	Clermont-Ferrand	84	0.106	0.167	0.510	0.360	21
50	Manche	Saint-Lô	83	0.030	0.144	0.339	0.299	13
26	Drôme	Valence	80	0.063	0.167	0.314	0.339	18
28	Eure-et-Loir	Chartres	73	0.163	0.183	0.568	0.397	32
73	Savoie	Chambéry	72	0.065	0.199	0.239	0.346	17
2	Aisne	Laon	72	0.117	0.150	0.767	0.373	20
82	Tarn-et-Garonne	Montauban	70	0.072	0.147	0.325	0.379	18
51	Marne	Châlons-en-Champagne	69	0.070	0.150	0.581	0.341	14
81	Tarn	Albi	68	0.074	0.165	0.293	0.398	15
87	Haute-Vienne	Limoges	67	0.034	0.191	0.428	0.238	15
71	Saône-et-Loire	Mâcon	64	0.029	0.133	0.278	0.290	16
86	Vienne	Poitiers	63	0.059	0.194	0.382	0.335	13
79	Deux-Sèvres	Niort	62	0.056	0.162	0.271	0.345	17
47	Lot-et-Garonne	Agen	62	0.048	0.125	0.258	0.392	14
88	Vosges	Épinal	62	0.018	0.104	0.250	0.305	12
11	Aude	Carcassonne	61	0.030	0.126	0.355	0.318	12
21	Côte-d'Or	Dijon	61	0.117	0.196	0.495	0.368	19
7	Ardèche	Privas	59	0.026	0.170	0.114	0.300	15
53	Mayenne	Laval	59	0.079	0.164	0.540	0.349	15
16	Charente	Angoulême	59	0.042	0.143	0.316	0.327	15
39	Jura	Lons-le-Saunier	52	0.033	0.163	0.168	0.320	15
41	Loir-et-Cher	Blois	52	0.043	0.135	0.287	0.330	17
10	Aube	Troyes	52	0.074	0.163	0.449	0.352	16
65	Hautes-Pyrénées	Tarbes	51	0.047	0.159	0.493	0.293	14
8	Ardennes	Charleville-Mézières	51	0.061	0.148	0.485	0.362	12
43	Haute-Loire	Le Puy-en-Velay	46	0.027	0.121	0.479	0.240	16
3	Allier	Moulins	45	0.091	0.160	0.492	0.394	15
61	Orne	Alençon	45	0.013	0.091	0.231	0.281	13
24	Dordogne	Périgueux	45	0.019	0.159	0.124	0.286	13
89	Yonne	Auxerre	45	0.033	0.143	0.205	0.308	17
40	Landes	Mont-de-Marsan	45	0.022	0.139	0.227	0.292	13
70	Haute-Saône	Vesoul	44	0.038	0.153	0.128	0.312	20
18	Cher	Bourges	41	0.056	0.176	0.492	0.313	13
19	Corrèze	Tulle	41	0.021	0.146	0.354	0.239	14
46	Lot	Cahors	33	0.021	0.140	0.368	0.271	11
36	Indre	Châteauroux	32	0.040	0.135	0.444	0.324	12
12	Aveyron	Rodez	32	0.020	0.133	0.365	0.258	12
9	Ariège	Foix	31	0.024	0.176	0.374	0.228	14
32	Gers	Auch	30	0.047	0.147	0.472	0.271	18
58	Nièvre	Nevers	30	0.014	0.133	0.163	0.282	11
52	Haute-Marne	Chaumont	27	0.018	0.105	0.309	0.308	10
15	Cantal	Aurillac	25	0.017	0.096	0.459	0.270	10
4	Alpes-de-Haute-Provence	Digne	24	0.068	0.138	0.197	0.430	16
23	Creuse	Guéret	21	0.015	0.106	0.155	0.315	11

Notes: Detailed data for each "*département*" regarding the key variables used to measure teleworking. "*Département*" code correspond to official administrative codes and the corresponding names can be found in the national statistical office (Insee) website. Density is the ratio of the population to the area in squared kilometers. Telework Index corresponds to the standardized synthetic index of teleworking that is obtained through PCA (see Section 2.2.2. The other variables are defined in Section 2.2. The main city is the French "Chef-Lieu", generally the most populated commune in the county.

FIGURE A3. Covid-19 stringency index in France



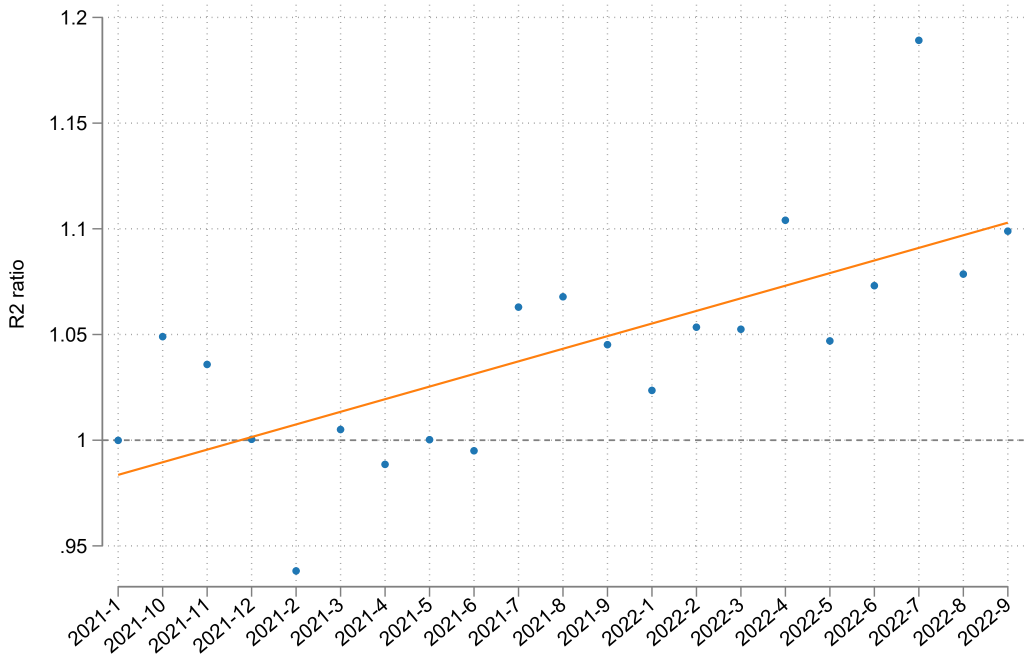
Notes: This reports the daily level of the Oxford Covid-19 stringency index that measures the intensity of government restrictions to limit the development of the pandemic. The shaded areas corresponds to the periods used to construct the measure of effective teleworking in Section 2.2

TABLE A2. Descriptive statistics transaction-based indicators

	Indicator	Num. Obs	Num. Dep	Min.	Q1	Median	Mean	Q3	Max.
Office	Price (growth in %)	1152	96	-99.01	-19.29	7.05	14.23	43.43	100.00
	Volume (growth in %)	1152	96	-95.42	-33.35	-0.09	7.52	46.64	100.00
Retail	Price (growth in %)	1152	96	-94.47	-26.22	1.39	7.76	39.87	100.00
	Volume (growth in %)	1152	96	-90.74	-27.16	3.05	11.70	46.83	100.00

Notes: Descriptive statistics on the variation of prices, rents and vacancy rates and Volume (all in %). Obs is the number of observations, Dep is the number of counties (*"département"*). Time period: 1998-2021 (top panel) and 2010-2021 (bottom panel). Transaction data have been winsorized at a maximal 100% growth rate. Source: MSCI for the top panel, DV3F for the bottom panel.

FIGURE A4. Dingel and Neiman (2020) and our index of teleworking



Notes: This Figure plots the ratio of the R2 of a regression of the occupancy rate of workplace against our index of teleworking over the R2 of the same regression but using the Dingel and Neiman (2020) index. The regression is done each month which is reported on the x-axis.

B Robustness

TABLE B1. Building level regression

	Baseline	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5
2021	0.083 (0.144)	0.090 (0.088)	0.083 (0.183)	0.083 (0.122)	0.153 (0.161)	0.077 (0.110)
2020	0.241* (0.125)	0.240*** (0.072)	0.241 (0.167)	0.241*** (0.066)	0.270** (0.123)	0.221*** (0.064)
2019	0.053 (0.123)	0.031 (0.075)	0.053 (0.165)	0.053 (0.088)	0.037 (0.118)	0.142* (0.075)
2018	0.080 (0.097)	0.071 (0.074)	0.080 (0.176)	0.080 (0.060)	0.062 (0.099)	0.050 (0.071)
2017	0.063 (0.077)	0.091 (0.066)	0.063 (0.152)	0.063 (0.061)	0.061 (0.077)	0.001 (0.047)
Sum Pre-treatments	0.723 (1.053)	0.684 (0.732)	0.723 (1.636)	0.723 (0.668)	0.581 (1.020)	0.771 (0.648)
Sum 2020q2-2021q1	1.020** (0.482)	1.022*** (0.295)	1.020* (0.599)	1.020** (0.378)	1.161** (0.475)	0.715** (0.352)

Notes: This Table reports the average value of the coefficients presented in Figure 3(a) and corresponding to the estimation of model (3) for each year. It also presents the sum of the pre-pandemics coefficients (2017q2 to 2019q4) and the sum of the coefficients focusing on the 4 quarters following the pandemics. Baseline estimates the same model as in Figure 3(a). All alternative models are described compared to this baseline. Alt 1 remove the building fixed effect. Alt 2 and Alt 3 changes the level of the clustering for standard errors by using respectively the identity of the REIF and the county. Alt 4 removes the REIF-real estate segment specific trend. Alt 5 adds a REIF times year fixed effect. $***$, $**$ and $*$ respectively indicate p-value below 1, 5 and 10% for the Student test of the nullity of coefficients.

TABLE B2. Regression using county-level stock data - alternative indexes

	Baseline **(1)**	Dingel and Neiman (2020) alone **(2)**	With fiber **(3)**	With commuting time **(4)**	With children **(5)**
Price growth	-18.821***	-12.149	-17.496***	-23.593***	-11.073
	(5.860)	(7.909)	(5.409)	(6.286)	(7.143)
Vacancy rate	28.333*	7.061	32.212**	38.286**	11.072
	(16.781)	(15.926)	(14.225)	(17.974)	(17.295)
Rent growth	1.485	1.161	3.671	1.642	-1.657
	(4.673)	(4.855)	(4.014)	(5.173)	(4.269)

Notes: This Table replicates columns 1, 2 and 3 of Table V with different measure for the index of teleworking. Each line corresponds to a separate regression. Line 1 corresponds to column 1 of Table V, line 2 to column 2 and line 3 to column 3. Column 1 is the same as columns 1-3 of Table V for reference. Column 2 uses the Dingel and Neiman (2020) index alone. Columns 3 to 5 interact the Dingel and Neiman (2020) index with each of the additional factors (the share of households connected to the optical fiber, the median travel time between work and residence for high skill workers and the share of high skill workers with a child under 18). Each factor has been transformed using an inverse logit on its standardized value (with mean 0 and standard deviation of 1). Number of observation is the same as in Table V.

TABLE B3. Construction regression - alternative indexes

	Baseline **(1)**	Dingel and Neiman (2020) alone **(2)**	With fiber **(3)**	With commuting time **(4)**	With children **(5)**
$T_c \mathbb{1}\left[t \geq 2020m5\right]$	-2.790***	-2.940**	-2.443**	-3.824***	-3.204**
	(0.955)	(1.336)	(1.055)	(1.105)	(1.270)

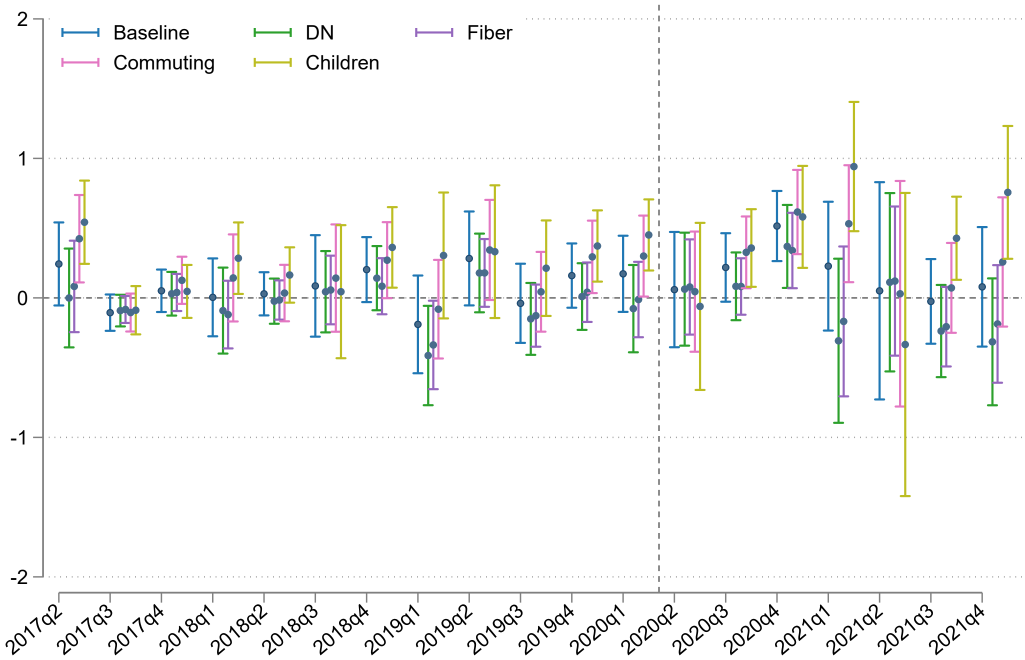
Notes: This Table replicates column 3 of Table VI with different measure for the index of teleworking. Column 1 is the same as column 1 of Table VI for reference. Column 2 uses the Dingel and Neiman (2020) index alone. Columns 3 to 5 interact the Dingel and Neiman (2020) index with each of the additional factors (the share of households connected to the optical fiber, the median travel time between work and residence for high skill workers and the share of high skill workers with a child under 18). Each factor has been transformed using an inverse logit on its standardized value (with mean 0 and standard deviation of 1). Number of observations: 9005.

TABLE B4. Regression using county-level stock data - excluding Paris

	Baseline			Excluding Paris		
	Price growth (1)	Vacancy rate (2)	Rent growth (3)	Price growth (4)	Vacancy rate (5)	Rent growth (6)
Telework index post 2020	-18.821***	28.333*	1.485	-17.434*	34.395	5.410
	(5.860)	(16.781)	(4.673)	(10.226)	(33.202)	(7.172)
R^2	0.639	0.307	0.348	0.629	0.313	0.296
N	597	606	492	501	512	404

Notes: This Table replicates Table V. Columns 1-3 reproduce columns 1-3 of Table V and columns 4-6 do the same but excludes 4 counties: Paris (75) and the three counties that constitute the suburb of Paris: 92, 93 and 94.

FIGURE B1. Building-level regression - alternative indexes



Notes: This Figure replicates Figure 3(a) but with different indicator (represented by different colors). From the right to the left: baseline; the Dingel and Neiman (2020) index alone (DN) and the Dingel and Neiman (2020) index interacted with each of the additional factors (the share of households connected to the optical fiber, the median travel time between work and residence for high skill workers and the share of high skill workers with a child under 18). Each factor has been transformed using an inverse logit on its standardized value (with mean 0 and standard deviation of 1). Number of observations: 137,870.

TABLE B5. Construction regression - excluding Paris

	Baseline			Excluding Paris		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
T_c	3.629***	4.046***		2.969***	3.651***	
	(0.930)	(0.930)		(1.022)	(0.758)	
$T_c \mathbb{1}[t \geq 2020m5]$			-2.790***			-2.288**
			(0.955)			(1.086)
R^2	0.132	0.254	0.576	0.071	0.186	0.577
N	91	91	9,005	87	87	8,610

Notes: This Table replicates Table VI. Columns 1-3 reproduce columns 1-3 of Table VI and columns 4-6 do the same but excludes 4 counties: Paris (75) and the three counties that constitute the suburb of Paris: 92, 93 and 94.

TABLE B6. Building level regression

	Baseline	Excluding Paris
2021	0.083 (0.144)	0.305** (0.155)
2020	0.241* (0.125)	0.237*** (0.108)
2019	0.053 (0.123)	0.095 (0.134)
2018	0.080 (0.097)	0.216 (0.135)
2017	0.063 (0.077)	0.074 (0.112)
Sum Pre-treatments	0.723 (1.053)	1.464 (1.260)
Sum 2020q2-2021q1	1.020** (0.482)	1.168** (0.457)

Notes: This Table replicates Table B1. Column 1 reproduces column 1 of Table B1 and column 2 does the same but excludes 4 counties: Paris (75) and the three counties that constitute the suburb of Paris: 92, 93 and 94. Number of observations: 137,870 (col 1) and 82,072 (col 2).