Telework and the Mobility of French Workers During and Post-Covid-19

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Abstract

The Covid-19 pandemic dramatically increased the uptake of telework in France, as in the rest of the world. Due to the sudden decline in commuting costs to workers when they transition to telework, teleworkers may wish to move out of high-cost, dense cities while retaining their employment and source of income. Thus, they take advantage of lower rents and amenity costs while retaining their earnings, a situation that could exacerbate inequalities between workers and lead to the redistribution of resources and income across space. This study endeavours to find direct evidence of whether such a migration of teleworkers occurred in France, with special emphasis on migration in and out of Paris. Using the *Enquête Emploi en Continu*, the paper infers mobility from the design of the survey in a novel approach and finds using visual and statistical evidence the characteristics and timing of the migration observed post-pandemic in France. Rather than the stark prediction of theory, the study finds that teleworkers and non-teleworkers moved out of Paris at similar rates during the pandemic, and that being in a middle-to-high earnings bracket increased the probability of moving out. However, telework capacity is not irrelevant to migration behaviour, as telework capacity does determine the rate of moving-into Paris in the trimesters after the first out-migration — those with jobs that can be performed from home do not return to Paris as quickly as those who cannot telework at all.

Keywords: Teleworking, Migration, Paris, Covid-19, Urban

JEL Codes: R23, J61

1 Introduction

The Covid-19 pandemic has transformed the nature of work around the world, predominantly through a dramatic shift towards working from home, or telework. France is no exception; prior to 2019, telework in France was entirely voluntary, but, increased significantly following two national lockdowns in March and October 2020. The first lockdown, though without mandate, encouraged all those with professions that could be teleworked to work from home. During the second lockdown, a national protocol mandated that all salaried employees who could perform their tasks remotely would be required to do so. This obligation coincided with some of the most severe months of the pandemic in France, and remained in force until June 2021, when it was loosened. Companies were allowed to set their own minimum telework days until December 2021, when it was announced that from January 2022 , teleworkable jobs would need to be performed from home at least three days a week. Thus, the first lockdown began the process of transition to the new work mode, which, by the second, became a norm for a large segment of the workforce.

In 2017, around 3% of the population tele-worked at least one day a week, with around half of them working only one day a week. (INSEE (2019)) Compared to this, in January 2021 the proportion of all workers tele-working at least one day a week had risen to 25%. The shift towards telework was particularly pronounced in IT-intensive jobs, with around 60% of managers and executives teleworking relative to 22% of intermediate workers.

At the same time, coinciding with the first lockdown from March 17th to May 11th, 2020, there was an observed change in population distribution across France (Galiana et al. (2020)), away from metropolitan centres such as Paris and towards smaller metropoles and rural areas. These trends are successors of previously observed distastes for larger metropoles beginning in 2019, and have also been seen to persist following 2020.

A shift to teleworking, an arrangement in which office time is minimised, reduces commuting costs for workers, and no longer necessitates that they live close to their place of work. Hence, workers that live in dense cities with high costs of amenities and housing may choose to relocate to smaller cities while maintaining their employment situation and income. If they did so, jobs would concentrate in urban centres while workers disperse away from them. Whether this has occurred following the considerably quick take-up of telework during the pandemic has been addressed in the American literature, but not directly in the literature on teleworking in France.

This question is particularly significant because teleworking intensity differs between professions and income levels. White-collar professions that require the use of information technology are more easily teleworkable, and these jobs are usually higher-paid than blue-collar jobs. Thus, the recallocation of people across space due to this migration would have implications for the distribution of resources. If the workers that earn at higher rungs of the wage ladder are better poised to move and take advantage of rent differentials across space, this could worsen inequality in the short run, as these workers have access to both lower rents and higher wages than their lower-wage counterparts in the big cities. In the long run, if teleworking persists, higher-income households moving to smaller towns may boost consumption expenditure in these areas and drive up local rents, while having the opposite effect in Paris and larger cities. The rent gradient between Paris and surrounding suburbs and smaller towns would thus flatten.

Thus, if this migration is observed, individuals with jobs that can be done from home would move out of larger cities (where their jobs are located) at higher rates than individuals with professions that cannot be done from home, in order to take advantage of the cheaper rents and other costs in smaller cities. Furthermore, these individuals should be less likely to move back after some time, as they can reasonably sustain their standard of living while living outside of the cities in which their jobs are located. In summary, the hypothesis of my study that teleworkable profession holders move out from larger cities (Paris in particular) at higher rates and move in at lower rates, indicating a general shift away from Paris.

There may, of course, be other reasons that individuals, especially higher-income individuals would stay in large cities regardless of high rents, such as the proximity to culture. These other amenities, however, would've diminished greatly in value during the pandemic, when restrictions were placed on gatherings, events and frequenting public spaces. Nevertheless, keeping this in mind, I acknowledge that any phenomenon of moving out in France may be smaller in magnitude than elsewhere.

Using the Continuous Labour Force Survey (*Enquête Emploi en Continu*) in France, in this study, I find evidence that households with members belonging to professions that are more suited to telework, and that adopted telework at higher rates in 2021, moved out of Parisian dwellings at historically unprecedented rates in 2020, and were less likely to move into Parisian dwellings in 2021. In particular, I look at the trimesters towards the end of 2020 and the beginning of 2021, which saw the strictest legally mandated telework arrangements. I also find that telework was not the only basis on which there was heterogeneity in moving in and out of Paris, and that household earnings also determined who was likelier to move out and move back in.

The study employs the Survey to answer novel questions of mobility that are not explicitly addressed in the survey questionnaire. Thus, for my study, I have inferred mobility based on changes in households within surveyed dwellings. Given that the Survey is one of the most accurate, reliable and representative data sources on individuals and their working conditions in France, and it is easily accessed, it is particularly useful that we can extract information about mobility from this dataset in particular.

The rest of this work is organised as follows: Section 2 reviews the literature on the relationship between telework and migration. Section 3 explains the context of my study and introduces features of the data and methods used. Section 4 presents a visual analysis of the patterns of migration by location and professional category that the Continuous Labour Survey reveals. Section 5 presents a regression analysis of migration rates. Section 6 conducts robustness checks and investigates my main results further. Section 7 concludes.

2 Related literature

Theoretical and empirical studies on telework have existed since the internet revolution of the 1990s. However, the scale of telework uptake during the pandemic has created an ideal setting to study how teleworking affects the economy, through the channels of migration, prices, and productivity. Aksoy et al. (2022), Barrero et al. (2021) designs original transnational surveys aimed at workers to understand the extent of WFH uptake and the degree to which workers prefer it, to estimate its potential longevity. Simultaneously during the pandemic, other papers (Couture et al. (2020), Haslag and Weagley (2022)) document migration out of big American cities to smaller ones. This migration has been named the 'donut effect' by Ramani and Bloom

(2021), as economic activity and actors shift to an outer ring around a city.

To understand the full extent of the uptake of telework, several papers have focused on understanding the heterogeneity in telework capacity across professional categories. Dingel and Neiman (2020) and Mongey et al. (2020) both estimate the ability of each of a set of occupations in the United States to be done from home, based on data from the United States Occupational Information Network, that gathers information on the essential tasks of thousands of professional positions. Using these, they create an index of the degree of telework that is possible for each job, given the appropriate infrastructure is provided.

Following this, in order to develop a theory of migration and assess its impact, Delventhal et al. (2020) create a spatial model of workers, real estate developers and firms, and then calibrate location decisions using the city parameters of San Francisco, to find that jobs remain in city centres while residents move away. They extend this model in Delventhal and Parkhomenko (2023) to account for differences in teleworking capability between jobs, and find that this new simulation robustly predicts observed movements and rent changes in the United States in 2019-22, as a result of decreased demand for inner-city housing.

The implications of this model have been observed in numerous studies in the United States. Ozimek (2020a) finds that around half of US survey respondents that worked from home were actively looking for new housing, and the later Ozimek (2020b) finds evidence of workers' moving outside of commuting distance to their workplace. The impact of this movement on house prices has been documented as well. Mondragon and Wieland (2022) find that teleworking adoption drove increases in US house prices over 2019-22. Liu and Su (2021) find that demand increased in 2020 for housing in less densely populated areas. Similar analyses have been done for commercial real estate and office space. Ling et al. (2020) find that areas with higher Covid infection rates experienced a large decrease in the abnormal returns on real estate assets, while the estimations run by Gupta et al. (2022) based on a novel asset pricing model find a potential 40 percent reduction in office space valuation in the long-run in the United States.

A significant work on the question of teleworkers migrating outside of large cities, and the impact thereof on rents and house prices, is Brueckner et al. (2021). This paper creates models for both intracity and intercity movements in the United States and uses census data to create an index of telework capacity by county. The paper finds that counties with higher telework potential saw a flattening of house price and rent gradients — implying that the declining gradient of house prices and rents as one shifts from the central business district to the suburbs weakened in magnitude, indicating that suburban accommodations became more expensive relative to city-centre accommodations. Similarly, Ramani and Bloom (2021) find that in 2021, US real estate demand shifted to suburbs, with the largest 'donut effect' in the larger cities (New York, San Francisco).

Bergeaud et al. (2021) develops a teleworkability index for France similar to Brueckner et al. (2021), which he then used to address the effects of telework on corporate real estate prices, as office space declines in value. They find a non-negligible impact of the pandemic on the corporate real estate market, with the areas in France worst affected by Covid-19 also experienced lower office real estate prices, less construction work and high vacancy rates.

To my knowledge, no similar work has been done in France directly concerning household mobility during the pandemic and its relation to teleworking. INSEE (2023) documents increased movement out of major urban centers in 2020 and 2021, and mentions this as an acceleration of a longer term trend of peripheral areas becoming more attractive places to live. Using data from La Poste, this study is able to trace an increased inflow of movements into small and mid-sized towns, and also marks the donut-shaped growth of cities as described Ramani and Bloom (2021). However, while this report theorises that telework uptake has significantly influenced this migration, more direct evidence of this is left to future work.

My study contributes to two major strands of the literature — one studying the impact of telework on household behaviour, and the second documenting the impact of the pandemic and pandemic-control measures on France.

Firstly, it makes a contribution to the growing body of work on the adoption of telework and its impact on mobility and urbanisation (Delventhal et al. (2020), Brueckner et al. (2021), Ramani and Bloom (2021)), by finding evidence of household-level movement patterns following the pandemic and the second lockdown order. The use of the Continuous Labour Force Survey allows us to understand the demographic details of movers, as well as observe the direct impact of professional category on propensity to move, rather than just the teleworking potential of an area.

Secondly, it contributes to the body of work that studies the effects of Covid-19 on France (Bergeaud et al. (2021)). Much of the existing literature on migration following the pandemic-era uptake of telework is based on the United States. The United States is unique in its size and population, and has contains several major urban centres where jobs are concentrated at comparable densities (New York City, San Francisco, etc.). On the contrary, in France, the population and white-collar jobs are relatively concentrated in the Paris and larger Île-de-France region. Therefore, migration out of dense regions and particularly Île-de-France would have significant implications for the French economy, and verifying whether this migration occurred is particularly relevant.

3 Context, data and methodology

Context

The characteristics of teleworkable jobs

Multiple studies by the Institut National de la Statistique et des Études Économiques (INSEE) document the patterns of telework and heterogeneity in the ability to telework across levels of seniority, ages and locations.

In the report Jauneau (2022), the author finds that in 2021, 55.4% of managers teleworked at least once in the week, relative to the working population average of 21.7%. The professions that teleworked more than average were public administration and corporate executives, while the professions that teleworked less than average were employees in health and social work, construction and transport services and accommodation services. Teleworkers were more likely to work at larger companies — 36% of employees in firms with 250 or more workers teleworked, compared to just 9% in companies with less than ten employees. Hence, teleworkers tend to be older, higher-level workers in larger firms with greater resources.

Teleworking is also spatially concentrated in Île-de-France, not just because the ÎDF has larger concentrations of office jobs (see Figure 1), but also because of urban density leading to greater risk of infection, therefore necessitating telework.

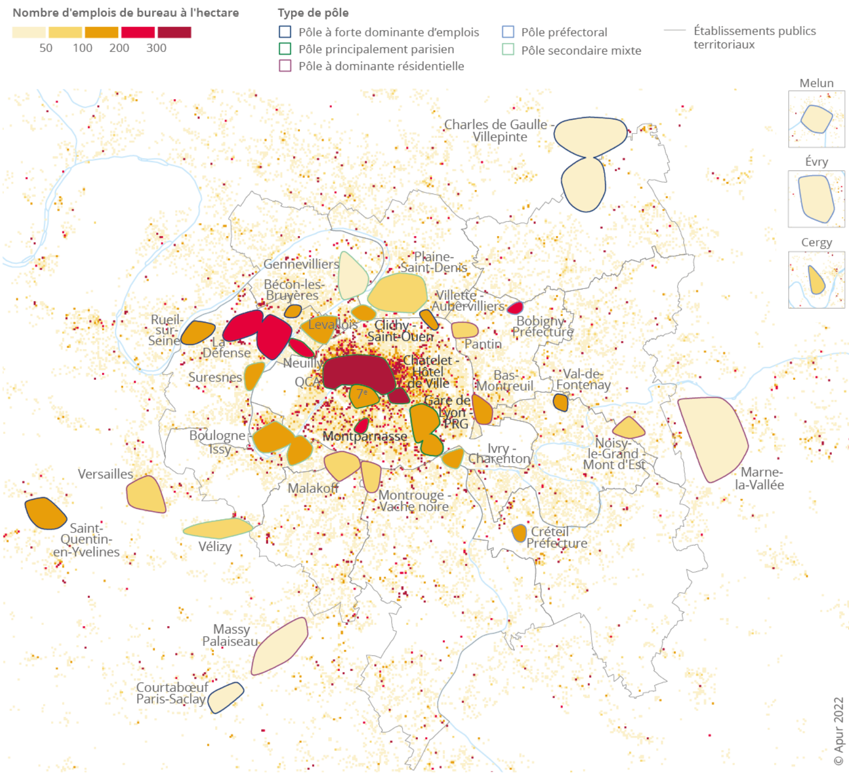


Figure 1: Concentration of office jobs in the Île-de-France region

Source: Abboudi et al. (2022)

In 2021, 56% of workers in Paris and 36% of workers in the larger Île-de-France teleworked. Even in densely populated non-ÎDF municipalities, only around 21% of workers teleworked. Therefore, in this context, if the phenomenon observed in the United States is repeated here, the direction of movement is likely to be movement away from Paris.

In the coming analysis, I observe the rates of moving in and out across two chief dimensions — telework capacity and location. Location serves as the origin when we consider movers-out, and the destination when we consider movers-in. However, the primary migration of interest is centered on Paris, given its significance in the economic geography of France. When I conduct regression analyses later in the work, I separate my sample into individuals surveyed in Paris and individuals surveyed outside of Paris. The data I use is uniquely suited to answering this question as well. While it does not record individuals' specific locations, it does record the degree of urbanisation of the surveyed area and also specifies if the area is Paris.

The timeline of teleworking mandates in France

The timeline of teleworking adoption corresponds for the most part to the timeline of complete lockdowns in France. The first lockdown in France was instated in March 2020 until May 11th, and while full-time telework was strongly encouraged for all those whose jobs could be performed from home, there were no formal mandates or laws created. Regardless, telework adoption was swift out of necessity, with 25% of French salaried workers at least partially teleworking in April 2020. The lifting of the first lockdown caused telework rates to fall significantly, with just 10% of workers teleworking in August 2020 (Batut (2022)).

Following a rise in cases, a second lockdown in France began on October 28th 2020. Alongside the announcement, the language used to refer to telework changed from an 'option' to an 'obligation' (Bissuel and Floch (2020)). A national protocol was drafted to require that 100% of working time was required to be remote, if possible. This mandate continued even after the lifting of the second lockdown in December 2020, and through to the third lockdown in May 2021.

The obligation was only softened in June 2021, wherein companies were required to determine a minimum number of teleworking days for their employees but not necessarily telework 100% of the time. Finally, this obligation too was lifted in September 2021. Towards the end of 2021, with the onset of the Omicron wave, France re-instituted a protocol of a three-days-per-week minimum telework obligations, to be enforced from January 2022 onwards.

The most intense period of protocol-mandated telework was therefore between October 2020 and June 2021. I consider this time period to be of particular interest in my analysis, and in the coming sections, we see that a significant increase in migration was observed in this period.

Data

The primary data source used is the **Enquête Emploi en Continu** (Continuous Labour Force Survey), conducted by INSEE in each week of every year. This wide-ranging, continuous survey serves primarily to measure short term changes in labour market conditions, and estimate employment and unemployment rates. The survey administers a detailed questionnaire that records the demographics of the individuals surveyed, their professional category and working conditions, and other non-work activities such as their studies or retirement. As elaborated upon in the coming section, mobility can also be identified using the survey, due to the survey design. I use survey data from years 2016 to 2021, but my years of interest are 2018 to 2021 — this is to complete the surveys of some dwellings that were recorded in 2018 but began their survey prior to this. Approximately 80,000 individuals are surveyed every year, and, alongside new rounds for previous years' interviewees, around 420,000 data points are made available every year. Some variables (such as those on professional category and urban bracket) have changed their coding in 2021, but not their definitions. Therefore, these variables have been re-coded in the analysis to be consistent with the previous years. Other data points were available in previous years but censored in 2021 (such as departments of the surveyed individuals). These have been replaced with other variables that convey similar information, and are consistently available across all the years.

To supplement my understanding of teleworking capability in France by professional category, the **'Enquête nationale sur le vécu du travail et du chômage pendant la crise sanitaire liée au Covid-19' (TraCov)** is also used. This was a national survey of around 19,000 working-age individuals conducted in January-March 2021 to measure the impact of the pandemic on working conditions and the health of workers. It contains several questions about the extent to which individuals do or desire to work from home, in addition to questions about their work satisfaction, about the sanitary measures undertaken at their workplace and whether they have ever been unemployed as a result of the Covid-related economic downturn. Though it is possible to use the EEC alone to discover which professions work from home, the TraCov provides a useful verification of the EEC's conclusions.

Methodology: identifying movers

As mentioned prior, the EEC questionnaire does not explicitly contain questions about whether households have recently moved into the house at which they are surveyed. However, it does record the round of interrogation of dwellings (the physical buildings surveyed) and households (the families and/or unrelated co-residents that live in those buildings) separately. As I elaborate upon in the following paragraphs, we can use discrepancies in the sequence of interrogation between the two to identify potential movements.

Under the EEC, dwellings are surveyed in clusters, with a new cluster being recorded every week of the year. Each dwelling is interviewed once every three months, for six consecutive rounds over one and a half years. Each time the dwelling (house or apartment) is surveyed, the round is recorded and labelled with a cluster survey rank (rang d'interrogation de la grappe or RGA). A dwelling with an RGA of 1 in 2020's first trimester therefore was interviewed for the first time in that trimester, and will be interviewed for the last time, with an RGA of 6, in 2021's second trimester.

Within each dwelling, the household is also interviewed, and assigned a survey rank. This is called the household survey rank (*rang d'interrogation de la ménage* or RGM). Notably, this is independent of the RGA. If a household is replaced in their dwelling by a new household in the middle of the dwelling survey, that new household begins its first survey with an RGM of 1 regardless of the dwelling survey round. As such, whenever a new household moves into a dwelling, the RGM 'resets'.

I aim to identify movers based on such reserts in the RGM. For example, if a dwelling's RGA (dwelling rank) and RGM (household rank) are both 1, it implies that it refers to the 'original residents' of that dwelling, or that this is the household that was first interviewed when the *dwelling* was first interviewed. The RGM may move along with the RGA following that, implying that the same household remains in their dwelling. However, if the RGM becomes 1 in an intermediate value of the RGA (2 to 6), it implies that in that round of the *dwelling* survey, a new household was interviewed for the first time. This is taken to mean that they moved into the dwelling in between the previous round and this one.

When a household moves in and the RGM resets, this naturally implies that the household that existed before it moved out. Thus, I make the assumption that the last trimester in which a household (and the individuals within) was interviewed was the trimester in which they moved out. These are referred to as *narrow* movers, as there are other households that can be assumed as movers as well (see the next section). When I account for these households that can be *assumed* to be movers, I create a *broad* mover sample.

Methodology: missing rounds

Given the breadth of situations faced by surveyors, many dwellings have missing or imperfectly reported rounds. For example, there are some that lack their first round, and some lack multiple starting rounds (approx 16%). Other dwellings lack a last or penultimate round (20%) [2]. Others have all six rounds, but do not report RGMs (24%). Given that these households make up more than half the sample taken together, it is unlikely that these are an anomaly in the data.

Dwellings with reported RGAs but not RGMs tend to otherwise contain complete information on other variables, and I therefore consider them as non-movers if there is no replacement observed (no intermediate reset of the RGM), and if the first and last RGA are reported.

However, dwellings that have no reported RGA are more relevant to my question. If a dwelling has no reported RGA, it is most likely that the dwelling could not be contacted or accessed. It is also possible that the dwelling has no resident.

Until now, the identification of movers has been rooted in the assumption that a new mover arrives immediately after an old mover leaves. However, it may be that for a trimester or more, a dwelling remains unoccupied. It may also be a freshly built dwelling that remains on the market for some time before it is first occupied.

Households that are surveyed for the first time in an intermediate round of a dwelling survey can be interpreted to have moved into an unoccupied dwelling. That is, if there is a dwelling for which RGM is 1, RGA is 3 and RGA $= 1$ and 2 do not exist, I assume that the dwelling was unoccupied for two survey rounds and was occupied in the third. Therefore, in addition to the *narrow* movers defined earlier, I also count households that are first interviewed at a third or later stage of the dwelling survey as movers-in. I use the third or later stage rather than second or later as I acknowledge the possibility that for the first round of dwelling interview, the household was not available (the occupants were not at home to take a face-to-face interview, for example). Therefore, they would not be considered movers-in. Thus, to be conservative, I consider those households that are interviewed for the first time during the *second* round of the dwelling survey as non-movers-in. In the robustness checks, I release this assumption. These

[2] This does not refer to households that are right-censored because their next rounds of survey are due to be conducted in 2022. The fact that we cannot be sure of the status of such households is explicitly dealt with in the analysis.

assumed movers, together with the movers that replaced a previous household in the dwelling are called *broad* movers.

Applying a similar logic to movers-out is less appropriate. One could consider any household that fails to complete their survey (ends the survey before RGA 6) as one that has moved out. However, a dwelling survey can end for reasons unrelated to the family moving out, such as loss of contact with the dwelling, administrative concerns, restrictions on movement or coding anomalies. Furthermore, I find that the moving behaviour of these assumed movers-out is not similar to the narrow movers-out, who are movers-out without question. In Section 4 and Appendix 4, I address the question of why I do not consider these movers-out in my analysis.

Finally, I note that a household interviewed in the first round of the dwelling survey could have just moved in — in this situation, we cannot confirm the household to be a non-mover. Similarly, in the last round of the dwelling survey, if a household is interviewed, we have no way of knowing whether they moved out and were replaced in the next trimester. Therefore, the first and last rounds of dwelling surveys are removed from the analysis, unless the first round is a mover-out or the last round is a move-in. Intermediate rows between a first and last round can be established as non-movers with certainty.

Methodology: identifying teleworkers

I now identify the group within my dataset that is likely to transition partially or entirely to working from home. This can be accomplished with the use of the MAISOC variable in the EEC, that asks whether the respondent worked from home in the reference week of the survey. The definition of 'working from home' here is very vast, and includes any job task that is done at home, even if the work contract mandates only office work. Thus, it is an upper bound on the number of individuals that work from home.

This MAISOC variable is unfortunately not available for individuals that are inactive in the labour force or unemployed. Furthermore, 61% of movers-in and 42% of movers-out lack this variable. Thus, this variable cannot be directly used to identify if a given individual teleworks or not. I use it only to gain an understanding of which professional categories are capable of working from home, and to judge the extent of adoption of telework across sectors.

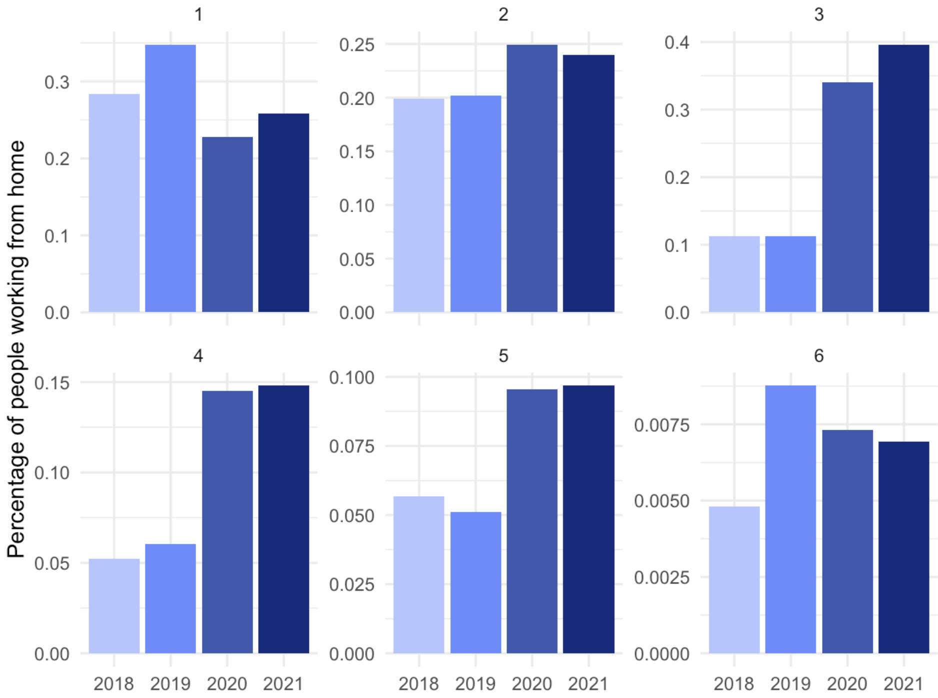


Figure 2: Proportion of workers from home in each PCS category over time

I begin with observing the rates of telework among the entire population by professional and socio-professional categories (*professionel et categories socioprofessionel* or PCS) laid out by INSEE (see Table 1 for category codes). 'Working from home' here is defined specifically as working from home for more than half of one's working hours, and thus excludes those who only do a small fraction of their job tasks at home. We also observe the same rates for socio-professional subcategories within each category of interest. Appendix A provides an explanation of subcategory codes, as well as additional figures for the other subcategories where teleworking is not expected, for completeness.

Code	Profession(s)
1	Farmers
2	Craftsmen, merchants and entrepreneurs
3	Executives and higher intellectual professions
4	Intermediate professions
5	Employees
6	Workers

Table 1: PCS1 Codes in the Enquête Emploi en Continu

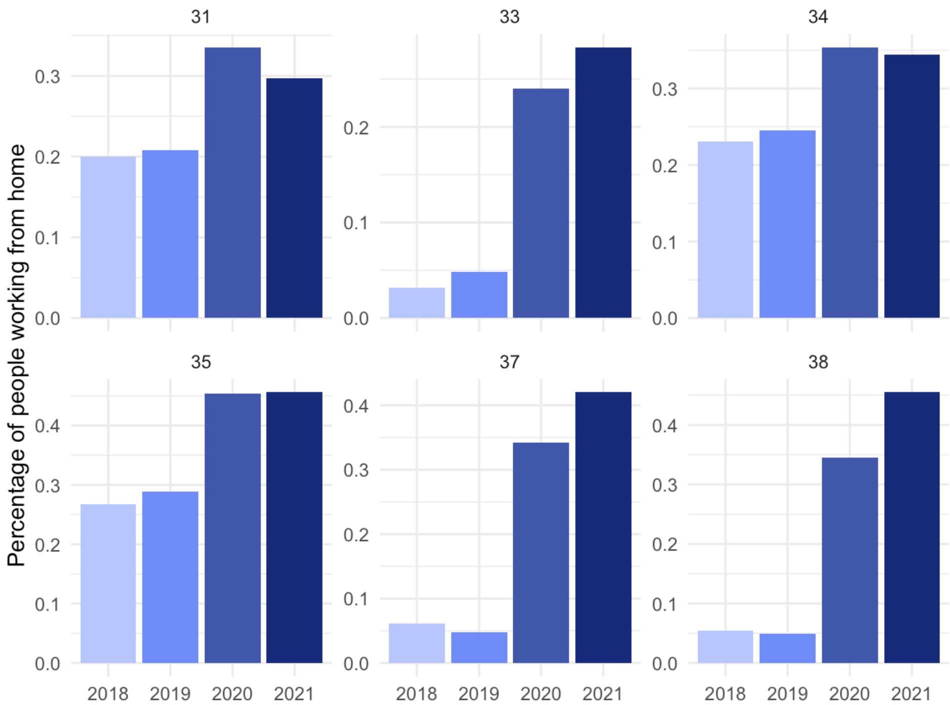


Figure 3: Proportion of workers from home in subcategories of PCS 3 over time

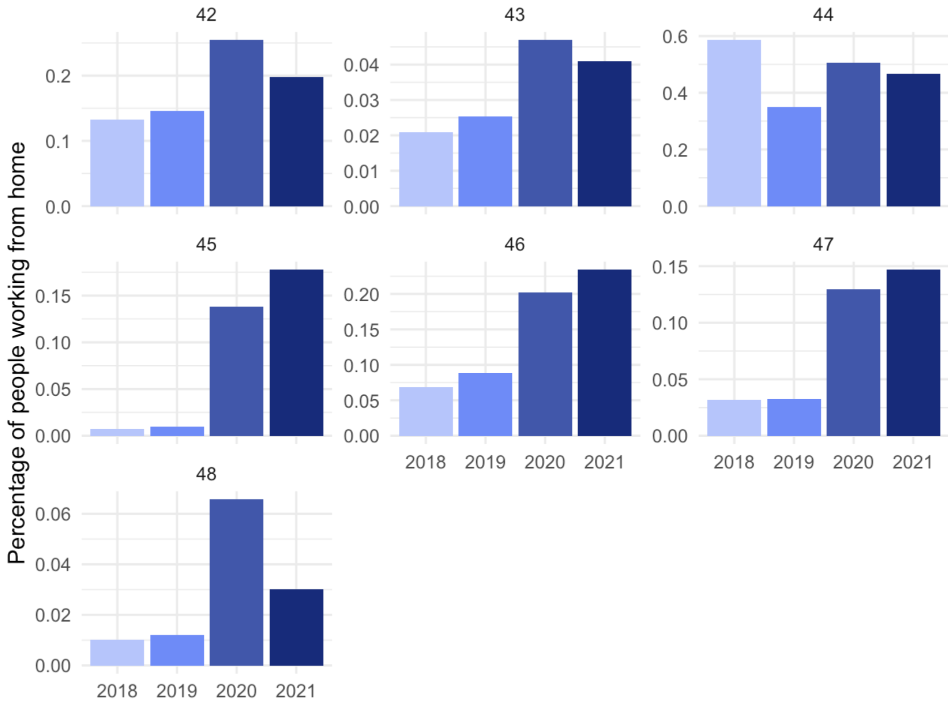


Figure 4: Proportion of workers from home in subcategories of PCS 4 over time

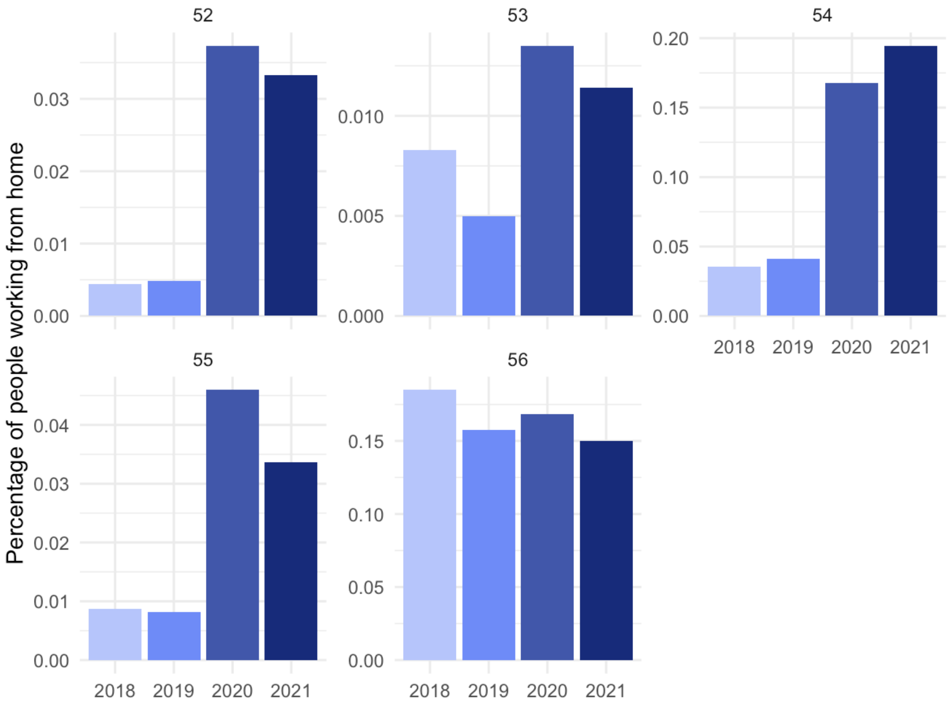


Figure 5: Proportion of workers from home in subcategories of PCS 5 over time

We see in Figures 2 to 5 that work-from-home (WFH) rates vary considerably across and within professional categories. Furthermore, the incidence of the pandemic affected different sectors' WFH rates differently. In particular, categories 3, 4 and 5, corresponding to executives, intermediate professions and salaried employees respectively, rapidly increased their rates of working from home in 2020, and this persisted in 2021 for all three categories as well. This is in line with evidence from INSEE presented prior.

Decomposing these categories further, I find that among the following professions, WFH rates have at least doubled since the beginning of Covid-19: business owners with 10 or more employees (23, pictured in Appendix B), civil service executives (33), managers of administrative and business services (37), engineers and technical company managers (38), intermediate public administrators (45), intermediate commercial administrators(46), technicians (47), non-administrative supervisors (48), public servants (52), corporate administrative employees (54), commercial employees (55). Furthermore, liberal professions (31), professors and scientists (34), information, arts and entertainment professions (35) and religious professions (44) have average WFH rates above 20% across all years, and I therefore consider these highly teleworkable as well.

In order to cross-validate this evidence, I use the TraCov survey. The results of a similar visual analysis on this data are presented in Appendix C. We find that in 2021, the WFH rate is higher than 20% for all the subcategories that experienced a doubling in WFH rates from 2019 to 2020 besides 52 and 55. In the coming analyses, I consider all the subcategories mentioned previously as teleworkable professions.

Methodology: location

The EEC does provide details on where households are situated to the level of the department, but the data available in 2021 does not contain departments to protect the privacy of the individuals surveyed. In this analysis, the specific location of dwellings is not required. Rather, it's necessary to know whether the dwelling is located in a larger urban area, a smaller urban area, or a rural area. A variable in the survey measures the urbanisation of the area in which the dwelling is located, with a specific category for Paris, and suits my needs well.

I note also that the survey extends beyond Metropolitan France to French overseas territories. As these would not exhibit the same migration patterns as Metropolitan France, they are excluded from the analysis.

I acknowledge that by the design of the survey it's not possible to record both origin and destination for a given household. Therefore, I also cannot be sure that movers moving out of, say, Paris, did not simply move to another place in Paris. There are several reasons why I believe that despite this fact, the analysis that follows is still insightful to explain movement between different types of areas (large urban, small urban, non-urban areas) rather than simply within them. Firstly, the movement rates we will see in 2020 and 2021 are historically large in *all* areas (see Figure 17) — and unprecedented high moving-out rates from Paris are accompanied with high moving-in rates in large urban areas as well. This enormous rise in movement cannot be explained solely by a rise in movement within Paris, particularly given that they coincide with periods of strict lockdowns (Nov-Dec 2020). Secondly, as I present later, the composition of the movers-out of Paris in particular does not exactly match the composition of the movers-in, indicating some degree of migration out of Paris altogether. Lastly, movement outside of Paris over the time period has also been documented in other reports (INSEE (2023) and Galiana et al. (2020)), and must therefore be at least partially captured by the moving rates the EEC provides.

4 Graphical evidence

Data profile

In this section, I present the characteristics of the data. Table 2 presents characteristics of the surveyed individuals relevant to the analysis.

Figures 6 and 7 show the professional category (Table 1) and telework capacity composition of individuals surveyed every year.

Variable of interest	2018	2019	2020	2021
Average age (in years)	50.1	49.5	49.8	46.7
Average age, movers (in years)	40.1	41.1	42.1	37.3
% Women	51.6	51.4	51.7	51.0
% Immigrants	9.3	9.9	10.2	10.3

Table 2: Summary statistics of movers

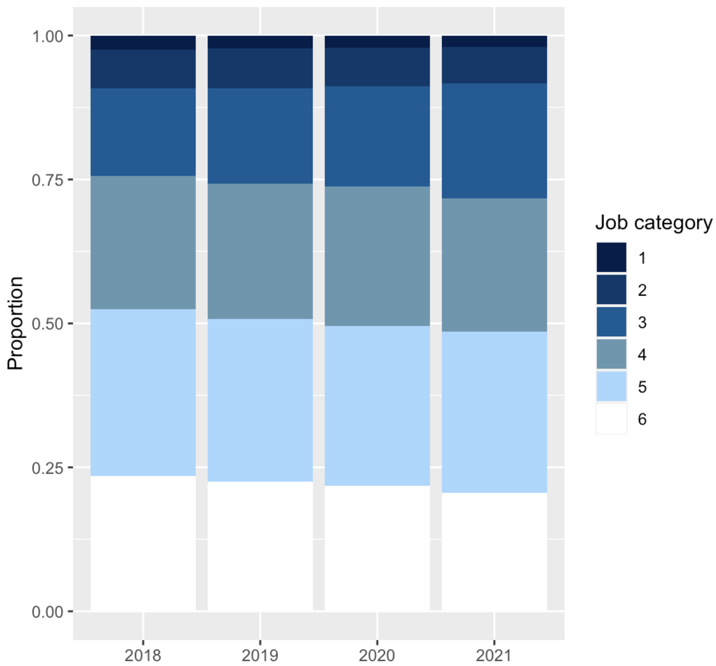


Figure 6: Proportion of individuals surveyed in each professional category per year

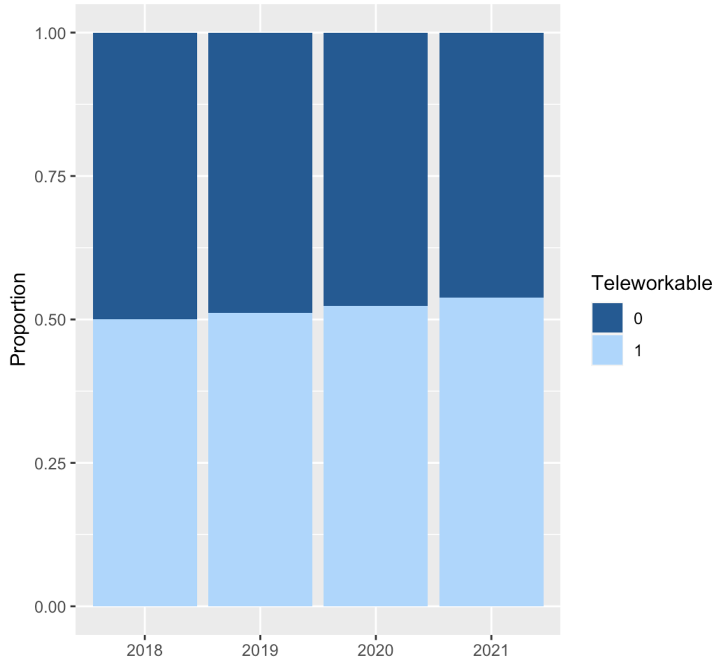


Figure 7: Proportion of individuals surveyed by occupation telework capacity per year

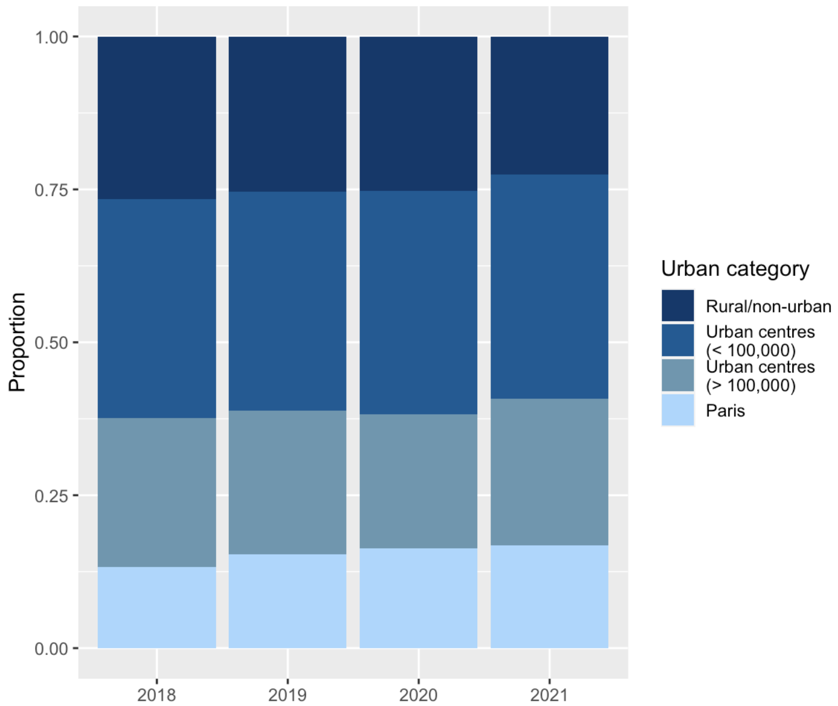


Figure 8: Proportion of individuals surveyed by location per year

Figure 8 shows the distribution of surveyed individuals by area of residence. This categorisation is elaborated upon in section 4.3.

We see that individuals over the four years are similar in terms of other characteristics besides moving rates, and any significant variation in moving rates is unlikely to be correlated with changes in the locations surveyed or the job categories of individuals.

4.1 Moving rates over time

I proceed by considering moving-in and moving-out rates across the four years, by trimester. In Figure 10, I plot the proportion of households that move in per trimester, relative to the total number of households surveyed in that semester. As mentioned earlier, I use two definitions of movers in and out, *narrow* (certain to be movers) and *broad* (contains both households certain to be movers and households assumed to be movers). Both are presented in the figure.

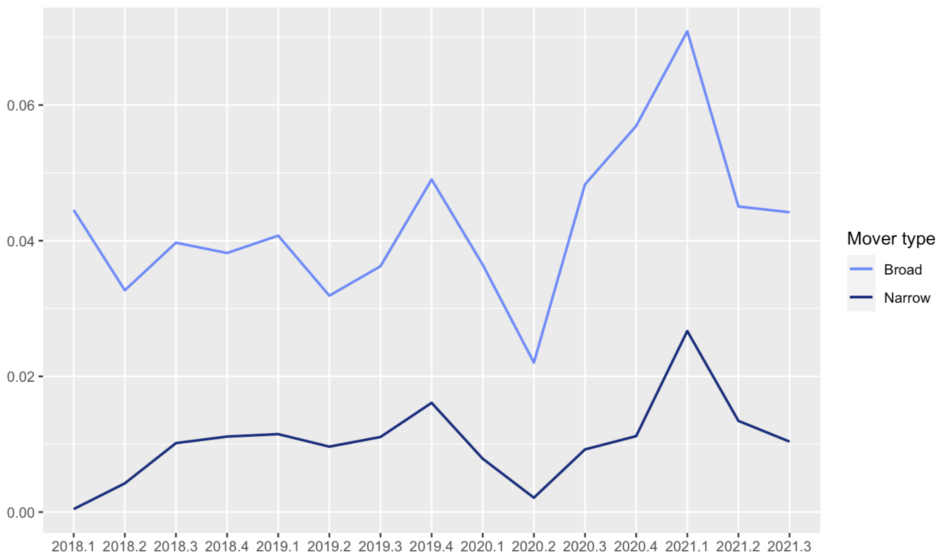


Figure 9: Proportion of individuals per trimester that move in

For these, I note that the peaks and troughs of the broad and narrow definitions of movers-in are similar, particularly from the third trimester of 2018. Given that the assumed movers follow the pattern of the narrow movers, I consider my assumption of broad movers reasonable.[3] Notably, the proportion of movers-in declines relative to the rest of the households surveyed in the second trimester of 2020, likely due to the lockdown imposed in March 2020 and the subsequent restrictions on movement. An unprecedented large proportion of households are

[3]I observe the behaviour of only narrow movers-in a robustness check.

seen to have moved in the first trimester of 2021, and as we will see, this corresponds directly to an increase in moving out in the trimester before it.

For movers-out, we display only the narrow mover-out rate. This is because the behaviour of the broad mover-out rate is unusual and indicates other data anomalies. We cannot reliably consider these movers-out. (See Appendix D for details).

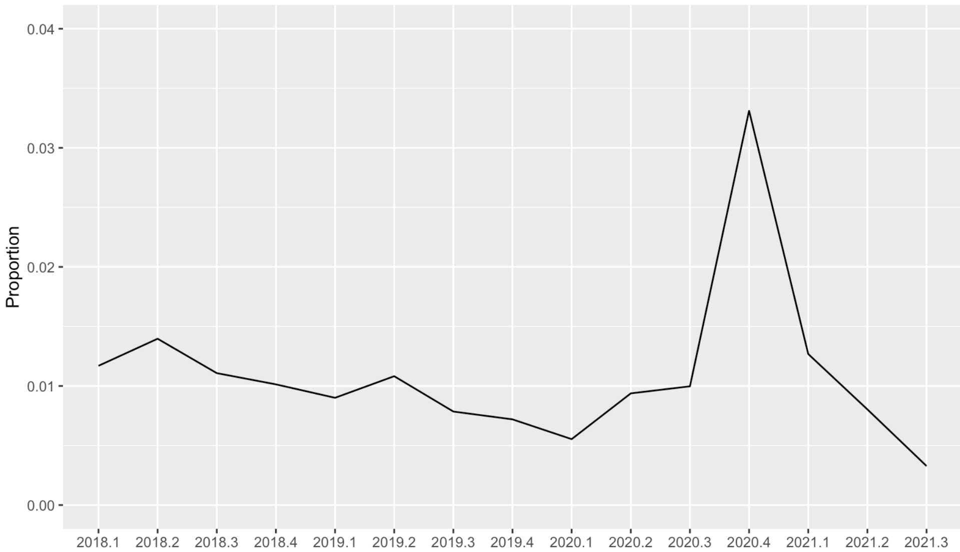


Figure 10: Proportion of individuals per trimester that move out

In magnitude, the narrow mover-out rate is similar to the narrow mover-in rate, and that the peak in the mover-out rate is exactly one trimester prior to the peak in the mover-in rate. Given that the telework mandate was instated in October 2020, this is consistent with migration following the telework mandate, and during the second wave of early 2021.

To summarise, I find that there are pronounced moving-rate changes that correspond to the specific lockdown period of October 2020 to around April 2021 (the first trimester of 2021). To gain a better understanding of which groups of people moved and from (and to) which places, I break down these moving-rates by professional category and area, which offer more nuanced interpretations.

4.2 Moving rates by professional category

I now consider moving rates by professional category, referenced in Table 1. I begin with the gross moving in rates across four of the major six occupational categories, with categories 1 and 2 excluded for clarity.

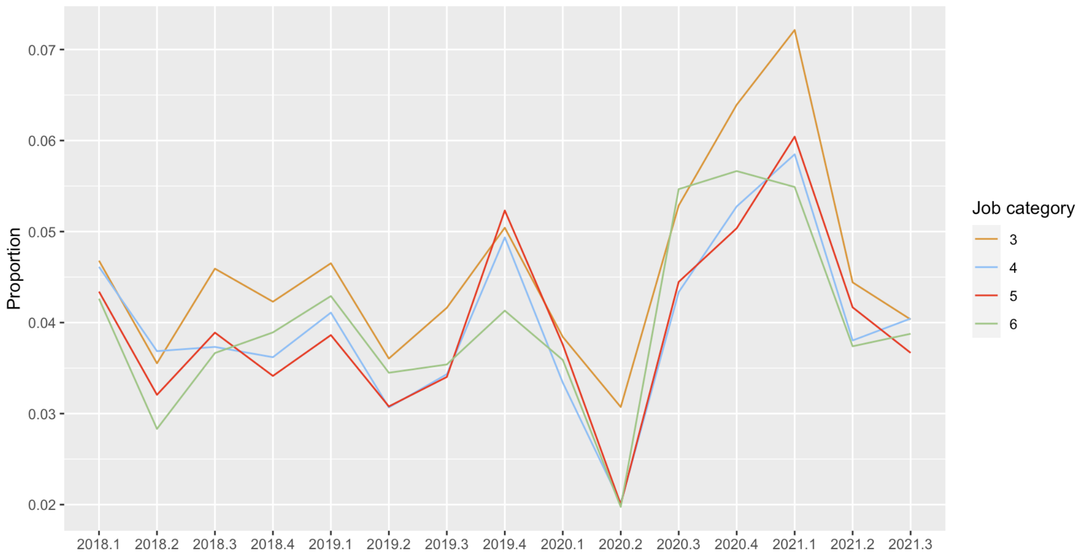
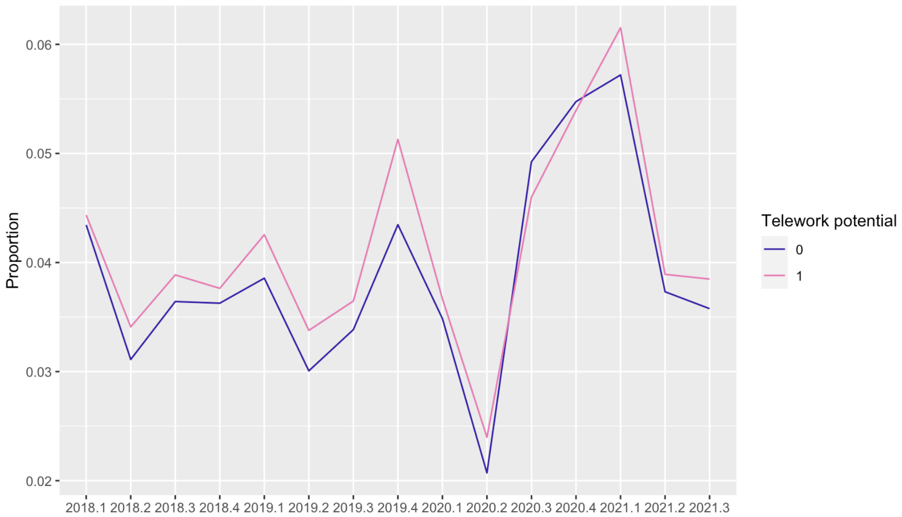
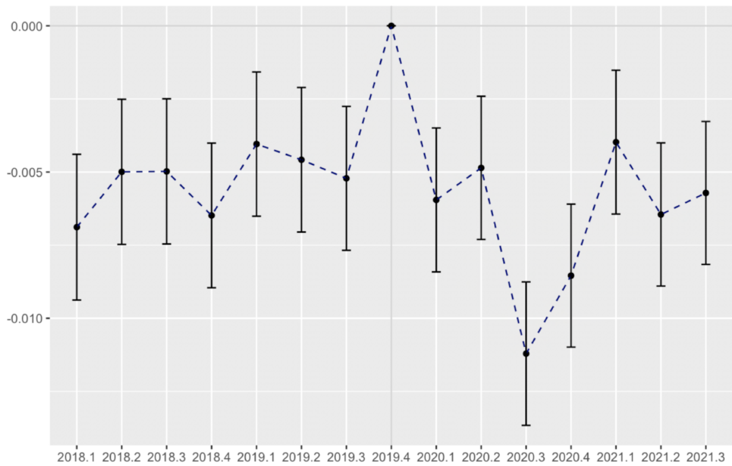


Figure 11: Proportion of individuals that move in, by trimester and professional category

We see that all job categories but Category 6 (blue-collar workers) experience a significant increase in moving-in rates over the course of 2020, peaking in the first trimester of 2021. Category 3 (executives, scientific and academic professions) has a far higher moving-in rate than even other salaried professions in 2021 T1. Interestingly, the peak in moving rates for professional category 6 comes before the peak for other job categories, and the moving-in rate is already a plateau when the other occupational categories reach their peak moving-in rates.



(a) Proportion of individuals that move in, by trimester and telework capacity



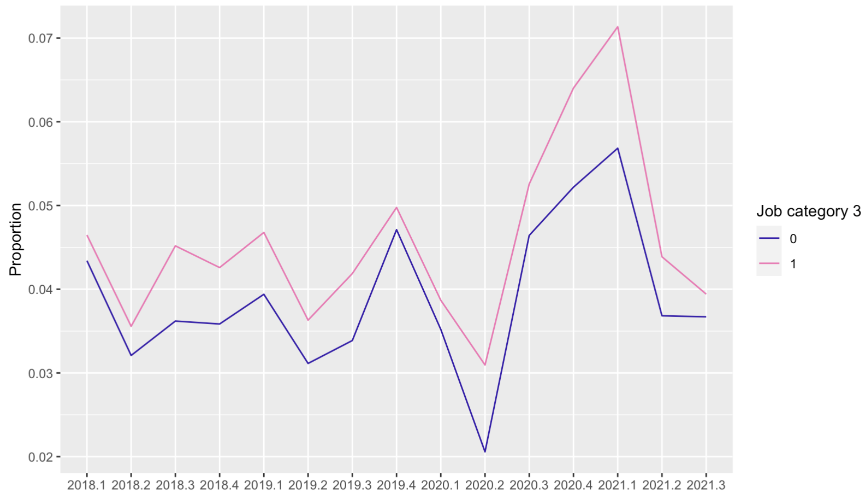
(b) Difference between telework and non-telework moving-in rates, relative to 2019 T4

Figure 12: Moving in by trimester and telework capacity

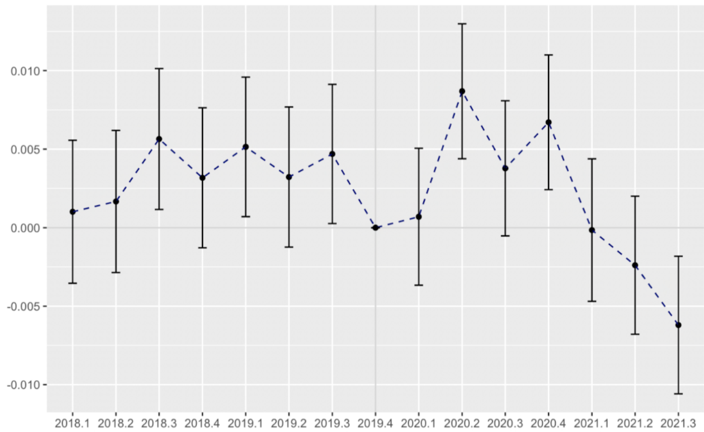
Now, I consider moving-in rates across a different categorisation — based on whether or not the job is teleworkable as per the previous section's assessment. Figure 12a presents the gross moving-in rates of the two categories (teleworkable and non-teleworkable), and Figure 12b presents the difference between the moving rates of teleworkable job-holders and non-teleworkable job-holders over time. In Figure 12b the difference between the moving-in rates in 2019.4 is normalised to 0, with the other trimesters' differences adjusted to be relative to 2019's last trimester. 95% confidence intervals are also established.

We see that the moving-in rates for teleworkable job holders are around 6.1% in the first trimester of 2021, and 5.7% for non-teleworkable job holders. The second figure above reveals, however, that this difference is not exceptional in the history of the moving rate, and is in fact smaller than the difference has been historically, with the difference between telework and non-telework moving-in rates in 2021 T1 being lower than the difference in 2019 T4.

To be thorough, I also check if the driving PCS category behind this difference is the category that is most likely to telework as per surveys — category 3 of executives, academic and scientific professions.



(a) Proportion of individuals that move in by trimester, professional category 3 and others



(b) Difference between category 3 and other moving-in rates, relative to 2019 T4

Figure 13: Moving in by trimester, category 3 and others

In Figure 13a, we see that the moving-in rates for category 3 jobs is around 7.1% compared to the other categories' 5.6% when aggregated. As per Figure 13b, we see that this difference in 2021 T1 is also greater than the historical difference between moving-in rates for category 3 jobs vis-a-vis the other categories, except in 2020 T2 (though moving-in rates were low in general in that trimester). Generally, we see that the moving-in rate for category 3 is higher than for other categories. This provides some evidence for the fact that mobility is tied to telework capacity.

With respect to **moving out**, moving rates in the first trimester of 2021 are broadly similar across category 6 (blue-collar workers), 5 (salaried employees), 3 (executives) and 4 (intermediate professions), in a range of 3% to 3.5%. It is also significant that category 6, which has the highest gross moving out rate of all categories, also is completely non-teleworkable.

In Figure 14, I find no consistent difference between moving rates by professional category, except in 2021 T2, where the moving-out rate for category 3 (executives) spikes briefly. This indicates potentially that moving out was phased out over a slightly longer period for this category relative to others.

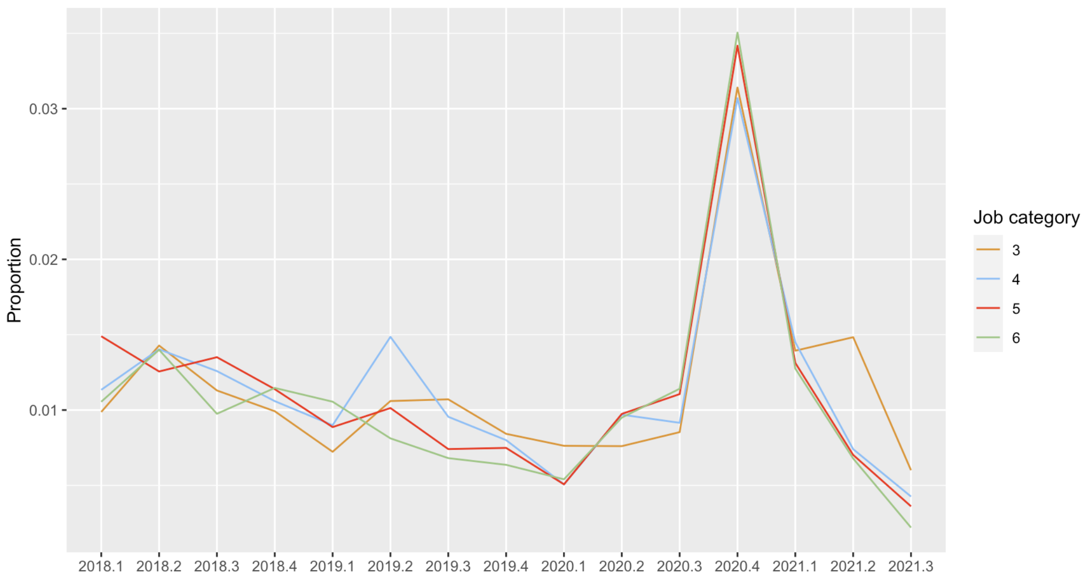
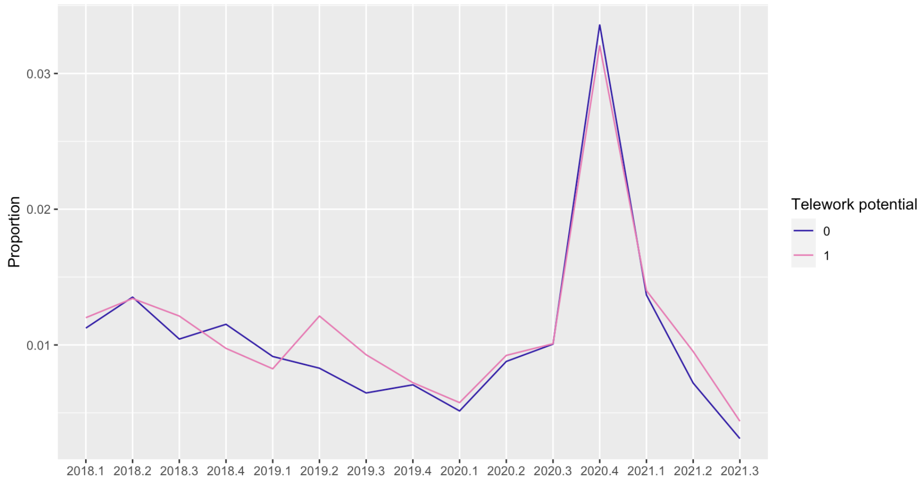
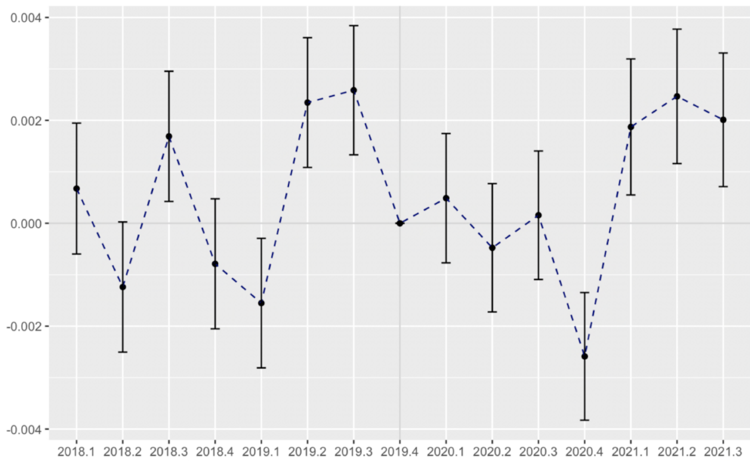


Figure 14: Proportion of individuals that move out, by trimester and professional category

I find that there is also very little discernible difference between teleworkable job-holders and non-teleworkable job holders in the year 2020, with the magnitude of differences ranging from -0.3 percentage points to 0.25 percentage points. In 2021, there seems to be a small uptick in moving-out among teleworkable job-holders, and this positive difference is significant.



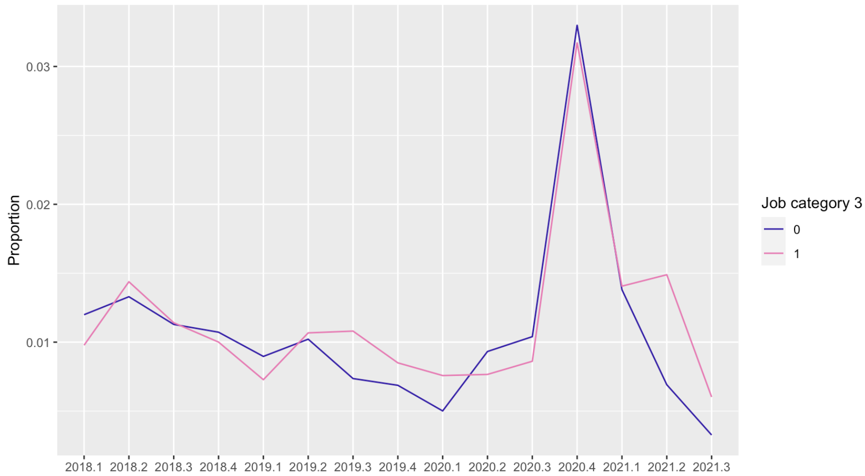
(a) Proportion of individuals that move out, by trimester and telework capacity



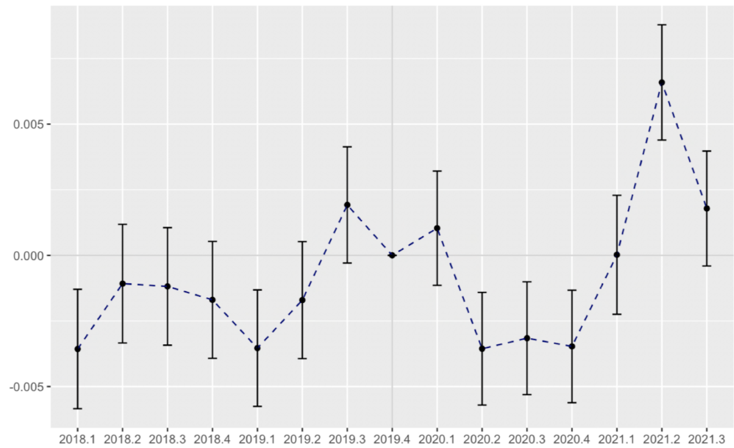
(b) Difference between telework and non-telework moving-out rates, relative to 2019 T4

Figure 15: Moving out by trimester and telework capacity

Observing the difference between category 3's gross moving-out rate and other categories, I have reason to believe that the difference between moving-out rates of teleworkables and non-teleworkables in 2021 may have been driven by a difference between category 3 (highly teleworkable) and other occupational categories. There is a significant positive difference in the moving-out rates between category 3 and other categories in 2021 T2, as observed in Figure 16b. However, this difference reduces in 2021 T3, which does not provide strong evidence for a sustained moving-out period among category 3.



(a) Proportion of individuals that move out, professional category 3 and others



(b) Difference between category 3 and other moving-out rates, relative to 2019 T4

Figure 16: Moving out by trimester, category 3 and others

4.3 Moving rates by destination

The third element of our graphical analysis is moving in and out by destination. For movers-in, this means the locations to which they move, and for movers-out, this means the locations that they move *out* of. As mentioned earlier, the survey does not contain specifics such as the city where a dwelling is located. Rather, it measures urbanisation of the area in which a dwelling is located based on the urban unit zoning defined in (Costemalle et al. (2023)) — assigning each dwelling a value of this variable based on the population of the area it is located in. The details of the original classifications are in Appendix E. For my purposes, I use the definitions in Table 3, for a simple aggregation. Category two includes the 40 largest cities in France besides Paris as of 2019 (INSEE (2022)), and category 1 contains cities and towns large enough to be called urban but still relatively small.

Code	Urban category
0	Non-urban (rural areas)
1	Urban, population between 2,000 to 99,999 inhabitants
2	Urban, population between 100,000 and 1,999,999 inhabitants
3	Paris

Table 3: Urban categories constructed for analysis

Figures 17 and 18 depict gross moving-in and moving-out rates by urban category. I consider movers-in first.

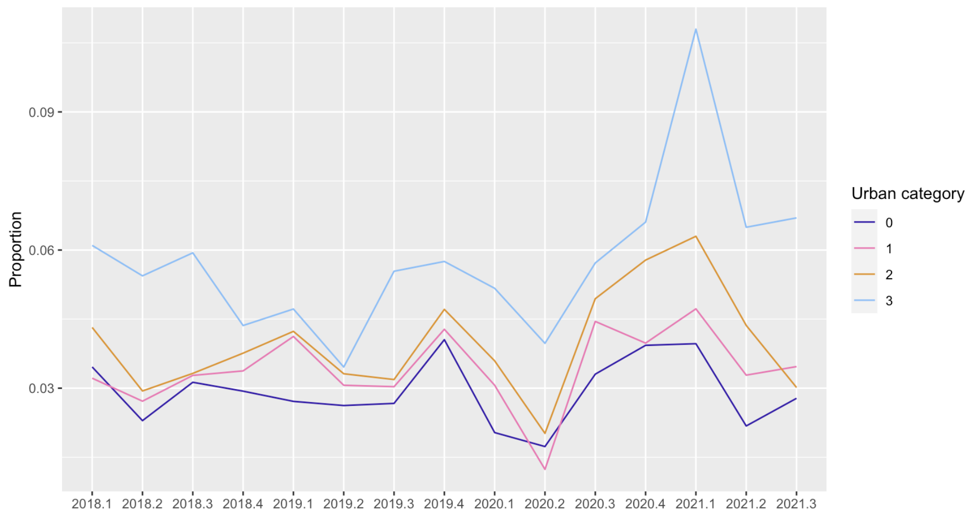


Figure 17: Proportion of individuals that move in, by trimester and urban category

The moving-in rate for Paris is consistently higher than other metropolitan cities and rural areas, indicating a high and consistent demand for Parisian dwellings across time. In 2021's first trimester, the moving-in rate is highest for Paris, but also peaks for Category 2, large cities besides Paris. For the other categories, namely smaller urban centres and rural areas, the moving-in rate is analogous to but not greater than the highest it has been in the past. The most interesting observation here is for urban category 2. Not only does it increase beyond its historical maximum in 2021's first trimester, this trimester also marks a divergence in moving-in rates from category 1 (smaller towns). There is evidence therefore of increased demand for housing in these larger towns in 2021, and that this demand started rising in the latter half of 2020.

We now consider moving-out rates.

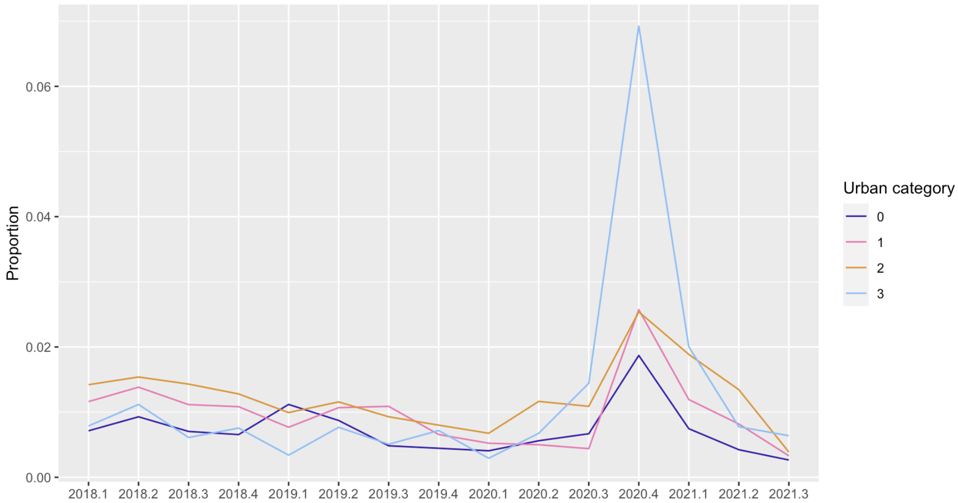
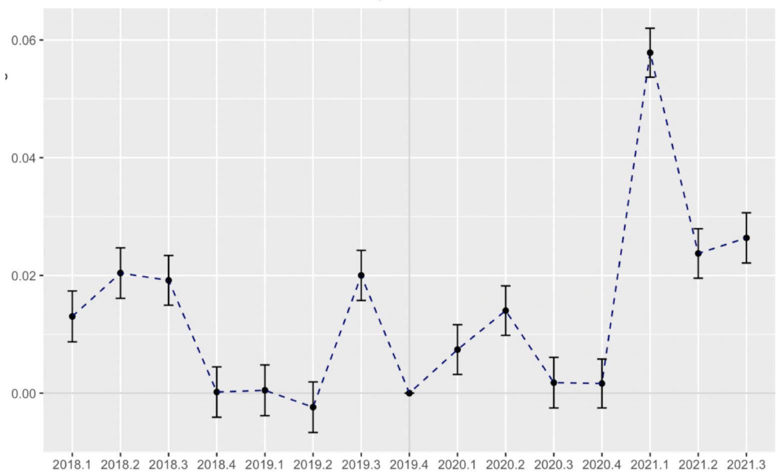
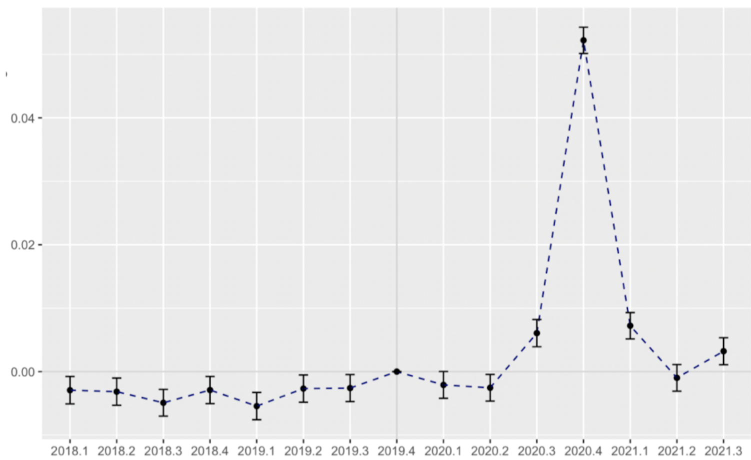


Figure 18: Proportion of individuals that move out, by trimester and urban category

The difference in moving out rates between Paris and other urban centers is far more pronounced in 2020's last trimester than the difference in moving-in rates. The moving-out rate for Paris in this trimester is around 7%, while the other urban categories see moving out at rates between 1.8% and 2.5%. This is especially notable considering that unlike for moving-in rates, the moving-out rates of Paris have historically not been significantly different from other urban categories prior to 2020's last trimester. This is evidence of a considerable increase in movement out of Parisian dwellings in this trimester. Furthermore, given that the population of Paris is considerably larger (2.1 million approx.) than even the second largest city in France (Marseilles, 870,000 approx.), this shows that the vast majority of movers-out across France were from Paris in this trimester. This is also in line with evidence presented in previous sections (INSEE (2023)) of a large migration out of Paris in 2020.



(a) Difference between Paris and other urban categories' moving-in rates, relative to 2019 T4



(b) Difference between Paris and other urban categories' moving-out rates, relative to 2019 T4

Figure 19: Differences between Paris and other urban categories moving rates

Presented in the above are the differences between the moving-in and moving-out rates for Paris and non-Paris urban areas, and these serve to reinforce my observations from the gross moving rates. Moving-in rates as well as moving-out rates seem to be significantly higher for Paris during the pandemic years, particularly in 2020 T4 (for moving out) and 2021 T1 (for moving in). If these spikes represent the same group of people, then there is little merit to studying further if telework capacity is related to this migration. As I establish in the coming sections, this is not the case, and there are other characteristics that make the out-migrating and in-migrating groups different.

4.4 Moving rates by destination and professional category

I now consider moving rates along all three axes — time, teleworking capacity and urban category. This is to isolate visually the specific occupational categories that move and to trace the direction of their movement more accurately. In the following figures, red bars represent the time before the the pandemic turning point of interest, which I take as 2021's first trimester for movers-in and 2020's last trimester for movers-out. Dark bars correspond to non-teleworkable occupational categories while light bars correspond to teleworkable job categories. The bars are arranged in groups representing each of the four urban categories. Figure 20 presents moving-in rates.

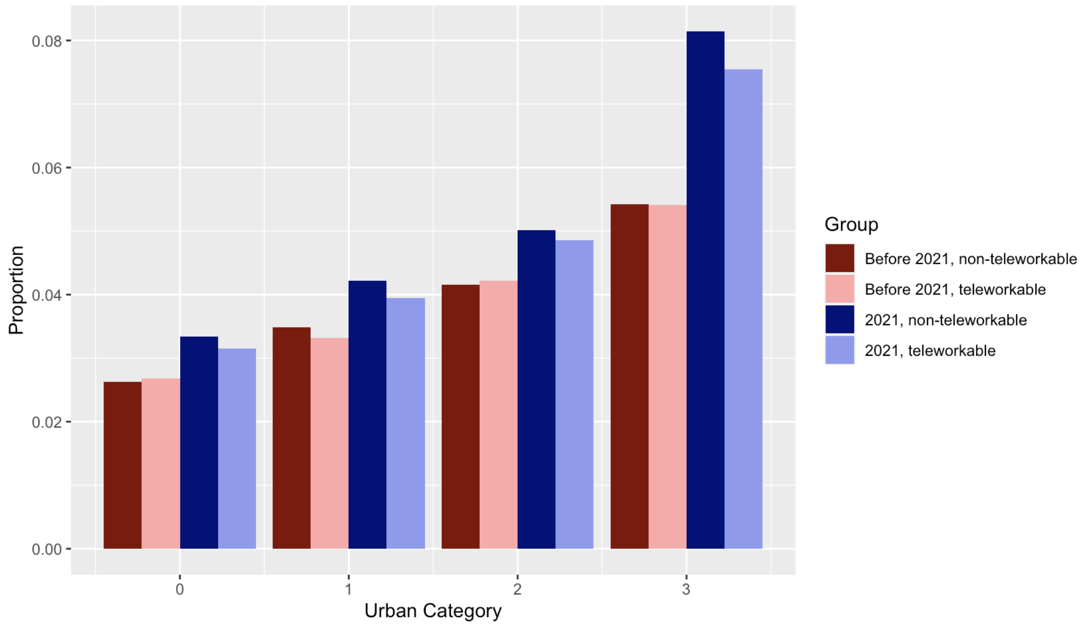


Figure 20: Proportion of individuals that move in, by trimester, telework capacity and urban category

Similar to our findings in Figure 17, moving-in rates among both teleworkables and non-teleworkables are highest in Paris (the right-most pair of bars). Prior to 2021, the rate among teleworkables was around equal to the rate among non-teleworkables, but this changes in 2021. In other words, before 2021, there were an equal proportion of movers-in among those who had teleworkable professions than among non-teleworkable professions. However, in 2021, a teleworkable profession holder in Paris was *less* likely to be a mover-in than a non-teleworkable profession holder.

I saw previously in Figure 13a that while there was a small difference between teleworkables and non-teleworkables in moving-in rates across time, there was a larger difference between professional category 3 (henceforth, executives) moving-in rates and the rest of the categories' aggregated moving-rates. I thus also examine the above figure separating executives from the rest.

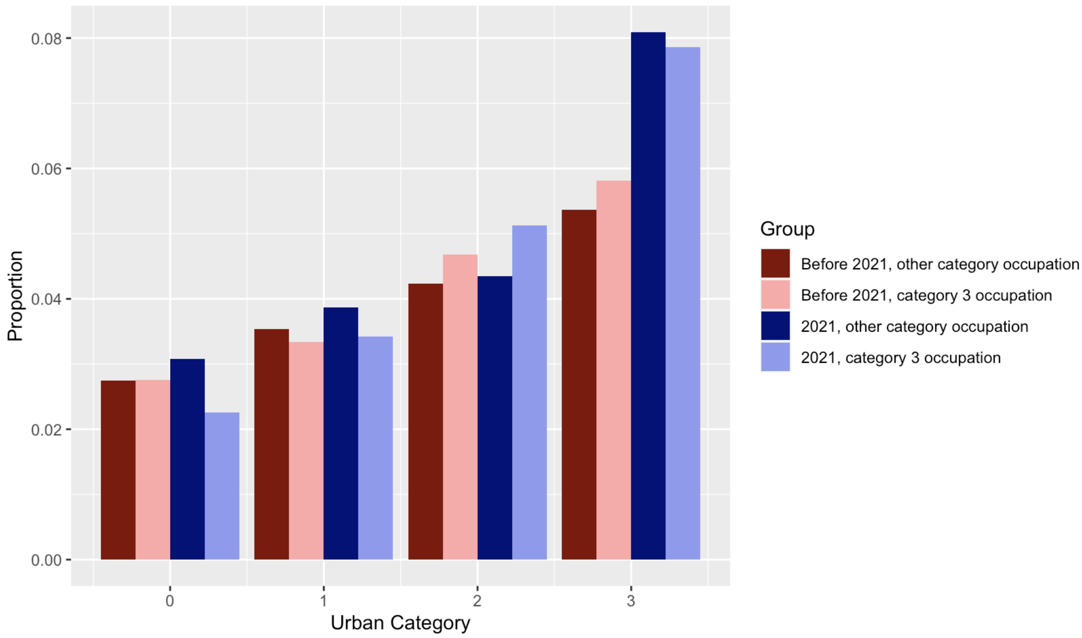


Figure 21: Proportion of individuals that move in, by trimester, professional category and urban category

In Figure 21, prior to 2021 (red bars), moving-in rates among professional category 3 have been higher than other aggregated professional categories in larger towns (urban category 2) and in Paris (urban category 3). However, in 2021, the moving-in rate for these professions in category 3 is higher than for other professional categories in large cities, while being lower in smaller cities and in Paris. This is potentially indicative of a high demand for dwellings in larger towns (but not Paris, urban category 2) among executives, scientists and academics, rather than other professional categories. Furthermore, when considering executives relative to other professions, the gap between moving-in rates to Paris (the blue bars, right-most) shrinks compared to the previous figure of teleworkables and non-teleworkables. Thus, non-executive teleworkables also moved-in less into Parisian dwellings in 2021.

We now consider movers-out. As we have seen, moving out peaked in the last trimester of 2020. Therefore, we adjust our time horizon slightly, to be before the 4th trimester of 2020 (henceforth, 2020:4) and after. Figure 22 shows moving out rates.

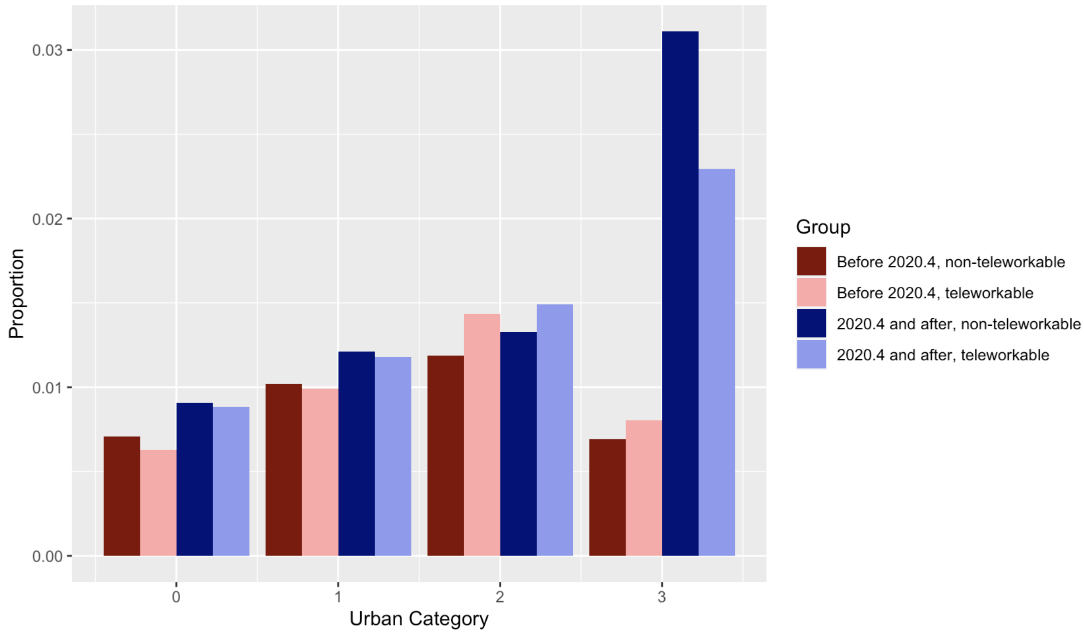


Figure 22: Proportion of individuals that move out, by trimester, telework capacity and urban category

As observed also in Figure 18, Paris' moving-out rate in 2020:4 far exceeded the moving-out rates of other urban categories, as well as the Paris moving-out rate prior to 2020:4. This is repeated here, and it appears that the sharp increase in the moving-out rate in Paris was driven largely by non-teleworkables rather than teleworkables. This means that non-teleworkables were more likely to leave Paris after 2020:4 than non-teleworkables. I also note that this pronounced difference between the teleworkable and non-teleworkable categories is found especially in Paris after 2020:4, not in other urban categories.

To summarise the general findings from this section:

- The peak in moving-out was observed in the last quarter of 2020, and the peak of moving-in was exactly the next trimester, 2021 T1. This period also coincides with the second lockdown in France and the strict teleworking mandate.

- Moving rates are low in early 2020, likely a result of the first lockdown in France.

- The visual evidence of moving-in rates by professional category suggests that professional category 6 (blue-collar workers) began to migrate a trimester before other job categories.
- Professional category 3 (executives) appears to have slightly higher mobility, particularly in 2021.
- Paris experienced both the highest rates of moving out as well as the highest rates of moving in during the pandemic.
- Movement out of Paris during the pandemic seems to be driven by those who *do not* telework, rather than those who do.
- There is slight evidence for a shift away from Paris among professional category 3 in 2021 (as in Figure 21 where the moving-in rate for large cities is higher for category three relative to other categories).

The theory discussed in the American literature implies that those with teleworkable jobs should leave large cities in larger proportions than those without such jobs. Some aspects, such as executives having higher mobility, and having a preference for smaller cities than Paris during the pandemic, are in line with this. However, the driving force of the moving-out rate in Paris being non-teleworkable jobs is unusual, and implies we may be confounding two different types and motivations for movement if we observe moves out of Parisian dwellings without considering the characteristics of the individuals that move out. To amend this, we turn more precise tools of analysis in linear regression.

5 Regression results

Graphical analyses allow me to gain a broad picture of what to expect in moving dynamics across urban and job categories. To be more concrete, I use regressions to check the statistical significance of my findings, and find subtle differences between groups of individuals that move. As elaborated upon below, I use a triple DiD analysis with controls and fixed effects.

5.1 Moving in

The model I use is as follows:

$$\begin{aligned} MOVEIN_{it} = \alpha \ + \ \gamma_i \ + \ \lambda_t \ + \ \beta_1 TELEit \ + \ \beta_2 POST2021_t \ + \ \beta_3 PARIS_{it} \\ + \ \beta_4 TELE_{it} \cdot POST2021_t \ + \ \beta_5 POST2021_t \cdot PARIS_{it} \ + \ \beta_6 TELE_{it} \cdot PARIS_{it} \\ + \ \beta_7 TELE_{it} \cdot POST2021_t \cdot PARIS_{it} \ + \ X_\delta \ + \ \varepsilon_{it} \end{aligned} \quad (1)$$

where $TELE_{it}$ takes the value 1 if the individual's job is teleworkable (0 otherwise), $PARIS_{it}$ is a location marker[4] and $POST2020_i$ is a time marker. $PARIS_i$ here corresponds to urban category 3 only, with the reference category being the aggregation of rural areas, small towns and larger towns besides Paris. I introduce fixed effects based on trimester (λ),, and dwelling (γ) (some dwellings may be suited to temporary stays, such as hostels). The controls (X_δ) included are age, citizenship status, martial gender, number of children in the household, and employment status, (See Table 4). Standard errors are clustered at the household level.

I suspect that the impact of some controls in my regression (namely age, marital status and the number of children) may have different impacts after the Covid-19 shock — for example, individuals with children may find it easier to make a relocation decision after the shock because of online schooling. Similarly, older people may particular want to avoid dense areas after the shock, due to being at higher risk of illness. Therefore, I intersect the controls governing family structure — marital status and the number of children, as well as age with the time dummy.

By this equation, the reference individual is an individual working outside of Paris before 2020 in a non-teleworkable job. I interpret the covariates as affecting the *probability* that an individual is a mover-in in a given location at a given time. β_7 is the coefficient of interest.

The regression results are placed in Table 4. If the reference individual worked in Paris post 2020 instead, all else equal, he would be 5.5 percentage points more likely to be a mover-in. If he was in a teleworkable job, he would be only 3.3 percent more likely to be a mover-in, indicating a small but significant difference in likelihoods of moving in for the two types of workers. There is no significant difference in the probability of being a mover for the reference individual compared to someone with a teleworkable job in Paris at the same time, or who someone with a teleworkable job outside of Paris after 2020.

[4]In the results, the effect of living in Paris is absorbed as part of the household fixed effects.

Table 4

	Dependent variable:
	MOVEIN
TELE	−0.001
	(0.001)
POST2021	0.026***
	(0.003)
UNEMP	0.001
	(0.001)
INACTIVE	−0.002***
	(0.001)
AGE	−0.001***
	(0.00003)
MARRIED	−0.023***
	(0.001)
FEMALE	−0.002***
	(0.0004)
IMMIGRANT	0.005***
	(0.001)
CHILDREN	−0.006***
	(0.001)
POST2021:AGE	−0.0003***
	(0.00004)
POST2021:MARRIED	−0.043***
	(0.002)
POST2021:CHILDREN	0.003***
	(0.001)
TELE:POST2021	0.001
	(0.001)
TELE:PARIS	0.003**
	(0.002)
POST2021:PARIS	0.055***
	(0.003)
TELE:POST2021:PARIS	−0.022***
	(0.003)
Observations	696,140
R^2	0.004
Adjusted R^2	−0.271
F Statistic	189.417*** (df = 16; 545772)
Note:	*p<0.1; **p<0.05; ***p<0.01

5.2 Moving out

I use a similar model to understand the behaviour of movers-out, only changing the time marker to be centred around the last trimester of 2020, rather than the beginning of 2021, due to the spike observed in the data in the last trimester of 2020. Fixed effects and controls (as well as the intersected controls) are identical to the previous analysis.

$$\begin{aligned} MOVEOUT_{it} = \alpha \; + \; \gamma_i \; + \; \lambda_t \; + \; \beta_1 TELEit \; + \; \beta_2 POST2020.4_t \; + \; \beta_3 PARIS_{it} \\ + \; \beta_4 TELE_{it} \cdot POST2020.4_t \; + \; \beta_5 POST2020.4_t \cdot PARIS_{it} \; + \; \beta_6 TELE_{it} \cdot PARIS_{it} \\ + \; \beta_7 TELE_{it} \cdot POST2020.4_t \cdot PARIS_{it} \; + \; POST2020.4.X_\delta \; + \; \varepsilon_{it} \end{aligned} \tag{2}$$

The results are presented in Table 5. Since the numbers of reliable movers-out in my data are far fewer than those of movers-in, the magnitude of the impact is much smaller.

Relative to the reference individual, an individual who lives in Paris after 2020.4 is more likely to move out by 1.4 percentage points. Being in a teleworkable job does not change this measure. The probability of moving out is not significantly different from a person with a teleworkable job to a person with a non-teleworkable job, across the period of 2020 T4 and 2021.

This directly contradicts my hypothesis that those with teleworkable jobs would be more likely to leave Paris. I investigate this finding further in the next section.

Table 5

	Dependent variable:
	MOVEOUT
TELE	0.0003
	(0.0004)
POST2020.4	−0.047***
	(0.002)
UNEMP	−0.002**
	(0.001)
INACTIVE	0.0003
	(0.0005)
AGE	0.0003***
	(0.00002)
MARRIED	0.015***
	(0.001)
FEMALE	0.001***
	(0.0003)
IMMIGRANT	−0.002***
	(0.001)
CHILDREN	0.009***
	(0.001)
POST2020.4:AGE	0.0005***
	(0.00003)
POST2020.4:MARRIED	0.037***
	(0.001)
POST2020.4:CHILDREN	0.001**
	(0.001)
TELE:PARIS	−0.0004
	(0.001)
TELE:POST2020.4	−0.0001
	(0.001)
PARIS:POST2020.4	0.014***
	(0.002)
TELE:PARIS:POST2020.4	−0.001
	(0.002)
Observations	696,140
R^2	0.004
Adjusted R^2	−0.271
F Statistic	239.525*** (df = 16; 545772)
Note:	*p<0.1; **p<0.05; ***p<0.01

6 Robustness checks and discussion

6.1 Robustness checks

To check the robustness of my findings, I change some specifications and previously made assumptions. In total, I conduct three robustness checks.

6.1.1 Changing the definition of movers-in

As specified in Section 3's methodology and Section 4, I assumed households that lacked at least two starting rounds of their dwelling survey had moved into an empty dwelling, and thus, could be included in the group of movers-in. I based this on missing two starting rounds rather than just one, as it was possible that in the first round, a present household was unavailable, rather than the house being empty. I rerun the analysis two times in Table 4 with the following changes — first, I consider only narrow movers-in, rather than those assumed to be movers-in, and second, I broaden the definition of movers-in to include individuals that miss *only* their first round of survey among movers.

From the analysis of narrow movers-in (see Appendix F), I find that the direction and significance of the relevant coefficients are unchanged. Compared to the reference individual, a teleworkable job-holder in Paris in 2021 is 4.6 percentage points more likely to be a mover-in, while a non-teleworkable job-holder is 6.5 percentage points more likely to be a mover-in. Hence, there continues to be a disparity between moving-in rates for non-teleworkable job-holders and teleworkable job-holders.

From the analysis of even broader movers-in (see Appendix G), I find a weaker effect than in Table 4, but one that remains significant and in the direction of the main analysis. That is to say, the teleworkable job-holders move into Paris after 2021 at lower rates than non-teleworkable job-holders. The difference between moving-in rates, however, is 1 percentage point, compared to the main analysis' 2.2 percentage points.

6.1.2 Changing my time frame

Next, with reference to the main analysis, I shorten my time-frame to exclude the year 2018 entirely, treating 2019 as my reference year for pre-Covid analysis. Then, I rerun the main analyses' regressions as per the specifications of the analyses in section 5. These results are presented in Appendices H and I.

My results regarding both movers-in and movers-out are in line with the main analysis results when the time-frame is shortened. For movers-ins, non-teleworkable job holders living in Paris in 2021 are 5.8 percentage points more likely to be movers-in than the reference category, while teleworkable job holders living in Paris in 2021 are 3.4 percentage points more likely.

For movers-out, the probability of moving out is not significantly different between teleworkable job-holders post 2020.4 in Paris and non-teleworkable job-holders post 2020.4 in Paris, as in the main analysis. Relative to the reference category of living outside of Paris prior to 2020.4, an individual living in Paris after 2020.4 is 1.3 percentage points more likely to move out of their residence (identical to the conclusion of the main analysis), and this does not differ for those with teleworkable jobs and those without such jobs.

6.1.3 Household telework capacity vs. individual telework capacity

In my main analysis, telework capacity is based at an individual level, based on each individual's professional category. However, I acknowledge that moving decisions could also be based on the entire household's ability to adapt to telework, rather than its individual members. Therefore, I generate a telework capacity for each household based on the average of the telework capacity of the individual members, and rerun the regressions in Tables 4 and 5 using this continuous definition of telework capacity. The results are placed in Appendix J and K.

My results regarding both analyses are in line with the main analysis, even given a continuous definition of the telework variable. An increase in the teleworking capacity of a household post-Covid in Paris makes it less likely that they have just moved in. Similarly to my main result, telework capacity of the household seems to have no effect on individuals moving out of Paris post the Covid shock.

6.2 Discussion and further investigation

Based on the pattern presented in the graphs as well as in the regression findings, movers-in and movers-out do not perfectly parallel each other. While there is evidence to suggest that those with teleworkable jobs were less likely to move into Parisian dwellings after 2021, there is no evidence to suggest that they were more likely to move out of Parisian dwellings in 2020.4, specifically explained by their ability to telework. As evidenced in Table 5 as well as Figure 22, non-teleworkables left Paris at similar rates to teleworkables.

Given that we have not been able to find an effect of teleworking on moving out of Parisian dwellings post the Covid shock, it is pertinent to consider other factors that may affect whether an individual moves out of Paris during the pandemic. Furthermore, we know that moving rates (both in and out) are highest for Paris. If the groups of movers-out and movers-in are different in composition to each other, we can infer some underlying motivations for migration.

For this, I investigate different bases on which people move out of Paris, which may then also serve as a foundation to characterise the group that is likelier to move into Paris one trimester later. In particular, I look at professional categories and salary quartiles.

6.2.1 Moving-out by professional category

To investigate whether moving-out of Paris post-Covid differs by professional category, I run another analysis interacting professional category as per Table 1 with the $POST$ and $PARIS$ variables. Table 6 presents a condensed version of the results that provides relevant insights. The full results can be found in the Appendix L (Table 18).

Here, the reference individual is a non-manager white-collar employee (professional category 5) living outside of Paris before 2021. We see that three categories (2, tradesmen, 4, managers and 6, blue-collars) have moving-out rates from Paris after 2020.4 that are not significantly different from the move out rates for employees. Two categories, however, have lower moving-out rates, which are farmers (category 1) and executives (category 3). Relative to employees living in Paris in 2020.4 and after, executives have a 0.5 percentage point lower probability of moving out of Paris.

From what we could see in Figure 22, moving out rates seemed to have been driven by non-teleworkable jobs. From this regression analysis, we see that in addition than being non-teleworkable, these were also non-executive jobs (there is a degree of overlap, as executives are the most likely professional category to telework). Among non-executives, there is considerable variation in telework capacity (see Figures 5 and Appendix C's figure 24), and this likely led to the inability to find a difference in moving-out rates between teleworkable and non-teleworkable professions.

Table 6

	Dependent variable:
	MOVEOUT
POST2020.4:PARIS	0.014***
	(0.002)
PROF1:POST2020.4:PARIS	−0.118***
	(0.036)
PROF2:POST2020.4:PARIS	−0.003
	(0.004)
PROF3:POST2020.4:PARIS	−0.005*
	(0.003)
PROF4:POST2020.4:PARIS	0.0004
	(0.003)
PROF6:POST2020.4:PARIS	0.005
	(0.003)
Observations	696,140
R^2	0.004
Adjusted R^2	−0.271
F Statistic	121.308*** (df = 32; 545756)
Note:	*p<0.1; **p<0.05; ***p<0.01

6.2.2 Moving-out by salary quartile

I now also check for heterogeneity in moving out of Paris post-Covid based on household earnings, particularly by quartile. I construct a household income variable from individuals' reported monthly earnings, and acknowledge that these are self-reported and also lower bounds for their household earnings (as one can have non-labour sources of income). Based on these, I can classify households into quartiles of earnings and run the regression in Table 5 using earning quartiles as a distinguishing feature rather than telework capacity. Table 7 contains a condensed version of these results, with the full results in Appendix M.

I consider quartile 2 as my reference category. From Table 7, we see that there is indeed heterogeneity in moving-out rates from Paris post-Covid, with the highest post-Covid moving rate being among the third quartile, 2.9 percentage points higher than the moving rate in quartile 2. The lowest post-Covid moving rate is among the lowest-earning households. This lowest quartile moved away from Paris at lower rates post-Covid than pre-Covid.

I note that the proportion of teleworkable job holders within each quartile is increasing with household earnings. 72% of the highest-earning quartile has teleworkable jobs, compared to 55% of the second highest-earning quartile. However, there is no difference in moving rates between teleworkable job-holders and non-teleworkable job-holders within any of the quartiles.

Household earnings seem to be more relevant than professional category to explaining moving-out rates in Paris post-Covid. The proportion of individuals that belong to the occupational categories less likely to move out per Table 6 (1, farmers and 3, executives) increases over the income quartiles (mostly driven by an increase in executives). If professional category is a stronger explanatory factor, this would mean that the earnings quartiles with a high representation of these less mobile occupational categories should also be less mobile — in fact, the reverse is true. Earnings quartiles three and four are more mobile than earnings quartile one, despite having a greater proportion of executives.

The direct and opportunity costs of finding a new dwelling are more likely to hinder those with limited household earnings. With higher earnings, an individual and their household gain additional mobility. These explanations of the moving rate are supported by the data. Whether or not individuals are able to telework does not seem to be a direct factor in the decision to move out of Paris post-Covid, but their ability to afford relocation does matter.

6.2.3 Moving in by professional category

As we saw in the main regressions of the previous section, the ability to telework explains the probability of an individual to be a mover-in in Paris post-Covid. Those that telework are less likely to move into Paris after the shock, which is in line with the theory described in the

Table 7

	Dependent variable:
	MOVEOUT
QUARTILE1	-0.195^{***}
	(0.002)
QUARTILE3	0.035^{***}
	(0.002)
QUARTILE4	0.099^{***}
	(0.003)
POST2020.4	-0.006^{*}
	(0.003)
QUARTILE1:PARIS	0.010^{*}
	(0.005)
QUARTILE3:PARIS	-0.014^{**}
	(0.006)
QUARTILE4:PARIS	-0.001
	(0.007)
QUARTILE1:POST2020.4	-0.062^{***}
	(0.003)
QUARTILE3:POST2020.4	-0.018^{***}
	(0.003)
QUARTILE4:POST2020.4	-0.014^{***}
	(0.003)
PARIS:POST2020.4	0.032^{***}
	(0.005)
QUARTILE1:PARIS:POST2020.4	-0.094^{***}
	(0.006)
QUARTILE3:PARIS:POST2020.4	0.029^{***}
	(0.007)
QUARTILE4:PARIS:POST2020.4	0.002
	(0.006)
Observations	347,404
R^2	0.086
Adjusted R^2	-0.130
F Statistic	$1,263.943^{***}$ (df = 24; 281056)
Note:	*p<0.1; **p<0.05; ***p<0.01

American literature.

In this section, I check for additional clarity whether there are differences in the probability of being a mover-in in Paris post-Covid among different occupational categories.

According to the standard theory in the American literature, teleworkers should show higher rates of moving out, as they are capable of continuing to work without being in close proximity to their workplaces. However, given the previous analysis, it is evident that individuals with non-teleworkable jobs also moved out of Parisian dwellings at unprecedented rates. Occupational categories explain differences in moving-out rates from Paris post-Covid somewhat better than teleworking capacity, and it is possible that these also explain moving-in better.

We saw that non-teleworkable job-holders moved into Parisian dwellings during the pandemic at higher rates than teleworkable job-holders (Table 4). Broader developments in the French economy can explain this. In 2020, France experienced an economic contraction of 7.9 % (INSEE (2021)), and the sectors most affected included those that employ several employee-tier (category 5) workers (accommodation, catering) as well as blue-collar workers (category 6, land, air and pipeline transport, warehousing, manufacturing of transport equipment) (INSEE (2020)). Hence, individuals working in these sectors that lost their jobs or were placed on leave could have chosen to leave Paris to avoid high costs. I note that blue-collar employees and white-collar employees that cannot telework (nurses, military, police) are well-represented (around 30-32%) among those earning quartiles that had the highest rates of moving out of Paris. It is possible that these were the first to return.

I rerun the regression in Table 4 changing the category of interest to professional category 6 alone, as this is a category that has minimal telework capacity. The results are presented in Table 8.

We see here that individuals belonging to the professional category 6 (that do not telework), in Paris post 2020, have a 2 percentage point *higher* probability of having recently moved in than individuals from other professions. Thus, it seems that category 6, which is non-teleworkable, moved-out of Paris post-Covid at higher rates than category 3, which is highly-teleworkable, and also moved in at higher rates in the months that followed. This is an indication that telework is not likely to affect the probability of moving-out of Paris post-Covid, but could potentially

Table 8

	Dependent variable:
	MOVEIN
PROF6	0.001
	(0.001)
POST2021	0.027***
	(0.003)
UNEMP	0.001
	(0.001)
INACTIVE	−0.002***
	(0.001)
AGE	−0.001***
	(0.00003)
MARRIED	−0.023***
	(0.001)
FEMALE	−0.002***
	(0.0004)
IMMIGRANT	0.005***
	(0.001)
CHILDREN	−0.006***
	(0.001)
POST2021:AGE	−0.0003***
	(0.00004)
POST2021:MARRIED	−0.043***
	(0.002)
POST2021:CHILDREN	0.003***
	(0.001)
PROF6:POST2021	−0.002
	(0.001)
PROF6:PARIS	−0.001
	(0.002)
POST2021:PARIS	0.038***
	(0.002)
PROF6:POST2021:PARIS	0.020***
	(0.005)
Observations	696,140
R^2	0.004
Adjusted R^2	−0.271
F Statistic	189.457*** (df = 16; 545772)
Note:	*p<0.1; **p<0.05; ***p<0.01

affect the *duration* of time spent outside of Paris.

6.2.4 Moving in by earnings quartile

As mentioned earlier, moving-in and moving-out rates post-Covid are highest in Paris relative to other urban categories, and comparing the composition of movers-in to movers-out may shed some light on the patterns of migration by professional category and earnings quartile. We have seen that it is primarily earnings that have affected the decision to move out, rather than professional category or telework capacity. There is strong evidence in the previous section that professional category, however, does affect the moving-in rate in Paris post-Covid.

To complete the closer investigation of moving-out and moving-in rates in Paris, I now consider whether household earnings quartile explains the probability of moving into Paris post-Covid. The analysis is presented in Table 9, with the full table in Appendix N.

We find that the lowest quartile had the lowest rate of moving out of Paris post-Covid, but has the highest rate of moving into Paris post-Covid. The other quartiles have lower rates of moving into Paris post-Covid, but the difference in moving-in rates among them is not significant. Thus, there is evidence to suggest a strong preference for Paris among the first quartile of household income.

To cross check this, I conduct regressions by quartile sub-sample to find a preference within earnings quartiles for large cities or smaller cities relative to Paris. The second, third and fourth quartiles had negligibly different rates of moving into dwellings in big and large cities alike. A preference across space is strongest for the first quartile, that prefers Paris to smaller cities, but prefers smaller cities to rural areas and bigger cities. The full results can be found in Appendix O.

Taken altogether, we see that the driver for moving out of Paris post-Covid was likely income, while professional category and the nature of work had a greater role to play in the decision of whether to move into Paris afterwards or not. Given that there are significant costs to relocating, the third quartile of household earnings moved out of Paris at higher rates post-Covid than other quartiles. Thus, we can envision the group that moved out of Paris as middle- and upper-middle income households, that do not disproportionately belong to the professional

Table 9

	Dependent variable:
	MOVEIN
QUARTILE1	0.153^{***}
	(0.002)
QUARTILE3	-0.014^{***}
	(0.002)
QUARTILE4	-0.054^{***}
	(0.003)
POST2021	0.007^{*}
	(0.004)
QUARTILE1:PARIS	-0.044^{***}
	(0.005)
QUARTILE3:PARIS	-0.008
	(0.006)
QUARTILE4:PARIS	-0.017^{**}
	(0.006)
QUARTILE1:POST2021	0.078^{***}
	(0.003)
QUARTILE3:POST2021	0.005
	(0.003)
QUARTILE4:POST2021	0.002
	(0.003)
PARIS:POST2021	0.001
	(0.006)
QUARTILE1:PARIS:POST2021	0.159^{***}
	(0.007)
QUARTILE3:PARIS:POST2021	-0.005
	(0.008)
QUARTILE4:PARIS:POST2021	-0.001
	(0.007)
Observations	347,404
R^2	0.067
Adjusted R^2	-0.154
F Statistic	964.418^{***} (df = 24; 281056)
Note:	*p<0.1; **p<0.05; ***p<0.01

category of executives, academic or scientific professions. They also do not disproportionately telework.

The group of movers-in to Paris post Covid, on the other hand, are from the first quartile of household earnings, and also less likely to have a job that can be teleworked. It is therefore possible that the preference for Paris is related to needing to earn, and the inability to sustain oneself at a distance from Paris. We also note that individuals in the first quartile of household earnings have a preference for smaller cities over bigger cities, which could indicate better opportunities for work in these cities as opposed to larger ones.

Thus, the role played by telework in migration in and out of Paris seems to be more subtle in the French context than the American context. We can infer that the ability to telework did not drive people to relocate out of Paris after the onset of the pandemic, but it likely allowed them to postpone their return to Paris by a few trimesters. As we saw in the visual analysis, there was evidence of a staggered moving-in rate among job category 3 that extended into 2021 T2 and T3. If we were to imagine a dataset that recorded the durations of stay outside of Paris spent by the group that left Paris in the last quarter of 2020, the non-teleworkable job-holders and the lowest-income bracket individuals would return to Paris sooner than teleworkable job-holders and those with higher incomes.

6.3 Limitations of the analysis

The goal of my study was to determine whether a pattern of migration centred around leaving and returning to Paris was correlated with individuals' ability to telework. Furthermore, using the EEC as my only data source, this study was an exercise in discovering whether reasonable conclusions about mobility can be drawn from a dataset that is not intended to measure mobility directly, and whether this study can provide motivation for future work.

Given that the EEC does not directly report mobility data, identifying movers is based on assumptions given the survey design, and therefore, my findings are not as strong as if I had had direct data on movement such as postal data. One key limitation is the inability to track both the origin and destination of movers. Data on working from home and earnings is also unavailable for all individuals in my data, and this, I have had to impute telework capacity rather than measuring it directly, and decrease the size of my sample while observing earnings quartiles. I was also unable to use a broader definition of movers-out, and thus, my sample of movers-out, though weighted as per survey weights, likely underestimates moving out rates.

This study is intended to find evidence of a phenomenon, but not to establish a direct causal relationship between teleworking and moving out. For this, I would need to account for other factors into the study, to resolve endogeneity issues. There are factors that are related to one's earnings and job that affect their ability and desire to move. High-income people may have a greater taste for amenities in large cities, and this may affect their desire to move out of Paris. Owning a second home would greatly diminish the costs of relocation. The demand for one's occupational skill-set from area to area is also relevant — certain jobs, such as those that are technologically intensive or managerial would be lower in demand in smaller towns and rural areas without large-scale industries. To establish causality, these factors would also have to be taken into account.

In other ways, there is potential for broadening the scope of this analysis, particularly in considering multiple large cities and out-migration from them. Furthermore, as an attempt to observe direct evidence of migration related to teleworking, my study does not elaborate on the implications of this for the larger economy, and the impact on productivity, rents and house prices, as has been done in the American literature (often as indirect evidence of migration). However, this creates avenues for future work on the subject, particularly with a longer time-frame post-pandemic.

7 Conclusion

Despite the fact that the Continuous Labour Survey does not contain an explicit question on mobility, the use of the dwelling and household survey rounds can provide a proxy of movement. Based on this I find that there are considerable differences in moving rates across professional category and location.

During the pandemic, teleworkers are theorised to be more likely to move out of large cities, in order to avoid high rent and amenity costs while retaining their jobs. While evidence to suggest this has been found in the American context, my study finds that the influence of telework capacity is more subtle in the context of France. Namely, telework capacity does not influence the likelihood of moving out of Parisian dwellings during the pandemic, but does affect moving into Parisian dwellings in the trimesters that follow. Further investigation yields that the group that is most likely to leave Paris is not more teleworkable, but in a higher earnings bracket. Additionally, those with non-teleworkable jobs and those in lower earnings-brackets are more likely to move-into Parisian dwellings.

Thus, teleworkable job-holders leave Parisian dwellings at similar rates to non-teleworkable job-holders, but come to Parisian dwellings in later trimesters at significantly lower rates. Furthermore, earnings quartiles with household earnings above the median do not move into Parisian dwellings at higher rates than they move into dwellings in other large cities or small cities. This evidence taken together characterises a group of relatively affluent teleworkable job-holders that are able to remain outside of Paris for longer periods of time (multiple trimesters) relative to lower-earning households and those with non-teleworkable jobs.

Several avenues can be taken in future work on the subject. Indirect evidence of migration is yet to be established in the literature for France, through the change in housing prices, wages and amenity prices due to diminished or increased demand. The absence of onsite workers could also affect productivity in large cities, and firm-side analyses on the impact of telework could be conducted to check these (as in Liu and Su (2023)). In addition to this, the same study on direct evidence of migration could be conducted using postal data and personalised surveys. Lastly, a wider time-frame, such as incorporating 2022 data could inform us of whether teleworkers are slowly returning to their main job locations, or if the persistence of telework would lead to a long-term redistribution of workers across space.

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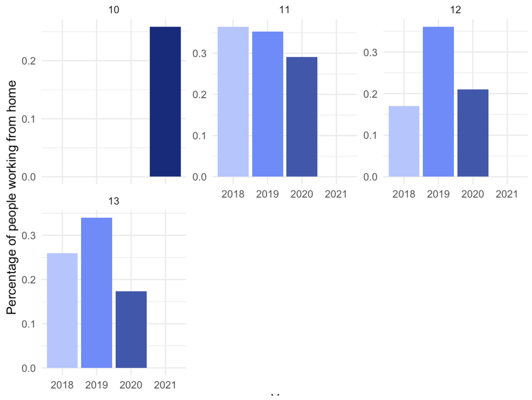
Appendix

A Guide to PCS Codes

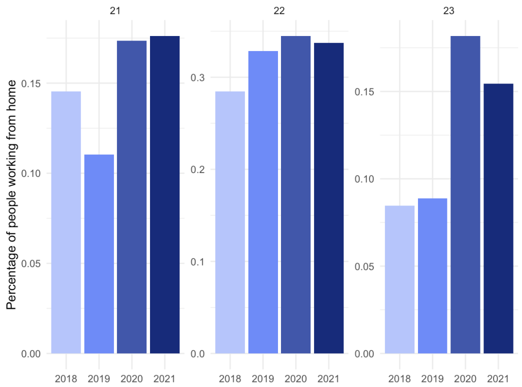
Code	Profession
10	Farmers
11	Small-scale farmers
12	Medium-scale farmers
13	Large-scale farmers
21	Craftsmen
22	Tradesmen or similar
23	Business owners with ten or more employees
31	Liberal professions
33	Civil service executives
34	Professors and scientific professions
35	Information, arts and entertainment professions
37	Managers of administrative and business services
38	Engineers and technical company managers
42	Primary, vocational and continuing education
43	Health and social work professions
44	Religious professions and clergy
45	Intermediate public adminstration
46	Intermediate commercial adminstration
47	Technicians
48	Supervisors (non-administrative)
52	Public service employees
53	Police, military, firefighters
54	Corporate adminstrative employees
55	Commercial employees
56	Personal service personnel
56	Industrial skilled workers
56	Craft skilled workers
56	Drivers
56	Skilled workers in handling, storage, transport
56	Industrial unskilled workers
56	Unskilled craftsmen
56	Agricultural workers

Table 10: EEC codes for professional categories

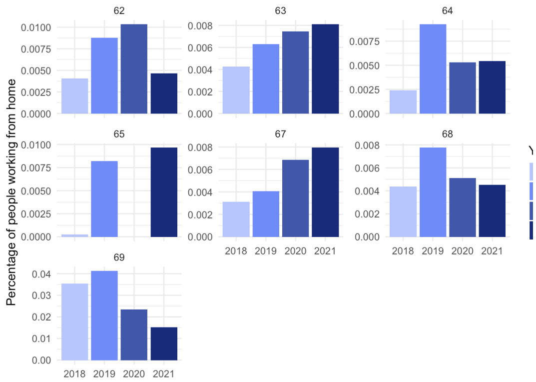
B PCS Category Analysis (Additional Graphs)



(a) Percentage of workers from home in subcategories of PCS 1, by year



(b) Percentage of workers from home in subcategories of PCS 2, by year



(c) Percentage of workers from home in subcategories of PCS 6, by year

The coding of Category 1 changed over time, with the three farmer categories in 2020 being grouped into a single category in 2021. WFH rates are relatively high in this category, likely because many farmers live on or near their farms, and any work conducted at home is considered WFH even if not contractual. WFH rates are low for category 6.

C TraCov Analysis

Figure 24 shows the teleworking rate (those who telework at least 3 days a week) for profession subcategories as per the TraCov survey, conducted in early 2021. While the EEC gives us information about changing WFH rates by profession over time, this is a measure of level at a point in time. Nevertheless, we see that the professions that are most likely to telework (with more than 30% of workers teleworking), are civil service executives (33), managers of administrative and business services (37), engineers and technical company managers (38), intermediate commercial administrators (46), and technicians (47), all of which were found in the EEC to also have high teleworking rates in 2021.

The professions that have at least 1 in 5 workers teleworking include the above as well as business owners with 10 or more employees (23), information arts and entertainment professions (35), religious professions (44), intermediate public administrators (45), non-administrative supervisors (48), and corporate administrative employees (54). There is therefore a large overlap in the occupational categories that are identified to have high teleworking rates by the TraCov survey, and those occupational categories I identify from the EEC data to be best suited for teleworking. We can hence be assured that the EEC's measures are reliable indicators of the uptake of teleworking across professions despite missing data.

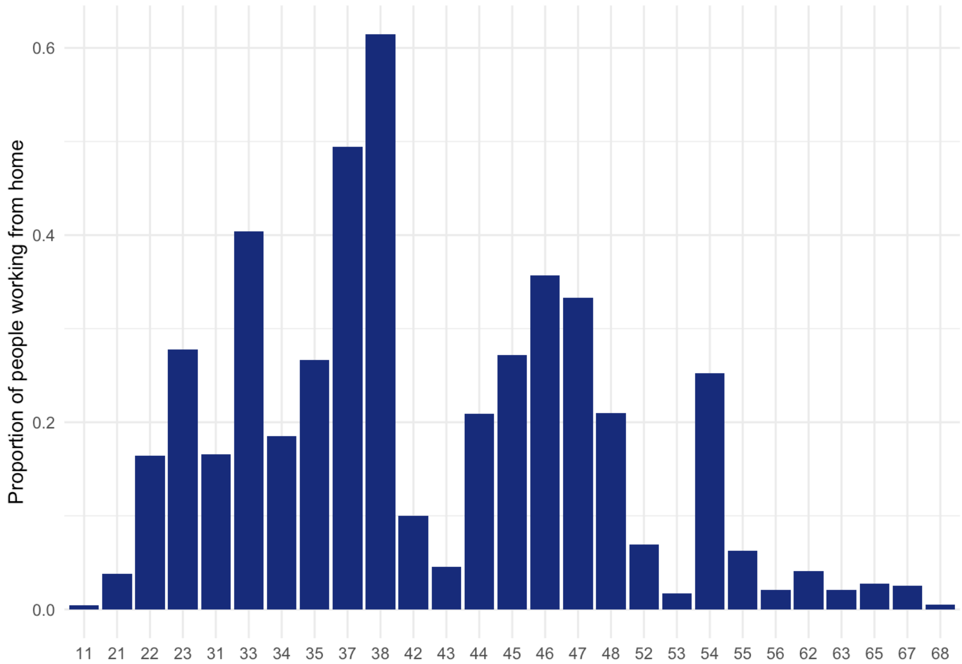


Figure 24: Proportion of workers from home by PCS subcategory

D Broad movers-out

As mentioned in the main text, I chose not to use a broader definition of movers-out that extends to all those households that lacked a final round (or multiple later rounds) of survey, as their behaviour was unusual relative to narrow movers-out. Shown below is the moving out rate when these households are included in the sample of movers-out. We see that there's an unusual peak in the moving out rate in 2019.4 and 2020.4, well above the moving-in rate. Given that the two rates should mirror each other, it's likely that this is an anomaly or a result of other administrative decisions related to the survey.

Without firmly considering these individuals as movers-out, their status remains ambiguous. All those entries (across trimester by individual) that have ambiguous status, such as the first and last rows, are removed from the analysis.

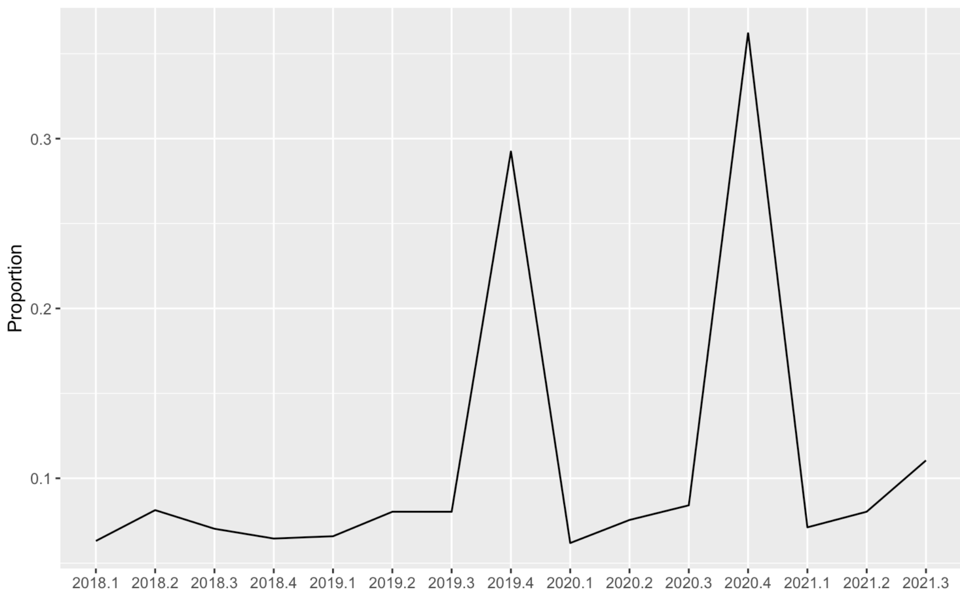


Figure 25: Proportion of households per trimester that have missing last round(s)

E Guide to urban zoning codes

In Table 11 are the detailed urban zoning codes used to define the origins and destinations of movers. The codes have been aggregated as in Table 3.

Code	Urban category
0	Municipality excluding urban unit
1	Municipality belonging to an urban unit of 2,000 to 4,999 inhabitants
2	Municipality belonging to an urban unit of 5,000 to 9,999 inhabitants
3	Municipality belonging to an urban unit of 10,000 to 19,999 inhabitants
4	Municipality belonging to an urban unit of 20,000 to 49,999 inhabitants
5	Municipality belonging to an urban unit of 50,000 to 99,999 inhabitants
6	Municipality belonging to an urban unit of 100,000 to 199,999 inhabitants
7	Municipality belonging to an urban unit of 200,000 to 1,999,999 inhabitants
8	Municipality belonging to the urban unit of Paris
9	No response

Table 11: TUU urban unit zoning codes

F Robustness check 1: narrow movers-in only

Table 12

	Dependent variable:
	MOVEIN_NARROW
TELE	-0.001^{*}
	(0.0004)
POST2021	0.072^{***}
	(0.002)
UNEMP	0.002^{**}
	(0.001)
INACTIVE	-0.003^{***}
	(0.0005)
AGE	-0.001^{***}
	(0.00002)
MARRIED	-0.021^{***}
	(0.001)
FEMALE	-0.002^{***}
	(0.0003)
IMMIGRANT	0.004^{***}
	(0.001)
POST2021:AGE	-0.001^{***}
	(0.00003)
POST2021:MARRIED	-0.040^{***}
	(0.001)
POST2021:CHILDREN	0.002^{***}
	(0.001)
CHILDREN	-0.003^{***}
	(0.001)
TELE:POST2021	0.001
	(0.001)
TELE:PARIS	0.002^{**}
	(0.001)
POST2021:PARIS	0.061^{***}
	(0.002)
TELE:POST2021:PARIS	-0.018^{***}
	(0.002)
Observations	696,140
R^2	0.013
Adjusted R^2	-0.259
F Statistic	654.276^{***} (df = 16; 545772)
Note:	*p<0.1; **p<0.05; ***p<0.01

G Robustness check 2: Even broader movers-in

Table 13

	Dependent variable:
	MOVEIN_COMPLETE
TELE	−0.001
	(0.001)
POST2021	−0.092***
	(0.004)
UNEMP	0.005***
	(0.002)
INACTIVE	−0.002**
	(0.001)
AGE	−0.001***
	(0.0001)
MARRIED	−0.030***
	(0.002)
FEMALE	−0.002***
	(0.001)
IMMIGRANT	0.005***
	(0.002)
CHILDREN	−0.010***
	(0.002)
POST2021:AGE	0.0001**
	(0.0001)
POST2021:MARRIED	−0.045***
	(0.002)
POST2021:CHILDREN	0.006***
	(0.001)
TELE:POST2021	0.002
	(0.002)
TELE:PARIS	0.003
	(0.003)
POST2021:PARIS	0.031***
	(0.005)
TELE:POST2021:PARIS	−0.021***
	(0.005)
Observations	696,140
R^2	0.012
Adjusted R^2	−0.261
F Statistic	447.543*** (df = 16; 545772)
Note:	*p<0.1; **p<0.05; ***p<0.01

H Robustness check 3: shortened timeframe, movers-in

Table 14

	Dependent variable:
	MOVEIN
TELE	-0.002^{*}
	(0.001)
POST2021	0.030^{***}
	(0.003)
UNEMP	0.001
	(0.001)
INACTIVE	-0.004^{***}
	(0.001)
AGE	-0.001^{***}
	(0.00004)
MARRIED	-0.028^{***}
	(0.001)
FEMALE	-0.001^{***}
	(0.0005)
IMMIGRANT	0.003^{**}
	(0.001)
CHILDREN	-0.0004
	(0.001)
POST2021:AGE	-0.0004^{***}
	(0.00004)
POST2021:MARRIED	-0.042^{***}
	(0.002)
POST2021:CHILDREN	0.001
	(0.001)
TELE:POST2021	0.001
	(0.001)
TELE:PARIS	0.006^{***}
	(0.002)
POST2021:PARIS	0.056^{***}
	(0.003)
TELE:POST2021:PARIS	-0.024^{***}
	(0.004)
Observations	475,241
R^2	0.005
Adjusted R^2	-0.300
F Statistic	170.180^{***} (df = 16; 363686)
Note:	*p<0.1; **p<0.05; ***p<0.01

I Robustness check 3: shortened timeframe, movers-out

Table 15

	Dependent variable:
	MOVEOUT
TELE	0.001*
	(0.001)
POST2020.4	−0.045***
	(0.002)
UNEMP	−0.002*
	(0.001)
INACTIVE	0.002***
	(0.001)
AGE	0.0004***
	(0.00003)
MARRIED	0.021***
	(0.001)
FEMALE	0.001***
	(0.0003)
IMMIGRANT	−0.003***
	(0.001)
CHILDREN	0.004***
	(0.001)
POST2020.4:AGE	0.0005***
	(0.00003)
POST2020.4:MARRIED	0.033***
	(0.001)
POST2020.4:CHILDREN	0.003***
	(0.001)
TELE:POST2020.4	−0.001
	(0.001)
TELE:PARIS	−0.001
	(0.001)
POST2020.4:PARIS	0.014***
	(0.002)
TELE:POST2020.4:PARIS	−0.001
	(0.002)
Observations	475,241
R^2	0.006
Adjusted R^2	−0.299
F Statistic	235.810*** (df = 16; 363686)
Note:	*p<0.1; **p<0.05; ***p<0.01

J Robustness check 4: Regression of moving-in rates on household teleworking capacity

Table 16

	Dependent variable:
	MOVEIN
TELECONT	-0.013^{***}
	(0.002)
POST2021	0.026^{***}
	(0.003)
UNEMP	0.001
	(0.001)
INACTIVE	-0.002^{***}
	(0.001)
AGE	-0.001^{***}
	(0.00003)
MARRIED	-0.023^{***}
	(0.001)
FEMALE	-0.002^{***}
	(0.0004)
IMMIGRANT	0.005^{***}
	(0.001)
CHILDREN	-0.006^{***}
	(0.001)
POST2021:AGE	-0.0003^{***}
	(0.00004)
POST2021:MARRIED	-0.043^{***}
	(0.002)
POST2021:CHILDREN	0.003^{***}
	(0.001)
TELECONT:POST2021	0.003
	(0.002)
TELECONT:PARIS	0.013^{*}
	(0.007)
POST2021:PARIS	0.081^{***}
	(0.004)
TELECONT:POST2021:PARIS	-0.062^{***}
	(0.006)
Observations	696,140
R^2	0.004
Adjusted R^2	-0.271
F Statistic	196.814^{***} (df = 16; 545772)
Note:	*p<0.1; **p<0.05; ***p<0.01

K Robustness check 4: Regression of moving-out rates on household teleworking capacity

Table 17

	Dependent variable:
	MOVEOUT
TELECONT	0.006***
	(0.002)
POST2020.4	−0.046***
	(0.002)
UNEMP	−0.002**
	(0.001)
INACTIVE	0.0003
	(0.0005)
AGE	0.0003***
	(0.00002)
MARRIED	0.015***
	(0.001)
FEMALE	0.001***
	(0.0003)
IMMIGRANT	−0.002***
	(0.001)
CHILDREN	0.010***
	(0.001)
POST2020.4:AGE	0.0005***
	(0.00003)
POST2020.4:MARRIED	0.037***
	(0.001)
POST2020.4:CHILDREN	0.001**
	(0.001)
TELECONT:POST2020.4	−0.001
	(0.001)
TELECONT:PARIS	−0.006
	(0.005)
POST2020.4:PARIS	0.016***
	(0.003)
TELECONT:POST2020.4:PARIS	−0.005
	(0.004)
Observations	696,140
R^2	0.004
Adjusted R^2	−0.271
F Statistic	240.357*** (df = 16; 545772)
Note:	*p<0.1; **p<0.05; ***p<0.01

L Regression of moving-out rate on professional category

Table 18

	Dependent variable:
	MOVEOUT
PROF1	−0.001
	(0.002)
PROF2	−0.001
	(0.001)
PROF3	−0.001
	(0.001)
PROF4	0.0001
	(0.001)
PROF6	−0.001
	(0.001)
POST2020.4	−0.047***
	(0.002)
UNEMP	−0.002**
	(0.001)
INACTIVE	0.0003
	(0.0005)
AGE	0.0003***
	(0.00002)
FEMALE	0.001**
	(0.0003)
IMMIGRANT	−0.002***
	(0.001)
CHILDREN	0.010***
	(0.001)
MARRIED	0.015***
	(0.001)
POST2020.4:AGE	0.0005***
	(0.00003)
POST2020.4:CHILDREN	0.001**
	(0.001)
POST2020.4:MARRIED	0.037***
	(0.001)

PROF1:POST2020.4	0.005
	(0.003)
PROF2:POST2020.4	0.0004
	(0.002)
PROF3:POST2020.4	−0.0001
	(0.001)
PROF4:POST2020.4	0.001
	(0.001)
PROF6:POST2020.4	0.002
	(0.001)
PROF1:PARIS	−0.012
	(0.018)
PROF2:PARIS	0.003
	(0.003)
PROF3:PARIS	0.001
	(0.002)
PROF4:PARIS	−0.003**
	(0.002)
PROF6:PARIS	−0.005***
	(0.002)
POST2020.4:PARIS	0.014***
	(0.002)
PROF1:POST2020.4:PARIS	−0.118***
	(0.036)
PROF2:POST2020.4:PARIS	−0.003
	(0.004)
PROF3:POST2020.4:PARIS	−0.005*
	(0.003)
PROF4:POST2020.4:PARIS	0.0004
	(0.003)
PROF6:POST2020.4:PARIS	0.005
	(0.003)
Observations	696,140
R^2	0.004
Adjusted R^2	−0.271
F Statistic	121.308*** (df = 32; 545756)
Note:	*p<0.1; **p<0.05; ***p<0.01

M Regression of moving-out rate on earning quartiles

Table 19

	Dependent variable:
	MOVEOUT
QUARTILE1	-0.195^{***}
	(0.002)
QUARTILE3	0.035^{***}
	(0.002)
QUARTILE4	0.099^{***}
	(0.003)
POST2020.4	-0.006^{*}
	(0.003)
UNEMP	-0.005^{***}
	(0.001)
INACTIVE	-0.0003
	(0.001)
AGE	0.0002^{***}
	(0.00004)
MARRIED	0.006^{***}
	(0.001)
FEMALE	0.001^{***}
	(0.0004)
IMMIGRANT	-0.005^{***}
	(0.001)
CHILDREN	0.008^{***}
	(0.001)
QUARTILE1:PARIS	0.010^{*}
	(0.005)

QUARTILE3:PARIS	-0.014^{**}
	(0.006)
QUARTILE4:PARIS	-0.001
	(0.007)
QUARTILE1:POST2020.4	-0.062^{***}
	(0.003)
QUARTILE3:POST2020.4	-0.018^{***}
	(0.003)
QUARTILE4:POST2020.4	-0.014^{***}
	(0.003)
PARIS:POST2020.4	0.032^{***}
	(0.005)
POST2020.4:AGE	0.0005^{***}
	(0.0001)
POST2020.4:MARRIED	0.025^{***}
	(0.002)
POST2020.4:CHILDREN	0.001
	(0.001)
QUARTILE1:PARIS:POST2020.4	-0.094^{***}
	(0.006)
QUARTILE3:PARIS:POST2020.4	0.029^{***}
	(0.007)
QUARTILE4:PARIS:POST2020.4	0.002
	(0.006)
Observations	347,404
R^2	0.086
Adjusted R^2	-0.130
F Statistic	$1{,}263.943^{***}$ (df = 24; 281056)
Note:	*p<0.1; **p<0.05; ***p<0.01

N Regression of moving-in rate on earning quartiles

Table 20

	Dependent variable:
	MOVEIN
QUARTILE1	0.153^{***}
	(0.002)
QUARTILE3	-0.014^{***}
	(0.002)
QUARTILE4	-0.054^{***}
	(0.003)
POST2021	0.007^{*}
	(0.004)
UNEMP	0.004^{***}
	(0.001)
INACTIVE	-0.002^{***}
	(0.001)
AGE	-0.001^{***}
	(0.00003)
MARRIED	-0.017^{***}
	(0.001)
FEMALE	-0.002^{***}
	(0.0004)
IMMIGRANT	0.006^{***}
	(0.001)
CHILDREN	0.001
	(0.001)
QUARTILE1:PARIS	-0.044^{***}
	(0.005)

QUARTILE3:PARIS	−0.008
	(0.006)
QUARTILE4:PARIS	-0.017^{**}
	(0.006)
QUARTILE1:POST2021	0.078^{***}
	(0.003)
QUARTILE3:POST2021	0.005
	(0.003)
QUARTILE4:POST2021	0.002
	(0.003)
PARIS:POST2021	0.001
	(0.006)
POST2021:AGE	−0.0001
	(0.0001)
POST2021:MARRIED	-0.025^{***}
	(0.002)
POST2021:CHILDREN	0.0002
	(0.001)
QUARTILE1:PARIS:POST2021	0.159^{***}
	(0.007)
QUARTILE3:PARIS:POST2021	−0.005
	(0.008)
QUARTILE4:PARIS:POST2021	−0.001
	(0.007)
Observations	347,404
R^2	0.067
Adjusted R^2	−0.154
F Statistic	964.418^{***} (df = 24; 281056)
Note:	*p<0.1; **p<0.05; ***p<0.01

O Regression of moving-in rates on urban categories by earnings quartile

Table 21

	Dependent variable:			
	MOVEIN			
EARNINGS QUARTILE	(1)	(2)	(3)	(4)
LARGECITY	0.124^{***}	-0.00000	-0.001	0.005
	(0.032)	(0.006)	(0.008)	(0.006)
RURAL	0.025	-0.0002	0.001	0.001
	(0.026)	(0.004)	(0.006)	(0.003)
POST2021	0.099^{***}	-0.001	-0.011^{***}	-0.008^{***}
	(0.010)	(0.002)	(0.003)	(0.002)
UNEMP	0.006^{**}	-0.0003	-0.002^{**}	0.001^{**}
	(0.003)	(0.001)	(0.001)	(0.001)
INACTIVE	0.003^{*}	-0.001^{***}	0.001^{***}	-0.001^{**}
	(0.002)	(0.0004)	(0.0004)	(0.0004)
AGE	-0.001^{***}	0.00003	-0.0002^{***}	0.00002
	(0.0001)	(0.00002)	(0.00003)	(0.00002)
MARRIED	-0.020^{***}	0.003^{***}	-0.005^{***}	0.001^{**}
	(0.003)	(0.001)	(0.001)	(0.001)
FEMALE	-0.002	-0.00000	-0.0002	0.0002
	(0.001)	(0.0002)	(0.0003)	(0.0002)
IMMIGRANT	0.008^{**}	0.0001	0.002^{**}	-0.003^{***}
	(0.003)	(0.001)	(0.001)	(0.001)
CHILDREN	-0.001	-0.003^{***}	-0.005^{***}	-0.011^{***}
	(0.003)	(0.001)	(0.001)	(0.001)
POST2021:AGE	-0.001^{***}	0.00001	0.0002^{***}	0.0001^{***}
	(0.0002)	(0.00003)	(0.00004)	(0.00003)
POST2021:MARRIED	-0.065^{***}	-0.001^{*}	0.004^{***}	-0.0005
	(0.005)	(0.001)	(0.001)	(0.001)
POST2021:CHILDREN	0.003	0.001^{*}	0.002^{***}	0.004^{***}
	(0.003)	(0.0005)	(0.001)	(0.0005)
LARGECITY:POST2021	-0.022^{***}	0.0003	0.0003	-0.0003
	(0.008)	(0.001)	(0.002)	(0.001)
PARIS:POST2021	0.086^{***}	0.0003	-0.00003	0.001
	(0.010)	(0.002)	(0.002)	(0.001)
RURAL:POST2021	-0.022^{***}	-0.0001	0.0001	-0.0001
	(0.008)	(0.001)	(0.002)	(0.001)
Observations	86,884	86,280	87,415	86,825
R^2	0.008	0.001	0.0003	0.004
Adjusted R^2	-0.294	-0.227	-0.296	-0.194
F Statistic	53.788^{***} (df = 16; 66610)	3.653^{***} (df = 16; 70253)	5.154^{***} (df = 16; 67424)	33.409^{***} (df = 16; 72432)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$