

Does Feasibility Explain the Unequal Development of Working From Home?

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Abstract

Using rich historical survey data on job tasks and machine learning techniques, we study which jobs can be moved from the office to home over three decades in France. The share of jobs with task content compatible with working from home has increased steadily from 14% in 1991 to 45% in 2021. At the same time, actual Working From Home (WFH) remained limited to less than one-fifth of its full potential before the COVID-19 crisis and is still below that level in 2021. The growth of WFH is largely unrelated to the evolution of job tasks, implying that the main obstacles to WFH have not been technical constraints. Low-skilled employees in particular have been performing tasks compatible with teleworking for a long time, but they were barely teleworking before the COVID-19 crisis and remained still below 50% of their full potential during it. This pattern is likely mostly explained by the cost to managers of supervising low-skilled remote workers and managerial trust in employees. It implies that the well-known large inequality in access to WFH along the earnings distribution cannot be attributed only to feasibility constraints and is potentially inefficient.

JEL codes: J22, J81, M54.

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1 Introduction

The COVID-19 pandemic has triggered a massive shift toward working from home (WFH), as well as intense debates over the quantitative importance of this shift and whether it will be permanent or temporary. Recent research has tried to evaluate both the share of jobs that can be done from home in the modern economy (e.g., Dingel and Neiman, 2020) and the likelihood that the high levels of WFH observed during the pandemic will persist (e.g., Barrero et al., 2021).

We contribute to these debates by examining the long-run evolution of the working practices that make WFH feasible in France, with an analysis that combines rich survey data and advanced machine learning techniques. By doing so, we assess how the task composition of jobs has changed over the past 30 years and how this change has increased the share of jobs whose task content is compatible with working from home. This allows us to study gaps between actual WFH and its task-based feasibility over time and across occupations, and to assess the extent to which WFH is, and has been, mostly limited by technical feasibility constraints. This historical approach sheds light not only on the barriers to the development of WFH just after the COVID-19 crisis, but also on the potential for its expansion at an even larger scale in the long run. Thus, we contribute to the debate on the likelihood that WFH could be widespread in the future. Our comparisons across occupations, then, allow us to study overall inequality in access to WFH conditional on its feasibility.

Our first contribution is to study the evolution of working practices (or tasks) that make WFH feasible. Following Hatayama et al. (2023), we consider four types of tasks or factors that can facilitate or impair WFH: (1) information and communication technology (ICT) use, (2) face-to-face interactions, (3) physical work, and (4) the quality of Internet connection at home. We present the evolution of the prevalence of these various fundamental aspects of work since 1991. We then use machine learning (ML) techniques to predict which job tasks or working practices make WFH feasible and validate the relevance of the factors considered by the existing

literature. This is done using a working conditions survey administered in early 2021 in France—a period with strong COVID-19 prevalence—and containing information on WFH feasibility of jobs (self-assessed by survey respondents) and the task content of jobs. We predict WFH task-based feasibility by the task content of jobs and apply this predictor to former surveys that include similar questions – allowing us to examine the evolution of predicted teleworking feasibility since 1991. A strength of this ML-based approach is to be agnostic regarding the factors that should be considered to assess which jobs can be done from home.

The second and main contribution of the paper is to provide an analysis of the gaps between actual WFH and WFH task-based feasibility over time and across occupations. This allows us to identify practical obstacles to WFH, and how they may have been lifted over time. Specifically, we study the evolution of WFH at the occupational-level using monthly information from the French Labor Force survey , and compare it to our measures of WFH task-based feasibility aggregated at the occupational level and their evolution over time.

Our analysis yields two main results: first, before the COVID-19 crisis, WFH remained very limited and increased much more slowly than its feasibility. The share of jobs whose task content is compatible with working from home increased steadily from 14% in 1991 to 35% in 2019 and 45% in 2021. At the same time, the share of the workforce teleworking increased from virtually 0% in the early 1990s to 6% in 2019 and 23% in early 2021. Even during the COVID-19 crisis, the recourse to teleworking remained far below its full potential. These results clearly show that the main obstacles to teleworking are not feasibility constraints that were progressively alleviated while turning to the digital economy.

Second, there is a large gap in actual WFH across occupations that cannot be explained by differences in WFH task-based feasibility: office employees that were already spending more than 80% of their time on a connected computer in the 2000s are much less likely to work from home than white-collar workers with similar working practices. This is remarkably true both before and after the COVID-19 crisis. It implies that the large inequality in access to WFH along

the earnings distribution cannot be attributed only to feasibility constraints: we estimate that, in 2019, the share of workers who actually teleworked among those who could do so increased from around 15% at the bottom half of the earnings distribution to 50% at the top decile.

To explain these gaps for the recent period, we use information on workers' desire to work from home and management practices such as workers' degree of autonomy, and hierarchical control. We find that in early 2021, among individuals who could telework but do not, low-skill workers are more likely to desire to telework than their higher-skill counterparts. This shows that the inequality in access to telework, conditional on its feasibility, that we document, could be inefficient from an economic point of view if the effect of teleworking for low-skilled jobs on firms' productivity is not negative. Hence, there is a strong margin for increasing teleworking at the bottom of the earnings distribution and this could be welfare-improving for both workers and firms.

We also find that both in 2019 and 2021, workers' autonomy and extent of hierarchical control play a role beyond pure feasibility constraints as they are positively associated with the probability to telework (conditional on feasibility). This suggests that managers' willingness to maintain control over their workers could be an important factor limiting teleworking for low-skilled workers today. We conclude that the evolution of teleworking in the future will depend more on the evolution of management practices than on changing the task content of jobs to make WFH feasible.

Related Literature. Our study relates to a rapidly growing literature on WFH. A first strand of this literature examines which jobs can be done from home. Dingel and Neiman (2020) have developed an axiomatic approach that consists in identifying the types of tasks that make jobs (not) amenable to WFH. Mongey and Weinberg (2020); Gottlieb et al. (2020); Saltiel (2020); Hatayama et al. (2023); Garrote Sanchez et al. (2021), among others, have built on the work of DN2020. Mongey and Weinberg (2020) propose a continuous measure of WFH feasibility.

Gottlieb et al. (2020) apply DN2020 to 57 countries and focus on biases induced by categorizing farmers as not WFH in developing countries. Saltiel (2020) and Hatayama et al. (2023) use skills data in several countries to examine if the task content of different occupations varies across countries, making US-based measures “à la DN2020” not applicable to other countries. Garrote Sanchez et al. (2021) develop a measure of WFH feasibility that also takes into account Internet access and apply it to 107 countries.

A last group of papers departs from the task-based approach and uses directly individual-level data on WFH (e.g., Hensvik et al., 2020), or on WFH feasibility directly self-assessed by workers. Alipour et al. (2023) and Adams-Prassl et al. (2022) highlight the strong heterogeneity of WFH feasibility within occupations or industries, while Alipour et al. (2023) study directly the link between tasks and WFH feasibility, showing in particular that a single indicator of personal computer (PC) usage does a good job in predicting WFH capacity. Finally, independently of the method they use, all papers focusing on WFH amenability conclude that it increases with workers’ earnings and education levels.

Our contribution relative to these papers is twofold. First, we analyze the evolution over 30 years of the tasks and working practices that make WFH feasible in a developed country. This allows us to estimate how the share of jobs that can be done from home has evolved over time. Doing so, we extend to job tasks prior work by Oettinger (2011), showing that the increase in WFH between 1980 and 2000 can be tied to the increasing usage of Internet technology. Our approach can be seen as similar in spirit to the work on job polarization that has examined the evolution over time of employment in occupations depending on their task content (e.g., routine versus non-routine tasks, see for example Autor et al. (2003) or Autor and Dorn (2013)). The difference is that we analyze tasks that are amenable to WFH, and we have access to direct information on the prevalence of these tasks at work at different points in time.

Second, we rely on two rich working conditions surveys administered just before and during the pandemic to propose alternative, more agnostic, approaches to assess the task content of

jobs that are associated with both actual WFH (before and during the COVID crisis) and WFH feasibility. Doing so, we follow and extend the work of Alipour et al. (2023). While they use a linear probability model to link job tasks to WFH feasibility, we use Random forests, allowing us to take into account interactions between predictors and nested effects of the tasks that make WFH feasible. The ML approach is also key to obtaining an accurate predictor of WFH or WFH feasibility that we can apply retrospectively without fearing that we are over-fitting the data.

We then relate to the papers that try to assess if WFH will stick durably after the COVID-19 crisis (Barrero et al., 2021; Bartik et al., 2020; Bick et al., 2023). These papers rely on theoretical arguments typically combined with survey data measuring, during the crisis, workers' desire to keep WFH and employers' plans to maintain it. Our retrospective analysis of the development of working practices that make WFH feasible complement these papers as it can shed light not only on the immediate persistence of WFH but also on its potential for even broader expansion in the long run.

Finally, we indirectly relate to literature that attempts to evaluate how workers and employers value WFH and are willing to pay for it (Mas and Pallais, 2017; Oettinger, 2011; Nagler et al., 2022; Lewandowski et al., 2025). We do so by analyzing the gaps between WFH feasibility and actual WFH, combined with information on workers' desire to WFH. We show in particular that gaps between actual WFH and WFH feasibility or workers' desire to work from home vary strongly across occupations.

Organization. The rest of the paper is organized as follows. Section 2 briefly describes the institutional context and presents the data and methods. Section 3.1 analyzes the tasks that predict WFH feasibility and actual WFH in the recent period. Section 3.3 shows the evolution of these tasks and more broadly of WFH feasibility in the labor market since 1991. Section 4 analyzes gaps between actual WFH and WFH feasibility before and during the COVID-19 crisis, and their determinants. The evolution of the gaps over time and their differences across skill groups are

highlighted. Section 6 provides a brief analysis of the variation in the take-up of teleworking given its feasibility along the earnings distribution. Section 7 summarizes the main results and discusses the possibility of a widespread usage of WFH in the economy in the long-run.

2 Context, Data and Methods

In this section, we provide contextual information on the development of WFH in France and in other countries, on the difference between WFH and teleworking, and on the regulations governing these practices. We then describe our data and the methods used to analyze it.

2.1 Context

Systematic quantitative evidence on teleworking and WFH arrangements prior to the COVID-19 crisis is remarkably scarce.

The former documents a 7.2% take-up of “working from home” in terms of days worked in the USA in 2019, while the latter reports that 22% of Dutch workers declared having a home-working day in 2018. This large cross-country variation may come from cultural and institutional differences, but also from differences in the definition and measurement of teleworking and WFH arrangements. These definitions matter, both for assessing international or regional differences, and the temporal evolution of the take-up of these practices.

Figure 1 shows the evolution of teleworking and WFH arrangements in France since the 1990s (see section 2.2 for a description of the data sources). The share of workers who telework at least sometimes—telework being defined as the combination of remoteness from the employing firm’s premises and usage of ICT—has been increasing in France since the early nineties, with a more rapid increase in the 2010s, prior to the pandemic. It reached about 6% of the labor force before the COVID-19 crisis and then jumped by more than 15 percentage points, reaching 24 % in 2021 before decreasing slightly to 21% in 2023. The share of workers who declare working at

least partly from home over the last month when surveyed increased by a similar magnitude in absolute terms during the COVID-19 crisis, but relative to a much higher baseline, at around 17% in 2019. It is 10 percentage points higher than the share of workers who telework throughout the studied period.¹ Finally, the large gap between the purple and red series illustrates that WFH outside regular hours, that is, extra time worked at home, represents a large share of the WFH prevalence before the COVID-19 crisis.

The *potential* for teleworking and WFH arrangements has received regular bursts of media and policy attention. The inception of the word “teleworking” dates back to the 1970s, and originates from the engineering literature. Ever since, periods of renewed interest have alternated with suggestive evidence that actual teleworking practices are less prevalent than anticipated. In France, the first instance of teleworking receiving official attention from policymakers dates back to the early 1990s (Breton, 1993).² It includes a study by the French statistical office (the Insee) that evaluates the take-up of telework at the time at 16 000 workers, or 0.1% of the labor force.³ Using survey data and projections on the evolution of sectoral and occupational structure of the workforce, it also projected the potential for an increase in telework in the future, with an estimated 200 000 to 300 000 workers practicing teleworking in 2005. In contrast to most other predictions, this one actually turned out remarkably close to the observed take-up of telework in 2006 at 2% (Figure 1). More generally, how close “realized” teleworking follows its “potential” has been debated for decades in non-academic work. In 1992, 54% of French workers declared being willing to stay at home to work at least part of their working time if given the chance to do so, illustrating that there has been a strong desire to work from home on the workers’ side for a very long time. In this paper, we explore the historical discrepancy between teleworking

¹These figures can be put into perspective with those of Barrero et al. (2023) and de Vos et al. (2019) who document increases of “working from home” to 28% in the US in 2022 and to 53% in the Netherlands in 2021.

²The report originated from the ministry in charge of land use planning. Historically, one of the main sources of academic and political interest for teleworking development, both in the US and France, has been connected to road congestion and transport infrastructure.

³In comparison Barrero et al. (2023) estimates 0.4% of days worked from home in 1965.

potential and teleworking practices in a data-driven way to see if workers' desires have been fulfilled when technical barriers to teleworking started to be removed in their jobs.

2.2 Data

Working Conditions Surveys 1991-2021. Working Conditions Surveys (*Enquêtes "Conditions de Travail"* in French) are administered by the statistical office (the *Dares*) of the French Ministry of Labor every 6 to 8 years to samples of 15,000 to 25,000 workers since 1991. Survey microdata are available for years 1991, 1998, 2005, 2013 and 2019 (hereafter, WC1991, WC1998, WC2005, WC2013, WC2019). The surveys include sampling weights allowing us to produce statistics representative for the whole workforce. They include an extensive questionnaire which is aimed to capture working conditions in a broad sense: family status, occupation, former career path, work schedule, work intensity, family-life balance, working practices and tasks executed at work, subjective health, psycho-social risks (since 2016) and WFH (since 2019). We have excluded occupations 31 "Independent Workers" 35 "Artists and Entertainment Occupations", 44 "Clergy" and 42 "Teachers" because they do not correspond to typical salaried jobs (see details in Appendix A).

In addition, the Ministry of Labor administered an adapted version of the survey ("Tracov") to 19,953 workers between January 25 and March 7, 2021 to capture the evolution of working conditions during the COVID-crisis. While former regular surveys contained little information on telework, Tracov2021 includes several questions allowing us to measure both telework, telework feasibility and workers' desire to Telework. Table 1 provides basic information on each survey (sample size, response rate, main topics included, measures of WFH and teleworking). A challenge for the purpose of this paper is that survey questions are not fully consistent across the whole period 1991-2021. We discuss how we address this in Section 2.3.

Labor Force Surveys 2003-2023. The Labor Force survey (LFS) is a household survey run on a quarterly basis by the national statistical institute (Insee) since 1950. We keep only employed individuals and use sampling weights in all analyses except regressions to get representative statistics. The LFS includes information on whether a worker has worked at least some time from their home in a consistent way since 2003. We use it to compute the evolution of *WFH* since 2003.

Archive Data on Teleworking. Data on teleworking practices are scarce. We use data from Breton (1993), which surveyed the French private sector extensively on teleworking practices in 1993. We also use survey data from the 1997 and 2006 waves of the Digitization and Organizational Changes survey (*Enquête sur les Changements organisationnels et l'informatisation*) ran by the Insee. The survey samples workers from the private sector and collects information about how often they work outside of their firms' premises, and their use of ICT.

Internet Coverage. We use data from the *Autorité de régulation des communications électroniques* (ARCEP), a public entity which depends on the Ministry of Economic and Financial Affairs. The data contains the coverage rate of Internet connections with a given download speed at the communal level from 2013 to 2019, broken down in five speed categories: ADSL (Asymmetric Digital Subscriber Line, with a speed of 512 kb per sec when it was introduced in 1999) and 4 broadband Internet connection speed levels: 3, 8, 30, and 100 Mb per second.⁴

⁴For earlier periods, we interpolate these series with an earlier snapshot of data in 2005 (introduction date of connection speeds faster than 30 Mb/sec), and with the knowledge that virtually no commercial household connection existed in 1998 other than via the phone network. For later periods, we extrapolate based on the 2013-2019 trends. For 2013-2019 we do not have the data for ADSL access only, but for access to ADSL or other forms of cable connection. This change in the variable should not be problematic if we reconsider it as a measure of the prevalence of low speed Internet connectivity over this latter period.

2.3 Methods

Measures of WFH, Telework, and Its Feasibility. As pointed out, the different surveys we use in our analysis encompass different concepts of working outside a firm’s premises. Telework is reported in the Working Conditions surveys of 2019 and 2021 (hereafter, WC2019 and Tracov2021), while WFH is reported in Labor Force surveys. We focus exclusively on the takeup of these practices at the extensive margin. In the WC2019 and Tracov2021 surveys, we construct a telework dummy variable that identifies individuals who telework at least “a few days per month”. In the LFS, we consider as our main measure of WFH, an indicator that identifies individuals that have worked from home at least partly during the month preceding the survey. Our main measure is obtained after excluding workers who report working during evenings or weekends. We argue that this latter measure is closer to telework because it excludes situations where WFH is not a substitution to working at the office (which telework is).

Tracov2021 asks an additional question that identifies individuals who report having a job that “is not concerned by telework because its tasks are not compatible with it”. We use it to construct a dummy variable that identifies telework feasibility: whether the individual is employed in a job that is teleworkable.

Machine Learning Prediction. To analyze the evolution of telework and its feasibility as a function of job tasks, we use the Random Forest machine learning technique as it appears particularly well-suited to predict outcomes in our particular case. Formally, a Random Forest is a non-linear prediction technique based on a set of decision-tree classifiers optimized for the prediction of an outcome (see Appendix Figure A.2 for an example for teleworking in 2021). Each tree is constructed with a number of randomly drawn explanatory variables among a set of potential predictors. Its advantage, common to other machine learning techniques, is that it is an agnostic method to rank the importance of predictors, and thus prevent issues related to cherry picking the explanatory variables of the model, or making other arbitrary choices. As opposed

to linear models like LASSO or Ridge Regression, the Random Forest is well suited to take into account hierarchies and nested effects between predictors, which are likely to be important in our case because teleworking feasibility depends on interacted conditions (e.g., it is not feasible if workers exert physical tasks or if they do not but have contact with the public). We provide further details on Random Forests in Appendix A.

The most important constraint we face in our analysis regarding the choice of our predictors comes from the fact that we cannot use all information available in the recent surveys (WC2019 and Tracov2021), to predict telework and its feasibility backwards using historical survey waves, which contain fewer variables. Nonetheless, to be fully transparent and informative about the performance of our models, we provide two sets of predictors. The first-best models use as predictors *all* survey variables in WC2019 and Tracov2021 that measure the nature of tasks at work or working practices. In contrast, the second-best predictors use the subset of these variables that are available in WC2019 and Tracov2021, as well as in all historical waves of Working Conditions surveys. Only these second-best models can be used to apply our predictors backwards. To establish the list of eligible predictors, we identify all variables in each survey that are directly reflecting the nature of the job, and exclude those that relate to management or organizational practices. Indeed, these latter variables reflect individual and/or collective choices regarding the way the job is accomplished rather than immediate feasibility constraints directly related to the nature of the job.

The variables retained as predictors are detailed in Table A.1 which provides the exhaustive list of survey questions capturing task features and the yearly surveys in which they are included. Most variables mainly characterize contacts at work, physical activities, and the use of ICT. We are left with 67 predictors in CT2019 and 13 predictors in Tracov2021 (see Table 2). However, we have only 5 variables common to these two surveys and all historical working conditions surveys. These variables are the share of hours spent using connected computers, whether one's job requires contact with the public, and whether one's job is sometimes, often, or always physically

demanding (3 variables).⁵ While this set of predictors is limited, it covers the three main aspects of work likely to affect workers' ability to telework.

Finally, in an additional exercise, we also add, as predictors to our second-best model, five measures capturing Internet coverage in the department or region of residence of survey respondents at the time of the survey (i.e., access to ADSL and four variables for access to broadband Internet with various speeds – from 3 Mb to 100 Mb per second).⁶ The reasons for doing this separately from the rest are that (i) we can only match Internet coverage to Tracov or Working Conditions surveys at a very aggregated level, and (ii) Internet coverage being already high in 2019 and 2021, these aggregated variables of coverage yield limited variation across regions and only have limited predictive power for teleworking feasibility.

Long-Run Evolution of Predicted Teleworking and Teleworking Feasibility. We construct historical series of predicted teleworking feasibility using the machine learning models. Let us denote $f_{2021}^{WFH feasibility}(X)$, $f_{2021}^{WFH}(X)$ and $f_{2019}^{WFH}(X)$ the “second-best” predictors of teleworking feasibility and teleworking depending on individual job task features X . We apply these functions to measures of tasks obtained backward in time. Formally, to illustrate the evolution of predicted teleworking feasibility, we show for years $t = 1991, 1998, 2005, 2013, 2019$ the empirical counterpart of:

$$\mathbb{E}_{2021}[Feasibility_t] = \int f_{2021}^{WFH feasibility}(X_t) dX_t$$

where X_t are task features observed among individuals surveyed at date t . The two predictors of teleworking applied backward are obtained similarly. They do not directly provide an estimation

⁵Categorical variables often take multiple modalities. In order to increase the performance of ML predictions, we split all categorical variables into dummies for each modality but the reference one. Therefore a single job feature (e.g., having a physically demanding job) can be accounted for by multiple predictors provided to the ML algorithm.

⁶In Tracov2021, WC2019 and WC2013, we observe respondents' *département* of residence (100 in total in France). In WC2005, we only observe the region (22 in total) while in earlier surveys we do not have any information and adopt a conservative scenario assuming that Internet coverage is 0 for all types of connections and all respondents.

of the share of jobs that could be teleworked at each examined date. Instead, they inform on the share of jobs that would have been teleworkable at these dates if the likelihood to work from home depending on the content of a job had been similar to what it was in 2019 and 2021. The results should only be seen as summary measures of the evolution of labor market amenability to telework. They are then useful to compare this evolution to the actual evolution of telework in the past decades.

Time Series on Teleworking. We reconstruct a time series of teleworking since 1993 by interpolating historical data points gathered from the various sources described above. Starting 2003, we also use a yearly measure of WFH prevalence from the Labor Force survey .

Gaps Between Teleworking and Its Feasibility. Finally, we compare the actual evolution of teleworking over the past three decades to the evolution of its feasibility. The objective is to understand if the increased implementation of teleworking in the economy has closely followed the removal of feasibility constraints, or if instead it should be attributed to other factors (e.g., cultural barriers, management practices, HR opposition, institutional context). More precisely, we compare the evolution of the actual share of jobs done from home to the following three statistics:

1. The evolution of the share of jobs that *can be teleworked* according to our Random Forest predictor fitted in 2021
2. The evolution of the share of jobs that *would be teleworked* if the adoption of telework was determined by the organizational constraints and practices during the peak of the COVID-19 pandemic.
3. The evolution of the share of jobs that *would be teleworked* if the adoption of telework was determined by the organizational constraints and practices in 2019, that is just before the peak of the COVID-19 crisis.

These comparisons allow us to discuss whether the main factors behind the evolution of teleworking before the COVID-19 crisis are technical or related to the nature of the work (e.g., Internet coverage, ICT use at work, face-to-face interactions, physical intensity of work). Since our Random Forest predictors of teleworking and its feasibility are only available for years $t = 1991, 1998, 2005, 2013, 2019$, we sometimes use simple linear interpolations to recover a measure for each year since 1991. To refine the analysis, we also present evidence for different occupations separately using the LFS since 2003.

3 The Tasks that Make Teleworking Feasible and their Evolution

3.1 Predicting Teleworking and its Feasibility in the Recent Period

Table 2 presents ML prediction results for our three outcomes: telework feasibility in 2021, and actual telework in 2021 and 2019. Column 1 reports results from first-best models using all available task descriptors, while column 2 uses second-best models with only five common predictors per survey.

First-best models perform well, with Mean Square Errors (MSE) below 0.15 and Q^2 above 0.4.⁷ The 2019 model performs well, explaining over 80% of telework variance with a MSE of 1.3% (based on 67 predictors). Predicting telework ($Q^2 = 0.43$) is harder than predicting feasibility ($Q^2 = 0.55$) using the same 13 variables, which supports the idea that feasibility is more directly linked to job content.⁸ Second-best models, though less accurate, still perform well given their sparsity. For instance, with just 5 predictors, Tracov2021's model explains 36% of the variance in teleworking feasibility, which is the main outcome of interest in the rest of the paper.

⁷ Q^2 is comparable to R^2 in linear models but evaluated on a hold-out test set; see Appendix A.

⁸Telework decisions also depend on employer and employee choices, beyond task-based feasibility.

Table 2 also shows that Ordinary Least Squares (OLS) models using all possible predictors as regressors consistently underperform ML models, with higher MSEs and lower Q^2 .⁹ OLS performs worst in 2019 when telework was particularly low, effectively predicting zero telework. Expectedly, the superiority of Random Forests is smaller in the models with fewer predictors (right column of the table).

Importantly for our backward-looking exercise, Table 2 shows that top predictors overlap across both model types. The share of working hours spent in front of connected devices, contact with the public, or the physical intensity of the job are systematically among the main predictors.¹⁰ This confirms that second-best models capture the core dimensions of telework feasibility.

Finally, when adding measures of Internet coverage at home to potential second-best predictors, we find that these measures rank systematically lower in terms of variable importance relative to our main predictors. We return to this point in the next sections.

3.2 The Long-Run Evolution of Tasks that Make Teleworking Feasible

Panel a) of Figure 2 shows the evolution of the key tasks that make teleworking feasible. The most striking feature of this evolution is the continuous increase in the share of hours worked spent using connected computers, from 11% in 1991 to 45% in 2019. This means in particular that slightly less than half of labor input in the French economy was provided in front of a computer before the COVID-19 crisis. The share of hours spent in front of a computer then jumped to almost 60% in 2021.

Only 30% of jobs are not physically demanding, and this share has remained remarkably stable over the past three decades. Finally, the share of jobs requiring contact with the public (e.g., clients, customers, patients) is large and has been slowly increasing from just above 60% in 1991 to above 70% in 2019. This trend tends to make teleworking less feasible in the present

⁹As for the ML models, we discretized the continuous prediction based on a cut-off at 0.5.

¹⁰All appear in the top five predictors, except physical intensity in the full 67-variable model, where it ranks within the top ten.

than in the past. We nevertheless observe that the extent of contacts with the public was strongly reduced during the COVID-19 crisis, illustrating that this feature of jobs can be adjusted more rapidly than others when incentives to do so are strong.

We also decompose in panel a) of Figure 2 the evolution of the task content of jobs in within- and between-occupations variations. To do so, we maintain constant the share of each 2-digit occupation at its 1991 level by weighting the 2-digit occupation level measures of our variables by the 1991 occupation weights, and compute the reweighted average for each task.¹¹ Most of the changes occur within occupations. This conclusion is obtained despite large changes in the occupational mix in the past three decades: for example the share of white-collar workers almost doubled, from 11% to 21%, and the share of blue-collar workers declined substantially, from 34% to 23%, between 1991 and 2021 (Figure A.3). This shows that the large transformations of the nature of work, and in particular the dramatic increase in the time spent in front of connected computers, have mostly occurred within occupations.

3.3 The Long-Run Evolution of the Task-Based Prediction of Teleworking Feasibility

We now study how the predicted feasibility of teleworking has increased since 1991 given the *task mix* observed on the labor market at different points in time. Feasibility is only predicted by job tasks in 2021 and, as already highlighted, this exercise should be seen as summarizing the constraints imposed on teleworking due to the task content of jobs only. Figure 2, Panel b), shows that the share of jobs that are predicted to be teleworkable has more than tripled over the past three decades, from around 14% in 1991 to more than 45% in 2021. The increase is close to linear between 1991 and 2019. Feasibility predicted by job tasks then jumps by more

¹¹This reweighting is applied on top of individual sampling weights $w_{i,t}$ which are systematically used in order to get representative statistics. Formally, the weight applied to worker i in occupation o at time t after reweighting is $w_{o,t}w_{i,t}$ where $w_{i,t}$ is the sampling weight available in the survey and $w_{o,t} = (\sum_{i \in o} w_{i,1991}) / (\sum_{i \in o} w_{i,t})$.

than 10 percentage points between 2019 and 2021. This jump is driven by an adaptation of working practices during the COVID-19 crisis to make teleworking feasible, showing that the task composition of jobs is endogenous and can be quickly adapted. The scope for adaptation in the short run remains however limited: even in a context of very strong incentives to switch to teleworking during the COVID-19 crisis, teleworking could be made possible for only an additional 10% of the economy.

Consistent with our analysis of job tasks, we also show in Panel b) of Figure 2 that the increase in predicted teleworking feasibility mostly occurred within occupations. If the occupational mix of the labor market had remained that observed in 1991, 31% and 39% of jobs would be teleworkable in 2019 and 2021, respectively ; compared to 35% and 45% when taking into account the evolution of the occupational structure.

Accounting for Internet Coverage. Predicted feasibility is almost identical at all points in time when we include Internet coverage in workers' region of residence among the set of predictors, as shown in Panel b) of Figure 2. This is despite the fact that the coverage of the Internet was much lower in the 2000s than it is now, and almost nonexistent in the 1990s (see Figure A.1). This result possibly reflects that the Internet is widespread across the French territory in 2021 and therefore does not represent anymore a significant constraint on teleworking. As a consequence, the ML predictors fitted in 2021 may not give a strong role to Internet coverage and may not be able to capture well the likely additional constraints induced by the limited coverage of (high-speed) access to the Internet in the 1990s and 2000s. To understand how this limitation might affect our conclusions in Section 4.1, we also provide a more conservative scenario for the evolution of teleworking feasibility, assuming that teleworking was completely constrained by *Internet usage*¹². We multiply our task-based measure of feasibility by the percentage of individuals that

¹²Teleworkable jobs may not have required Internet access in the 1990s: a phone and possibly a non-connected computer at home may have been considered sufficient to perform them. Hence, one should keep in mind that we focus on the feasibility of the most common form of teleworking today, that is, teleworking using a connected computer.

use the Internet in France over the period we study¹³. Because Internet was introduced in France only in 1994, under this alternative measure, telework was impossible in 1991 as shown by panel a) of Figure A.5. Over the 2000s, connectivity constraints were alleviated progressively and almost fully disappeared in 2013 (see the high and flattening coverage of low to mid-speed Internet in 2013 in Figure A.1 as well as in Panel c) of Figure A.5¹⁴). Thus, under this alternative measure, the predicted feasibility of teleworking would have increased even faster over time, from 0% in 1991 to 40% in 2021.

4 Gaps Between Teleworking and Predicted Teleworking Feasibility

In this section, we compare actual teleworking with its feasibility, both over time and across major occupational groups.

4.1 Comparison of Teleworking and Teleworking Feasibility Since 1991

Figure 3, Panel (a), provides a direct comparison over time of teleworking and its feasibility as predicted by the task content of jobs. Teleworking remained very limited compared to its predicted feasibility until the COVID-19 crisis. Even during the COVID-19 period (2021) and the beginning of the post-COVID-19 era (2022), teleworking remained significantly below its predicted (and, for the later years, observed) feasibility. To further illustrate this point, we plot in Panel (b) the ratio and the absolute gap between teleworking and its task-based predicted feasibility. The ratio was close to 0 in the early 1990s, when teleworking was almost nonexistent

¹³This is also conservative because it assumes that the correlation between Internet deployment and the geographical distribution of teleworkability is zero, while it is likely to be positive.

¹⁴Note that the aggregate data measuring Internet usage that we rely on to construct this alternative measure reports Internet usage over the last three months, as opposed to Internet access, which is what is reported in Figure A.1. It peaks at a lower level than the latter measure but it is a better suited variable to construct our lower-bound feasibility variable.

according to our archival data sources. It then rose quickly to 10% and remained remarkably stable at that level between 1997 and 2016. Hence, for almost two decades after the advent of teleworking, only one tenth of jobs predicted to be teleworkable were actually teleworked. During this period, the gap between teleworking and its feasibility steadily increased from 10 to 30 percentage points. A change in trend started to occur in 2016, with the ratio between teleworking and its predicted feasibility rapidly increasing from 10% to 20% between 2016 and 2019, while the absolute gap stabilized. This increase coincides with a law passed in 2017 to facilitate firm-level collective agreements allowing for teleworking on a large scale, suggesting that the institutional environment can also play a role. The wedge between teleworking and its feasibility was further reduced after the advent of the COVID-19 crisis but remained substantial: in early 2021, only 50% of workers who could telework did so at least to some extent, and a gap of 20 percentage points remained between actual teleworking and its declared feasibility. These comparisons suggest that technical and feasibility constraints were not the main drivers preventing workers from teleworking before the COVID-19 crisis and that, even after the pandemic, teleworking remains largely under-used relative to its feasibility. This conclusion is reinforced by the fact that our measure of teleworking is broad: workers are counted as teleworkers as soon as they telework at least half a day per week. Considering measures of teleworking at higher intensity would further increase the gap between teleworking and its feasibility. Similarly, considering the additional constraints imposed on feasibility by the availability of the Internet in the region of residence does not alter our main conclusions. First, in the recent period, these constraints have little impact on the feasibility of teleworking, as almost all French territory has access to an Internet connection (Figure A.1). Hence, they cannot explain the large gap between actual teleworking and its feasibility. Second, as discussed in Section 3.3, these constraints imply that we might overestimate teleworking feasibility in past decades. With regard to our conservative scenario for the predicted feasibility of telework, the share of teleworkable jobs that were indeed teleworked decreased over the period 1997–2013, as shown in Panel (b) of Figure A.5. Hence,

even under conservative assumptions regarding Internet-access constraints, actual recourse to teleworking given its feasibility remained very limited during the three decades preceding the COVID-19 crisis. Figure 3, Panel (a), also compares the evolution of teleworking since 1991 to what it would have been if recourse to teleworking given the task content of jobs had remained similar to (i) what is observed in 2019 (teleworking predicted from job tasks in 2019) and (ii) what is observed during the COVID-19 pandemic (teleworking predicted from job tasks in 2021). Actual teleworking practices increased slightly more rapidly—i.e., from a lower level in 1991—than predicted based on the tasks and teleworking levels observed in 2019. This is largely driven by the late increase in the 2010s, which aligns with the gradual removal of non-technical barriers to teleworking in the few years before the pandemic. However, teleworking increased much more slowly and remained much lower than one would predict if the relationship between tasks and teleworking had remained similar to that observed in 2021. This illustrates that the prevalence of teleworking jumped during the COVID-19 crisis not only because jobs and their task content were adapted but also—and, more importantly—because a much larger share of jobs that could already be done remotely given their task content began to be teleworked.

4.2 Evolution of WFH and WFH Predicted Feasibility by Occupation: 1991 – 2022

In this section, we study the gaps between actual teleworking and its feasibility across different occupations.

Identifying Relevant Groups of Occupations. Figure 4 shows, based on Tracov2021, actual teleworking and teleworking feasibility for each 2-digit occupation in early 2021. We divide these occupations into four groups.

The first group includes all “non-connected employees”, that is, occupations with a share of teleworking below 20% during the COVID-19 period. All these occupations have a teleworking

feasibility below 30% and are therefore not the main focus hereafter. They include all blue-collar workers (occupations starting with digit “6”, corresponding mostly to ISCO-08 groups 7, 8, and 9, and ISCO skill levels 1 or 2); most low-skilled clerical occupations (occupations starting with digit “5”, corresponding mostly to ISCO-08 groups 4, 5, and 9, and ISCO skill levels 1 or 2); and one mid-skill occupation (health and social workers). None of the high-skilled occupations (so-called *Cadres* in French, starting with digit “3” and corresponding mostly to ISCO-08 groups 1 and 2 and ISCO skill levels 3 and 4) falls into this category.

The second group, named “low-skilled connected employees”, corresponds to one large low-skilled occupation: administrative employees. More than 70% of employees can telework in this group, and about 45% do so. The third group (“mid-skilled connected employees”) includes four mid-skilled occupations (starting with digit “4” and corresponding mostly to ISCO-08 groups 3 and 4 and ISCO skill level 2), all having a teleworking feasibility above 50%. The fourth group includes all 2-digit high-skilled occupations (also referred to as “executives” hereafter), all with a feasibility above 60%. Except for professors and science-related high-skilled occupations, the gaps between teleworking and its feasibility are smaller in the fourth group than in the second and third groups.¹⁵

Teleworking Predicted Feasibility by Occupation Group Since 1991. Figure 5, Panel (a), shows the evolution of predicted teleworking feasibility for each of these four groups using the historical working-conditions surveys since 1991. A striking result is that feasibility used to be higher for connected low-skilled employees (i.e., office workers) than for executives. In 1991, 40% of connected low-skilled employees could telework, while this was true for only 23% of executives. This is largely explained by the early and high prevalence of ICT tools among office employees.

¹⁵There is no direct mapping from the official classification of occupations available in the data to the International Standard Classification of Occupations (ISCO). This prevents us from using the latter. For further details, see Brousse et al. (2010) or the probabilistic transition matrix available on the French statistical office website: <https://www.insee.fr/fr/information/8292892>.

High-skilled workers experienced a stronger transformation of their job-task content and progressively caught up with connected low-skilled employees in terms of teleworking feasibility. Just before the COVID-19 crisis, 60% of executives and 65% of connected low-skilled employees could telework. Teleworking feasibility was identical among mid-skilled connected occupations and high-skilled occupations in 1991, but it increased less over time in the former group. Finally, teleworking feasibility increased only slightly and remained limited—below 20%—for non-connected employees over the studied period.

During the COVID-19 crisis, the increase in tasks that make teleworking feasible was mostly observed among mid-skilled connected occupations and executives. The latter group eventually became the most teleworkable, with almost 85% of jobs that could be teleworked. By contrast, the absence of a large break in the time series for office employees (low-skilled connected workers) suggests that most factors making teleworking possible for them remained relatively stable throughout the COVID-19 crisis.

Overall, these differences across occupations appear to be driven mostly by the use of connected computers and the amount of physically demanding tasks (Figure A.4). The share of hours spent on a connected computer has historically been much larger for connected employees. In this group, 42% of hours worked were already spent using computers in 1991 (60% in 1998), compared with only 18% and 21% among high-skilled and mid-skilled connected occupations, respectively, and 5% among non-connected employees. Executives experienced the largest transformation of their job content, with a quadrupling of their time spent in front of a computer between 1991 and 2019 (from 18 to 72%). This is the main reason teleworking feasibility increased more for them than for other groups, while other factors were more comparable across groups and much more stable over time.

Gaps Between Teleworking and Its Predicted Feasibility by Occupation Group Since 2003.

For years prior to 2019, only aggregated statistics on teleworking are available. To provide

statistics by occupation, we therefore use the LFS and focus on WFH during regular hours, which we can observe since 2003. Panel (b) of Figure 5 shows that, even though teleworking has been more feasible for connected employees than for executives, WFH during regular hours has been much more prevalent among executives since 2003. This remains true after the COVID-19 crisis in 2023.

Consequently, the ratio between WFH and teleworking feasibility is much larger for high-skilled workers. It ranges between 5 and 10% for connected low-skilled employees before the COVID-19 crisis. It is slightly higher for connected mid-skilled occupations and, strikingly, three to five times higher among executives (Panel (c)).¹⁶

This shows that, conditional on its feasibility, the actual recourse to WFH varied substantially across occupations, with the most skilled occupations being much more likely to use it.

In all three groups of connected workers, the ratio strongly increased during the COVID-19 crisis. In relative terms, the largest increase occurred among connected low-skilled employees, whose ratio rose almost fivefold over a two-year period. This large increase also illustrates that WFH was particularly under-used compared with its feasibility among connected low-skilled employees before the COVID-19 crisis, making possible the sharp increase observed during the pandemic.

5 Explaining the Gaps in Telework Across Occupations

Working-from-home arrangements increased during the COVID-19 crisis, and this is even more true for connected low-skilled employees; yet a large gap remains across occupations conditional on their feasibility. In this section, we study different explanations for this result. We provide evidence on potential demand- and supply-side factors, namely organizational practices

¹⁶The ratio between WFH and teleworking feasibility is actually highest among non-connected workers, but as both teleworking and feasibility are very low in this group, the ratio is of limited interest and is not shown. For the remainder of the paper, we focus on connected employees and include non-connected ones only in robustness checks.

and workers' desire to WFH (i.e., to supply work done from home).

5.1 Organizational Factors

We focus on two main dimensions of the collective organization of work that might influence employers' willingness to allow their employees to telework: the degree of autonomy of workers and the extent of hierarchical control at work. These variables are natural candidates because they differ between low-, mid-, and high-skilled workers (Table A.7) and are likely related to managers' willingness to let their subordinates telework. Indeed, teleworking implies a more remote and difficult control of workers' effort. In settings where workers are closely monitored (e.g., because management worries about shirking or because the job is highly collaborative), managers may be more reluctant to allow them to telework, as this would mean a partial loss of their ability to control them or a higher cost of interaction.¹⁷

We first test this hypothesis during the COVID-19 crisis in 2021 using a series of linear regressions estimated among workers who declare they can telework and who belong to one of the three groups of teleworkable occupations (in the spirit of Alipour et al. (2023)). Namely, we estimate the following models using OLS:

$$T_{ij} = \beta Occ_i + \delta X_{ij} + \varepsilon_{ij}, \quad (1)$$

where T_{ij} is an indicator variable equal to 1 if worker i in firm j teleworks at least half a day per month, Occ_i denotes two occupation indicators for connected low-skilled and connected mid-skilled employees (high-skilled workers are the reference group), and X_{ij} is a set of control variables including worker i 's desire to work from home, her degree of autonomy and control in her job, basic demographics, and firm size and industry.

Results in Table 3 show that, among workers who can telework, occupations strongly pre-

¹⁷In some jobs, such as call centers (Bloom et al., 2015), the individual productivity of remote workers can be directly monitored, and this argument does not apply.

dict actual teleworking. Executives telework more than mid-skilled connected employees (7.5 percentage points more) and much more than low-skilled connected employees (17.4 percentage points more), as shown in column (1). These differences shrink but remain large—around +6 and +10 percentage points, respectively—even after controlling for a broad set of covariates, including workers’ demographics or desire to work from home, their degree of autonomy and hierarchical control, as well as the task content of jobs (columns 3 to 5).¹⁸ The latter do exhibit some correlation with the practice of teleworking, but of small economic magnitude.

In Appendix Table A.2, we show that results are very similar in a specification where we keep the group of non-connected workers in the analysis sample and use it as the reference group.¹⁹ In Table A.3, we also show that using the official one-digit French occupation groups yields qualitatively similar results.²⁰

These results largely carry over to the pre-COVID period, as shown in Table 4. In 2019, because we do not directly observe jobs that cannot be teleworked as in 2021, we do not exclude them and instead control for predicted teleworking feasibility. The prevalence of teleworking in 2019 strongly depends on both its feasibility and broad occupational groups: executives (connected mid-skilled workers) are 21.8 (4.4) percentage points more likely to telework than connected low-skilled workers—a result qualitatively similar to that in Table 3. These differences across occupations are largely robust to controlling for basic worker demographics (column 3) and management practices, workers’ autonomy and hierarchical control, and work organization (column 4).

These latter variables affect teleworking beyond feasibility constraints: facing no deadline in

¹⁸Part of the relationship between the “Wants to telework” dummy and the “Teleworking” dummy is mechanical, as the latter implies the former for a substantial share of employees.

¹⁹With no controls (column 1 of Table A.2), the gaps across occupational groups are identical, as expected. With controls, the differences drop to +6.1 percentage points between Executives and Connected Mid-Skilled, and +10.3 percentage points between Executives and Connected Low-Skilled. We prefer the main specification where the linearity of the model seems *ex ante* less of a strong assumption, given that teleworking among non-connected workers may differ substantially from that among connected ones.

²⁰We prefer to keep as the main classification the one emerging from our empirical investigation in Section 4 (see Figure 4).

one's daily work is associated with a 9 percentage points lower probability of teleworking, while having no hierarchy is associated with a 13.1 percentage points higher probability of teleworking. Given that 16.3% of the connected workforce teleworked in 2019, these magnitudes are large, showing that the organizational aspects of work and management practices were related to the probability of teleworking before the COVID-19 crisis. We further control for workers' education and firm size (observed in the 2019 working-conditions survey), with broadly similar conclusions (column 5). Appendix Tables A.4 and A.5 test for the robustness of our results to alternative occupational classifications in the same way as Tables A.2 and A.3 do for 2021; our conclusions remain qualitatively the same.

Our main specification for 2019 (Table 4) differs from that for 2021 (Table 3) in two main ways: the sample is different, because we excluded in 2021 workers who do not declare their work to be teleworkable, and the specification is different, because we included in 2019 the predicted feasibility. In Table A.6, we lift the sample restriction and include predicted feasibility for 2021. Results for 2021 are essentially unaffected by this modification, with the gaps between high-skilled connected workers and mid-skilled and low-skilled workers standing at +5.6 and +9.6 percentage points, respectively.

Two main results emerge from these analyses. First, management practices and the collective organization of work (e.g., granting workers autonomy, setting deadlines, or maintaining hierarchical links) are related to teleworking beyond feasibility constraints. Their link with teleworking was quantitatively large in 2019 but became less significant during the COVID-19 crisis in 2021, when teleworking became much more prevalent. Second, there are very large differences in the prevalence of teleworking between high-skilled and low-skilled occupations, even when comparing occupations and jobs that can be done from home to the same extent. These differences cannot be accounted for by feasibility constraints or by supply-side factors (workers' desire to telework and their attitudes or risks related to the pandemic in 2021). They are also largely unexplained by management practices that directly relate to teleworking and differ across

occupations.

5.2 Workers' Desire to Telework

As shown in Table 3, workers' desire to telework is a strong predictor of teleworking in regression analyses. However, it does not seem to explain much of the variation in teleworking across skill groups, since its inclusion as a control does not change the magnitude of gaps in teleworking between occupations. In this section, we investigate this result further.

Panel (a) of Figure 6 first shows, for each occupation category, how workers who telework or could telework are distributed according to their desire to telework. Two key patterns emerge. First, among workers who could telework but do not, a greater share would like to telework than not, a finding that holds for all three skill groups.

Panel (a) of Figure 6 also shows that supply-side factors are not likely to be the main determinant of differences in teleworking *across skill groups*. Indeed, the share of connected low-skilled employees who could telework but do not, despite wanting to, is the highest. By contrast, the share of workers who telework but would prefer not to is the largest among executives. If teleworking were fully aligned with workers' preferences (among workers who can telework), the share of teleworkers would increase from 7 to 11% among non-connected employees, from 41% to 57% among connected low-skilled employees, from 51% to 64% among connected mid-skilled workers, and from 66% to 74% among executives. Hence, if workers' desire to telework were taken into account, differences across skill groups would decrease.²¹

Looking at the intensive margin of teleworking, Panel (b) of Figure 6 further shows that, among workers who already teleworked in 2021, connected low-skilled employees were more willing to increase their teleworking time (21% of them versus 17% and 12% of connected mid-skilled and executive workers, respectively). They were also more likely to report that they did

²¹This larger mismatch between desired and actual WFH at the bottom of the earnings distribution is consistent with what Barrero et al. (2021) predict for the U.S. in the post-COVID-19 era.

not expect their desire to telework more to be met in the near future. This further confirms that gaps across occupations are not primarily driven by supply-side factors.

However, the differences across skill groups observed in Figure 6 could reflect the ability of executives and mid-skilled connected workers to disproportionately sort into teleworking-friendly firms. This could occur, for example, if their desire to telework, their ability to commute, or their willingness to forgo earnings to telework were larger than those of connected low-skilled workers. We explore this possibility by reproducing our main regressions on subsamples of workers split according to their willingness to telework, controlling for their demographic characteristics.

Table 5 shows that the gaps in teleworking between connected low-skilled employees and executives are largest among workers who want to telework two days or less per week (columns 2 and 3), as well as among workers who do not want to telework (column 4). These results highlight two mechanisms. First, the large gap across occupations among workers who do not want to telework shows that involuntary telework among executives plays a role in the overall gap. However, it is not the sole explanation. The large gap among workers who want to telework even the smallest amount possible (one day or less per week) suggests that connected low-skilled employees may face strong constraints from their supervisors in accessing this work arrangement. This interpretation is reinforced by the fact that the coefficients on hierarchical control (negative) and autonomy (positive) are the strongest in absolute terms for this group.

5.3 WFH Productivity in Routine or Conceptual Tasks

The literature on working from home (WFH) has identified productivity concerns in remote jobs as significant potential impediments to the implementation of telework. The conceptual nature of tasks has been an important dimension along which existing studies report positive or

negative effects.²² Overall, this literature suggests that differences across skill groups could be explained by differences in the productivity effects of WFH depending on workers’ task content.

We test this hypothesis in WC2019 by including in our baseline regression a variable asking employees whether their job involves “continuously repeating the same series of gestures or operations”, and in Tracov2021 by including a variable capturing the degree to which employees have to “think about multiple things simultaneously”.²³ Columns (2) and (5) of Table A.8 display the results; differences across skill groups are not meaningfully reduced. This further suggests that the nature of tasks (beyond what determines teleworking feasibility) is not a major factor explaining differences in teleworking across occupations.

5.4 WFH-Specific Amenities: Commuting Time, Housing Characteristics and Taxation

Finally, we investigate whether non-wage job amenities—such as commuting costs, home workspace availability, and tax-related incentives—help explain occupational gaps in telework. Controlling for urban density, which proxies commuting costs, does not reduce telework differences across occupations (Table A.8, column 6), suggesting that location-driven commuting costs are not a key factor. Similarly, accounting for housing size using second-order polynomials in the number of rooms and household size (column 7) fails to explain the gaps, implying that unequal access to dedicated home workspaces is not the main driver.

²²Dutcher (2012) directly examines this dichotomy in a laboratory experiment, finding that WFH has more negative impacts on productivity in routine tasks compared with more conceptual ones. Several recent studies report negative impacts of WFH on productivity in routine tasks (Atkin et al., 2023; Emanuel and Harrington, 2024; Jalota and Ho, 2024; Ho et al., 2024), though not universally (Bloom et al., 2015). Conversely, for more conceptual or analytical jobs, the effects are often positive (Barrero et al., 2023; Emanuel et al., 2023), but again, not universally (Gibbs et al., 2023).

²³The WC2019 variable directly identifies routine tasks. It is not a major predictor of working from home: it ranks 42nd among the 67 predictors in terms of importance in our full Random Forest model—which contrasts with Alipour et al. (2023), who identify the cognitive nature of tasks as one of the three major determinants of WFH feasibility. This variable is unavailable in Tracov2021, which is why we turn to the degree to which employees have to “think about multiple things simultaneously” as the best possible proxy for the routine degree of tasks.

We also test whether telework serves as a tax-favored form of compensation for high earners by controlling for monthly earnings interacted with marital status. Again, results remain unchanged (column 3), indicating that these non-wage considerations do not account for the observed occupational disparities in teleworking.

5.5 The Role of Managers: Monitoring Costs, Expected Productivity and Trust

The previous sections have not found robust empirical evidence for any of the candidate explanations of the gaps in teleworking across occupations. The remaining explanations are related to the willingness of managers to let their employees telework, but they are harder to test in our data. We nonetheless discuss this potential role of managers and provide suggestive evidence for its importance when possible.

A first factor is akin to taste-based discrimination: managers may have a distaste for, or incur a larger cost from, managing low-skilled workers remotely, for example because it is more complicated to do so. Providing explanations to lower-skill workers remotely may simply be more complicated and costly for managers (e.g., due to communication difficulties). Managers may derive a direct utility from monitoring and supervising their subordinates in face-to-face interactions, which is reduced with remote work. Indeed, remote monitoring introduces frictions in managerial relationships that may be larger for lower-skill workers. Managers may find it harder to reach out to their subordinates as easily and directly as they would in an office setting. Walking over to an employee's desk can allow for quicker resolution of an issue compared with communicating via chat or scheduling a remote call.

A second explanation related to managers is akin to statistical discrimination: they may have more negative priors regarding the productivity of low-skilled workers. This could be because these workers are perceived as less work-oriented than their higher-skill counterparts and may

be thought to be more likely to shirk. As a consequence, managers may be less willing to trust low-skilled workers to exert sufficient effort when working from home.²⁴

Both explanations are likely to play a role in explaining the remaining teleworking gap across occupations. Consistent with our findings, Lewandowski et al. (2025) provide evidence that employers are less willing to let workers holding routine tasks telework than they are for non-routine workers. They further show that employers' unwillingness to let workers telework is explained both by negative priors regarding productivity and by a personal cost of managing remote workers.

Using Tracov2021, we find suggestive evidence of statistical discrimination against low-skilled connected workers: the gaps across occupations conditional on teleworking feasibility are much smaller among workers with higher tenure. For example, the gap between executives and office employees is reduced from 20.4 percentage points among workers with less than a year of tenure to 5.7 percentage points among workers with more than five years of tenure (Table A.9). These results are consistent with the idea that employers may initially hold negative priors regarding the productivity of low-skilled workers at home, and that these priors disappear to a large extent once employers have had more time to observe their employees and consider them trustworthy.²⁵ Note that the order of magnitude of the gaps remains the same when we categorize workers based on official one-digit occupation groups (Table A.10).

The gaps across occupations are also smaller among workers whose main task is to supervise others and among workers who often take initiatives or who do not need much help from their supervisors (Table A.11).²⁶ Supervision tasks and autonomy, as measured by these variables, are

²⁴This explanation relates to the ability of workers to exert effort when working from home. It therefore differs from the differences in WFH productivity according to the task content of jobs tested in Section 5.3.

²⁵The fact that a gap remains among workers with more than five years of tenure could indicate that there still are asymmetries of information or moral hazard concerns that prevent managers from allowing some of their low-skilled subordinates to telework. Alternatively, the gap could suggest that for a fraction of low-skilled workers, productivity is lower when working from home. Finally, it could reflect that managers engage in taste-based discrimination or incur a higher cost in supervising low-skilled workers remotely, as discussed above.

²⁶Note that the existence of these heterogeneous gaps across skill groups depending on work practices is not in contradiction with the results in Section 5.1, which show that these practices cannot directly account for the gaps

likely to be offered to workers who are considered trustworthy by their hierarchy. Hence, the smaller gaps in teleworking among workers featuring such work practices suggest that trust from managers is an important determinant of teleworking among low-skilled workers.

6 Inequality in Access to Teleworking

The gaps in teleworking across occupations, conditional on its feasibility, suggest that the well-documented inequality in access to teleworking along the earnings distribution (Barrero et al., 2021; Bonacini et al., 2021) is not only driven by feasibility constraints. To support this point and conclude the paper, we compare teleworking and its feasibility along the earnings distribution in 2019.

Figure 7, Panel (a), first shows that the probability for a worker to hold a job in one of the three groups of “connected” occupations (connected low-skilled, connected mid-skilled, or executives) steadily increases along the earnings distribution, from 13% in the bottom decile to 90% in the top one.

Panel (b) shows the gaps between teleworking and its predicted feasibility *for these connected workers only*, along the deciles of the overall earnings distribution. We see that feasibility is almost flat, ranging between 50% and 60%: among connected workers, high wage-earners are not more likely to have a job that can be done from home. However, they are more likely to telework, implying that the share of jobs that are teleworked among those that are teleworkable increases along the earnings distribution—from around 10% in the bottom decile to more than 30% in the top one. This increase takes place mainly in the top half of the earnings distribution.

In Panel (c), we include all workers, so that variations in teleworking along the earnings distribution capture both the increase in teleworking feasibility and the increase in the intensity of teleworking given its feasibility. The key result is that there are large inequalities in access across occupations.

to teleworking given its feasibility: 50% of high-wage earners who can telework do so in 2019, while this is the case for only 10% to 20% of low-wage earners.

7 Conclusion

Our analysis shows that the obstacles to teleworking over the past thirty years have been mostly non-technical and go beyond feasibility constraints. Teleworking and WFH practices have increased in two distinct phases. The first phase, from the early 1990s to the brink of the COVID-19 crisis, saw a gradual increase. Over this period, work practices that are today the strongest predictors of telework feasibility—particularly the share of total working time that workers spend using ICT and computers—increased continuously. If these were the only factors determining teleworking, one would have expected it to increase much earlier, especially for office workers, who were already spending more than half of their working time on ICT tools by the late 1990s.

During the COVID-19 crisis, teleworking increased dramatically for the workers for whom it was feasible. For executives, teleworking came closer to its full potential and to their desired level, while their actual job tasks evolved substantially toward making teleworking more feasible. For office employees, a larger gap remains between actual teleworking and its feasibility, implying that these workers are still far from their desired level of teleworking. Working practices that make teleworking feasible were also much less affected during the COVID-19 crisis for these workers. This shows that the COVID-19 crisis alleviated some of the non-technical obstacles to teleworking, but not all of them—and mostly for skilled workers—leaving substantial room for extending teleworking among their low-skilled counterparts.

The gaps in teleworking across occupations conditional on feasibility have been observed since the early 2000s. They are statistically very robust. Some of them can be explained by organizational factors such as autonomy or monitoring. However, a larger share remains unex-

plained and is likely related to employers' distaste or difficulty in managing low-skilled workers remotely, as well as to their priors regarding the productivity of these workers at home.

This last explanation is crucial from a normative perspective. The gaps across occupations imply that the well-documented inequality in access to teleworking along the earnings distribution is not only driven by feasibility constraints. This source of inequality could therefore be alleviated by allowing low-skill workers to telework more. However, this would be efficient from an economic point of view only if employers' priors are incorrect—namely, if low-skilled workers would be as productive, or more productive, at home—something we are not able to fully test.²⁷ Existing studies find contrasting results, making it difficult to draw general conclusions. This is likely because the productivity of (low-skilled) workers at home depends on the precise type of job considered, how teleworking is implemented and organized, and on workers' ability to adapt to a novel work practice over time. Hence, there may be room to efficiently extend WFH among low-skilled workers. Our results indeed suggest that, independently of productivity considerations and feasibility constraints, managerial trust toward employees—and, more broadly, managerial discretion over the decision to allow WFH—may limit its development.

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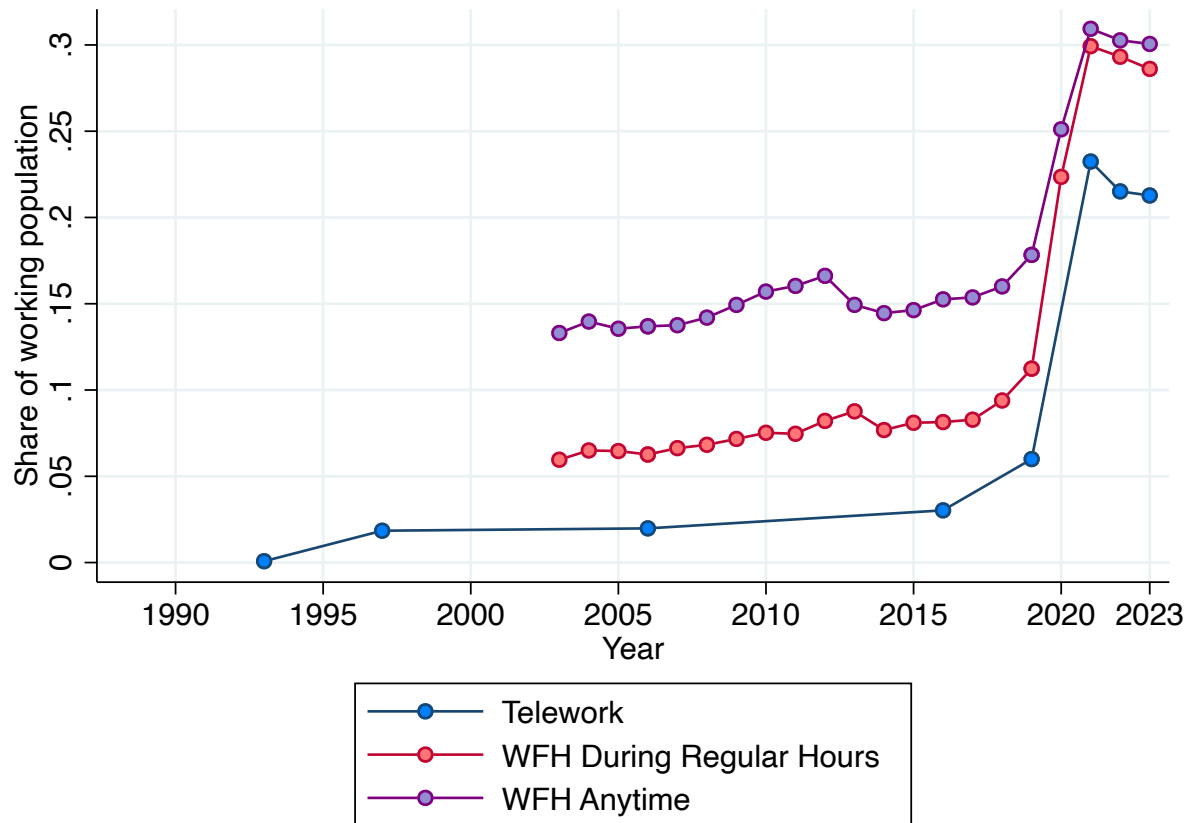
²⁷Yet, we have shown in Section 5.3 that measures of the task content of jobs (routine or conceptual work), which are likely to affect the productivity of remote work (see, e.g., Bloom et al. (2015), Bergeaud et al. (2023), Atkin et al. (2023), Emanuel and Harrington (2024), and Fenizia and Kirchmaier (2024)), cannot account for the lower incidence of remote work among low-skill workers.

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Figures and Tables

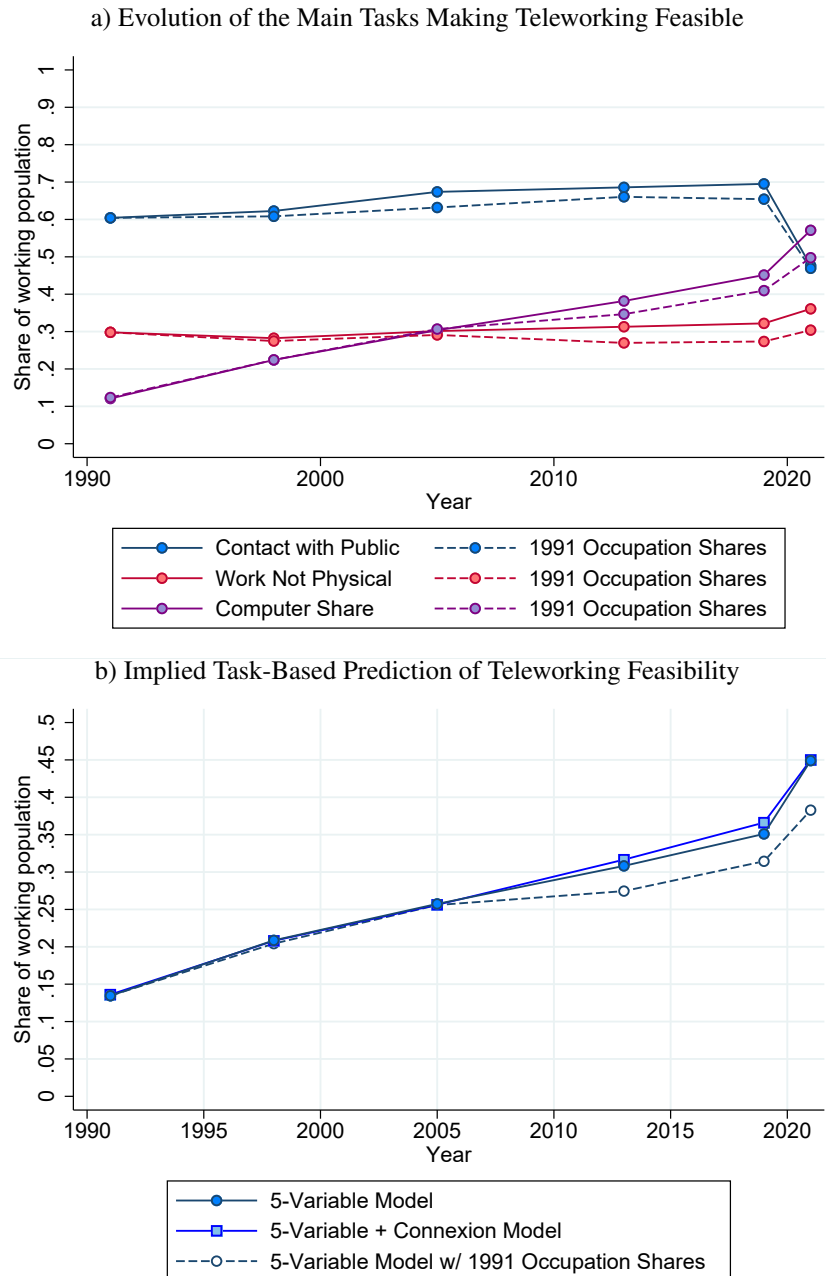
Figure 1: Evolution of Teleworking and Working From Home Since 1993



Source: Teleworking is obtained from various sources described in Section 2.2. WFH is measured using the Labor Force surveys.

Note: Regular working hours are typical shift hours or contractual hours.

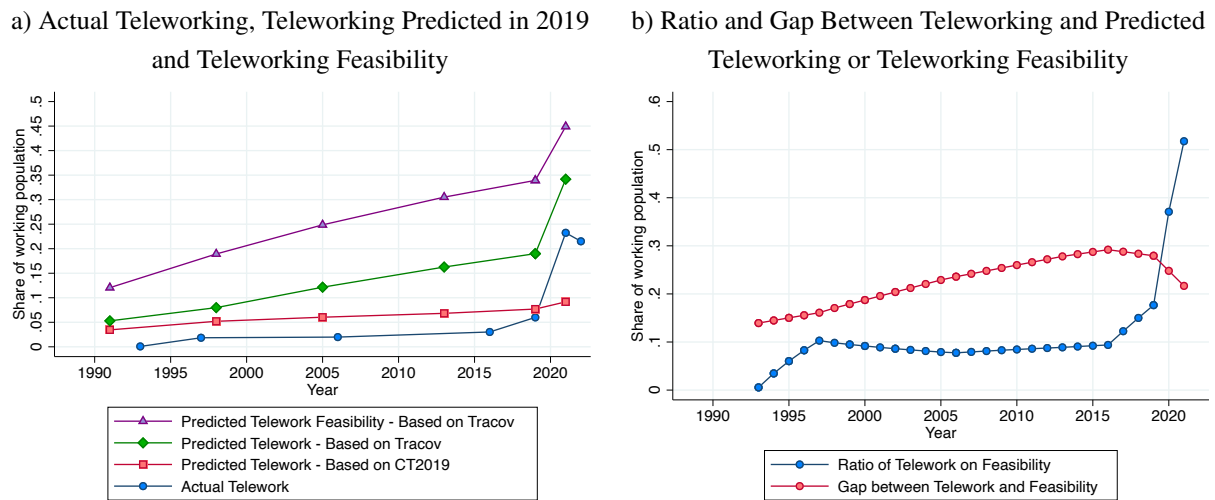
Figure 2: Evolution of Tasks Making Teleworking Feasible and Implied Task-Based Teleworking Feasibility Since 1991



Source: Working Conditions surveys 1991 to 2019, and Tracov survey 2021.

Note: Random forests are used to predict teleworking feasibility based on job tasks in early 2021. Before 2021, teleworking feasibility is no longer directly observed. In Panel a), we use the same observed tasks as in 2021 in earlier years to predict the extent of ML feasibility in the labor market the corresponding year. In Panel b), we show the evolution of the tasks that predict teleworking feasibility the most. The dotted lines show within-occupation variations, i.e., after reweighting individual observations at each period to maintain the share of each 2-digit occupation in the weighted population at its 1991 level.

Figure 3: Gaps Between Teleworking and Teleworking Feasibility Since 1991



Source: Working Conditions surveys 1991 to 2019 and Tracov2021 for teleworking feasibility, archive data for teleworking.

Note: In Panel b), before computing the ratio and gap, we use a simple linear interpolation between Working Conditions surveys to recover teleworking feasibility in every year.

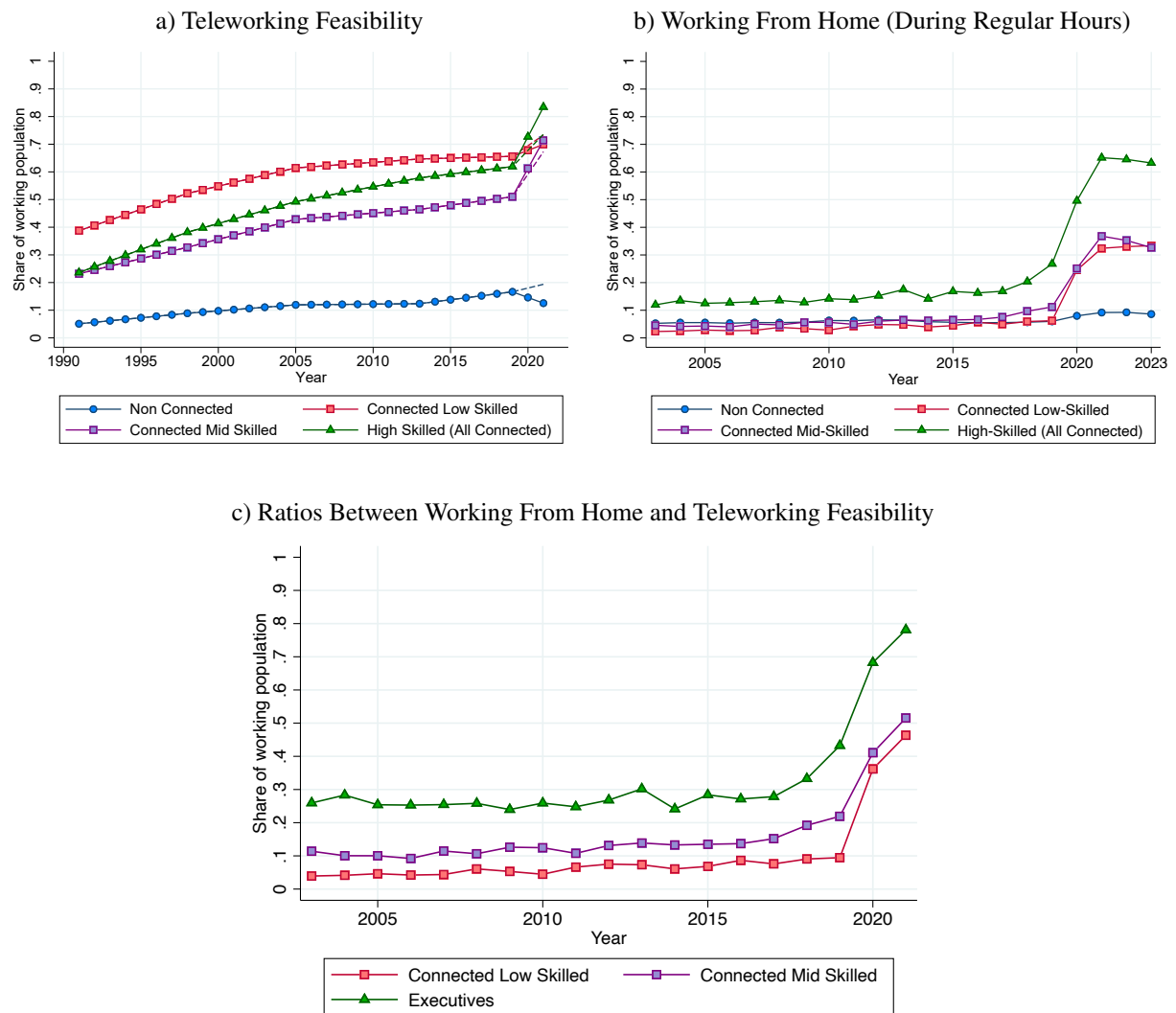
Figure 4: Teleworking and Teleworking Feasibility by 2-Digit Occupation in Early 2021



Source: Tracov2021.

Note: The Figure shows the share of jobs that are teleworked and could be teleworked in early 2021 in each 2-digit occupation. The absolute gap between the two is also shown.

Figure 5: Evolution of Working From Home and Teleworking Feasibility by Occupation

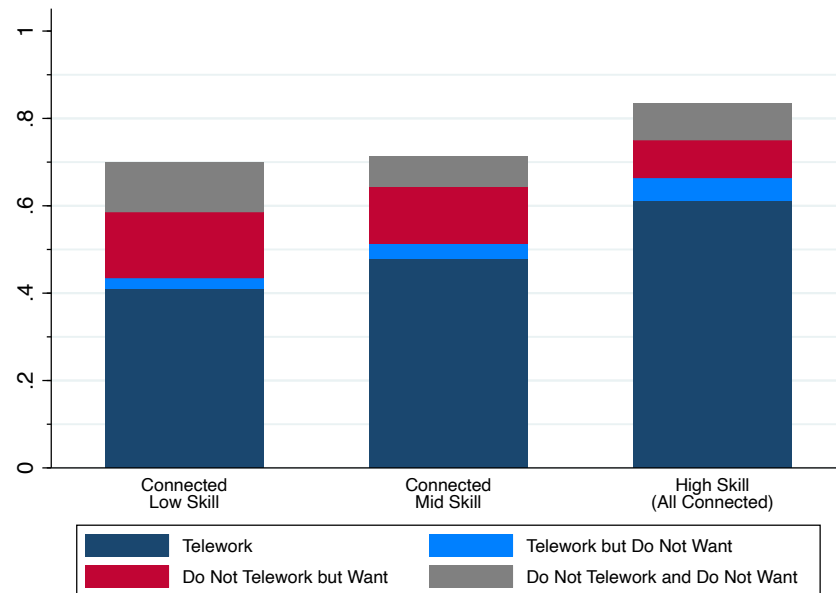


Source: Working Conditions surveys from 1991 to 2019, Tracov2021, and Labor Force surveys.

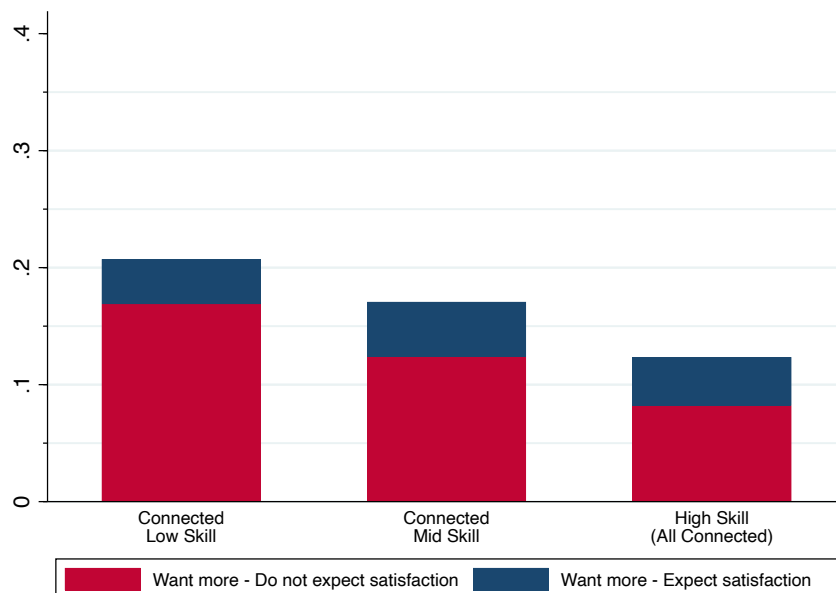
Note: Panel a) displays the evolution of our predicted measure of teleworking feasibility across occupation skill groups. The series are interpolated between years of Working Conditions surveys (1991, 1998, 2005, 2013, 2019). The dashed lines at the end display the actual measure of feasibility that can only be constructed in the Tracov2021 version of the survey. Panel b) shows the evolution of working from home during regular hours as reported in the Labor Force surveys across occupation skill groups. Panel c) displays the ratio between the working from home series of panel b) and the feasibility series in panel a).

Figure 6: Mismatch Between Telework and Desired Telework by Occupation Categories

a) Extensive Margin



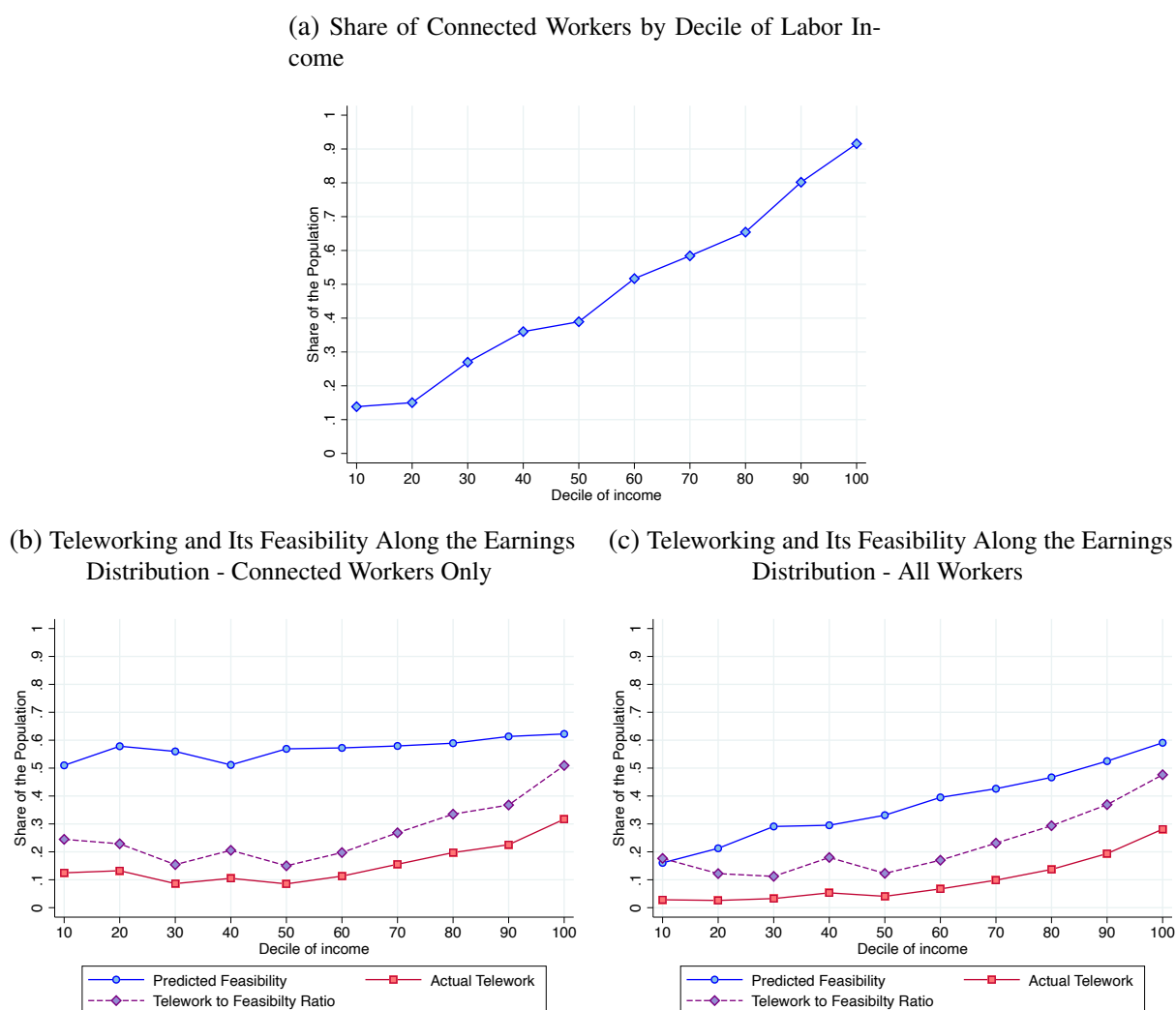
b) Intensive Margin: Share of Teleworkers Who Would Like to Telework More and Who Expect This Desire to Be Satisfied by the Employer



Source: Tracov2021.

Note: In Panel a), the bars total height correspond to share of workers whose job is teleworkable in each group. In Panel b), it is restricted to individuals who telework.

Figure 7: Inequality in Access to Teleworking and Teleworking Feasibility Along the Earnings Distribution in 2019



Source: Working Conditions survey 2019.

Note: Connected workers are those working in one of the three groups of connected occupations (i.e., occupations with a share of teleworkers larger than 30% in Tracov2021, see Figure 4). In Panel b) and (c), we compute average rate of teleworking and the average predicted teleworking feasibility in each earnings decile, as well as the ratio of the two. Panel b) restricts the analysis to connected workers (still considering the deciles of the whole working population) while Panel c) focuses on the whole working population.

Table 1: Summary of Micro-Data Sources

	Sample Size (Nb Workers)	Response Rate	Measure of Telework / WFH	Job Task Coverage
<i>a) Working Conditions Surveys</i>				
Tracov2021	19,953	39%	Telework + its feasibility	Limited
WC2019	19,569	69%	Telework	Very large
WC2013	33,676	70%	None	Very large
WC2005	18,789	85%	None	Large
WC1998	21,380	93%	None	Large
WC1991	20,929	NA	None	Large
<i>b) Labor Force surveys</i>				
2003Q1 to 2022Q4	280,00 to 350,000 per quarterly survey	80% to 90%	Working from home	None

Note: The Table describes the micro data-sources used in the paper. Details on the job tasks included in each working conditions survey are provided in Table A.1.

Table 2: Random Forest Prediction Results

		First Best (All Predictors)	Second Best (Common Predictors)
a) Telework Feasibility 2021 (mean= .451)	Nb Var	13	5
	MSE	0.111 (OLS=0.161)	0.158 (OLS=0.165)
	Q^2	0.552 (OLS=0.350)	0.362 (OLS=0.349)
	Five Most Important Predictors (Ordered)	Computer Share Work always physical Work often physical Contact with public/clients Work sometimes physical	Work always physical Computer Share Work often physical Work sometimes physical Contact with public
b) Telework 2021 (mean= .321)	Nb Var	13	5
	MSE	0.142 (OLS=0.176)	0.183 (OLS=0.183)
	Q^2	0.427 (OLS=0.338)	0.261 (OLS=0.260)
	Five Most Important Predictors (Ordered)	Computer Share Work always physical Work often physical Work close to other people Contact with public/clients	Work often physical Work always physical Computer Share Contact with public Work sometimes physical
c) Telework 2019 (mean = 0.078)	Nb Var	67	5
	MSE	0.013 (OLS = 0.071)	0.055 (OLS = 0.071)
	Q^2	0.820 (OLS = -0.076)	0.238 (OLS = -0.076)
	Five Most Important Predictors (Ordered)	Computer Share Does not work alone Work depends on external demand* Contact with public Reads small letters/numbers	Work always physical Computer Share Contact with public Work sometimes physical Work often physical

Note: The Table summarizes the performance of, and main predictors from Random Forests predictions of teleworking and teleworking feasibility in Tracov2021 and CT2019. The two columns provide results from the first-best predictors (when all items describing job tasks or the organization of work in a given survey are used as predictors) and second-best predictors (when only items common to all surveys since 1991 are used). In parenthesis we report the statistics from benchmark OLS models estimated on the same set of variables, which predictions have been categorized to 0 and 1 based on a 0.5 cut-off (as those of the ML models). The data sources (Tracov2021 and CT2019) are described in the main text. “Computer share” means the share of working time spent using connected computers (see details in Appendix A). In Panel c), the exact predictor for “Work depends on external demand” is “Work depends on external demand that does not require immediate response”. The Q^2 is akin to a R^2 in an OLS model except that it is computed on a separate test sample (not the sample used for prediction): $Q^2(Y) = 1 - \frac{MSE(Y)}{Var(Y)}$.

Table 3: Drivers of Teleworking in 2021 (Linear Probability Model)

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Teleworking Dummy				
Connected Mid Skilled	-0.075*** (0.014)	-0.047*** (0.014)	-0.057*** (0.013)	-0.062*** (0.013)	-0.056*** (0.013)
Connected Low Skilled	-0.174*** (0.020)	-0.105*** (0.021)	-0.097*** (0.019)	-0.104*** (0.019)	-0.097*** (0.019)
Wants to TWK			0.460*** (0.016)	0.459*** (0.016)	0.432*** (0.016)
No Hierarchy				0.026 (0.026)	0.037 (0.026)
Degree of Hierarchy Control				-0.015* (0.008)	-0.011 (0.008)
Autonomy				0.062*** (0.007)	0.057*** (0.007)
Computer Share					0.273*** (0.036)
Contact with Public					-0.088*** (0.014)
Work Always Physical					-0.116*** (0.039)
Work Often Physical					-0.094*** (0.029)
Work Never Physical					-0.039*** (0.014)
Observations	4,279	4,279	4,278	4,277	4,276
R-squared	0.019	0.119	0.269	0.292	0.318
Covid-related Controls	No	No	Yes	Yes	Yes
Demographic Controls	No	Yes	Yes	Yes	Yes

Source: Tracov2021.

Note: The regression sample is restricted to connected employees with the reference category being Executives, and amongst those, to employees declaring that their job can be teleworked. Appendix A.2 reports results on the full sample. Covid-related Controls capture the fear of catching COVID-19 while commuting, being particularly vulnerable to COVID-19, living with people particularly vulnerable to COVID-19, and working in an environment when catching COVID-19 is likely. Demographic controls include gender, age, seniority, continent of Birth, region of living. Firm size controls are a second order polynomial in the number of employees. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4: Regressions of Teleworking on Predicted Feasibility and Occupation Groups in 2019

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Teleworking Dummy				
TWK Feasiblility Prediction	0.109*** (0.016)	0.101*** (0.016)	0.068*** (0.017)	0.059*** (0.018)	-0.035 (0.047)
Connected Mid Skilled	-0.174*** (0.009)	-0.160*** (0.009)	-0.151*** (0.010)	-0.131*** (0.011)	-0.115*** (0.012)
Connected Low Skilled	-0.218*** (0.013)	-0.197*** (0.014)	-0.174*** (0.014)	-0.134*** (0.016)	-0.127*** (0.017)
Autonomy in Deadlines			-0.004 (0.010)	-0.001 (0.010)	-0.004 (0.010)
No Deadlines			-0.090*** (0.015)	-0.079*** (0.015)	-0.072*** (0.015)
Surveiled by Hierarchy			-0.049*** (0.011)	-0.029*** (0.011)	-0.023** (0.011)
Can Interrupt Work			0.043*** (0.014)	0.043*** (0.014)	0.026* (0.014)
No orders			-0.035* (0.020)	-0.023 (0.020)	-0.024 (0.020)
No Hierarchy			0.130*** (0.024)	0.125*** (0.024)	0.091*** (0.024)
Autonomy regarding orders			0.027*** (0.009)	0.015* (0.009)	0.013 (0.009)
Autonomy regarding workload			-0.001 (0.004)	-0.003 (0.004)	-0.000 (0.004)
Works autonomously			0.020*** (0.005)	0.018*** (0.005)	0.012** (0.005)
Degree of supervision of other			0.003 (0.004)	0.008* (0.004)	0.009** (0.004)
Observations	7,602	7,582	7,507	7,480	7,320
R-squared	0.067	0.092	0.111	0.172	0.201
Demographic Controls	No	Yes	Yes	Yes	Yes
Education and firm size	No	No	No	Yes	Yes
Complete Task Variables	No	No	No	No	Yes

Source: WC2021.

Note: The regression sample is restricted to connected employees with the reference category being Executives. Appendix Table A.4 reports results on the full sample. Demographic controls include gender, age, seniority, continent of Birth, region of living. Firm size controls are a second order polynomial in the number of employees. "Complete task variables" corresponds to the 67 identified task variables used for the first-best predictor of teleworking in 2019. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5: Regressions of Teleworking on Occupation Groups in 2021 Based on Willingness to Telework

	(1)	(2)	(3)	(4)
	Dependent Variable: Teleworking Dummy			
	Wants TWK ≥ 3 Days	Wants TWK 2 Days	Wants TWK ≤ 1 Day	Does Not Want TWK
Connected Mid Skilled	-0.039** (0.016)	-0.076*** (0.020)	-0.070** (0.033)	-0.022 (0.043)
Connected Low Skilled	-0.034 (0.024)	-0.113*** (0.033)	-0.089* (0.049)	-0.148*** (0.057)
No Hierarchy	-0.006 (0.032)	0.035 (0.041)	0.011 (0.072)	0.109 (0.086)
Degree of Hierarchy Control	-0.005 (0.011)	-0.028** (0.013)	-0.038* (0.022)	0.013 (0.028)
Autonomy	0.045*** (0.009)	0.068*** (0.011)	0.111*** (0.018)	0.028 (0.023)
Observations	1,267	1,301	993	686
R-squared	0.169	0.231	0.204	0.244
Mean TWK in Subsample	.925	.855	.643	.328
Demographic Controls	Yes	Yes	Yes	Yes

Source: Tracov2021.

Note: The regression sample is restricted to connected employees with the reference category being Executives. Appendix A.2 reports results on the full sample. Demographic controls include gender, age, seniority, continent of Birth, region of living. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Online Appendix to

Gaps between working from home and its feasibility over time and across occupations

Thomas Breda, Paul Dutronc-Postel and Vladimir Pecheu

Wednesday 21st January, 2026

List of Appendices

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A Details on Machine Learning Prediction

The Random Forest Method. As mentioned in the main text, Random Forest is a non-linear technique that predicts an outcome based on a set of optimized tree classifiers. Each tree is constructed to predict the outcome variable using a number of randomly drawn explanatory variables among a set of potential predictors.

Figure A.2 illustrates an example of a tree classifier for telework in 2021 based on three variables: computer share, a dummy for whether the job is physically demanding, and a dummy for whether the individual interacts with the public. The outcome of the tree can be either continuous (the tree predicts the probability of teleworking in a given leaf as the share of individuals in the sample who telework in that leaf) or categorical (the prediction is 0 or 1 depending on whether the share is below or above 50%). For example, the tree predicts that an individual will telework if she works on a computer more than 86% of the time and her job is not physically demanding, or if her computer share is between 50% and 86% and her job is neither physically demanding nor involves interaction with the public. Because our objective is to best predict the average share of the population that teleworks, or can telework, within large subgroups of workers, we favor continuous models in most of our applications.

A forest is a collection of tree classifiers which outcome for a given individual is the average prediction over all trees. A random forest is a forest in which each tree's predictors are limited and randomly drawn from the set of explanatory variables. Randomly drawing and limiting the set of explanatory variables used to predict the outcome prevents overfitting the model, as opposed to using simple trees or forests without randomization. This ensures that out-of-sample performance is maximized.

In practice, we tune the number of explanatory variables randomly drawn using cross-validation. For each model with a given number of explanatory variables, we divide our training sample into ten subsamples and repeatedly compute the cross-validation error for a given number of features randomly drawn. We do this by alternately estimating the Random Forest model on nine pooled subsamples and predicting its mean square error (MSE) on the remaining one. We then average these ten MSEs and repeat the procedure for all possible numbers of explanatory variables to be randomly drawn. We ultimately select the model with the number of randomly drawn explanatory variables that minimizes the MSE. The formula of the MSE is the following:

$$MSE(Y) = \frac{1}{n} \sum_{i=1}^n (Y_i - \tilde{Y}_i)^2, \quad (\text{A.1})$$

where Y_i is the outcome variable for individual i , and $\tilde{Y}_i$ is the prediction of this variable given

the characteristics of the job of individual i .

The other tuning parameter that we can adjust is the number of trees that constitute the forest. In principle, the larger the forest, the better the prediction. We therefore set this number to be very large (500 trees). For more details on the Random Forest technique, see Breiman (2001) and Louppe (2014).

Construction of Predictors for First- and Second-Best Predictions and Evaluation of Their Performance. To evaluate the quality of our predictions, we proceed with the cross-validation method described above on the training sample of our data. This training sample is a randomly drawn subsample containing 80% of the observations in our base dataset. After fine-tuning our Random Forest model, we estimate it and compute its MSE on the remaining 20% of observations, which constitute the prediction sample. Thereby we apply the common “80:20” rule (Joseph, 2022), but note that our results are robust to alternative splits. Our first-best models are trained using as potential predictors all variables describing tasks or the nature of the job. The second-best models use only variables that are common across all surveys and years.

Note also, that we split non-continuous variables with multiple modalities into separate dummies (e.g., “Work sometimes physically demanding,” “often physically demanding,” “always physically demanding”). We do this for three reasons. First, the initial coding of these variables (usually a series of integers) does not necessarily provide the correct scale to order modalities, especially when “not applicable” categories arise. Second, because questions do not always have the same modalities in different surveys, this approach allows for a better matching of variables across surveys. Third, it improves the flexibility and, therefore, the performance of the model. Hence, all predictors are either continuous or dummy variables.

We evaluate the performance of the models using two criteria: the Mean Square Error (MSE), presented above, and the Q^2 , as in Quan (1988), defined for outcome variable Y as follows:

$$Q^2(Y) = 1 - \frac{MSE(Y)}{Var(Y)}. \quad (A.2)$$

The Q^2 measures the predictive relevance of a model. The higher its value, the more relevant the model is in predicting the outcome variable. The difference with the R^2 is that Q^2 is computed using the MSE on the prediction sample, which is not used in estimating the model.

Performance of Alternative ML Methods. Alternative popular machine learning methods include LASSO, Ridge Regressions, Trees, Forests, Gradient Boosting, and Neural Networks. Random Forests are better suited than LASSO and Ridge Regressions in our case (and in-

deed offer better predictions) due to the non-linear flexibility they provide. We experimented with LASSO and Ridge Regression models, and their predictions systematically underperformed compared to Random Forests.

Simple trees and forests are less sophisticated than Random Forests and more prone to overfitting, as is also the case for gradient boosting (an extension of Random Forests). Neural networks can potentially perform better than Random Forests but only in large datasets, which is not the case in our analysis where the number of observations varies between 12,000 and 20,000. See Hastie et al. (2009) for a general introduction to these methods and Varian (2014) or Mullainathan and Spiess (2017) for surveys of applications in economics.

Sample Selection in Working Conditions Surveys. We restrict the sample to salaried workers and exclude occupations 31 (“Independent Workers”), 35 (“Artists and Entertainment Occupations”), 44 (“Clergy”), and 42 (“Teachers”). We do so because their jobs do not correspond to typical salaried work and their relation to working from home differs from that of other occupations. Many independent workers, artists, and members of the clergy declare working from home all the time because their home and workplace are the same environment. Teachers, on their side, almost systematically work from home to prepare lessons or grade tests and exams.

Sample Selection in Tracov2021. For predictions based on Tracov2021, we exclude workers who worked fewer than 15 hours during their reference week (i.e., short part-time work, representing 8.9% of the sample). We do this to construct a measure of the share of hours worked on a computer that is comparable to that obtained from other Working Conditions surveys.

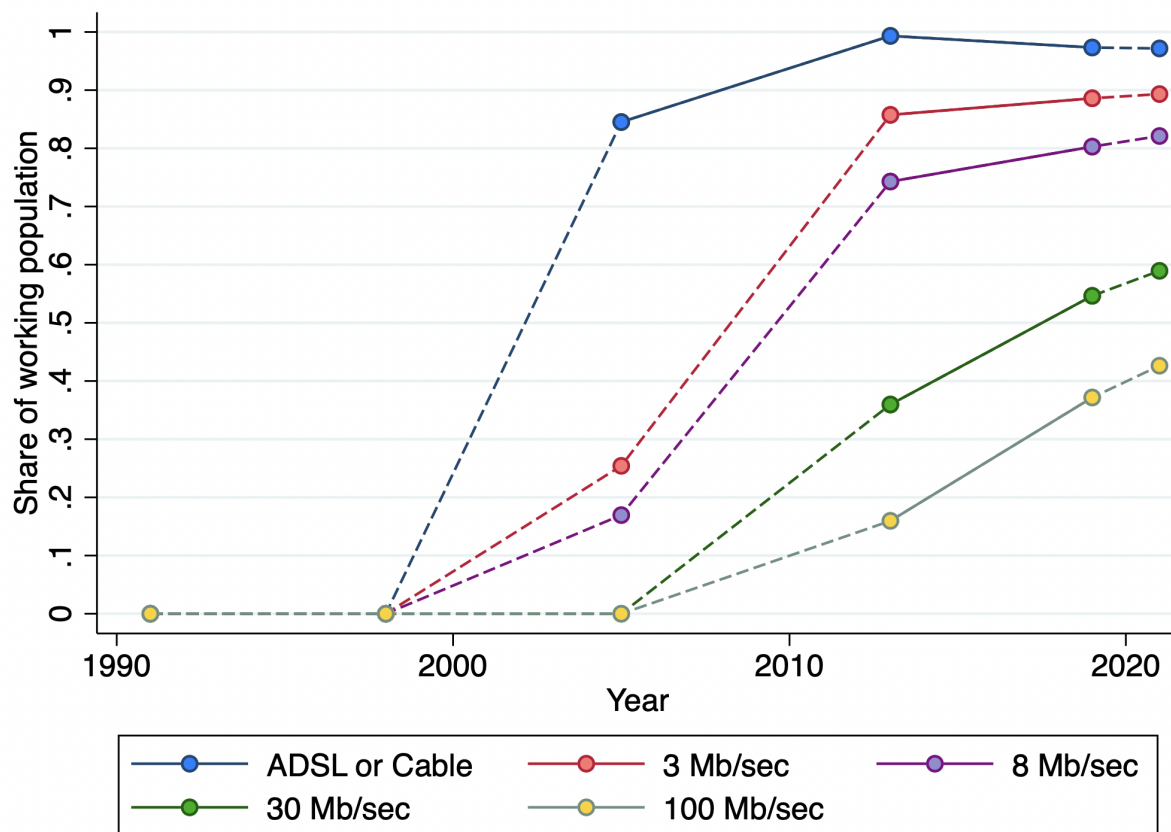
Indeed, as in other Working Conditions surveys, Tracov2021 provides the number of hours worked in front of a connected computer during a typical day. However, unlike other Working Conditions surveys, it does not provide the total number of hours worked in a typical day, but only the number of hours worked per week. To avoid overestimating the share of hours spent in front of a computer, we remove short part-time workers and divide the number of hours an individual declares to work on a computer by seven (the legal daily working time in France) to obtain a reasonable measure of the computer share.^{A.1}

Since the other Working Conditions surveys report typical daily hours worked, we have not applied this restriction there in order to keep a sample representative of the whole working population. We have, however, performed robustness analyses applying this restriction to all yearly samples, and results are almost identical.

^{A.1}Overestimation is less of a concern as we winsorize the share at one.

B Additional Figures and Tables

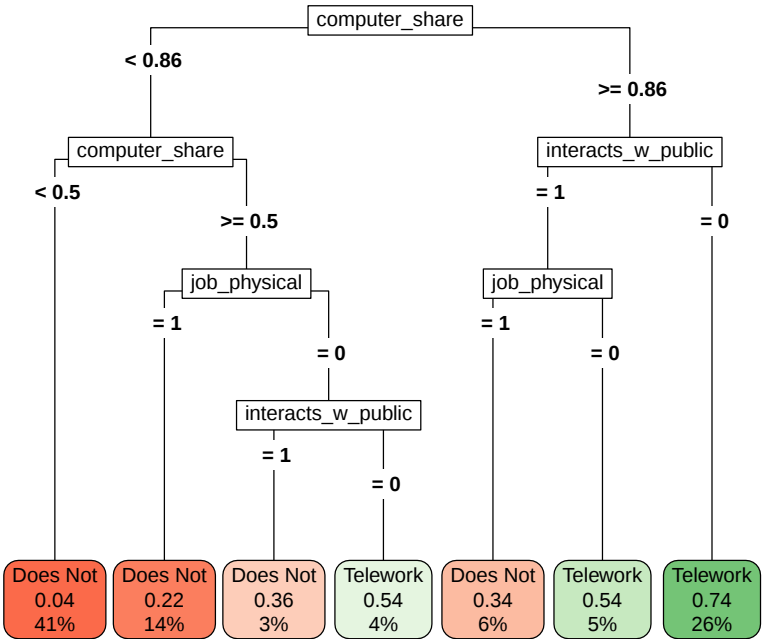
Figure A.1: Evolution of Internet Coverage



Source: ARCEP Internet Coverage.

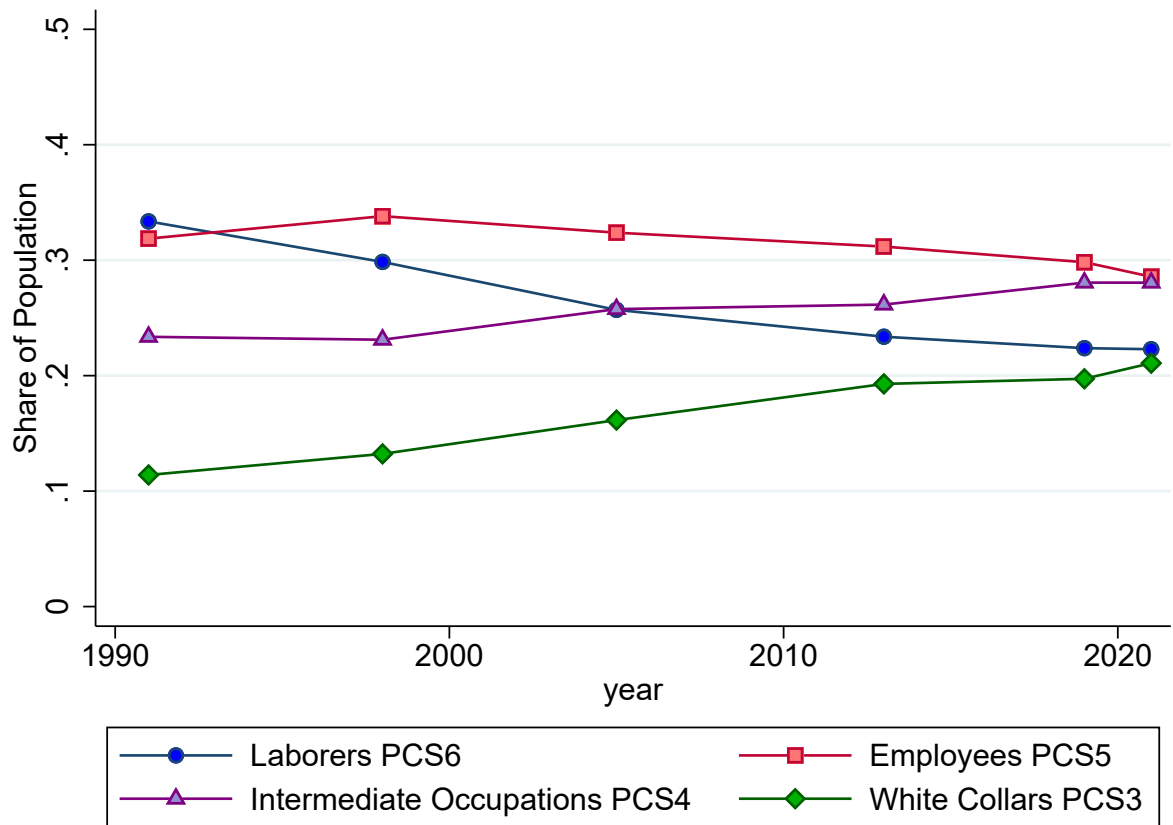
Note: The figure displays the percentage of the French population with access to different Internet connection types over time: ADSL (Asymmetric Digital Subscriber Line, with a speed of 512 kb/sec when it was introduced in 1999) until 2005 and ADSL or cable afterwards, and 4 broadband Internet connection speed levels: 3, 8, 30, and 100 Mb/sec. Dashed lines are based on linear interpolations for earlier periods (we know that in 1998 none of the connection types were existing, and that in 2005 there was no connection speed equal or larger than 30 Mb/sec) and extrapolations for the period of 2019-2021.

Figure A.2: Example of an Optimized Decision Tree for Teleworking in 2021



Note: The first row of results indicates the prediction regarding teleworking or not, the second row, the average proportion of individuals teleworking in the corresponding class, the third one the percentage of individuals the class represents in the total sample.

Figure A.3: Evolution of 1-Digit Occupation Shares, 1991-2021

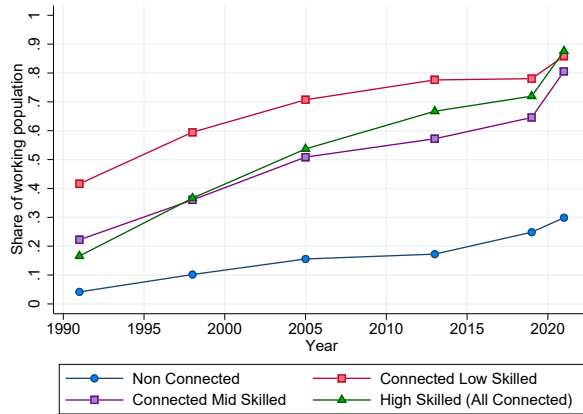


Source: Labor Force survey 1991-2021.

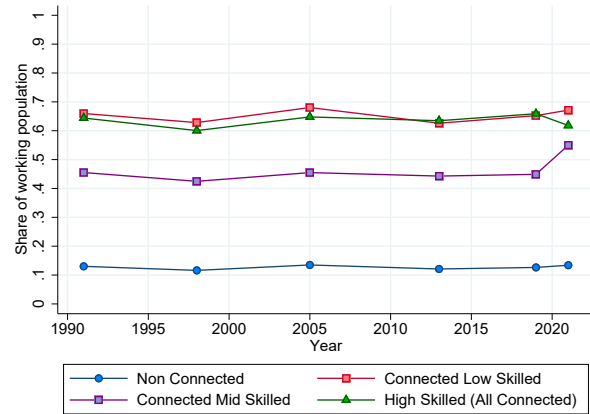
Note: The Figure shows the evolution of the share of the working population in our sample of analysis in each main 1-digit occupation group.

Figure A.4: Evolution of Tasks That Make Teleworking Feasible by Occupation

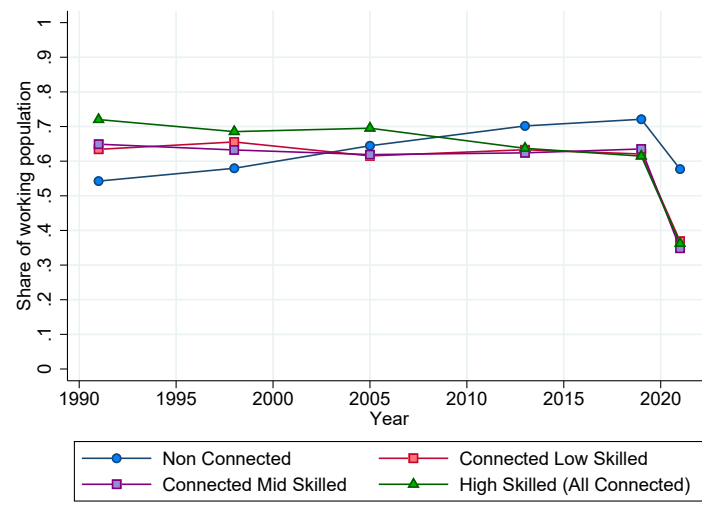
a) Share of Hours Spent Using Connected Computers



B) Share of Not Physically Demanding Jobs

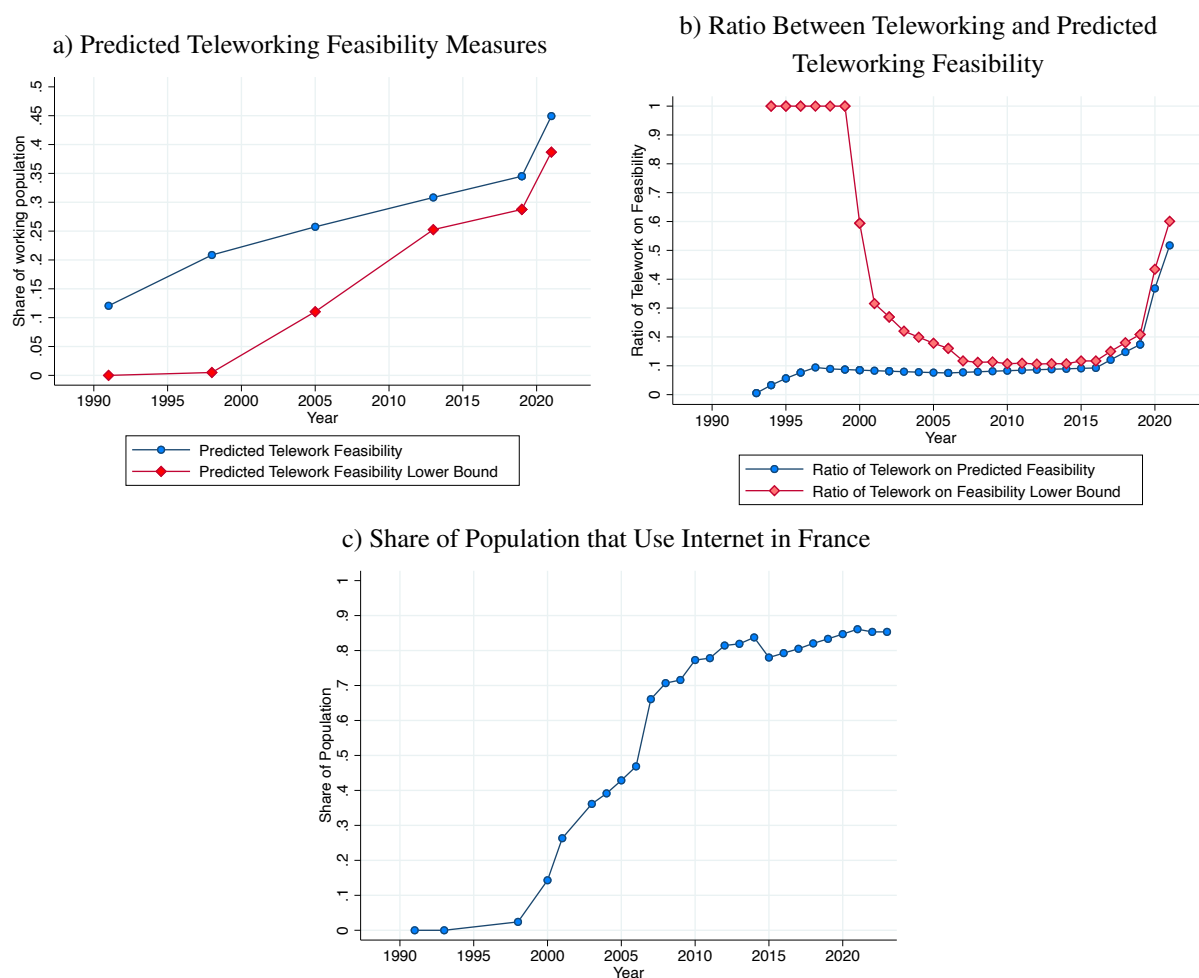


c) Share of Jobs Requiring Contacts With the Public



Source: Working Conditions surveys from 1991 to 2019, Tracov2021.

Figure A.5: Alternative Measure for the Gap between Teleworking and Teleworking Feasibility Since 1991



Source: Working Conditions surveys 1991 to 2019 and Tracov2021 for teleworking feasibility. Archive data for teleworking. International Telecommunication Union for Internet Usage in France between 2000 and 2021, *Médiangles* survey for 1998.

Note: Panel a) displays our base measure of task-based predicted telework feasibility (blue) against an alternative lower bound constructed by multiplying the base measure by the percentage of individuals connected to the Internet in France over the period (red). In Panel b), we display the ratio of actual teleworking to each one of these measures of feasibility. If the ratio exceeds unity, we cap it to one. Note also that before computing it, we use a simple linear interpolation between Working Conditions surveys to recover teleworking feasibility at each date. We also interpolate Internet usage data for years 1995-1997 and 1999.

Table A.1: Questions of the Working Conditions Survey

A-10

Question	Working Conditions Survey					Tracov
	1991	1998	2005	2013	2019	2021
Intensity of ICT Use at Work						
During your work, do you use (even occasionally) a)... a desktop computer?				✓	✓	
During your work, do you use (even occasionally) a)... a microcomputer connected to a network or to other computers?		✓	✓			
During your work, do you use (even occasionally) a)... a standalone microcomputer?		✓	✓			
During your work, do you use (even occasionally) b)... a laptop computer?		✓	✓	✓	✓	
During your work, do you use (even occasionally) c)... a tablet, a PDA, a mobile or embedded terminal? c)... a terminal or computer console (1998, 2005)		✓	✓		✓	
Do you have a professional email inbox?			✓	✓	✓	
Aside from messaging, do you use the Internet for professional purposes?		✓	✓	✓	✓	
Do you use an Intranet or internal communication network?			✓	✓	✓	
When you are not at your workplace, can you access... b)... your organization's or institution's computer system?				✓	✓	
In total, how much time do you spend professionally using the computer equipment we have just discussed?	✓	✓	✓	✓	✓	✓
Intensity of Face-To-Face Interactions With Either Colleagues or the Public						
<i>...interactions with the public</i>						
Are you in direct contact with the public? (users, patients, students, travelers, clients, suppliers, etc.)	✓	✓	✓	✓	✓	✓
... face-to-face?			✓	✓	✓	
... by phone?			✓	✓	✓	

... electronically (email, forum, chat, social networks)?			✓	✓	✓	
Is your work pace dictated by external demands (clients, patients, public) requiring an immediate response?	✓	✓	✓	✓	✓	
Do you experience tense situations in your interactions with the public (users, patients, students, travelers, clients, suppliers, etc.)?	✓	✓	✓	✓	✓	
<i>...interactions with colleagues</i>						
Do you work alone?				✓	✓	✓
Is your work pace dictated by immediate dependency on the work of one or more colleagues?	✓	✓	✓	✓	✓	
Do you experience tense situations in your interactions with your colleagues? 3. (no colleagues)	✓	✓	✓	✓	✓	
Is your work pace dictated by constant monitoring or surveillance (permanent or at least daily) exercised by management?	✓	✓	✓	✓	✓	

Measures of Physical Intensity and Manual Work

A-11

Does your work involve ...						
... long periods of standing?	✓	✓	✓	✓	✓	
... long periods in another uncomfortable posture or tiring in the long run?	✓	✓	✓	✓	✓	
... frequent and long walks?	✓	✓	✓	✓	✓	
... lifting or moving heavy loads?	✓	✓	✓	✓	✓	
... other significant physical efforts?	✓	✓				
... painful or tiring movements?		✓	✓	✓	✓	
... exposure to shocks or vibrations?	✓	✓	✓	✓	✓	
... not being able to take your eyes off your work?	✓	✓	✓	✓	✓	
... reading small letters or numbers (or poorly printed, or poorly written) ?	✓	✓	✓	✓	✓	
... examining very small objects, fine details?	✓	✓	✓	✓	✓	
... paying attention to brief visual or auditory signals, unpredictable or difficult to detect?	✓	✓	✓	✓	✓	
... wearing work clothes?	✓					

When you work, if a person, standing 2 or 3 meters away from you, speaks to you ... 1. you hear them if they speak normally 2. you hear them if they raise their voice 3. you cannot hear them

✓ ✓ ✓ ✓ ✓

Is your work pace dictated by ...

a) ... the automatic movement of a product or a part?

✓ ✓ ✓ ✓ ✓

Is your work pace dictated by ...

b) ... the automatic rhythm of a machine?

✓ ✓ ✓ ✓ ✓

Where do you spend most of your working time?

5. Traveling (e.g., flight attendant, sales representative, truck driver, driver...)

✓ ✓

8. On one or more construction sites

✓ ✓

Is this mainly because ... ?

3 - you are on a mission, working on a construction site, or intervening at clients' premises

✓

Do you use a vehicle for work or for your professional needs, outside of commuting?

✓ ✓

Health and Safety

At your workplace, are you required to ...

a) ... breathe fumes or dust?

✓ ✓ ✓ ✓ ✓

b) ... be in contact with hazardous substances?

✓ ✓ ✓ ✓ ✓

c) ... be exposed to infectious risks?

✓ ✓ ✓ ✓ ✓

d) ... risk being injured or having an accident?

✓ ✓ ✓ ✓ ✓

e) ... risk traffic accidents during work?

✓ ✓ ✓ ✓ ✓

Does your employer provide you with personal protective equipment such as gloves, goggles, safety shoes, harnesses, ... ?

✓ ✓

Do you use them?

✓ ✓

Quality of internet connection at home

Residential municipality

✓

Table A.2: Regressions of Teleworking on Actual Feasibility and Occupation Groups in 2021

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Teleworking Dummy				
Executives	0.248*** (0.019)	0.192*** (0.019)	0.168*** (0.018)	0.168*** (0.018)	0.102*** (0.018)
Connected Mid Skilled	0.173*** (0.019)	0.143*** (0.020)	0.109*** (0.018)	0.102*** (0.018)	0.041** (0.018)
Connected Low Skilled	0.074*** (0.024)	0.082*** (0.024)	0.065*** (0.022)	0.055** (0.022)	-0.001 (0.022)
Wants to TWK			0.455*** (0.015)	0.454*** (0.015)	0.427*** (0.015)
No Hierarchy				0.042* (0.025)	0.051** (0.025)
Degree of Hierarchy Control				-0.009 (0.008)	-0.003 (0.008)
Autonomy				0.065*** (0.006)	0.060*** (0.006)
Computer Share					0.218*** (0.031)
Contact with Public					-0.088*** (0.013)
Work Always Physical					-0.088*** (0.034)
Work Often Physical					-0.144*** (0.026)
Work Never Physical					-0.046*** (0.013)
Observations	5,050	5,050	5,048	5,047	5,046
R-squared	0.038	0.121	0.262	0.287	0.312
Covid-related Controls	No	No	Yes	Yes	Yes
Demographic Controls	No	Yes	Yes	Yes	Yes

Source: Tracov2021

Note: Covid-related Controls capture the fear of catching COVID-19 while commuting, being particularly vulnerable to COVID-19, living with people particularly vulnerable to COVID-19, and working in an environment when catching COVID-19 is likely. Demographic controls include gender, age, seniority, continent of Birth, region of living. Firm size controls are a second order polynomial in the number of employees. Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Regressions of Teleworking on Actual Feasibility and 1-Digit Official Occupation Groups in 2021

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Teleworking Dummy				
Executives (PCS 3)	Ref	Ref	Ref	Ref	Ref
Mid Skilled Employees (PCS 4)	-0.097*** (0.014)	-0.066*** (0.014)	-0.071*** (0.013)	-0.078*** (0.013)	-0.063*** (0.013)
Low Skilled Employees (PCS 5)	-0.197*** (0.017)	-0.135*** (0.018)	-0.123*** (0.016)	-0.132*** (0.016)	-0.104*** (0.016)
Laborers (PCS 6)		-0.164*** (0.039)	-0.153*** (0.036)	-0.139*** (0.036)	-0.091*** (0.035)
Wants to TWK			0.456*** (0.015)	0.455*** (0.015)	0.427*** (0.015)
No Hierarchy				0.043* (0.025)	0.051** (0.025)
Degree of Hierarchy Control				-0.008 (0.008)	-0.003 (0.008)
Autonomy				0.067*** (0.006)	0.060*** (0.006)
Computer Share					0.224*** (0.031)
Contact with Public					-0.090*** (0.013)
Work Always Physical					-0.088*** (0.034)
Work Often Physical					-0.144*** (0.026)
Work Never Physical					-0.046*** (0.013)
Observations	5,050	5,050	5,048	5,047	5,046
R-squared	0.030	0.114	0.259	0.284	0.312
Covid-related Controls	No	No	Yes	Yes	Yes
Demographic Controls	No	Yes	Yes	Yes	Yes

Source: Tracov2021.

Note: The specifications in this table are similar to those of Table A.2 but the categorization of workers is based on the official French PCS 1-digit occupation categorization. Covid-related Controls capture the fear of catching COVID-19 while commuting, being particularly vulnerable to COVID-19, living with people particularly vulnerable to COVID-19, and working in an environment when catching COVID-19 is likely. Demographic controls include gender, age, seniority, continent of Birth, region of living. Firm size controls are a second order polynomial in the number of employees. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.4: Regressions of Teleworking on Predicted Feasibility and Occupation Groups in 2019

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Teleworking Dummy				
TWK Feasibility Prediction	0.093*** (0.008)	0.092*** (0.008)	0.083*** (0.008)	0.062*** (0.009)	0.040* (0.022)
Executives	0.236*** (0.006)	0.224*** (0.007)	0.203*** (0.007)	0.159*** (0.008)	0.144*** (0.008)
Connected Mid Skilled	0.061*** (0.006)	0.057*** (0.006)	0.046*** (0.006)	0.025*** (0.006)	0.017** (0.007)
Connected Low Skilled	0.019** (0.009)	0.017* (0.009)	0.013 (0.009)	0.007 (0.010)	-0.001 (0.010)
Autonomy in Deadlines			0.003 (0.005)	-0.001 (0.005)	-0.003 (0.005)
No Deadlines			-0.038*** (0.006)	-0.037*** (0.006)	-0.035*** (0.006)
Surveiled by Hierarchy			-0.019*** (0.005)	-0.012*** (0.005)	-0.010* (0.005)
Can Interrupt Work			0.014*** (0.005)	0.012** (0.005)	0.007 (0.005)
No orders			-0.000 (0.010)	0.004 (0.010)	0.007 (0.010)
No Hierarchy			0.059*** (0.011)	0.071*** (0.013)	0.062*** (0.013)
Autonomy regarding orders			0.014*** (0.004)	0.010** (0.004)	0.006 (0.004)
Autonomy regarding workload			-0.001 (0.002)	-0.000 (0.002)	-0.001 (0.002)
Works autonomously			0.008*** (0.002)	0.009*** (0.002)	0.006*** (0.002)
Degree of supervision of other			0.005** (0.002)	0.007*** (0.002)	0.006*** (0.002)
Observations	17,583	17,530	17,342	16,946	16,458
R-squared	0.142	0.154	0.163	0.207	0.222
Demographic Controls	No	Yes	Yes	Yes	Yes
Education and firm size	No	No	No	Yes	Yes
Complete Task Variables	No	No	No	No	Yes

Source: WC2019.

Note: Demographic controls include gender, age, seniority, continent of Birth, region of living. Firm size controls are a second order polynomial in the number of employees. "Complete task variables" corresponds to the 67 identified task variables used for the first-best predictor of teleworking in 2019. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Regressions of Teleworking on Predicted Feasibility and 1-digit Official Occupation Groups in 2019

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Teleworking Dummy				
TWK Feasibility Prediction	0.100*** (0.007)	0.097*** (0.007)	0.083*** (0.008)	0.056*** (0.009)	0.033 (0.022)
Executives (PCS 3)	Ref	Ref	Ref	Ref	Ref
Mid-Skilled Employees (PCS 4)	-0.183*** (0.006)	-0.172*** (0.006)	-0.161*** (0.006)	-0.139*** (0.007)	-0.131*** (0.007)
Low-Skilled Employees (PCS 5)	-0.232*** (0.006)	-0.215*** (0.007)	-0.197*** (0.007)	-0.148*** (0.008)	-0.137*** (0.009)
Laborers (PCS 6)	-0.237*** (0.007)	-0.231*** (0.007)	-0.215*** (0.008)	-0.185*** (0.009)	-0.169*** (0.010)
Autonomy in Deadlines			0.001 (0.005)	-0.001 (0.005)	-0.003 (0.005)
No Deadlines			-0.042*** (0.006)	-0.040*** (0.006)	-0.037*** (0.006)
Surveiled by Hierarchy			-0.018*** (0.005)	-0.012** (0.005)	-0.010** (0.005)
Can Interrupt Work			0.018*** (0.005)	0.014*** (0.005)	0.008 (0.005)
No orders			0.000 (0.010)	0.005 (0.010)	0.008 (0.010)
No Hierarchy			0.059*** (0.011)	0.071*** (0.013)	0.062*** (0.013)
Autonomy regarding orders			0.013*** (0.004)	0.009** (0.004)	0.006 (0.004)
Autonomy regarding workload			-0.000 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Works autonomously			0.009*** (0.002)	0.010*** (0.002)	0.006*** (0.002)
Degree of supervision of other			0.004* (0.002)	0.006*** (0.002)	0.006*** (0.002)
Observations	17,583	17,530	17,342	16,946	16,458
R-squared	0.142	0.154	0.163	0.209	0.223
Demographic Controls	No	Yes	Yes	Yes	Yes
Education and firm size	No	No	No	Yes	Yes
Complete Task Variables	No	No	No	No	Yes

Source: WC2019.

Note: The specifications in this Table are similar to those of Table A.4 but the categorization of workers is based on the official French PCS 1-digit occupation categorization. Demographic controls include gender, age, seniority, continent of Birth, region of living. Firm size controls are a second order polynomial in the number of employees. “Complete task variables” corresponds to the 67 identified task variables used for the first-best predictor of teleworking in 2019. Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.6: Regressions of Teleworking on *Predicted* Feasibility and Occupation Groups in 2021

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Teleworking Dummy				
TWK Feasiblility Prediction	0.861*** (0.021)	0.795*** (0.021)	0.345*** (0.020)	0.329*** (0.020)	0.300*** (0.093)
Connected Mid Skilled	-0.093*** (0.012)	-0.068*** (0.012)	-0.056*** (0.010)	-0.057*** (0.010)	-0.061*** (0.010)
Connected Low Skilled	-0.228*** (0.017)	-0.168*** (0.017)	-0.114*** (0.015)	-0.109*** (0.015)	-0.111*** (0.015)
Wants to TWK			0.549*** (0.011)	0.553*** (0.011)	0.551*** (0.011)
No Hierarchy				0.008 (0.020)	0.008 (0.020)
Degree of Hierarchy Control				-0.008 (0.007)	-0.008 (0.007)
Autonomy				0.045*** (0.005)	0.045*** (0.005)
Computer Share					0.002 (0.063)
Contact with Public					-0.056*** (0.015)
Work Always Physical					0.040 (0.045)
Work Often Physical					0.003 (0.036)
Work Never Physical					-0.006 (0.018)
Observations	5,719	5,718	5,716	5,714	5,713
R-squared	0.258	0.316	0.524	0.531	0.534
Covid-related Controls	No	No	Yes	Yes	Yes
Demographic Controls	No	Yes	Yes	Yes	Yes

Source: Tracov2021.

Note: Covid-related Controls capture the fear of catching COVID-19 while commuting, being particularly vulnerable to COVID-19, living with people particularly vulnerable to COVID-19, and working in an environment when catching COVID-19 is likely. Demographic controls include gender, age, seniority, continent of Birth, region of living. Firm size controls are a second order polynomial in the number of employees. Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.7: Hierarchical Control and Autonomy by Groups of Employees

	Unconnected Employees	Connected Low-Skill	Connected Mid-Skill	Executives
<i>Standardized variables:</i>				
Degree of Control by Hierarchy	.01	.047	.08	-.084
Autonomy	-.146	.044	.152	.14
<i>Indicator variables:</i>				
No Hierarchy	.138	.126	.083	.09
Supervision is Main Task	.063	.036	.194	.244
Supervision is Secondary Task	.237	.199	.316	.381
No Supervision	.7	.765	.491	.374
Takes Initiatives	.591	.496	.751	.87
Needs Help of Supervisor	.238	.222	.23	.251

Note: The table displays weighted averages by occupation groups. The variable “Degree of Control by Hierarchy” is a standardized measure of the response to the question “at what frequency are you controlled or monitored by your supervisors?” (5 modalities). The variable Autonomy is a standardized measure of the degree to which employees agree with the statements “Can organize myself” (4 modalities).

Table A.8: Teleworking Gaps Across Occupations When Including Productivity Proxies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Data: WC2019			Data: Tracov2021			
	Dependent Variable: Teleworking Dummy						
TWK Feasiblility Prediction	0.102*** (0.016)	0.092*** (0.016)	0.095*** (0.018)				
Connected Mid Skilled	-0.160*** (0.009)	-0.151*** (0.010)	-0.164*** (0.011)	0.001 (0.014)	0.000 (0.014)	0.002 (0.014)	0.001 (0.014)
Connected Low Skilled	-0.198*** (0.014)	-0.179*** (0.014)	-0.188*** (0.015)	-0.054*** (0.020)	-0.060*** (0.020)	-0.047** (0.020)	-0.054*** (0.020)
Repetitive Task Control		Yes					
Income Controls			Yes				
Controls for Frequency Employee “Think About Multiple Things Simultaneously”					Yes		
Density Controls						Yes	
Housing Space Controls							Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,584	7,584	6,185	5,050	5,050	5,050	5,048
R-squared	0.089	0.093	0.093	0.097	0.101	0.102	0.097

Note: Columns (1) and (4) report baseline gaps in 2019 and 2021. Telework feasibility is the actual measure in 2021 and the predicted one in 2019. Demographic controls include gender, a second order polynomial in age, and job tenure. Location controls are region fixed effects for 2019 and department fixed effects for 2021. Repetitive Task Control is a dummy for when employees identify their work as repetitive manually or intellectually. Income controls is self declared income interacted with marital status. Freq. Think About Multiple Things Simultaneously is a 4-modality categorical variable for the frequency which employees declare to have to think about multiple things simultaneously in their work (always, often, sometimes, never. Density controls is 4-modality categorical variable officially defined by Insee for French cities (dense, intermediately dense, little dense, very little dense). Housing space controls include second-order polynomials of the number of rooms and the number of individuals living in the individual's home. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table A.9: Teleworking Gaps Across Occupations for Different Tenure Groups, Excluding Non Connected Groups

	(1) Tenure $\leq$ 1 Year	(2) 1 Year < Tenure $\leq$ 5 Years	(3) Tenure > 5 Years
Connected Mid Skilled	-0.103** (0.049)	-0.082*** (0.026)	-0.001 (0.018)
Connected Low Skilled	-0.280*** (0.068)	-0.120*** (0.037)	-0.057** (0.029)
Observations	440	1,252	2,568
R-squared	0.337	0.163	0.123

Source: Tracov2021.

Note: The sample of estimation excludes non connected employees, executives are the reference group. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.10: Teleworking Gaps Across Official Occupation Groups for Different Tenure Groups

	(1) Tenure $\leq$ 1 Year	(2) 1 Year < Tenure $\leq$ 5 Years	(3) Tenure > 5 Years
Mid Skilled (PCS 4)	-0.135*** (0.048)	-0.115*** (0.026)	-0.017 (0.019)
Low Skilled (PCS 5)	-0.278*** (0.057)	-0.169*** (0.032)	-0.088*** (0.024)
Laborers (PCS 6)	-0.205 (0.166)	-0.171** (0.071)	-0.144*** (0.051)
Observations	527	1,478	3,027
R-squared	0.322	0.158	0.113

Source: Tracov2021.

Note: Employees are split according to the French official PCS 1-digit occupation categorization. The reference group are Executives (PCS=3). Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.11: Teleworking Gaps Across Occupations Depending on Supervision and Autonomy

	Supervisory Function			Has to Take Initiatives		Help From Supervisor	
	Supervision is Main Task	Supervision is Secondary Task	Does Not supervise	Often or Always	Sometimes or Never	Does not Need Help of Supervisor	Needs Help of Supervisor
Connected Mid Skilled	0.002 (0.038)	-0.041* (0.024)	-0.076*** (0.020)	-0.036** (0.016)	-0.095*** (0.034)	-0.008 (0.032)	-0.063*** (0.017)
Connected Low Skilled	0.032 (0.110)	-0.129*** (0.043)	-0.136*** (0.026)	-0.058** (0.027)	-0.201*** (0.040)	-0.008 (0.047)	-0.127*** (0.025)
Observations	690	1,423	2,144	3,229	1,041	961	2,975
R-squared	0.214	0.157	0.177	0.118	0.214	0.198	0.132

Source: Tracov2021.

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1