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The birthplace bias of teleworking: consequences for working conditions

Eva Moreno - Galbis* Felipe Trillos Carranza†

Abstract

The massive shift towards teleworking during the COVID pandemic relatively deteriorated working conditions of people occupying positions that could not be teleworked since they were more exposed to the risk of infection. Exploiting French data, we analyze the differential changes in sorting across occupations of immigrants and natives during years preceding the pandemic. Immigrants sorted relatively more into occupations intensive in non-routine manual tasks. These occupations cannot be teleworked. We find an increase in immigrants' sorting into occupations intensive in non-routine interactive and analytical tasks. However, in contrast with natives, immigrants were moving away from occupations intensively using new technologies.

Keywords: immigrants; occupational sorting; telework; ICT; working conditions

JEL: J15; J61; J81

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1 Introduction

Immigrants in France are traditionally over-represented in the construction sector where they make up more than 23% of workers (while the share of immigrants in France is around 10%).¹ They also represent more than 33% of all houseworkers and around 25% of security guards while they represent barely 5% of educators, less than 4.5% of doctors, nurses and para-medical staff and 4% of employees and technicians in the financial sector. All in all, immigrants in France have traditionally been over-represented in riskier sectors and more strenuous occupations involving less desirable working conditions. While immigrants were under-represented among front-line workers (doctors, nurses and para-medical staff) during the extreme lockdown in spring 2020, they may have been over-represented among supermarket cashiers, delivery workers and construction workers, who often worked at least part-time during the lockdown.

In the months following the extreme lockdown period that ended in June 2020, the return to the “new normal” implied a new workplace organization seeking to protect workers and reduce spread of coronavirus. The wide majority of companies and public administrations adopted a total or partial teleworking policy, implying that, in most cases, workers could work from home at least two or three days per week. Evidently, depending on the tasks involved in the job, it is easier to telework and be then protected from the risk of COVID infection. Due to differences in risk of exposure, people employed in positions which could not be done from home saw their relative working conditions deteriorated with respect to people in occupations that could telework.

In this paper we investigate the role of native-immigrant differences in occupational propensity to telework, and we highlight the role it may have had in the COVID-19 context. Using French data from 2005 to 2019, we propose a conditional logit approach to compare immigrants’ and natives’ sorting choices across occupations in years preceding the COVID pandemic with respect to an indicator capturing the propensity to telework within the occupation.² When deciding their occupational choices before 2020, neither immigrants nor natives internalized the possibility of teleworking, since working from home was far from being the social norm in France and in most occidental economies before the pandemic. Occupational sorting was then exogenous to the possibility of teleworking. We exploit this exogeneity to identify workers whose relative working conditions deteriorated during the first months of the pandemic. Several months after the strict lockdown of 2020, when people understood that the “new normal” could last much longer than expected, they adjusted their occupation choices, internalizing the possibility to telework. The allocation of workers across occupations then became endogenous to the possibility to telework, which diminishes the potential value of any analysis across socio-demographic groups.³

¹See the 2012-01 note from the Centre d’Analyse Strategique, France.

²Basso et al. (2017) use occupational choices of high and low qualified immigrants and natives to infer the evolution of the supply of manual, routine and analytical tasks in the US following the diffusion of computers. Moreno-Galbis et al. (2019) relate immigrants’ and natives’ sorting across occupations to (1) returns to occupation-specific skills and (2) the occupational task content. They compare allocation choices between 1990-1992 and 2010-2012.

³Additionally, there are some data issues that prevent us from studying the period following 2019. First, data

The economic rationale of the paper is easily explained by the seminal Roy (1951) model, according to which occupational specialization is due to workers' self-selection based on comparative advantage. Following that line of inquiry, Peri and Sparber (2009, 2011a,b), Amuedo-Dorantes and la Rica (2011), D'Amuri and Peri (2014) or Basso et al. (2017) underline that natives and immigrants differ in their relative skill endowments. In these studies, immigrants' and natives' unobserved skill endowments are assessed using the task requirement of the occupations.⁴ Moreno-Galbis et al. (2019) consider the long-term wage dynamics of immigrants and natives in France between 1993 and 2012. They investigate to what extent changes in task-specific returns to skills have contributed to the differential wage dynamics. In their setting workers need a bundle of skills whose importance depends on the type of occupation-specific tasks. Thus, immigrants and natives employed in occupations with different task content will have different skill endowments.⁵

Our paper takes the conceptual framework based on Roy (1951) and proposed by Moreno-Galbis et al. (2019), where income maximizing workers choose the job offering the highest wage per efficient unit of labor given their relative skill endowment. Any technological change modifying the quantity of efficient units of labor produced by a given skill endowment or any change in the unitary price of the workers' skills will induce the reallocation of workers across occupations, since they will seek to maximize their income given the new productive configuration. We frame this setup within a random utility choice model. We hypothesize that, aside from income potential related to task composition of the occupation, ICT (Information and Communication Technologies) use and the unitary price of workers' skills, individuals take into account some stochastic and idiosyncratic characteristics of occupations when choosing their occupation. This occupational choice model is

concerning Information and Communication Technologies (ICT) is only available until 2019 (the last available wave of the French Working Condition Survey), so it would not be possible to study changes in the propensity to telework after 2019. We can only estimate (as we do in Figure A.1 in Appendix A) the evolution in the share of people that were employed in each occupation depending on the propensity to telework for each occupation in 2019. Second, the only exploitable LFS wave is 2020, since, from 2021, the LFS was deeply modified so as to respect the regulation framework IESS (Integrated European Social Statistics). This framework defines the domains covered by the LFS, as well as methodological constraints (distribution of the sample, the sample rotation scheme, the precision, etc). One of the major changes in the LFS questionnaire concerns the classification of occupations at the 4-digit level. Currently it is not possible to have time consistent series of occupations at the four-digit classification before and after 2021 since the National Statistical Institute has not issued any correspondence tables. Finally, the LFS allows us to study the progression in employment level by occupation, but not unemployment, since we do not have information on the previous occupation at the 4-digit level for unemployed individuals. Because analyzing changes in employment or unemployment in years following the pandemic is above the scope of this paper, we simply present in Appendix A the main highlights of the French labor market evolutions in 2020 and the beginning of 2021; the rest of the paper is exclusively focused on the impact of occupational sorting on relative working conditions when the pandemic began.

⁴A major limitation of this migration literature, which places occupations and their task content at the heart of the economic analysis, is that task content of occupations is assumed time-constant. This assumption is preset by the data sources used (such as O*NET). While we acknowledge this limitation, time-constant task composition of occupations affects both natives and immigrants. Since we are analyzing the differential occupational allocation between both birth groups, we should be less concerned by this data limitation.

⁵In Yamaguchi (2018) workers combine skills with experience in the task requiring those particular skills.

estimated through a conditional logit.

We combine individual-level data from the French Working Condition Survey 2005, 2013 and 2019 (WCS), the French Labor Force Survey (LFS) 2005-2006, 2012-2013, 2018-2019 and task composition data by occupation provided by O*NET. The WCS 2005, 2013 and 2019 provide individual data on ICT use as well as on non-pecuniary working conditions such as learning new things on the job, being supported by colleagues, autonomy, physical risks, etc. A main limitation of the WCS is that it covers a smaller sample than the LFS, which implies that the sample of immigrants is reduced. Therefore, we use the WCS to compute ICT use and working conditions at the four digit occupation level and from this, we impute this information by occupation for individuals in the LFS. To increase the number of observations by period we stack pairs of years from the LFS. More precisely, we stack data from LFS 2005 and 2006 and, using the WCS 2005, we impute working conditions and ICT use by occupation. We apply the same procedure for years 2012 and 2013 which are matched with working conditions and ICT use from WCS 2013 and for years 2018-2019 which are matched with WCS 2019. Finally, the EurOccupations table is used to match task composition of occupations provided by O*NET to the LFS.

The empirical analysis allows us to draw two major conclusions. First, during years preceding the pandemic, immigrants sorted into occupations using intensively non-routine manual tasks, which, by nature require physical proximity and are done onsite. Second, between 2005 and 2019, the probability of immigrants allocating towards occupations using intensively non-routine analytical and interactive tasks has increased, suggesting that they have adapted their skills to the new requirements of the labor market. These occupations are easy to telework but only in the presence of ICT. However, we find that the relative probability that immigrants will allocate towards occupations intensively using ICT has decreased (over time and with respect to natives), implying that when the pandemic arrived, immigrants were less likely than natives to occupy positions with a high propensity to telework.

Our paper contributes to three streams of literature. On the one hand, it contributes to the literature explaining the allocation of immigrants and natives across occupations based on their differential skill endowment and thus differential comparative advantages depending on task composition of occupations. As shown by Peri and Sparber (2009), Peri (2012, 2016), Ottaviano et al. (2013) or D'Amuri and Peri (2014) following an immigration-induced labor supply shock, natives reallocate towards communication and language intensive tasks, while immigrants become specialized in manual intensive tasks which tend to be concentrated at the bottom of the wage distribution. This literature focuses then on the effect of immigration on natives' and immigrants' wages (see Basso et al., 2017 or Moreno-Galbis et al. (2019)), without considering further consequences of this allocation in terms of non-pecuniary working conditions. Moreno-Galbis (2020) goes then a step further and analyzes how the over-representation of immigrants in occupations located at the bottom of the wage distribution becomes an issue in the presence of a binding minimum wage. If during the bargaining process monetary wages cannot be downward adjusted,

working conditions become the only adjustment variable. People employed in occupations paid at the minimum wage may then suffer a deterioration in their working conditions.

Evidently, none of these papers, which were published before the pandemic, consider the teleworking dimension when analyzing occupational choices of natives and immigrants. Because of their relative skill endowment immigrants benefit from a comparative advantage in occupations intensive in manual tasks. These tasks are more difficult to telework since they use ICT less intensively and require physical presence on site to be implemented. Consistent with this literature, we also find that immigrants were over-represented in occupations intensive in manual tasks, which are difficult to telework. As a result, their relative working conditions with respect to natives, who are in contrast over-represented in occupations intensive in communication and language tasks, deteriorated during the pandemic as immigrants were now exposed to the risk of infection.

In contrast with this literature (but consistent with Moreno-Galbis et al., 2019), we also find that, over the past decades, immigrants have progressively adapted their skills to labor market requirements (*i.e.* increased demand for non-routine analytical and interactive skills) so as to promote their upward occupational mobility. However, they do not seem to be sorting into the same type of occupations as natives since, even if we find that they are increasingly likely to allocate towards positions intensive in non-routine analytical and interactive tasks, we also find that they are less likely to allocate towards positions using ICT intensively, while natives increasingly allocate towards these occupations. The immigrant-native technological gap contributes to understanding why immigrants were less likely to allocate into occupations with a higher propensity to telework and why their relative working conditions deteriorated compared to natives when the pandemic started.

Our paper also contributes to the literature analyzing the factors behind immigrants' occupational choices and the consequences for both immigrants' and natives' working conditions. Several elements may explain why immigrants should be willing to accept riskier jobs than their natives counterparts: differences in risk perception, social capital, lower levels of education, poor language proficiency (see Loh and Richardson, 2004, Orrenius and Zavodny, 2009 or Moreno-Galbis, 2020), legal status (see Passel, 2006), the healthy immigrant effect (see McDonald and Kennedy, 2004, Antecol and Bedard, 2006, Park et al., 2009 or Giuntella and Mazzona, 2015⁶) and lower outside employment opportunities (see Nanos and Schluter, 2014, Dustmann and Gorlach, 2016, Moreno-Galbis and Tritah, 2016 or Moreno-Galbis, 2020) are the most common driving factors studied in the literature that push immigrants to accept more strenuous work conditions.⁷ Immigrants' occupational sorting also affects non-pecuniary working conditions borne by natives. Using German and UK data respectively, Giuntella and Mazzona (2015) and Giuntella et al. (2019) show

⁶As remarked by Giuntella and Mazzona (2015), immigrants are positively selected on health with respect to their population of origin but are characterized by lower education and less wealth than natives. This pushes them to trade their health capital for money by accepting poorer working conditions in exchange for higher wages.

⁷Health economics papers have focused on the short and long term impact of working conditions on the health status and dynamics of immigrants (see Case and Deaton, 2005, Fletcher and Sindelar, 2009 or Fletcher et al., 2011).

that immigration leads to a reallocation of native workers towards jobs characterized by lower physical burden and injury risk (with differences across skill groups). Similarly, Giuntella (2012) with Italian data and Bond et al. (2020) or Dramski (2017) with US data, show that immigration reduces natives' likelihood of working night shifts or non-standard shifts.⁸

Our paper contributes to this stream of literature by analyzing the relative deterioration of immigrants' working conditions as a result of a non-anticipated exogenous shock rather than as a result of the immigrants' deliberate occupational choice. The pandemic shock was biased against occupations that could not be teleworked, were immigrants were over-represented. We argue that immigrants' relative working conditions were then deteriorated since they had to face the new risk of infection while native were over-represented in positions that could be teleworked. This implied a relative improvement of natives' working conditions. We also show that the reduced sorting of immigrants into occupations with a high propensity to telework was not compensated by an increased sorting (with respect to natives) into occupations proposing other improved non-pecuniary working conditions.

Finally, our paper contributes to the emerging literature following the pandemic and the associated lockdowns of 2020 and 2021. The existing literature has tried to identify jobs that could be teleworked. Using US data from the Work Context Questionnaire and the Generalized Work Activities Questionnaire, Dingel and Neiman (2020) classify occupations as being possibly done from home depending on the nature of the tasks involved in the occupation. They estimate that 37% of jobs in the United States can be performed entirely at home, with significant variation across cities and industries. These jobs typically pay more than jobs that cannot be done at home.⁹ These findings are also confirmed by Mongey et al. (2020). The authors exploit US data from O*NET to construct two measures of an occupation's potential exposure to social distancing measures: the ability to conduct a job from home and the degree of physical proximity to others the job requires. They estimate that workers in low-work-from-home and high-physical-proximity jobs are more economically vulnerable (less educated, lower income, have fewer liquid assets relative to income, and are more likely renters), are less likely to be married (which can diversify household income against individual income risk), are also less likely to be US citizens or born in the US and experienced greater declines in employment during the pandemic.

⁸The intuition behind this finding is presented by Bond et al. (2020) through a theoretical framework in which immigrants have lower disamenity costs for working at night and a comparative advantage in nighttime production. As a result, immigrants specialize in nonstandard shifts. Immigration increases then the supply of night shifts, pushing natives towards daily schedules.

⁹Dingel and Neiman (2020) apply their US occupational classification to 85 other countries and conclude that lower-income economies have a lower share of jobs that can be done at home. This approach is also implemented by Lekfuangfu et al. (2020), who construct a new set of pandemic-related indices from O*NET using factor analysis. The authors map the indices to the labor force survey of Thailand. They find first that low income individuals tend to work in occupations that require less physical interaction (lower risk of infection) but are less adaptable to work from home (higher risk of income/job loss) than high income individuals. Second, the positive occupational sorting among low-income couples amplifies these differences at the household level.

Adams-Prassl et al. (2020) exploit real time survey evidence from the UK, the US and Germany to analyze the immediate labor market impacts of COVID. Their findings confirm that labor market impacts of the COVID lockdowns are unequally distributed. Both the percentage of tasks workers can do from home and individual work arrangements are highly predictive of job loss. Firms have played some role in smoothing the shock for permanent and salaried employees and for those who usually work on fixed schedules. In the US and UK, women and workers without a college degree are significantly more likely to have lost their jobs, while younger individuals are significantly more likely to have experienced a fall in their earnings.

With respect to this last stream of literature the contribution of our paper is to consider differences in occupational allocation between native and immigrants just before the pandemic. The advantage of this approach is that occupational choices were not driven by any consideration associated with the pandemic. Moreover, while we also use O*NET to determine the task composition of occupations (at the four digit level), we combine this data with information on ICT use by occupation obtained from the French WCS. The possibility to telework is determined by the type of task implemented in the position (*i.e.* non-routine analytical and interactive tasks are more easy to telework than non-routine manual task) and the use of ICT. Our paper provides insights on the driving factors behind the differential allocation of immigrants and natives across occupations depending on the propensity to telework. We analyze occupational sorting using as explanatory variables the individual components of the telework indicator, that is ICT use, non-routine analytical, non-routine interactive and routine cognitive indices. Moreover, we go a step further with respect to the existing literature and analyze whether non-pecuniary working conditions (such as learning new things on the job, being autonomous at work, receiving support from managers and colleagues, physical risks, etc.) have also induced a differential occupational sorting between natives and immigrants.

The paper is organized as follows. Section 2 describes our databases, variables and descriptive statistics. The conceptual framework is explained in Section 3. The econometric strategy is presented in Section 4. Results are presented in Section 5. Section 6 concludes.

2 Data sources, variables and descriptive statistics

2.1 Data sources and variables

The O*NET index is provided by the Department of Labor’s Occupational Information Network. For the United States, the O*NET database provides a detailed description of workers, occupations or jobs. We use information about occupation requirements that detail typical activities required across occupations to summarize the specific types of job behavior and tasks that may be performed within occupations.

The O*NET index is built according to the American Standard Occupational Classification (SOC) 2010. We consider the task content of occupations in France to be similar to the U.S. so

we use the O*NET classification to analyze the task content of French occupations. Indeed, for our purpose, it is sufficient to suppose that there are no systematic differences between France and the U.S. in the ranking of occupations. Thus, an occupation ranking high in one dimension in the U.S. also ranks high in the same dimension in France.¹⁰

We first match the French PCS-ESE occupational classifications with the EurOccupations database, which covers 1,594 occupational titles within the ISCO-08 classification.¹¹ Then, we use an ISCO-08 to SOC-2010 mapping table to link the PCS-ESE to the O*NET index. There is a perfect match for 453 occupations.

O*NET provides information on work activities, very close to the notion of task, ranking 41 different tasks from 0 to 100 and indicating the degree (or point along a continuum) to which a particular descriptor is required or needed in the occupation. Because the O*NET database does not provide information on workers, we are unable to monitor the evolution of task requirements within a given occupation¹² but any change in the task content of an occupation will affect both immigrants and natives, implying that this limitation should not impede our analysis.

From the 41 tasks in O*NET, we use the strategy of Autor et al. (2003), which consists of breaking down the different tasks in broad categories based on the Dictionary of Occupational Titles (DOT) provided by the US Department of Labor. Autor et al. (2003) define five task categories : non-routine manual tasks, routine manual tasks, routine cognitive tasks, non-routine analytical tasks, and non-routine inter-personal tasks. The content of each category is defined in Table B.1 in Appendix B.

We normalize the task indices across occupations. Given the task content of each of the five categories and given the existing literature on teleworking (see Dingel and Neiman, 2020 or Mongey et al., 2020), we consider that tasks included in non-routine analytical, non-routine interactive and routine cognitive categories can be easily implemented from home. The higher the degree of ICT use in the occupations which feature these tasks, the higher the propensity to telework of the occupation.

¹⁰In the extended version of their paper, Laffineur and Mouhoud (2015) use the German “Qualification and Career Survey” to build occupational task indices that they apply to the French professional classification of occupations. They take as a starting point the estimations of Tidjens et al. (2011) who, working with eight European countries (among them Germany and France), find that tasks performed in occupations in these countries are similar. Laffineur and Mouhoud (2015) show that differences between estimates using the German “Qualification and Career Survey” and those using O*NET cannot be attributed to differences in the task content of occupations between the U.S. and Germany (and thus France). They use estimates from the O*NET index since the O*NET allows to have more details on task intensity over a bigger range of tasks.

¹¹The EurOccupations project was aimed at building a publicly available database containing the most common occupations in a multi-country data collection. The database includes a source list of 1,594 distinct occupational titles within the ISCO-08 classification, country-specific translations and a search tree to navigate through the database. It also provides a mapping table between the EurOccupations classification and the ISCO-08 classification, as well as a French translation of these occupations.

¹²This is done in Atalay et al. (2018). Using the text from job ads, the authors construct a data set for occupational content from 1960 to 2000.

Data on ICT use per occupation is provided by the WCS 2005, 2013 and 2019.¹³ This survey aims to obtain a concrete description of work, its organization and its conditions from various angles: schedules, work rhythms, physical efforts or risks incurred, hardship, work organization, safety, cooperation, conflicts, etc. The survey has been conducted for the past 40 years (every seven years until 2005 and every three years since 2013), and allows us to analyze the evolution of work conditions. Until 2005, the WCS was conducted on a representative sample of around 21000 employed workers sampled in the the Labor Force Survey. The WCS covered four fields of interest: i) organization and timetable of working days, ii) workplace organization and job content, iii) working risks, and iv) degree of harmfulness of the job. The second field includes information concerning the use of new technologies by the workers.

The 2013 wave included 34000 employed people and it covered topics on professional activity, schedules and working time, workplace organization, ICT use, rhythms of work, physical risks and their prevention, psychological risks, relations with customers and violence at work. The WCS 2016 included all respondents to the WCS 2013, including people who have left employment since the 2013 survey (unemployed or inactive persons, retired persons, and persons on sick leave for more than one year) and it added new employed people to the sample. This wave was more focused on psychological risks at the workplace and neglected other topics such as ICT use. The WCS 2019 interviewed all respondents to the WCS 2016, including people who had left employment since that survey plus new employed people that were added to the sample. Topics covered in the WCS 2019 are similar to those of the WCS 2013.

Using waves 2005, 2013 and 2019, we define the degree of ICT use as follows. First, we define three dummy variables for using a computer at work, having a work laptop, or having a professional email address, respectively. For every individual we define then an informatics use indicator resulting from the addition of the three dummy variables, so that the higher the value of this indicator the more informatics tools the individual uses at work. Second, we define a dummy equal to unity if the individual uses internet at their job. Third, we define our ICT indicator as the product of the informatics tools' indicator and the internet dummy. The ICT indicator captures then the complementary relationship between informatics material and internet. The intuition behind this indicator is that the informatics material is useless for teleworking if it is not connected to the internet.

We additionally define the nine non-pecuniary working conditions indicators: (i) *Learning new things* equals unity if the individual declares learning new things on the job; (ii) *Autonomy* results from the addition of four discrete variables defined between 0 and 1 and increasing with the degree of autonomy of the worker in solving problems, choosing methods, deciding the speed of working and determining the quality of the good or service; (iii) *Support* results from the addition of two dummy variables which equal unity if the individual declares receiving support

¹³There is also a wave in 2016 but it does not contain information on ICT use by the worker, so we neglect this wave rather than imputing a value resulting from the average use of ICT by occupation between 2013 and 2016.

from colleagues and/or from their manager; (iv) *Security* equals unity if the individual believes they will not lose her job in the following six months; (v) *Training* equals unity if the individual receives training financed by the employer; (vi) *Physical risk* is an indicator which increases if the exposure to physical risks for the individual at work is lower. It results from the addition of seven discrete indicators defined between 0, when the individual is exposed to the corresponding physical risk, and 1 when the individual is not exposed to the risk. We consider the following physical risks: vibrations, loud noises, smoke, exposure to chemical products, working in a painful position, moving loads and/or implementing repetitive actions; (vii) *Psychological risk* equals 0 if the individual has to deal with angry customers and 1 if the individual does not have to deal with them; (viii) *Known timetables* equals unity if the individual is informed by the employer about her timetable at least one month in advance: it equals $2/3$ if the individual knows her timetable one week in advance, $1/3$ if she knows the timetable for the following day and 0 if she is not aware of the timetable until the very last moment; (ix) *Hours off* equals 1 if it is possible for the individual to take easily 1-2 hours off during the day. To summarize, the higher the value of each of these indicators the better the working conditions.

ICT and working conditions variables are defined for every individual interviewed in the WCS 2005, 2013 and 2019. We then collapse every wave by four digit occupation and impute these values to the LFS 2005-2006, 2012-2013 and 2018-2019, respectively. As previously remarked, we stack pairs of years (2005 with 2006, 2012 with 2013 and 2018 with 2019) to increase the number of observations for every considered sub-period. The French Labor Force Survey (LFS), was established as an annual survey in 1982. Redesigned in 2003, it is now a continuous survey providing quarterly data. Participation is compulsory and it covers private households in mainland France. All individuals in the household older than 15 are surveyed. The LFS provides detailed information on individual characteristics of the respondent.¹⁴

For our purpose, the main topics covered by the LFS concern employment, four digit occupation classification, wages, status in employment and demographic characteristics (such as education/qualification, civil status, age, gender, etc.). There is not much information on employers since the worker is simply asked to indicate the approximate size of the workforce in their plant or establishment (the questionnaire proposes several size-intervals). Weights provided by the French National Statistical Institute (INSEE) ensure the national representativity of the sample of individuals covered by the LFS.

We impute to the LFS information on task intensity indices by occupation computed from

¹⁴The quarterly sample is divided into 13 weeks. From a theoretical point of view, the sampling method consists of a stratification of mainland France into 189 strata (21 French regions \times 9 types of urban unit) and a first stage sampling of areas in each stratum (with different probabilities, average sampling rate = $1/600$). Areas contain about 20 dwellings and among them only primary residences are surveyed. Each area is surveyed over 6 consecutive quarters. Every quarter, the sample contains 6 sub-samples: $1/6$ of the sample is surveyed for the first time, $1/6$ is surveyed for the second time, \dots , $1/6$ is surveyed for the 6th (and last) time. The collection method has always been a face-to-face interview. However, since 2003, a telephone interview has been employed for intermediate surveys (2nd to 5th).

O*NET and information on ICT use and working conditions computed from the WCS. We have 264,826 employed individuals for the period 2005-2006, 380,117 for 2012-2013 and 347,131 for 2018-2019. When considering only immigrants, we have 27,752 employed individuals for 2005-2006, 32,438 for 2012-2013 and 31,570 for 2018-2019, which are actually sufficiently large samples to implement our analysis using occupations at the four digit level.¹⁵ In the LFS each household is surveyed over 6 consecutive quarters, but questions about wages are only asked in the first and last interview. Therefore, when considering wages our sample size is reduced to 77,343 individuals (7,776 immigrants) in 2005-2006, 109,961 (9,090 immigrants) in 2012-2013 and 100,100 (9,083 immigrants) in 2018-2019.

By enriching the LFS with task content data by occupation from O*NET as well as with ICT use and working conditions data from the WCS, we are able to define for every four digit occupation and for every year, a propensity to telework indicator as follows:

$$\text{Propensity to telework} = \text{ICT} \cdot (\text{Non-routine analytical} + \text{Non-routine interactive} + \text{Routine cognitive})$$

where, as previously explained, the ICT indicator is defined as the product between the informatics tools' indicator and the internet dummy; *Non-routine analytical*, *Non-routine interactive* and *Routine cognitive* are task intensity indexes coming from O*NET database. This definition of the propensity to telework allows us to capture the complementary relation between ICT use and tasks that can be easily implemented from home if and only if the individual has access to ICT.

Occupations with a higher propensity to telework are those that could be implemented from home during the COVID pandemic, which prevented workers employed in these occupations from being exposed to the virus. We then argue that the relative working conditions of these workers were relatively improved with respect to the working conditions of people in occupations that could not be teleworked. This does not mean that jobs with a higher propensity to telework are of better absolute quality (including both pecuniary and non-pecuniary aspects) than jobs with a lower propensity to telework, we simply refer in this paper to a relative deterioration in working conditions coming from the exposure to a new risk (*i.e.* the risk of infection) for people employed in positions with a lower propensity to telework during the pandemic.

In this paper, immigrants are defined as people born abroad.

2.2 Descriptive statistics

Table C.1 in Appendix C compares socio-demographic and professional characteristics of the native and immigrant sample. It reveals that the proportion of females is larger in the native sample (49.2% vs. 45.4%). Immigrants are on average older and over-represented in the extremes of the educational distribution (“No diploma” and “Higher degree”). Immigrants are more often married

¹⁵By considering only employed people we are also partially eliminating return migration issues of older migrants, also know as “Salmon Bias”, which have been proved relevant in countries like the US (see Palloni and Arias, 2004).

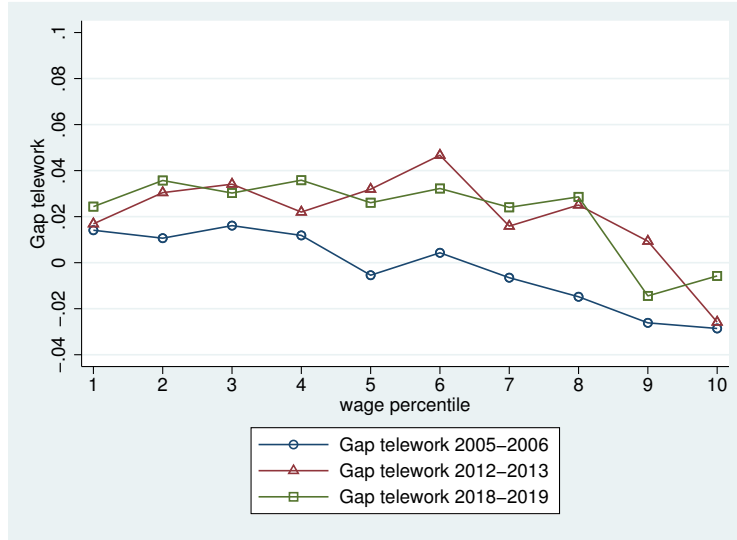
and are more likely to have children. Their average wage is lower and use ICT at work less often. They are employed in jobs that less intensively use non routine analytical and interactive tasks as well as routine cognitive tasks. As a result, they have a lower propensity to telework (see the previous section for how we compute this indicator). On average they bear worse non-pecuniary working conditions than natives, excluding the fact that they more often receive training from the employer, they are less exposed to angry customers (*i.e.* psychological risk) and it is easier for them to interrupt their work for 1-2 hours for personal reasons.

Rather than comparing the average propensity to telework across birth groups during the period 2005-2019, a more rigorous descriptive analysis of the situation would involve comparing the propensity to telework along the wage distribution.¹⁶ We compute the wage distribution of natives for each of the three considered periods: 2005-2006, 2012-2013 and 2018-2019. We divide this wage distribution into 10 deciles. For each of the three periods and for each of the 10 deciles, we estimate, separately for immigrants and natives, the propensity to telework. Then, we estimate for every decile the gap in the propensity to telework between natives and immigrants and present the result in Figure 1. As revealed by the figure, in 2005 the propensity to telework was larger among natives in the first half of the wage distribution while immigrants occupying positions in the second half of the wage distribution had higher propensity to telework.¹⁷ The situation changes in 2012-2013 and 2018-2019, where natives have a larger propensity to telework until the last decile of the wage distribution.

¹⁶For these descriptive statistics we only consider immigrants and natives with a permanent contract, so that the distribution of working conditions and hourly wages is not driven by a potential over-representation of short term contracts among one particular birth group. Moreover, to control for potential differences in working time across birth groups, we apply standard weights provided by the LFS multiplied by the number of hours worked by individuals.

¹⁷Note that while the number of immigrants with permanent contracts smoothly declines as we move up in the wage distribution, the number of immigrants in the 10th decile of the wage distribution is around 500 which remains a sufficiently large sample. More precisely, in 2005-2006 there are 819 immigrants in the first decile and 543 in the 10th decile. In 2012-2013 there are 1069 immigrants in the first decile and 537 in the 10th, while for 2018-2019 these numbers become, respectively, 1030 and 500.

Figure 1: Native-Immigrant gap in the propensity to telework along the wage distribution.



Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019.

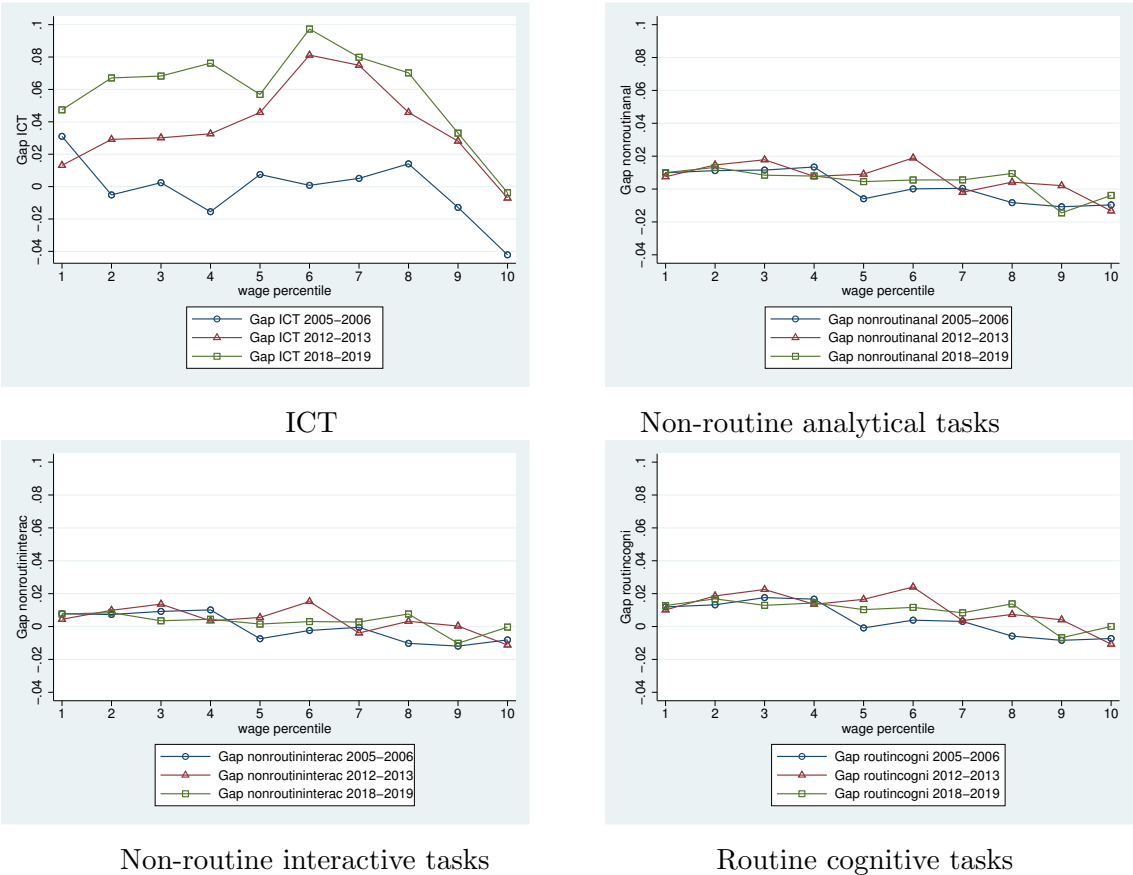
The propensity to telework is the main driver of the differential immigrant-native COVID-exposure. Therefore, it is interesting to study which factors contribute to explaining the increase in the native-immigrant gap in the propensity to telework between 2005 and 2019. Because the propensity to telework indicator results from multiplying the ICT indicator times the addition of the three task intensity indices (corresponding to non routine analytical, non routine interactive and routine cognitive tasks), Figure 2 presents evidence on these four components. The upper left-hand side panel points to ICT use as the main driver of the increase in the native-immigrant gap in the propensity to telework. This panel reveals that in 2005, the native-immigrant gap in ICT use was positive in the first decile of the wage distribution and negative from the 8th decile on. Between the second and the eighth decile it remained fairly constant around zero. The situation alters in 2012-2013 and in 2018-2019, when the native-immigrant gap in ICT use is positive in the first decile of the distribution and follows a rising path until the 6th decile. It then decreases (but remains positive) until reaching zero at the 10th decile of the distribution. Moreover, the gap is larger in 2018-2019 than in 2012-2013. As shown later in the paper, this technological gap across birth groups is explained by differences in occupational choices between immigrants and natives. Relative to natives, foreign born workers have decreased their probability to allocate into occupations intensively using ICT.

The other three panels in Figure 2 reveal non-significant changes in the native-immigrant gap along the considered periods concerning exposure to non-routine analytical, non-routine interactive and routine cognitive tasks. Given the definition of the propensity to telework indicator, Figure 2 suggests that the decreased presence of immigrants in occupations that are easy to telework is

driven by the lower use of ICT by immigrants in their jobs.

Figure C.1 in Appendix C reveals that the increase in the native-immigrant gap in the propensity to telework in 2012-2013 and 2018-2019 is driven by males. The upper panels of the figure represent the progression in the native-immigrant gap by gender in the propensity to telework. The increase in the gap between 2005-2006 and the two following periods is clearly more important for men (upper left-hand side panel). ICT use seems again to be the driving force behind this progression. As shown by the bottom left hand side panel of the figure, whereas the native-immigrant gap in ICT use remained negative or close to zero all along the wage distribution for males in 2005-2006, during 2012-2013 and 2018-2019 it became strongly positive and increases until the median of the wage distribution, then decreases but remains positive (it only reached a negative value in the last decile). For women, the ICT use gap (bottom right hand side panel) slightly increased between the 3rd and 7th decile between 2005-2006 and 2012-2013. For the last period 2018-2019, the native-immigrant gap for females remains above the gap of previous years all along the distribution.

Figure 2: Native-Immigrant gap in ICT use and task intensity along the wage distribution.



Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019.

The decrease in the presence of immigrants in occupations with larger propensity to telework in years preceding 2020 suggests a deterioration of immigrants' relative working conditions during the pandemic, since they were relatively more exposed to the new risk of infection. However, since working conditions cover many dimensions, it could be that immigrants increased their allocation towards occupations intensive in other positive non-pecuniary working conditions. Figure C.2 in Appendix C displays the native-immigrant gap along the wage distribution for different indicators of working conditions. There does not seem to be an overall improvement in immigrants' working conditions that could have eventually compensated for their relatively greater exposure to the risk of infection. Moreover, immigrants are more often exposed to vibrations, loud noises, smoke, chemical products, painful positions, repetitive actions or/and moving loads (*i.e.* physical risks). These exposures imply a physical presence in the workplace, which also implies that immigrants are more likely than natives to be allocated into occupations that would be difficult to telework.

3 Conceptual framework

Our conceptual framework is taken from Moreno-Galbis et al. (2019). We present here the main lines of the framework, however interested readers may refer to this paper for more details. We consider a perfectly competitive environment with exogenous wages. The production side employs labor, measured in efficiency units, as a unique production input using a linear technology (*i.e.* marginal productivity of labor equals unity). At the competitive equilibrium the price of the produced good will then equal the wage per efficient unit of labor.

Workers differ in their relative skill endowments. We focus on a particular skill S (*e.g.* cognitive skills) which is heterogeneously distributed across workers within the interval $[\underline{S}, \bar{S}]$. We normalize to unity the remaining skill bundle (*e.g.* manual skills) and we assume that it is homogeneously distributed across workers.

We consider three occupation categories : (*i*) those highly intensive in skill S (denoted H); (*ii*) those requiring both skills and in which tasks performed have a middle requirement in skill S (denoted M); and (*iii*) those weakly intensive in tasks requiring skill S (denoted L). For a given relative skill endowment S_i the quantity of efficient units of labor, s_{ij} , provided by worker i depends on her occupation according to:

$$s_{ij} = \begin{cases} e^{\beta_L + \gamma_L S_i} & \text{for } j = L \\ e^{\beta_M + \gamma_M S_i} & \text{for } j = M \\ e^{\beta_H + \gamma_H S_i} & \text{for } j = H \end{cases}$$

Since we assume a linear technology, s_{ij} is also the quantity of potential output produced by a worker in each occupation. The coefficients β_j and γ_j are respectively the contributions of the general skill bundle and skill S to the production of efficient units of labor in each type of job, where $\gamma_H > \gamma_M > \gamma_L$ and $\beta_L > \beta_M > \beta_H$. The earning capacity of skills S will then be the highest in H occupations and the lowest in L occupations, while for the complementary skill bundle we assume

the opposite — its earning capacity is the highest in L jobs. Similarly to Gibbons et al. (2005) these differential weights generate a sorting of workers based on their comparative advantage.

The wage received by a worker in each occupation is equal to: $W_{ij} = s_{ij} \times p_j$ or in log-specification $\text{Log } W_{ij} = \text{Log}(p_j) + \beta_j + \gamma_j S_i$, for $j = L, M, H$, where p_j stands for the price index of the specific goods or services provided by the occupation. Income maximization implies that each worker i chooses the job j offering the highest wage given her relative skill endowment:

$$W_{ij}^* = \arg \max_{j=L,M,H} \{W_{iL}, W_{iM}, W_{iH}\} \quad (1)$$

At the equilibrium, the mapping of abilities into efficient units of labor and the optimal decision rule (1) define two thresholds:

- (i) $S_l = \frac{\ln(p_L/p_M) + \beta_L - \beta_M}{\gamma_M - \gamma_L}$, which corresponds to the skill level such that $W_{iL} = W_{iM}$. All workers i with $S_i < S_l$ choose the L occupation. Actually, workers with the lowest endowment of S allocate towards L occupations, where the earning capacity of skill S is the lowest and the earning capacity of the complementary bundle of skills is the highest.
- (ii) $S_h = \frac{\ln(p_M/p_H) + \beta_M - \beta_H}{\gamma_H - \gamma_M}$, which stands for the skill level such that $W_{iH} = W_{iM}$. All workers i with $S_l < S_i < S_h$ choose the M occupation and those with $S_i > S_h$ choose the H occupation.

Any exogenous variation in the price p_j , or any technological change modifying the relative contribution of skills, β_j or γ_j , to efficient units of labor, will trigger a change in these threshold values and thus workers' reallocation across occupations. Differential occupational sorting is then the result of income maximizing choices based on comparative advantages driven by the worker's skill endowment.

In the econometric section, we characterize these differences in occupational sorting between immigrants and natives by relating their choices to the propensity to telework in an occupation. The propensity to telework depends itself on both task content and ICT use. According to our framework, task content of an occupation determines the quantity of efficient units of labor (and thus output) that can be produced by an individual with a given skill endowment. ICT use modifies the quantity of efficient units of labor (and thus output) produced by this same individual in the same occupation if she has the required skills to use ICT. All in all, we relate occupational choices of immigrants and natives to task content and ICT use in order to understand the main drivers behind occupational choices when considering the propensity to telework (*i.e.* we are able to determine if differences in comparative advantages come from skills related to tasks or skills related to ICT use). Finally, we complement the analysis by relating occupational sorting to other non-pecuniary working conditions.

4 Econometric strategy

The occupational choice model is framed within a probabilistic or random utility choice model. Among the variety of occupations available, individuals choose their occupation, taking into ac-

count not only income potentials related to their relative skills endowment but also some stochastic and idiosyncratic characteristics of occupations, which we assume are distributed independent of workers' skill endowments. Therefore, when choosing an occupation j , a worker i derives an indirect utility (depending on her potential earnings in the occupation), which we assume is a linear function of individual characteristics X_i , occupation-specific characteristics Z_j (such as working conditions, task composition and ICT use in the occupation), and an idiosyncratic stochastic component:

$$U_{ij}^* = \rho_i X_i + \kappa_{ij} Z_j + \varepsilon_{ij} \quad (2)$$

where κ_{ij} stands for the effects of occupation-specific characteristics on individual utility. We assume that these effects vary across individuals, due to for instance their specific skill endowments (when considering tasks or ICT use) or preferences (when considering working conditions). An individual will choose occupation j if $U_{ij}^* > U_{ik}^* \forall k \neq j$. Among all available occupations, the individual chooses the one providing the highest utility.

We define $U_{ij} = 1$ if individual i chooses occupation j and $U_{ij} = 0$ otherwise. Assuming that the disturbance term is iid and follows a Type-I extreme value distribution¹⁸, we can estimate this random utility model using McFadden (1974)'s conditional logit:

$$\Pr(U_{ij} = 1) = \frac{\exp\{\rho_i X_i + \kappa_{ij} Z_j\}}{\sum_{j=1}^J \exp\{\rho_i X_i + \kappa_{ij} Z_j\}} \quad (3)$$

Because individual characteristics, X_i , do not vary across alternatives occupations, they are irrelevant and fall out of the probability. Therefore, we cannot estimate the effect of individual characteristics on the occupational choice (ρ) since they are invariant to the choice. In contrast, occupational characteristics (κ) affect the occupational choice and it is then possible to estimate their effect. To track the effect of changes in occupation-specific characteristics, we allow the effects to vary over time by interacting each characteristic with a dummy variable *Period*. *Period* equals 1 for years 2018-2019, while it equals 0 for 2005-2006 and 2012-2013.¹⁹ Therefore, we interpret the coefficients from a dynamic point of view, with respect to the base period. Coefficients associated with these interaction terms capture the change in the probability of choosing an occupation depending on its characteristics in the period 2018-2019, relative to the base period (2005-2006 and 2012-2013). By comparing these coefficients between natives and immigrants, we can compare changes in occupational sorting across birth groups over the past decade.

¹⁸We should invoke here the independence of irrelevant alternatives (IAA) assumption. Choices are then independent from irrelevant alternatives and therefore the omission of a choice does not significantly alter estimates.

¹⁹We adopt the 2018-2019 value of ICT use and working conditions as occupation-specific characteristics.

5 Results

Main results are presented in Figures 3-7. The 10th, 25th, 50th, 75th and 90th percentiles of the occupation characteristics (*i.e.* propensity to telework, ICT use, task indices or working conditions) are represented in the X-axis of Figures 3-7 (as well as in the figures in Appendix E). Our analysis focuses on the coefficients associated with the interaction terms $Period \times Occupation\ Characteristic_j$, where the “*Characteristic_j*” may correspond to the propensity to telework, ICT use, task composition or working conditions.²⁰ These coefficients capture changes over time in the probability of choosing an occupation which is relatively more intensive in the corresponding characteristic.²¹ The Y-axis represents the variation between the base period (2005-2006, 2012-2013) and 2018-2019 in the probability of choosing an occupation located at the corresponding percentile of the occupation characteristic (*i.e.* relative marginal effect of the percentile).

An upward profile along the distribution of the occupation characteristic indicates that occupations in which the considered characteristic is used more intensively, are more likely to be chosen in 2018-2019 than they were in the base period (*i.e.* 2005-2006 and 2012-2013). In contrast, a downward probability choice profile indicates that occupations in which the considered characteristic is used the most intensively are less likely to be chosen over time. The interpretation of results must then focus on the slope of the curve and not on the absolute values of the marginal effects which are actually defined in relative terms. Comparing the slopes obtained for immigrants and natives allows us to draw conclusions on the differential evolution of occupational sorting between both birth groups. In the figures, the lines representing natives use a circle as a symbol while the lines representing immigrants use a square.

Our results are evidently influenced by differences in the socio-demographic composition of immigrants and natives. For example, if young people are more likely to sort towards occupations using ICT intensively, and if natives are on average younger than immigrants in our sample, we will find that natives are more likely to choose occupations that intensively use ICT in 2018-2019. For the object of study, these composition effects are not a problem, since we seek to analyze differences in occupational sorting of immigrants and natives, whatever the reason behind the occupational choice. However, to evaluate the importance of this socio-demographic composition effect in our results, we additionally implement the conditional logit estimation applying counterfactual weights to ensure that the socio-demographic composition of both birth groups is equal and time invariant (see Appendix D for more details on the computation of counterfactual weights). More precisely, the counterfactual weights impose age, education and gender composition of immigrants to be

²⁰Table E.1 in Appendix E provides the estimation results from the conditional logit estimations. Predictions from this model are then used to calculate the marginal effect of the dummy *Period* at specified values (*i.e.* 10th, 25th, 50th, 75th and 90th percentiles) of the covariate “*Characteristic_j*”. These marginal effects are then graphically represented.

²¹We also control for the share of minimum wage earners in occupations. Immigrants and natives may be differentially attracted to occupations with wages tightly linked to minimum wage changes if they have different propensities to be minimum wage earners, owing to some specific characteristics.

equal to that of natives and equal to the composition of natives in the base period. In contrast, standard weights provided by the LFS allow socio-demographic characteristics of both birth groups to differ and to progress differently along the considered period. We multiply the standard weights provided in the LFS by the number of hours worked by the individual so as to control for potential differences in working time across birth groups. Figures 3-7 will present both estimation results obtained using standard weights provided by the LFS (multiplied by the number of hours) and counterfactual weights (denoted $C1$) imposing equal and time invariant socio-demographic composition across birth groups. This allows us to estimate to what extent changes in socio-demographic characteristics across groups may explain differences in occupational sorting.

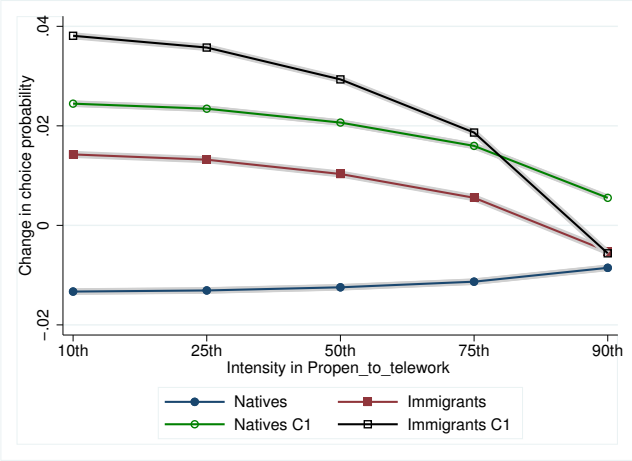
Additionally, differences in occupational choices within birth groups during 2018-2019 with respect to the base period could simply be the result of a cohort effect. To control for this possibility we implement an alternative counterfactual weight approach (denoted as $C2$) using the same strategy as the one described in Appendix D but where we impose immigrants to have a time invariant composition in terms of age, education, gender and years of residence. Similarly natives are imposed to have a time invariant composition in terms of age, education and gender. Note that, with respect to the first counterfactual weight approach, we allow the socio-demographic composition of immigrants and natives to differ. This second approach simply imposes a time invariant socio-demographic composition *within* groups, which allows us to evaluate the role of cohort effects in occupational sorting within a birth group.

5.1 Propensity to telework

In Figure 3, the X-axis displays the 10th, 25th, 50th, 75th and 90th percentiles of the distribution of the propensity to telework, and the Y-axis displays the variation (between the base period and 2018-2019) in the probability of choosing an occupation located at the corresponding percentile of the propensity to telework distribution. The curves with solid symbols (the solid circle for natives and the solid square for immigrants) represent the results for the observed population sample while curves with hollow symbols (the hollow circle for natives and the hollow square for immigrants) represent a constant age-education-gender population composition over time and across birth groups. Figure E.1 in Appendix E compares instead results obtained when considering the standard LFS weights with results obtained when controlling for cohort effects within birth groups, *i.e.* the socio-demographic composition of each birth group is imposed to be time invariant.

Figure 3 reveals that the probability that immigrants choose an occupation with a higher propensity to telework has declined between the base period and 2018-2019. Instead, natives were increasingly sorting into occupations with a higher propensity to telework in 2018-2019.

Figure 3: Change in the probability of choosing an occupation depending on the propensity to telework between the base period (2005-2006, 2012-2013) and 2018-2019.



Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France. The X-axis shows the distribution of the propensity to telework across the 10th, 25th, 50th, 75th and 90th percentiles. In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change in the probability of choosing an occupation located at the corresponding percentile of the distribution of the propensity to telework from the base period to 2018-2019. The shadowed area corresponds to the 95% confidence interval.

Once we control for differences in the age*education*gender composition over time and between both birth groups, we still find a strong decline in the probability that immigrants choose occupations with a higher propensity to telework. This also holds if we control instead for differences in the socio-demographic composition along time within birth groups. As revealed by Figure E.1 in Appendix E, even if we impose the composition of immigrants to be constant in terms of age*education*gender*years of residence we still find that the probability to allocate towards occupations with a higher propensity to telework strongly decreases for this group between the base period and 2018-2019. Figures 3 and E.1 confirm then that changes in the age, education, gender or years of residence are not the factors responsible for immigrants moving away from occupations with a higher propensity to telework.

In contrast, we conclude that age*education*gender composition of the natives' sample drives their sorting into occupations with a higher propensity to telework, as once we control for these changes in observable socio-demographic characteristics there is a decrease in the probability that natives choose occupations with a higher propensity to telework in 2018-2019. We can then conclude that changes in the socio-demographic composition of natives between the base period and 2018-2019 favors the sorting of natives towards occupation with a higher propensity to telework. This evolution is in great contrast with that of immigrants, among whom changes in the socio-demographic composition did not fundamentally modify their reduced sorting into occupations

with a higher propensity to telework.

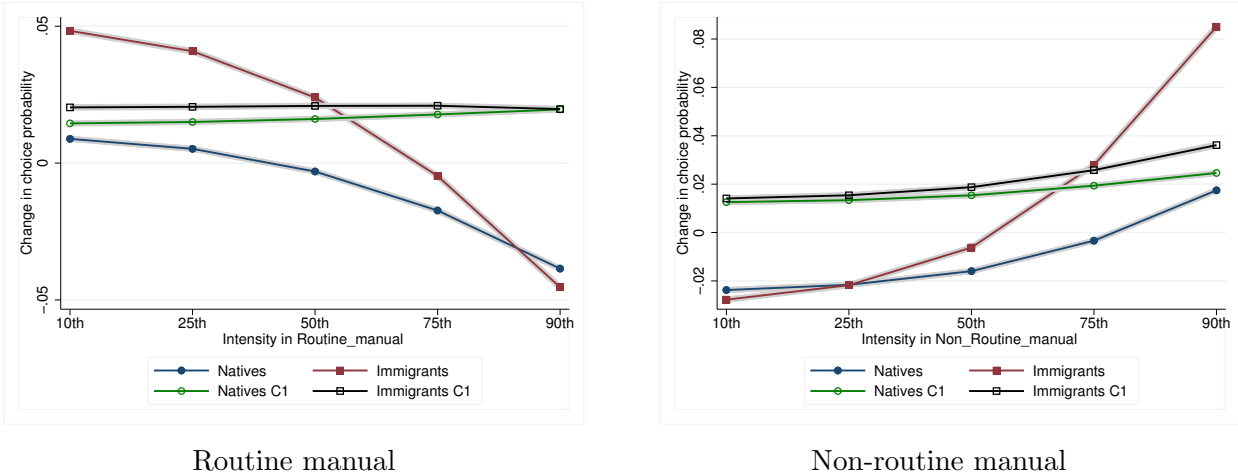
If immigrants are departing occupations with a higher propensity to telework, where are they going? The left hand side panel from Figure 4 reveals that the probability that immigrants and natives sort into a particular occupation decreases with the intensity of routine manual tasks in the occupation. This decrease in the probability is even more important for immigrants, suggesting that they have moved away from these occupations relatively more than natives. When imposing an identical and time invariant composition across birth groups, we find that both natives and immigrants' probability to choose occupations intensive in routine manual tasks slightly increases. This suggests that changes in the age, education and gender composition of natives (which is the reference group for our counterfactual approach) have led to a decreased sorting into this type of occupations.

Interestingly, if we consider instead identical and time invariant socio-demographic composition *within* birth groups (see the left-hand side panel in Figure E.2 Appendix E), we find a decline in the probability that immigrants allocate towards occupations intensive in routine manual tasks. This decline is less steep, however, than when we do not control for composition effects: this suggests that the age*education*gender*years of residence composition of new cohorts of immigrants explains an even more important decrease in the allocation towards occupations intensive in routine manual tasks.

The right hand side panel of Figure 4 reveals that, between the base period and 2018-2019, the increase in the probability of choosing occupations that are intensive in non-routine manual tasks is much higher for immigrants. They are then more likely than natives to allocate towards occupations intensive in non-routine manual tasks. By definition, these tasks are not repetitive and therefore, they are not programmable. They often require physical proximity and therefore on site work. If we impose an identical and time invariant age*education*gender composition for natives and immigrants, we find a smoother but still positive slope for both birth groups. If we control for changes in socio-demographic composition *within* groups (see the right-hand side panel in Figure E.2 Appendix E) the positive slope of immigrants becomes steeper while still having a smaller slope than in the absence of counterfactual weights.

We conclude that between the base period and 2018-2019 immigrants allocated relatively more than natives into occupations intensively using non-routine manual tasks where, in line with the literature (see Peri and Sparber, 2009, Peri, 2012, 2016, Ottaviano et al., 2013 or D'Amuri and Peri, 2014), they benefit from a comparative advantage. Moreover, changes in socio-demographic characteristics (age, education, gender, years of residence) of new cohorts of immigrants have reinforced this sorting pattern. These tasks require onsite work, which contributes to explaining why immigrants were less present than natives in occupations with a higher propensity to telework.

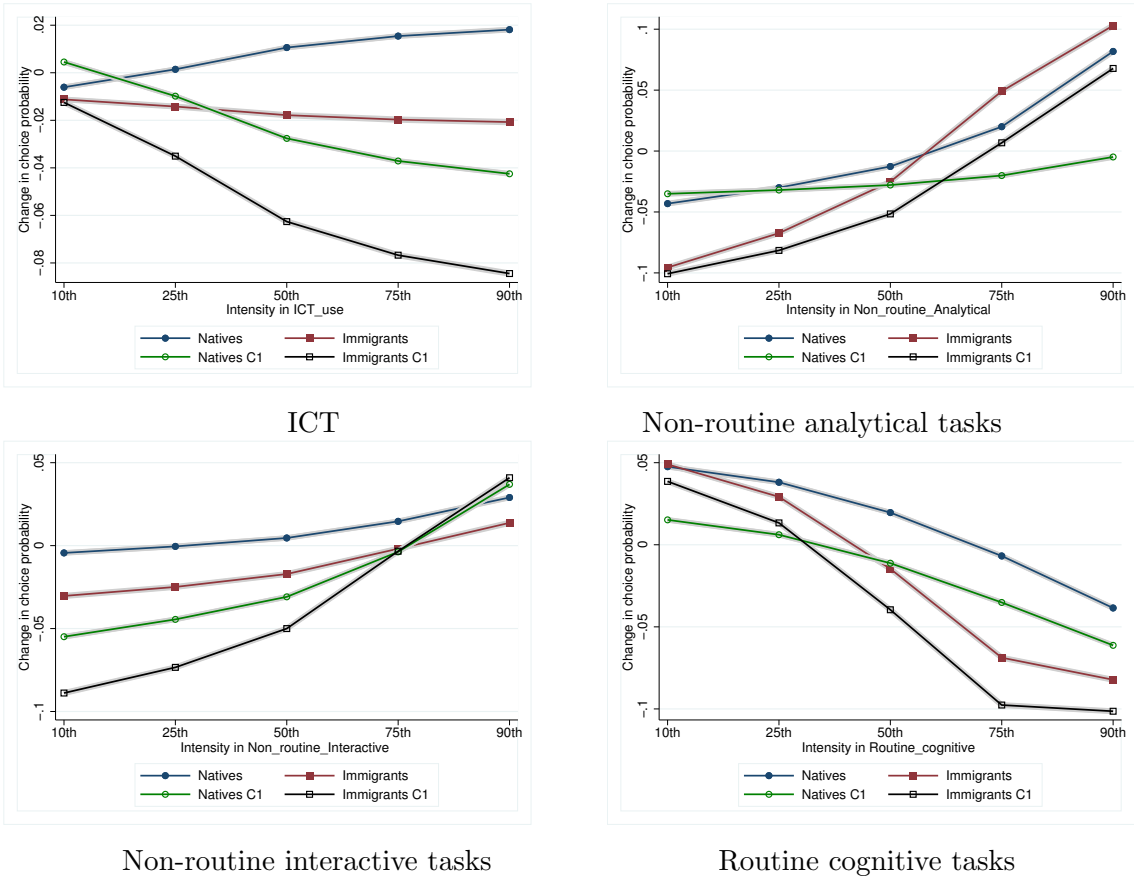
Figure 4: Change in the probability of choosing an occupation depending on manual task composition in the occupation between the base period (2005-2006, 2012-2013) and 2018-2019.



Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France. The X-axis marks the 10th, 25th, 50th, 75th and 90th percentiles of the routine manual and non-routine manual task index distribution. In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change in the probability of choosing an occupation located at the corresponding percentile of the distribution of the routine manual and non-routine manual task index, from the base period to 2018-2019. The shadowed area corresponds to the 95% confidence interval.

The propensity to telework indicator has been defined as the product of ICT use in the occupation and the non-routine analytical, non-routine interactive and routine cognitive tasks indices. We now implement the conditional logit analysis introducing these four occupation characteristics instead of the aggregate telework indicator. The objective is to understand the driving force behind the exit of immigrants from occupations having a higher propensity to telework.

Figure 5: Change in the probability of choosing an occupation depending on ICT use and task composition between the base period (2005-2006, 2012-2013) and 2018-2019 .



Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France. The X-axis marks the 10th, 25th, 50th, 75th and 90th percentiles of the ICT use and tasks index distribution. In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change in the probability of choosing an occupation located at the corresponding percentile of the distribution of the ICT use and tasks index, from the base period to 2018-2019. The shadowed area corresponds to the 95% confidence interval.

Figure 5 represents the progression in the probability of choosing an occupation depending on the intensity of ICT use, non-routine analytical, non-routine interactive and routine cognitive tasks. The upper left-hand side panel reveals that ICT use is the main driving force behind our results. We observe that while natives have increased their probability to allocate towards occupations using intensively ICT between the base period and 2018-2019, immigrants are moving away from these occupations. If we impose natives and immigrants to have the same time invariant composition in terms of age*education*gender, we find a steeper decrease in the probability that immigrants sort into occupations using ICT intensively. For natives we also find a decreasing curve. This pattern confirms that changes in age*education*gender characteristics of natives (reference group for this counterfactual weight approach) have led to an increased sorting into technologically intensive occupations. Even if immigrants are still decreasingly likely to sort into these occupations with respect to the base period, the situation would have been worse if they have had the same socio-demographic characteristics as natives during the entire considered period.

The same conclusion is drawn if we consider time invariant socio-demographic composition *within* birth groups (see the upper left-hand side panel of Figure E.3 in Appendix E). Socio-demographic characteristics of new cohorts have tended to smooth the decreased sorting of immigrants towards ICT intensive occupations.

Concerning occupational sorting depending on task composition (upper right hand side panel and the two bottom panels in Figure 5), we find that immigrants and natives are increasingly sorting towards occupations which intensively include non-routine analytical and interactive tasks. In particular, immigrants have increased their relative probability to allocate towards occupations intensive in non-routine analytical tasks with respect to natives. In contrast, both birth groups are forgoing occupations intensive in routine cognitive tasks. This allocation pattern holds even once we impose identical and time invariant socio-demographic composition across birth groups or within birth groups (see Figure E.3 in Appendix E). Note though that, while changes in socio-demographic characteristics of new cohorts of natives and immigrants have reinforced the increasing probability to allocate towards non-routine analytical tasks, they have rather smoothed the increased sorting into non-routine interactive tasks and they have not modified the sorting pattern against routine cognitive positions.

All in all, between the base period (2005-2006 and 2012-2013) and 2018-2019, immigrants have moved away from occupations using ICT intensively and into occupations intensive in non-routine manual, analytical and interactive tasks. By nature, non-routine manual tasks require physical proximity and are difficult to telework. Non-routine analytical and interactive tasks are easier to telework with ICT, but since immigrants refrained from ICT intensive occupations, in 2018-2019 they were actually sorting into occupations that could not be done from home. There are two main drivers behind the decreased sorting of immigrants with respect to natives into occupations with a higher propensity to telework: their increased likelihood to allocate towards non-routine manual intensive occupations and their decreased likelihood with respect to natives to

allocate towards technology intensive occupations. Thus, the main factors behind the decreased representation of immigrants in positions with a higher propensity to telework are the comparative advantages explained by the relative skill endowment of immigrants with respect to natives and the immigrant-native technological gap.

Interestingly, changes in the socio-demographic characteristics (*i.e.* age, education, gender, years of residence) have contributed to the decreasing allocation of immigrants towards occupations intensive in routine manual tasks and the increased allocation towards occupations intensive in non-routine manual and analytical tasks. These changes in socio-demographic characteristics have also smoothed the decreased sorting into technology intensive occupations and the increased sorting into non-routine interactive tasks. Cohorts effects have then two opposite impacts on the main drivers of the propensity to telework. On the one hand, cohort effects have reinforced the allocation of immigrants into non-routine manual intensive occupations, which are difficult to telework because they need physical proximity. On the other hand, they have smoothed the decrease in the relative probability of immigrants to allocate towards technology intensive occupations. In the absence of cohorts effects, the decrease would have been even steeper.

Our paper complements the existing literature on immigrant and native allocation across occupations based on comparative advantages driven by their relative skill endowment (see Peri and Sparber, 2009, Peri, 2012, 2016, Ottaviano et al., 2013 or D’Amuri and Peri, 2014). In line with this literature, we find that immigrants, with respect to natives, are increasingly likely to allocate towards positions intensive in non-routine manual occupations, where they have a comparative advantage due to their relative skill endowment. Even if differences in skill endowments provide natives a comparative advantage in occupations requiring strong communication skills (*i.e.* intensive in non-routine interactive or analytical tasks), we find that between the base period and 2018-2019 immigrants have increased their relative probability to sort into these occupations (even if they remain less represented in these occupations than natives), suggesting that immigrants have adapted their skills. Note though that immigrants are less likely than natives to sort into technologically intensive occupations, which makes them more difficult to telework, even if these occupations are intensive in non-routine analytical and interactive tasks. This sorting pattern indicates the relative deterioration of immigrants’ working conditions during the pandemic.

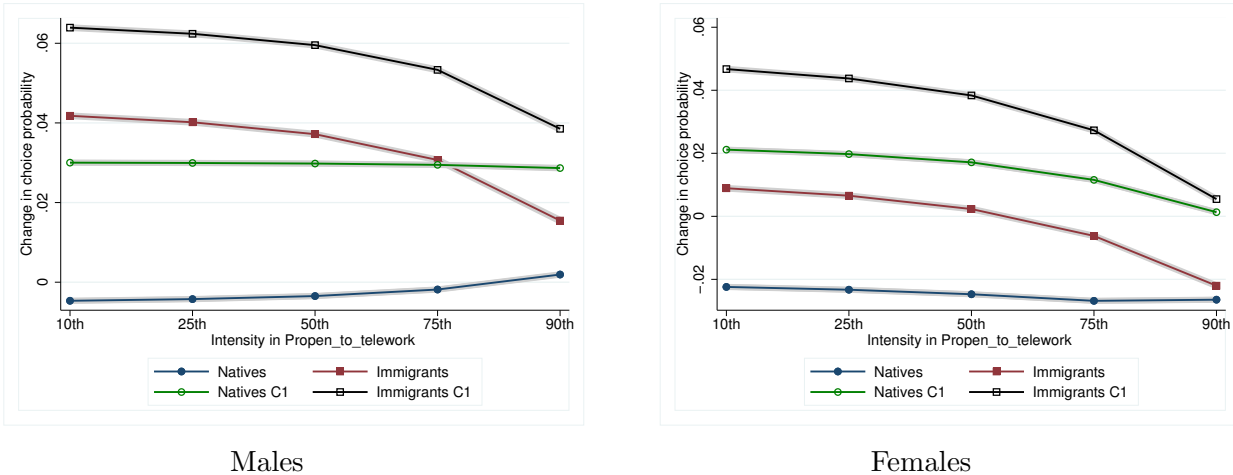
5.1.1 Gender differences in the propensity to telework

Figure 6 replicates the same analysis, distinguishing between males and females. The main conclusions do not change for immigrants. Regardless of gender, we still find a decline in the probability of choosing occupations with a higher propensity to telework. In both cases, cohort effects do not modify this allocation pattern. For natives the situation is different. The probability that males sort into occupations with a higher propensity to telework follows a slightly positive sloped path between the base period and 2018-2019 (see left-hand side panel). This effect is driven by socio-demographic composition effects, since once those are controlled for, native males are equally likely

to choose an occupation with a higher propensity to telework in the base period as in 2018-2019.

For native women (right-hand side panel of Figure 6) the change in the probability to choose occupations located between the 10th and the 75th percentile of the propensity to telework distribution follows a slightly decreasing path between the base period and 2018-2019. In contrast, the slope becomes positive for occupations located above this percentile. Again, changes in socio-demographic characteristics have positively contributed to this sorting pattern.

Figure 6: Change in the probability of choosing an occupation depending on the propensity to telework between the base period (2005-2006, 2012-2013) and 2018-2019. Males vs. Females



Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France. The X-axis marks the 10th, 25th, 50th, 75th and 90th percentiles of the propensity to telework distribution. In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change in the probability of choosing an occupation located at the corresponding percentile of the distribution of the propensity to telework from the base period to 2018-2019. The shadowed area corresponds to the 95% confidence interval.

Figure E.4 in Appendix E confirms that for males, the allocation of birth groups across occupations intensive in ICT use is the main driver of the estimated sorting pattern concerning the propensity to telework. More precisely, the probability that immigrant males allocate into ICT intensive tasks has decreased between the base period and 2018-2019 (upper left-hand side panel), while that of natives increases. Cohort effects have promoted again this sorting pattern.

When considering tasks, the upper right hand side panel and the two bottom panels of Figure E.4 reveal that, in contrast with natives, immigrant males are more likely to allocate towards occupations intensive in non-routine analytical tasks. Both native and immigrant males are more likely to allocate towards occupations intensive in non-routine interactive tasks but less likely to allocate towards occupations intensive in routine cognitive tasks (particularly immigrants).²² The decreasing trend in the relative probability of immigrant males to sort into occupations with a higher propensity to telework is then mainly driven by their lower presence in occupations using

²²Changes in socio-demographic characteristics of immigrants over time have tended to reinforce this sorting pattern.

ICT intensively.

The driving forces behind the lower probability of immigrant women to allocate towards occupations with a higher propensity to telework are slightly different. As revealed by the upper left-hand side panel in Figure E.5, the probability to sort into occupations using ICT intensively has increased between the base period and 2018-2019. Immigrant women have increased their relative probability with respect to native women to allocate towards occupations intensive in non-routine analytical task, but they are less likely to allocate into occupations intensive in routine cognitive and non-routine interactive tasks.²³ The decreasing allocation of immigrant women into occupations with a higher propensity to telework is then explained by their reduced sorting into occupations intensively using non routine-interactive tasks and routine cognitive tasks.

All in all, our findings suggest that during years preceding the pandemic, both immigrant males and females were moving away from occupations with a higher propensity to telework. While for men this sorting pattern is mainly driven by their decreasing probability to allocate towards technologically intensive occupations, for women the decreased probability to sort into occupations intensive in non-routine interactive tasks and routine cognitive tasks has led to decreased sorting into occupations with a higher propensity to telework. Cohort effects have reinforced this allocation pattern.

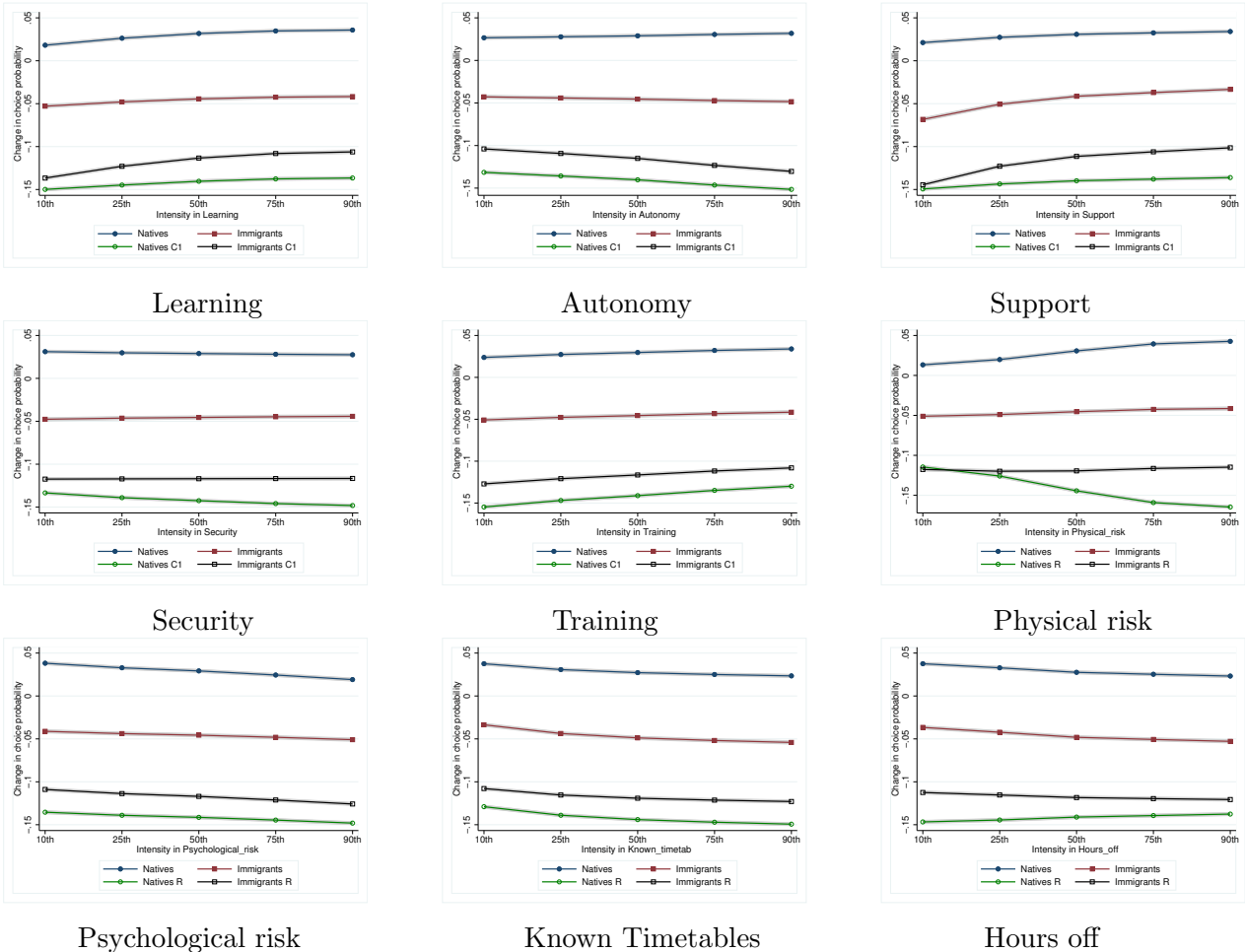
5.2 Non-pecuniary working condition

The departure of immigrants from occupations with a high propensity to telework between the base period and 2018-2019 has relatively deteriorated the working conditions of immigrants with respect to natives during the pandemic. This potential deterioration in relative working conditions of immigrants with respect to natives may have been at least partially compensated for by an improvement in other non-pecuniary working conditions of immigrants during the same considered period.

Figure 7 reveals that this was not the case. The occupational sorting of immigrants and natives essentially did not differ across the intensity of various non-pecuniary working conditions. For the majority of the working conditions indicators we find parallel trends across both birth groups (even when controlling for composition effects). The only exception would be the support received from managers and colleagues, where we find a slightly more significant increasing trend in the likelihood that immigrants allocate towards occupations where support is higher compared to natives. In contrast, natives have increased the probability to allocate towards occupations with lower physical risk, compared to immigrants (note that the higher the physical risk indicator, the lower the exposure to the risk). Moreover, in contrast with previous findings, changes in socio-demographic composition did not modify these allocation patterns.

²³Changes in the socio-demographic characteristics of the most recent cohorts are the main drivers behind this progression.

Figure 7: Change in the probability of choosing an occupation depending on non-pecuniary working conditions, between the base period (2005-2006, 2012-2013) and 2018-2019.



Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France. The X-axis marks the 10th, 25th, 50th, 75th and 90th percentiles of non-pecuniary working condition index distribution. In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change in the probability of choosing an occupation located at the corresponding percentile of the distribution of the non-pecuniary working condition from the base period to 2018-2019. The shadowed area corresponds to the 95% confidence interval.

6 Conclusion

The COVID pandemic has completely transformed workplace organization for millions of workers around the world. The major shift of private companies and public administrations towards telework has altered relative working conditions of socio-demographic groups who had traditionally displayed differences in occupational sorting. In just a few months, people allocated into occupations which were difficult to telework saw their relative working conditions deteriorate with respect to the rest of the population, as they now had to face the new risk of infection.

This paper exploits French data from 2005 to 2019 to study the allocation pattern of immigrants and natives just before the beginning of the pandemic, when occupational choices were not driven by any consideration regarding the probability to telework. We find that, between 2005 and 2019, immigrants (both men and women) were decreasingly likely to allocate towards occupations with a higher propensity to telework while natives were more likely. This occupational pattern is explained by two facts. First, immigrants are more likely to allocate towards occupations that are intensive in non-routine manual tasks, which are difficult to telework as they require physical proximity.

Second, immigrants have forgone occupations that use ICT intensively, meaning it is likely more difficult to telework. Between the base period and 2018-2019, immigrants sorting choices towards occupations intensive in tasks that are easy to telework (non-routine analytical, interactive and routine cognitive tasks) does not differ from that of natives (particularly for men). However, there seems to be a technological gap between immigrants and natives which prevents them from occupying similar positions. Therefore, immigrants are less likely to sort into occupations with a higher propensity to telework. This resulted in a relative deterioration in immigrants working conditions during the pandemic. This deterioration was not compensated for by an improvement in other non-pecuniary working conditions.

While it seems difficult for governments to modify comparative advantages driven by skill endowments, the persistence of a technological gap between immigrants and natives could be at least partially reduced through the promotion of on the job training programs aimed at developing technological skills of workers. Moreover, since 2021, teleworking is internalized as a new working condition by individuals when making their occupational choices. Because of heterogeneous preferences concerning teleworking, we expect that some socio-demographic groups (maybe parents or older workers) having a preference to work from home will become over-represented in positions with a higher propensity to telework. It still remains an open research question how this new occupational allocation pattern will affect social mobility of these socio-demographic groups.

Compliance with Ethical Standards

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References

- Adams-Prassl, A., Boneva, T., Golin, M., and Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics*, 189:104245.
- Amuedo-Dorantes, C. and la Rica, S. D. (2011). Complements or substitutes? task specialization by gender and nativity in Spain. *Labour Economics*, 18(5):697–707.
- Antecol, H. and Bedard, K. (2006). Unhealthy assimilation: Why do immigrants converge to American health status levels? *Demography*, 43(2):337–360.
- Atalay, E., Phongthientham, P., Sotelo, S., and Tannenbaum, D. (2018). The evolving U.S. occupation structure.
- Autor, D., Levy, F., and Murnane, R. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4):1279–1333.
- Basso, G., Peri, G., and Rahman, A. (2017). Computerization and immigration: Theory and evidence from the United States. *Working paper, National Bureau of Economic Research*, (23935).
- Bond, T., Giuntella, O., and Lonsky, J. (2020). Immigration and work schedules: Theory and evidence. *IZA Discussion Paper*, (13236).
- Case, A. and Deaton, A. (2005). Analyses in the economics of aging. *NBER Chapters*, 7588:185–212.
- D’Amuri, F. and Peri, G. (2014). Immigration, jobs, and employment protection: Evidence from Europe before and during the Great Recession. *Journal of the European Economic Association*, 12(2):432–464.
- DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica*, 64(5):1001–1044.
- Dingel, J. and Neiman, B. (2020). How many jobs can be done at home? *Journal of Public Economics*, 189:104235.
- Dramski, P. (2017). On the clock. how immigrants fill gaps in the labor market by working nontraditional. Technical report, New American Economy.
- Dustmann, C. and Giorlach, J. (2016). The economics of temporary migrations. *Journal of Economic Literature*, 54:98–136.
- Fletcher, J. and Sindelar, J. (2009). Estimating causal effects of early occupational choice on later health: Evidence using the PSID. *NBER Working Paper*, (15256).

- Fletcher, J., Sindelar, J., and Yamaguchi, S. (2011). Cumulative effects of job characteristics on health. *Health Economics*, 20(5):553–570.
- Gibbons, R., Katz, L., Lemieux, T., and Parent, D. (2005). Comparative advantage, learning, and sectoral wage determination. *Journal of Labor Economic*, 23(4):681–724.
- Giuntella, O. (2012). Do immigrants squeeze natives out of bad schedules? evidence from italy. *IZA Journal of Migration*, 7(7):1–21.
- Giuntella, O. and Mazzona, F. (2015). Do immigrants improve the health of natives? *Journal of Health Economics*, 43:140–153.
- Giuntella, O., Mazzonna, F., Nicodemo, C., and Vargas-Silva, C. (2019). Immigration and the reallocation of work health risks. *Journal of Population Economics*, 32:1009–1042.
- Laffineur, C. and Mouhoud, E. (2015). The jobs at risk from globalization: the french case. *Review of World Economics*, 151(3):477–531.
- Lekfuangfu, W., Piyapromdee, S., Porapakkarm, P., and Wasi*, N. (2020). On covid-19: New implications of job task requirements and spouse’s occupational sorting. *Covid Economics - Vetted and Real-Time Papers*, 12.
- Lemieux, T. (2002). Decomposing changes in wage distributions: a unified approach. *Canadian Journal of Economics*, 35:646–688.
- Loh, K. and Richardson, S. (2004). Foreign-born workers: Trends in fatal occupational injuries, 1996–2001. *Monthly Labor Review*, 127(6):42–53.
- McDonald, J. and Kennedy, S. (2004). Insights into the healthy immigrant effect: Health status and health service use of immigrants to canada. *Social Science and Medicine*, 59:1613–27.
- McFadden, D. (1974). *Frontiers in Econometrics*, chapter Conditional Logit Analysis of Qualitative Choice Behavior of, pages 105–142. New York: Academic Press, New York, p. zarembka edition.
- Mongey, S., Pilossoph, L., and Weinberg, A. (2020). Which workers bear the burden of social distancing? *NBER Working Paper*, (27085).
- Moreno-Galbis, E. (2020). Differences in working conditions between natives and immigrants: preferences vs. outside employment opportunities. *European Economic Review*, 130:103586.
- Moreno-Galbis, E., Tanguy, J., Tritah, A., and Laffineur, C. (2019). Immigrants’ wage performance in a routine biased technological change era: France 1994–2012. *Industrial Relations*, 58(4):623–673.
- Moreno-Galbis, E. and Tritah, A. (2016). The effects of immigration in frictional labor markets: Theory and empirical evidence from eu countries. *European Economic Review*, 84:76–98.

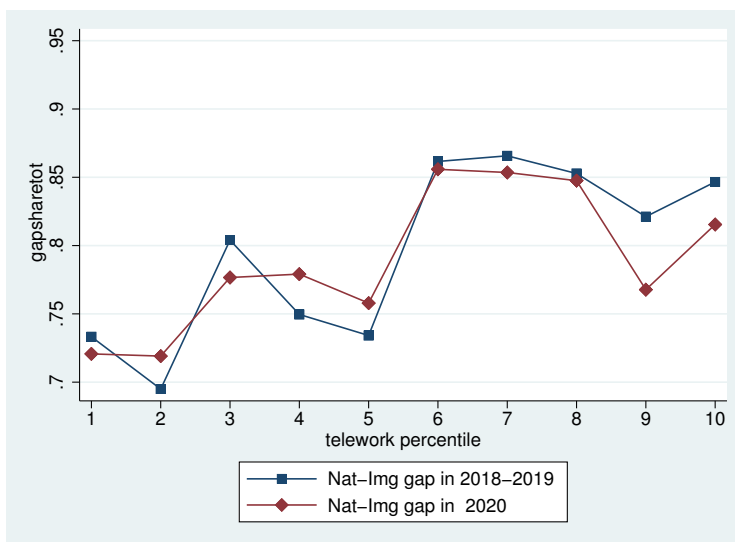
- Nanos, P. and Schluter, C. (2014). The composition of wage differentials between migrants and natives. *European Economic Review*, 65:23–44.
- Orrenius, P. and Zavodny, M. (2009). Do immigrants work in riskier jobs? *Demography*, 46(3):535–551.
- Ottaviano, G., Peri, G., and Wright, G. (2013). Immigration, offshoring, and american jobs. *American Economic Review*, 103(5):1925–1959.
- Palloni, A. and Arias, E. (2004). Paradox lost: explaining the hispanic adult mortality advantage. *Demography*, 41(3):385–415.
- Park, J., Myers, D., Kao, D., and Min, S. (2009). Immigrant obesity and unhealthy assimilation: Alternative estimates of convergence or divergence 1995-2005. *Social Science and Medicine*, 69:1625–1633.
- Passel, J. (2006). The size and characteristics of the unauthorized migrant population in the u.s.: Estimates based on the march 2005 current population survey. Technical report, Pew Hispanic Center, Washington, DC.
- Peri, G. (2012). The effect of immigration on productivity: evidence from us states. *Review of Economics and Statistics*, 94(1):348–358.
- Peri, G. (2016). Immigrants, productivity, and labor markets. *Journal of Economic Perspectives*, 30(4):3–30.
- Peri, G. and Sparber, C. (2009). Task specialization, immigration, and wages. *American Economic Journal: Applied Economics*, 1(3):135–169.
- Peri, G. and Sparber, C. (2011a). Assessing inherent model bias: An application to native displacement in response to immigration. *Journal of Urban Economic*, 69(1):82–91.
- Peri, G. and Sparber, C. (2011b). Highly-educated immigrants and native occupational choice. *Industrial Relations*, 50(3).
- Roy, A. D. (1951). Some thoughts on the distribution of earnings. *Oxford Economic Papers*, 3(2):135–146.
- Tidjens, K., DeRuijter, E., and DeRuikter, J. (2011). Inside occupations: comparing the task description of 160 occupations across eight eu member states. Technical report, ISOL.
- Yamaguchi, S. (2018). Changes in returns to task-specific skills and gender wage gap. *Journal of Human Resources*, 53(1):32–70.

A Appendix: France labor market evolutions in 2020

A.1 Changes in the immigrant-native employment share along the distribution of propensity to telework

Given that we do not have information concerning ICT use per occupation for 2020, we need to assume that the propensity to telework indicator by occupation remained unchanged between 2019 and 2020. While we agree that this may be a limiting hypothesis, it provides at least a lower bound of the indicator by occupation. We can then compare immigrant and native employment changes by occupation, depending on the propensity to telework. To do so, we first consider the distribution of the propensity to telework indicator across occupations. We then split the distribution into 10 deciles and, for every decile, we compute the share of native and the share of immigrant employment. Figure A.1 presents the difference between the native and the immigrant employment share for every decile of the distribution in 2018-2019 vs. 2020. The Figure does not reveal major changes in the composition of employment in 2020. We observe a slight increase in the gap in the bottom half of the distribution and a slight decrease from the 9th decile of the distribution, but we cannot claim that there are major changes in the employment composition along the propensity to telework distribution in 2020.

Figure A.1: Native-Immigrant gap in the employment share along the propensity to telework distribution.

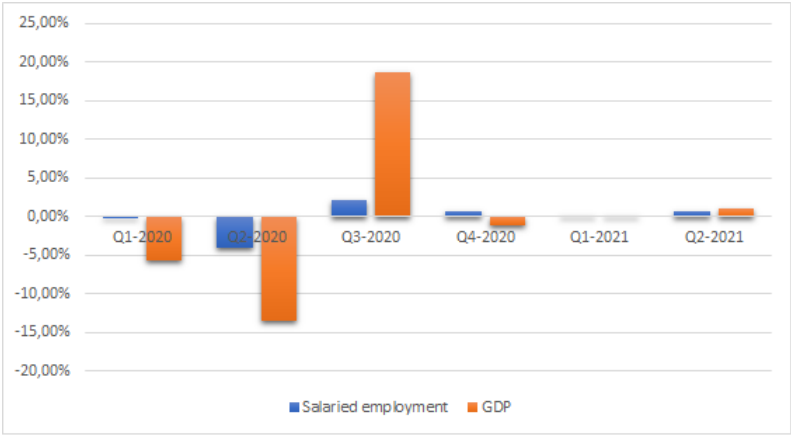


Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, 2020. The propensity to telework indicator is computed using data on ICT for 2019. For every decile of the propensity to telework indicator we have computed the differences between the employment share of natives and the employment share of immigrants.

A.2 Employment evolution in 2020

During 2020, employment fell by 1.5% (i.e., -356,000 losses in salaried employment between the end of 2019 and the end of 2020), a smaller decline than that observed in 2009 (-2.2%), while the fall in activity is much greater (-8.0% in 2020 compared to -2.8% in 2009). A few sectors accounted for the majority of job losses, including accommodation and food services (i.e. hotels and restaurants), arts and entertainment and trade. Employment support policies, notably the exceptional partial activity scheme, helped to contain the effect of health restrictions on employment. Approximately 2.4 billion hours of partial activity were mobilized in 2020, the equivalent of nearly 1.5 million employees working full-time on average over the year. The economic recovery and the easing of sanitary constraints promoted employment recovery in the first half of 2021.

Figure A.2: Quarterly average changes in employment and GDP.



Notes: Quarterly National Accounts, French Statistical Institute. Employment is defined in terms of people.

All in all, whereas support policies prevented major employment loses, they could not prevent the deterioration in relative working conditions of people that could not telework. This paper focuses on this issue.

B Appendix: Data

Table B.1: Occupational tasks.

Non-routine Analytical	Organizing, Planning, and Prioritizing Work ; Getting Information ; Analyzing Data or information; Making Decisions and Solving Problems ; Developing Objectives ; Judging the Qualities of Things, Services, or People ; Updating and Using Relevant Knowledge ; Interacting with Computers ; Thinking Creatively ; Estimating the Quantifiable Characteristics of Products, Events, or Information ; Evaluating Information to Determine Compliance with Standards; Scheduling Work and Activities ; Interpreting the Meaning of Information for Others ; Processing Information and Strategies.
Non-routine inter-personal	Guiding, Directing, and Motivating Subordinates ; Communicating with Supervisors, Peers, or Subordinates ; Communicating with Persons Outside the Organization ; Developing and Building Teams ; Resolving Conflicts and Negotiating with Others ; Performing for or Working Directly with the Public ; Staffing Organizational Units Providing Consultation and Advice to Others ; Coordinating the Work and Activities of Others ; Selling or Influencing Others ; Training and Teaching Others ; Assisting and Caring for Others ; Coaching and Developing Others ; Establishing and Maintaining Interpersonal Relationships ; Monitoring and Controlling Resources.
Routine Cognitive	Performing Administrative Activities, Documenting/Recording Information.
Routine Manual	Handling and Moving Objects ; Performing General Physical Activities ; Repairing and Maintaining Mechanical Equipment ; Repairing and Maintaining Electronic Equipment.
Non-routine Manual	Operating Vehicles, Mechanized Devices, or Equipment ; Inspecting Equipment, Structures, or Material ; Monitoring Processes, Materials, or Surroundings ; Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment.

Source : Constructed using data from O*NET.

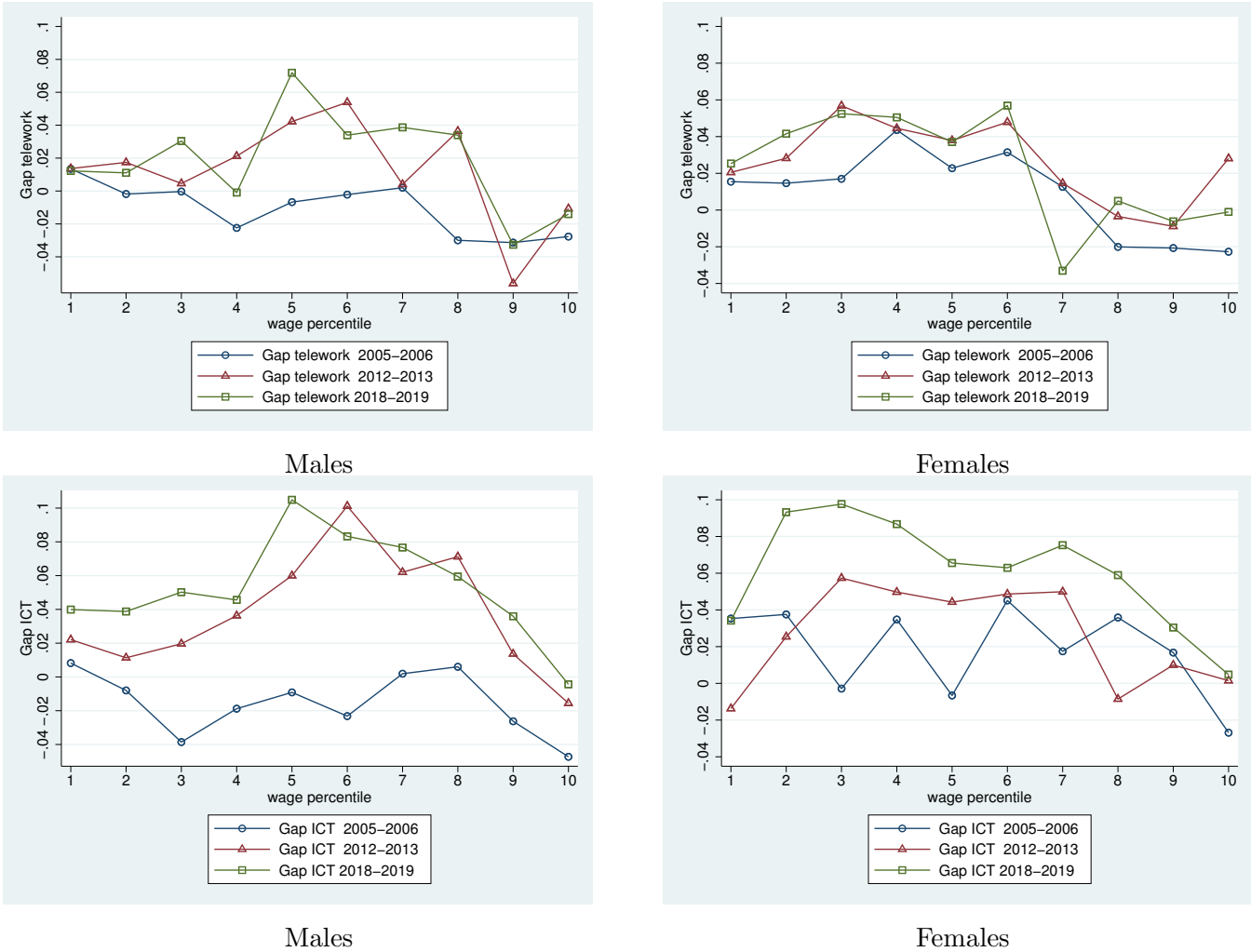
C Appendix: Descriptive Statistics

Table C.1: Sample composition - Natives vs Immigrants

	Natives	Immigrants	P-value
Female	0.492	0.454	0.000
Age	36.482	39.086	0.000
No diploma	0.123	0.327	0.000
BEPC only	0.062	0.057	0.000
CAP, BEP or equiv.	0.261	0.160	0.000
Bac. degrees or equiv.	0.194	0.151	0.000
Bac+2	0.159	0.085	0.000
Higher degree	0.200	0.220	0.000
Married	0.480	0.653	0.000
Children	0.522	0.623	0.000
Permanent contract	0.594	0.634	0.000
Log(Hourly real wage)	2.480	2.417	0.000
(mean) ICT	0.438	0.381	0.000
Non routine analytical	0.121	0.101	0.000
Non routine interactive	0.124	0.107	0.000
Routine cognitive	0.124	0.099	0.000
Telework	0.197	0.147	0.000
Learning new things	0.806	0.763	0.000
Autonomy	1.979	1.981	0.215
Support	1.381	1.287	0.000
Security	0.780	0.762	0.000
Training	0.692	0.706	0.000
Physical risk	5.019	4.596	0.000
Psychological risk	0.578	0.616	0.000
Known timetables	0.876	0.860	0.000
Hours off	0.669	0.671	0.027
Low intensity	2.003	2.014	0.000

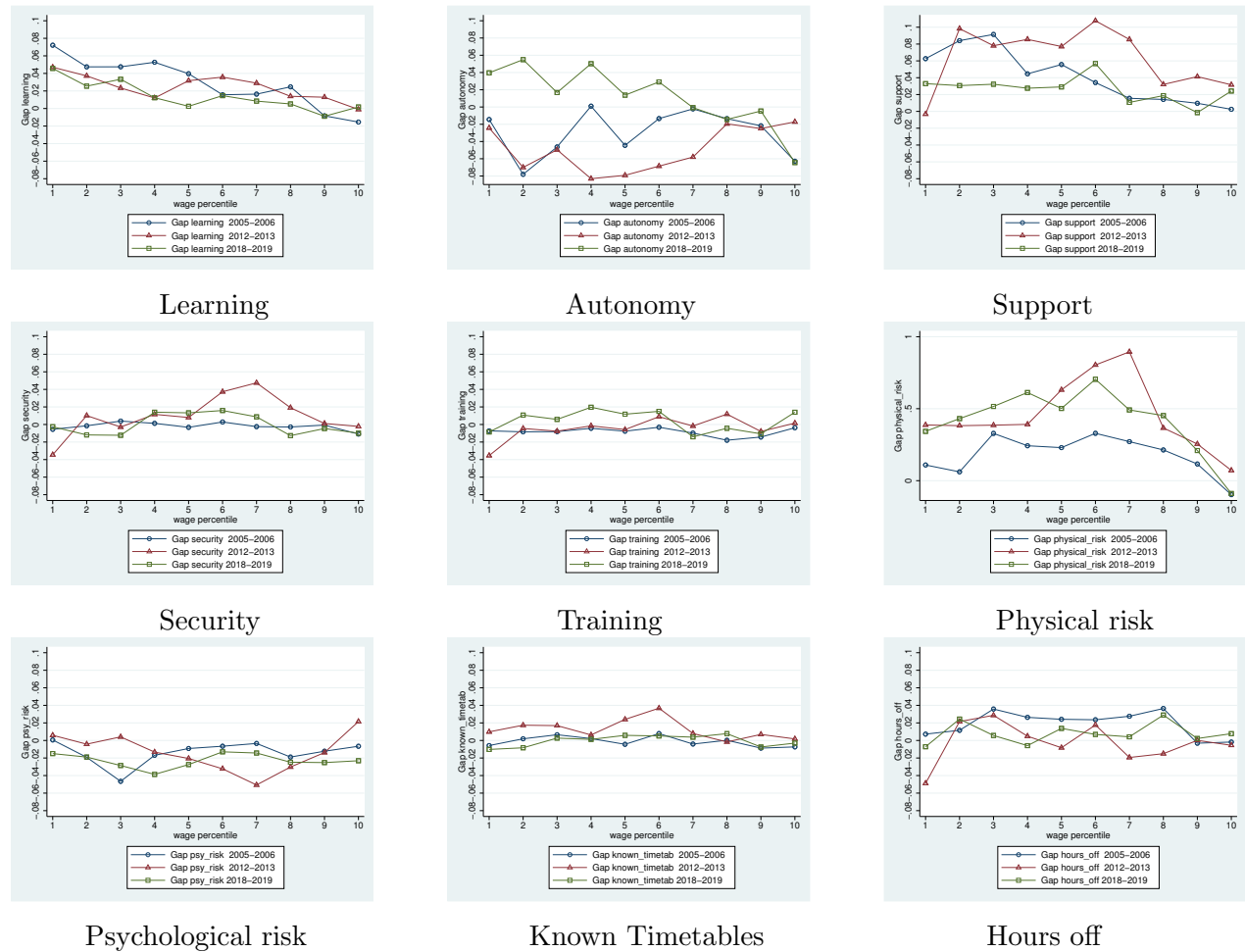
Source: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France.

Figure C.1: Native-Immigrant gap in the propensity to telework and ICT use along the wage distribution, by gender.



Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France.

Figure C.2: Native-Immigrant gap in non-pecuniary working conditions along the wage distribution.



Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France.

D Appendix: counterfactual weight construction

For our counterfactual approach, we rely on the cell-by-cell approach suggested by Lemieux (2002), which is equivalent to the reweighting method of DiNardo et al. (1996) but has the advantage to be more flexible. This non-parametric procedure consists first in dividing the data of every period t into a limited number C of cells according to a set of dummy variables $x_{it} = (x_{i1t}, \dots, x_{ict}, \dots, x_{iCt})$. This procedure is based on the definition of the same age-education-gender cells for natives and immigrants.

We use the following dummies to define age-education-gender cells: we consider nine distinct 5-year interval age groups (from 15 to 60), and within each age group we distinguish four education degrees (below baccalaureate, baccalaureate or equivalent, baccalaureate+2 years, higher degree). Moreover, within each age-education cell we distinguish between men and women.

For each cell c , in occupation j and at period t , we then estimate a reweighting factor Ψ_{cjt} that will be used to calculate a counterfactual sample weight : $\omega_{cjt}^a = \Psi_{cjt} \omega_{cjt}$, where ω_{cjt} is the original sample weight of cell c , in occupation j and period t . The reweighting factor of each cell c is built up first from the sample share of natives in the cell, in occupation j and period $t = 0$, denoted $\eta_{cjt=0}$, which is given by the sample average of the dummy variable $x_{ict=0}$:

$$\bar{x}_{cjt=0} = \sum_{i \in \text{Natives}} \omega_{it} x_{icjt} = \sum_{x_{icjt}} \omega_{it} = \eta_{cjt}, \quad (4)$$

where ω_{it} is the original LFS sample weight, that we have multiplied by monthly hours of work. To ensure that the age-education-gender composition is time invariant and the same for natives and immigrants, we assign the same average weight of the cell to each cell c in the base period. This implies including the sample share of cell c for natives in the base period in the calculation of the corresponding reweighting factors. Thus, the reweighting factor of cell c in occupation j and period t is defined as:

$$\Psi_{cjt} = \frac{\eta_{ct=0}}{\eta_{cjt}}, \quad (5)$$

where η_{cjt} corresponds to the observed share of cell c (defined by a particular age-education-gender) in occupation j in period t , and $\eta_{ct=0}$ is the same share computed for natives in the base period. That is, the numerator stands for the counterfactual sample share of cell c in occupation j that we want to impose to be identical for both periods and for both birth groups.

The resulting counterfactual sample weights $\omega_{cjt}^a = \Psi_{cjt} \omega_{cjt}$ allow to estimate the differences in work conditions that would have arisen if the age-education-gender composition had remained time invariant with respect to the base period and equal to the age-education-gender composition of natives for both birth groups.

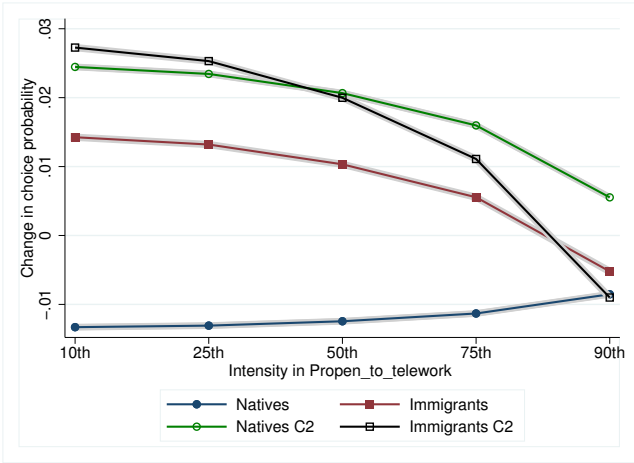
E Appendix: Additional results

Table E.1: Occupational choice: conditional logit estimations

	Dependent variable: occupation chosen											
	1.269*** (0.000104)	1.268*** (0.000104)	1.268*** (0.000104)	0.698*** (0.000337)	0.698*** (0.000338)	0.698*** (0.000338)	-0.577*** (0.00203)	-0.587*** (0.00203)	-0.587*** (0.00203)	8.368*** (0.00634)	8.351*** (0.00635)	8.351*** (0.00635)
Propensity to telework												
Non routine analytical							8.593*** (0.00138)	8.614*** (0.00138)	8.614*** (0.00138)	-13.86*** (0.00515)	-13.83*** (0.00516)	-13.83*** (0.00516)
Routine cognitive							-4.661*** (0.00118)	-4.677*** (0.00118)	-4.677*** (0.00118)	9.209*** (0.00406)	9.184*** (0.00407)	9.184*** (0.00407)
Non routine Interactive							2.488*** (0.000596)	2.489*** (0.000596)	2.489*** (0.000596)	1.548*** (0.00186)	1.541*** (0.00187)	1.541*** (0.00187)
Routine manual	2.661*** (0.000472)	2.661*** (0.000473)	2.661*** (0.000473)	3.803*** (0.00149)	3.790*** (0.00149)	3.790*** (0.00149)	-4.961*** (0.000927)	-4.956*** (0.000928)	-4.956*** (0.000928)	-4.868*** (0.00291)	-4.855*** (0.00291)	-4.855*** (0.00291)
Non routine manual	-4.263*** (0.000617)	-4.259*** (0.000617)	-4.259*** (0.000617)	-4.441*** (0.00197)	-4.426*** (0.00197)	-4.426*** (0.00197)	0.0362*** (9.57e-05)	0.0350*** (9.58e-05)	0.0350*** (9.58e-05)	-0.505*** (0.00283)	-0.505*** (0.00283)	-0.505*** (0.00283)
ICT use							1.033*** (0.000102)	1.033*** (0.000102)	1.033*** (0.000102)	1.137*** (0.000291)	1.137*** (0.000291)	1.137*** (0.000291)
Proportion w^{in} 1.037***	1.040*** (8.94e-05)	1.040*** (8.94e-05)	1.455*** (8.94e-05)	1.454*** (0.000262)	1.454*** (0.000263)	1.030*** (0.000263)						
Period-Propensity to telework	0.0263*** (0.000175)	-0.166*** (0.000179)	-0.166*** (0.000179)	-0.195*** (0.000576)	-0.428*** (0.000598)	-0.358*** (0.000597)	2.461*** (0.00338)	0.587*** (0.00352)	0.587*** (0.00352)	8.845*** (0.0105)	6.864*** (0.0108)	6.876*** (0.0109)
Period-Non routine analytical							-2.877*** (0.00238)	-2.633*** (0.00241)	-2.633*** (0.00241)	-9.767*** (0.00890)	-12.24*** (0.00908)	-10.16*** (0.00911)
Period-Routine cognitive							0.762*** (0.00199)	2.096*** (0.00205)	2.096*** (0.00205)	1.522*** (0.00720)	5.334*** (0.00739)	3.378*** (0.00738)
Period-Non routine Interactive							-0.702*** (0.00100)	-0.100*** (0.00102)	-0.100*** (0.00102)	-1.525*** (0.00318)	-1.384*** (0.00328)	-1.193*** (0.00328)
Period-Routine manual	-0.903*** (0.000791)	0.152*** (0.000814)	0.152*** (0.000814)	-1.863*** (0.00249)	0.188*** (0.00257)	-0.476*** (0.00257)	0.311*** (0.00154)	0.0915*** (0.00160)	0.0915*** (0.00160)	0.509*** (0.00493)	0.852*** (0.00512)	0.627*** (0.00510)
Period-Non routine manual	0.883*** (0.00102)	0.189*** (0.00106)	0.189*** (0.00106)	2.310*** (0.00326)	0.332*** (0.00340)	1.005*** (0.00339)	0.148*** (0.000164)	-0.285*** (0.000162)	-0.285*** (0.000162)	-0.0606*** (0.000480)	-0.455*** (0.000474)	-0.297*** (0.000482)
Period-ICT use							-0.0896*** (0.000174)	0.162*** (0.000171)	0.162*** (0.000171)	0.142*** (0.000492)	0.305*** (0.000481)	0.181*** (0.000491)
Period-Proportion w^{in}	-0.148*** (0.000154)	0.286*** (0.000151)	0.286*** (0.000151)	0.229*** (0.000445)	0.534*** (0.000435)	0.346*** (0.000444)						
Weight	Standard	Counterfactual 1	Counterfactual 2	Standard	Counterfactual 1	Counterfactual 2	Standard	Counterfactual 1	Counterfactual 2	Standard	Counterfactual 1	Counterfactual 2
Population	Natives	Natives	Natives	Immigrants	Immigrants	Immigrants	Natives	Natives	Natives	Immigrants	Immigrants	Immigrants
Observations	215,168	215,168	215,168	215,168	215,168	215,168	215,168	215,168	215,168	215,168	215,168	215,168
Occupations per period	328	328	328	328	328	328	328	328	328	328	328	328

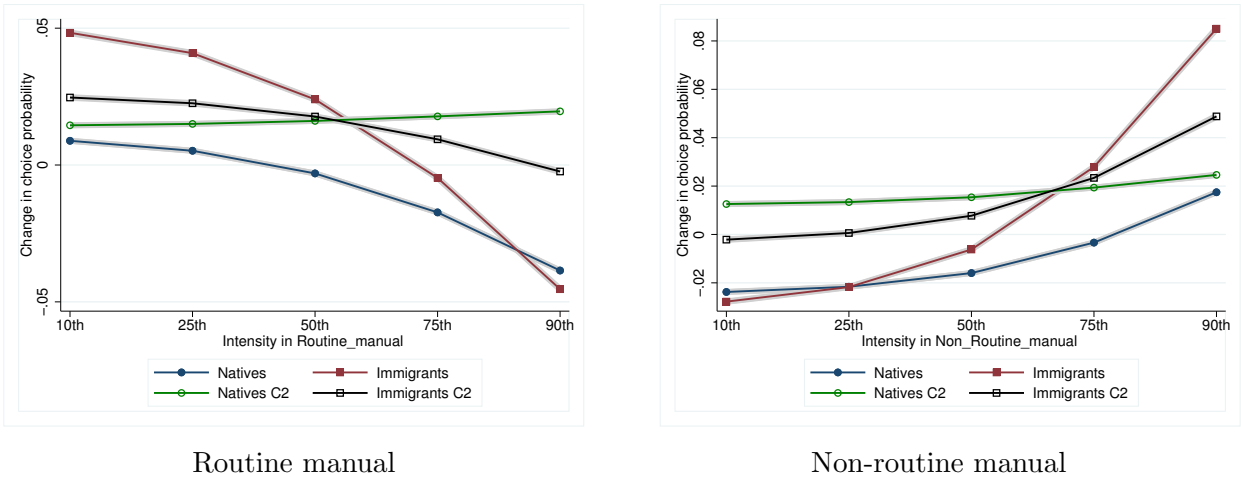
Source: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France. Notes: Weighted conditional logit estimation of equation 3 with counterfactual weights imposing time-invariant socio-demographic composition within each birth group (*i.e.* natives and immigrants). Standard weights are weights provided by the Labor Force Survey. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure E.1: Change in the probability of choosing an occupation depending on the propensity to telework between the base period (2005-2006, 2012-2013) and 2018-2019.



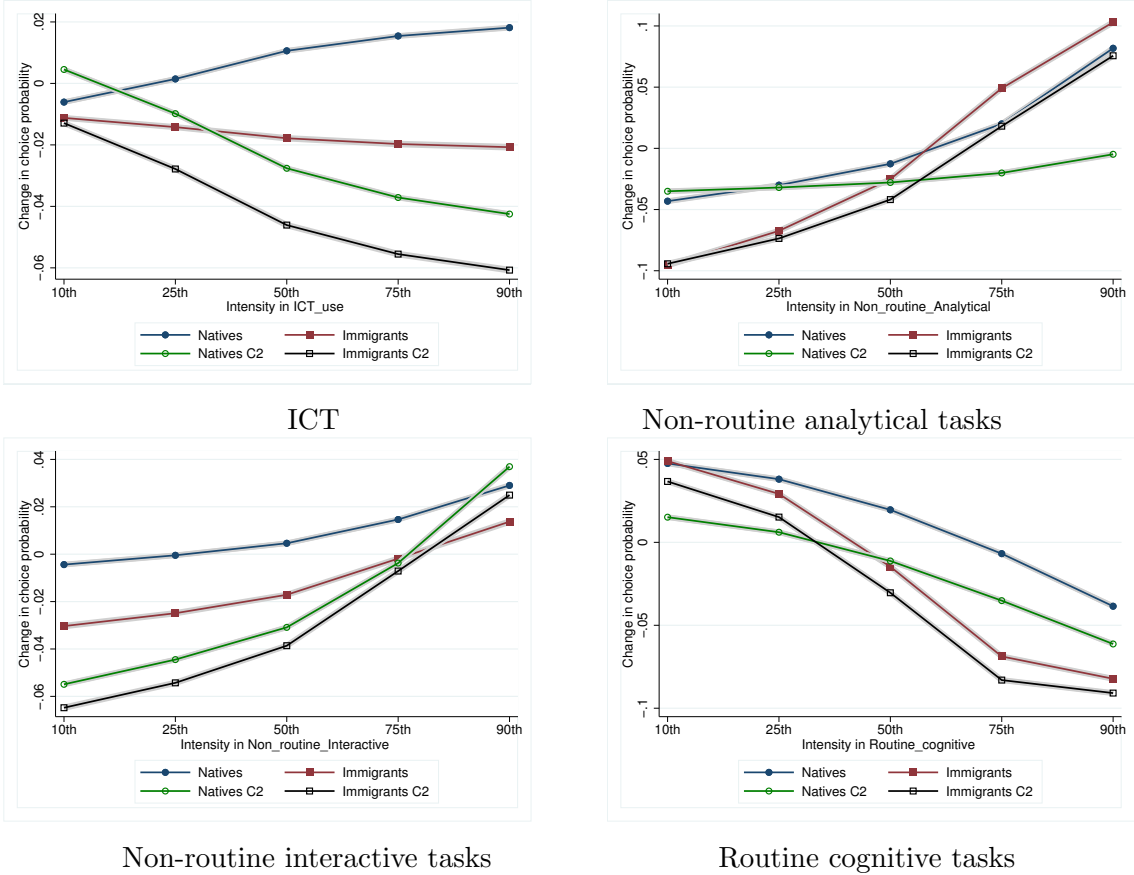
Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France. The X-axis marks the 10th, 25th, 50th, 75th and 90th percentiles of the propensity to telework distribution. In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change in the probability of choosing an occupation located at the corresponding percentile of the distribution of the propensity to telework from the base period to 2018-2019. The shadowed area corresponds to the 95% confidence interval.

Figure E.2: Change in the probability of choosing an occupation depending on manual task composition in the occupation between the base period (2005-2006, 2012-2013) and 2018-2019.



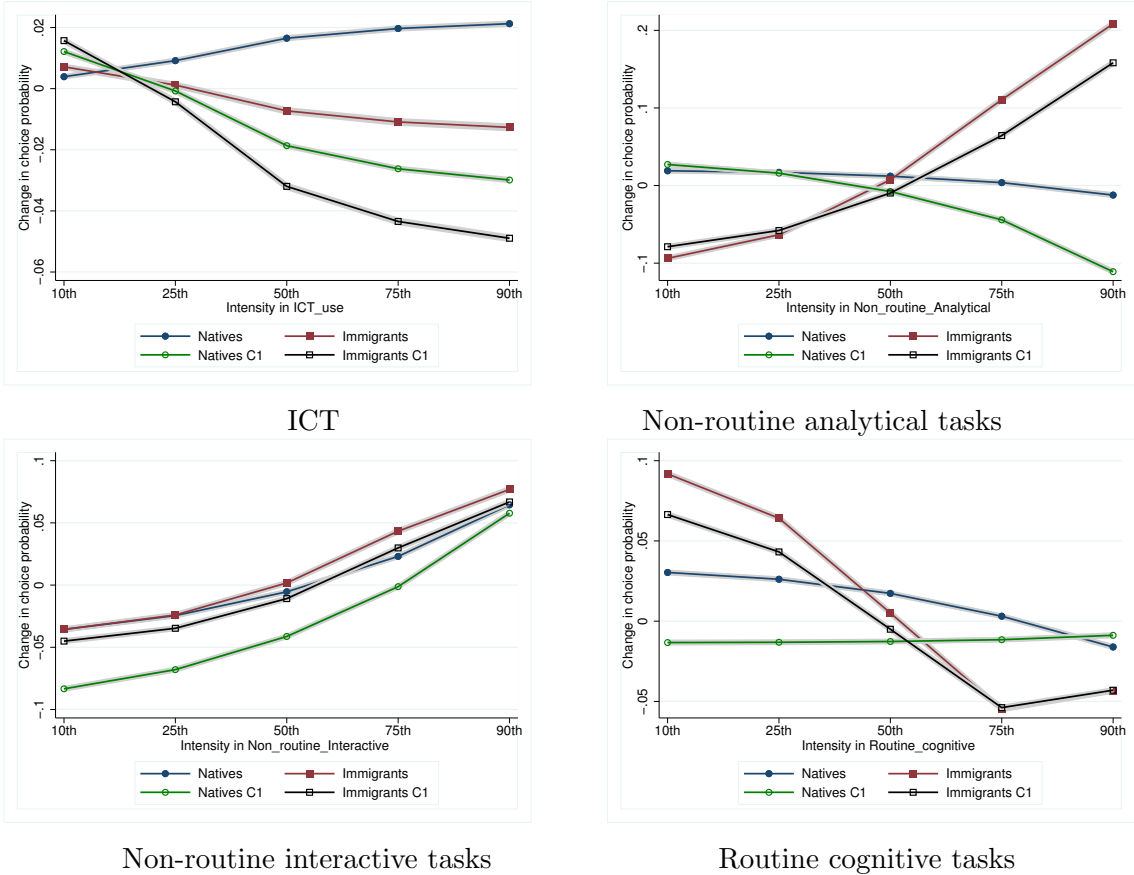
Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France. The X-axis marks the 10th, 25th, 50th, 75th and 90th percentiles of the routine manual and non-routine manual task index distribution. In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change in the probability of choosing an occupation located at the corresponding percentile of the distribution of the routine manual and non-routine manual task index from the base period to 2018-2019. The shadowed area corresponds to the 95% confidence interval.

Figure E.3: Change in the probability of choosing an occupation depending on ICT use and task composition between the base period (2005-2006, 2012-2013) and 2018-2019.



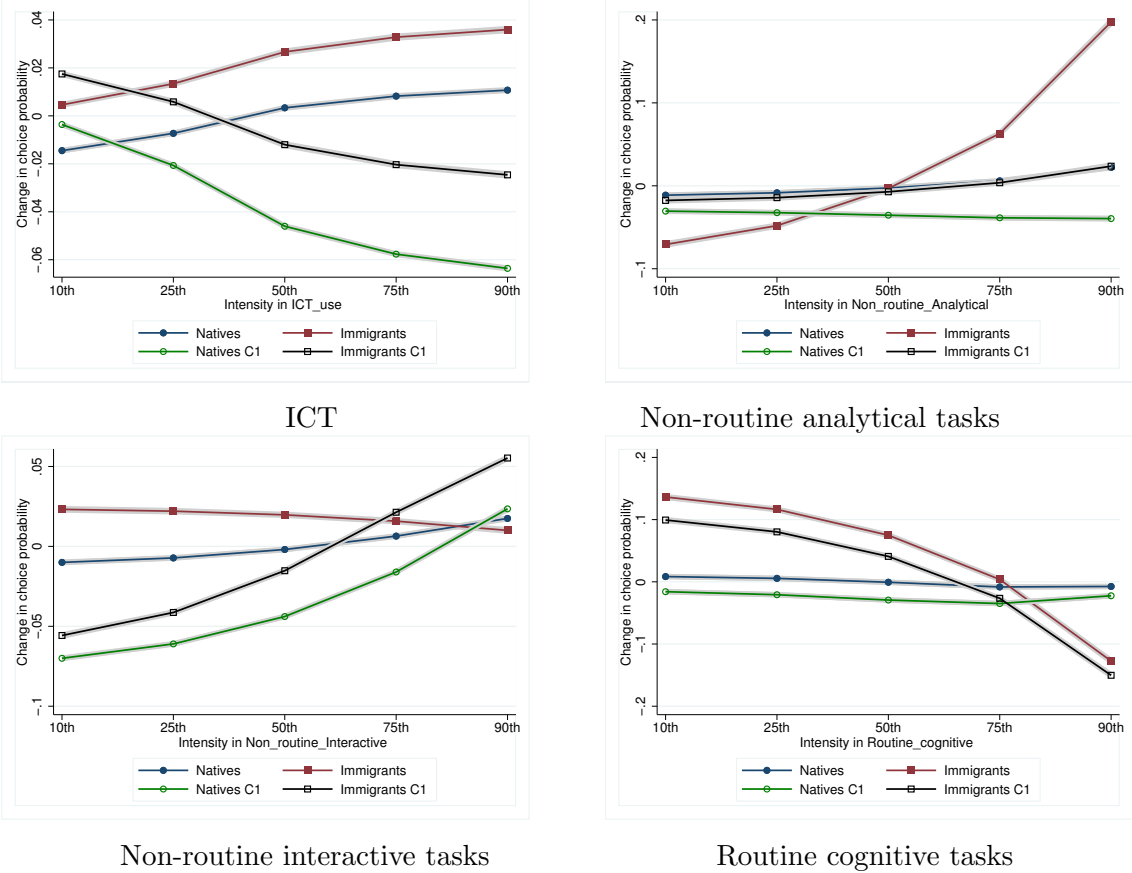
Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France. The X-axis marks the 10th, 25th, 50th, 75th and 90th percentiles of the ICT use and tasks index distribution. In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change in the probability of choosing an occupation located at the corresponding percentile of the distribution of the ICT use and tasks index from the base period to 2018-2019. The shadowed area corresponds to the 95% confidence interval.

Figure E.4: Change in the probability of choosing an occupation depending on ICT use and task composition, between the base period (2005-2006, 2012-2013) and 2018-2019. Males.



Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France. The X-axis marks the 10th, 25th, 50th, 75th and 90th percentiles of the ICT use and tasks index distribution. In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change in the probability of choosing an occupation located at the corresponding percentile of the distribution of ICT use and tasks index from the base period to 2018-2019. The shadowed area corresponds to the 95% confidence interval.

Figure E.5: Change in the probability of choosing an occupation depending on ICT use and task composition, between the base period (2005-2006, 2012-2013) and 2018-2019. Females.



Notes: O*NET; WCS 2005, 2013, 2019; LFS 2005-2006, 2012-2013, 2018-2019, France. The X-axis marks the 10th, 25th, 50th, 75th and 90th percentiles of the ICT use and tasks index distribution. In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change in the probability of choosing an occupation located at the corresponding percentile of the distribution of the ICT use and tasks index from the base period to 2018-2019. The shadowed area corresponds to the 95% confidence interval.