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Essays on the labor market : remote work, economic consequences of COVID-19 lockdowns, and establishments' relocation

Malak Kandoussi

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Essays on the Labor Market : Remote Work, Economic Consequences of COVID-19 Lockdowns, and Establishments' Relocation

*Essais sur le marché du travail :
Télétravail, Conséquences économiques des
confinements liés au COVID-19, et Délocalisation des
établissements*

Thèse de doctorat de l'Université Paris-Saclay

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Thèse soutenue à Paris Saclay, le 07 Décembre 2023, par

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Titre : Essais sur le marché du travail : Télétravail, Conséquences économiques des confinements liés au COVID-19, Délocalisation des établissements.

Mots clés : Télétravail, COVID-19, Recherche et appariement, taux de chômage, délocalisation des entreprises, expérience naturelle.

Résumé : Cette thèse se compose de trois chapitres qui étudient le marché du travail.

Le premier chapitre se concentre sur l'impact du télétravail sur le marché du travail en utilisant une extension du modèle de recherche et d'appariement. En considérant les changements survenus dans l'économie avant et après la pandémie de COVID-19, l'objectif est de combler le fossé de données pour (i) expliquer l'augmentation de la part de travailleurs à distance suite à la crise de la COVID-19; (ii) étudier les effets de ce changement sur le marché du travail dans deux zones distinctes; et (iii) évaluer les avantages potentiels du travail à domicile pour réduire les inégalités entre les régions urbaines et rurales.

Le deuxième chapitre introduit un modèle d'équilibre général qui intègre les frictions d'appariement pour analyser l'impact du confinement lié à la COVID-19 sur le chômage. Le modèle est calibré sur l'expérience de la crise des subprimes, puis utilisé pour identifier les chocs de confinement spécifiques à l'emploi, ce qui lui permet de prédire les flux observés de travailleurs par diplôme. L'étude conclut que la persistance du modèle, nettement plus élevée que dans le modèle Diamond-Mortensen-Pissarides, est atténuée par les effets du CARES Act. Cette loi joue un rôle significatif dans la réduction de l'augmentation du chômage en

réduisant la dynamique des séparations de travailleurs et en favorisant les embauches. Des expériences contrefactuelles menées dans l'étude montrent que l'intégration du risque variable dans le temps et des externalités liées aux coûts d'embauche est nécessaire pour expliquer efficacement la dynamique de ces crises.

Le troisième et dernier chapitre se concentre sur la compréhension du processus décisionnel des entreprises lorsqu'elles choisissent les emplacements de leurs établissements. L'étude examine comment les changements de temps de trajet domicile-travail résultant d'un déménagement d'un établissement affectent la probabilité de destruction de l'emploi et les salaires. Une augmentation du temps de trajet due à un déménagement conduit à une probabilité plus élevée de séparation, avec des effets deux fois supérieurs pour les déménagements du centre en banlieue. Afin de préserver la relation d'emploi, les établissements qui déménagent en banlieue augmentent les salaires des travailleurs qualifiés, en particulier ceux résidant dans le centre de Paris. En revanche, nous ne trouvons pas que les entreprises baissent les salaires des travailleurs bénéficiant d'une baisse du temps de trajet suite au déménagement.

Title : Essays on the Labor Market : Remote Work, Economic Consequences of COVID-19 Lockdowns, and Establishments' Relocation.

Keywords : Working from home, COVID-19, Search and matching, unemployment, firms' delocalisation, natural experiment.

Abstract : This thesis consists of three chapters that study labour market.

The first chapter focuses on examining the impact of working from home on the labor market outcomes using an extension of the search and matching model. By considering the changes that have occurred in the economy before and after the COVID-19 pandemic, the objective is to address the data gap to (i) explain the increase in the share of remote workers following the COVID-19 crisis; (ii) investigate the effects of this shift on labor market outcomes in two distinct areas; and (iii) assess the potential benefits of working from home in reducing inequalities between urban and rural regions.

The second chapter introduces a general equilibrium model that incorporates matching frictions to analyze the impact of the COVID-19 lockdown on unemployment. The model is calibrated on the subprime-crisis experience and is then used to identify the job-specific lockdown shocks, allowing it to predict the observed worker flows by diploma. The study finds that the persistence of the model, which is notably higher than in the Diamond-Mortensen-Pissarides model, is mitigated by the effects of the CARES Act. This act plays a significant role

in reducing the increase in unemployment by reducing the dynamics of worker separations and promoting job hires. Counterfactual experiments conducted in the study demonstrate that incorporating time-varying risk and externalities related to hiring costs are necessary to effectively explain the dynamics of these crises.

The third and final chapter focuses on understanding the decision-making process of firms when selecting the locations for their establishments. The study investigates how changes in commuting time resulting from different types of relocations impact job separation and wages. The findings indicate that an increase in commuting time due to a relocation leads to a higher probability of job separation. In order to maintain the employment relationship, establishments that move to the suburbs tend to increase the wages of skilled workers, particularly those residing in the city center. Conversely, no evidence is found to support wage adjustments for establishments relocating to the center, and there is no indication of wage cuts for workers for whom commuting time decreases as a result of the relocation of their establishment.

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Completing this PhD wouldn't have been as smooth without the support of many people. Therefore, I would like to express my sincere gratitude to those who played significant roles in this journey.

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On the other side, François Langot was the one who kindled my love for research in the first place. The first time I met François, I was searching for my master's thesis supervisor, when I left his office not only did I discover the perfect guide for my academic endeavors, but I also found someone who helped me grasp the true essence of the research analysis and the fluidity of thinking. Even today, I stand amazed by his incredible mind, sometimes wishing I were the magical yellow bus navigating through it.

Therefore, yes, I consider myself one of the luckiest PhD students to have two supervisors with not only extensive academic knowledge and experience but also an innate ability to share it with me in the most natural way. Gregory, François, thank you for your unwavering support, guidance, and encouragement.

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Introduction

Researchers find fulfillment in encountering rare events that provide them with the opportunity to dig into the inner workings and mechanisms of the surrounding reality. COVID-19 emerged as one such unique occurrence. Within a short span of time, hundreds and thousands of papers were published as researchers seized this rare event, meticulously dissecting and thoroughly examining it to gain understanding and derive valuable insights. This sanitation crisis presented researchers with a unique event that allowed them to comprehend various aspects of our world. As economists, we were presented with a fresh crisis that affected economies differently and triggered distinct responses from public policies.

In the first two chapters, we explore two crucial aspects of this COVID-19 experience. The first chapter centers around the aftermath of the working-from-home trend while the second chapter focuses on the direct impact of this crisis on unemployment, separations, and public policies. Both chapters employ an expanded version of the well-known [Diamond \(1982\)](#)-[Mortensen \(1982\)](#)-[Pissarides \(1985\)](#) matching model, commonly referred to as the DMP model.

Although many works concentrate on the impact of various crises on the labor market, there is a broader range of tools allowing us to understand the factors that instigate shifts in this market. One of these tools is the econometrics studies and the analysis of the data.

In fact, while the first two chapters draw conclusions from a theoretical framework, the third chapter employs a quasi-natural experiment to investigate the determining factors of firm localization and test the significance of commuting time in workers' bargained wages. Specifically, the study aims to explore the relationship between wages and commuting time, examine the possibility of downward wage rigidity, assess how local amenities influence workers' satisfaction, and investigate whether firms are inclined to easily replace existing workers.

0.1 Search and Matching

The DMP model revolves around the concept that both workers and firms invest time and resources in finding a suitable match. Workers dedicate their time and financial resources to search for and apply for job opportunities, while firms expend funds on advertising vacancies and reviewing applications. Consequently, the process of matching unemployed individuals with available job openings can be time-consuming. Within the DMP framework, this dynamic is captured by a matching function. This function takes into account the stock of unemployed workers and vacancies as inputs and produces a flow of matches as an output. Essentially, this function represents the friction that arises during the interaction between workers and firms throughout the matching process.

Various methods exist for determining wages, with one of the most used approach being Nash Bargaining. When a firm and a worker establish a match, an economic rent is generated. This rent is influenced by factors such as the firm's profits, wages, and the costs associated with the search process. During wage negotiations, workers secure a portion of this rent in addition to compensation for the expenses incurred in forming the match. For example, if workers have to pay some commuting costs, they may negotiate for a part of these expenses in their wages.

The DMP model has emerged as a crucial framework within labor literature. While it may not encompass every field of study, it has found extensive application in several areas. Some notable contributions include: understanding the cyclical nature of unemployment and vacancies;¹ propagation mechanisms of economic crises;² explaining the impact of volatility and uncertainty on the labor market;³ exploring business cycles, economic growth and public policies.⁴ These are just a few examples, and the range of applications for the DMP model extends beyond these areas.

In this thesis, we use the frictional framework of the DMP model to investigate important mechanisms within the labor market. Chapter 1 of the thesis extends the framework by considering three key factors: (i) regional heterogeneity between urban and rural areas, (ii) the choice of occupation between fully on-site, remote, or hybrid arrangements, and (iii) the intensity of working from home (WFH) in the hybrid setup. On one hand,

¹See [Pissarides \(1985\)](#), [Shimer \(2005\)](#), [Mortensen and Nagypal \(2007\)](#) and [Hagedorn and Manovskii \(2008\)](#).

²See [Hall \(2005\)](#), [Petrosky-Nadeau et al. \(2018\)](#) and [Petrosky-Nadeau and Zhang \(2021\)](#).

³See [Schaal \(2017\)](#), [Den Haan et al. \(2021\)](#) and [Kandoussi and Langot \(2022\)](#).

⁴See [Merz \(1995\)](#), [Andolfatto \(1996\)](#), [Gertler and Trigari \(2009\)](#), [Pissarides \(2009\)](#), and [Christiano et al. \(2016\)](#).

by incorporating these elements, we aim to forecast the potential evolution of the post-pandemic economy, accounting not only for the changes due to COVID-19 (such as shifts in the perception of remote work and changes in worker's productivity) but also for the impact of the ongoing fuel crisis. On the other, the large increase in WFH can impact the labor market, as unemployed workers can be more encouraged to search intensively in other areas than the one they are residing in, creating henceforth some search externalities to be analyzed.

Furthermore, there is limited available data on the heterogeneous effects of WFH in urban and rural areas. Urban and rural regions differ in their capacity for remote work, as urban areas possess more infrastructure and resources that support remote work, while rural areas are more inclined to have more agriculture and manufacturing jobs with physical presence and face-to-face interactions. Consequently, this disparity creates inequalities that compound existing disparities in wages, welfare, wealth, and other socioeconomic factors. Thus, this chapter aims to address this data limitation by examining the effects of the emerging trend of WFH, highlighting how it can benefit both economies and impact ongoing inequalities.

In Chapter 2 of the thesis, a distinct extension of the DMP model is employed. This extension incorporates the following elements: *(i)* worker heterogeneity, *(ii)* time-varying microeconomic risks linked to the business cycle, *(iii)* congestion externalities affecting hiring costs, and *(iv)* real-wage rigidity. The primary objective of this chapter is to analyze the impact of the lockdown measures on unemployment for heterogeneous workers and examine how public policies have assisted in mitigating these negative effects.

Two different policies that have influenced the labor market in distinct ways are explored. Firstly, in the United States, the CARES Act introduced the Paycheck Protection Program, which incentivized firms to retain their employees. Secondly, in France, the government implemented measures that allowed companies to temporarily separate from certain employees while maintaining their employment contracts through partial unemployment. This approach facilitated a quicker return to work once the crisis subsided. Using this extended DMP model, the chapter evaluates the extent to which these diverse policies contributed to the adjustment of unemployment levels during and after the crisis.

Therefore, the first two chapters use the search and matching framework to analyse the impact of the COVID-19 crisis on the labor market focusing on two distinct perspectives. To gain a more comprehensive understanding of the mechanisms underlying the labor market, we explain in the following how the third chapter, through natural experiment, enables us to do so.

0.2 Natural Experiment

Theoretical frameworks serve various purposes, including addressing data limitations, analyzing underlying mechanisms, and simulating alternative scenarios of events. Another approach to gaining insights into the foundations of the labor market is through the use of natural experiments. Angrist and Pischke (2010) explain that a better research design using real or natural (quasi-)experiments represents a huge improvement in econometrics studies. By comparing outcomes between two groups (treated and control group), the causal effect can be estimated, as any differences observed are attributed to the treatment.

Natural experiments have been extensively employed in economics for various purposes.⁵ Researchers compare outcomes between different sets of populations (*i.e.* states, groups, schools, or individuals) to evaluate the impact of these policies and determine whether it is beneficial or not to expand it to other subsets of the population. Chapter 3 of this paper, firms' relocations serves as a quasi-natural experiment to understand firms' localization decisions and the impact of commuting time on wages and separation probabilities.

Drawing robust conclusions about how establishment location affects labor supply to the firm cannot be achieved by simply comparing wages between establishments in the center and suburbs. Therefore, in this chapter, we utilize establishment relocations within the Paris metro area in France as a quasi-natural experiment. By doing so, we can estimate how wages and job separation probabilities vary among employees in response to individual differences in changes in commuting time resulting from the relocation. If the findings reveal that firms offer higher wages and experience higher separation rates after relocating to more remote locations, it would confirm that low commuting time is a crucial and beneficial factor associated with being located in the center. Additionally, if establishments are more likely to adjust wages for a specific subset of skilled workers who tend to reside in the center, it suggests that one advantage of being located in the center is the ability to provide these workers with a shorter commute time.

Therefore, using this firm relocation as a quasi-natural experiment allows us to examine the complex interaction between commuting, labor supply, and firm behavior, providing a more comprehensive understanding of the dynamics involved.

⁵In this exhaustive list you can find: the examination of the effects of minimum wage policies (Card and Krueger (2000) and Dube et al. (2010)) education interventions (Krueger (1999) and Angrist (2004)) and health insurance policies (Card et al. (2008) and Finkelstein et al. (2012)).

0.3 Research Objectives

This thesis is dedicated to gaining a deeper understanding of certain factors that have the potential to influence outcomes in the labor market. It will be explored through three chapters, each focusing on different aspects related to these influencing factors. Hence, the purpose of this research is to enhance our comprehension of the labor market by addressing three key research questions:

1. How does the emerging trend of remote work influence labor market outcomes and inequalities within two distinct spatial zones?
2. How did COVID-19 impact unemployment for different types of workers, and how did public interventions mitigate its negative effects?

The first two questions emphasize the heterogeneity of labor markets and underscore the crucial role of public interventions in not only mitigating the negative effect of crisis but also reducing inequalities across unequally affected markets. After investigating the initial two questions using a theoretical search and matching model, it is important to gain empirical insights into the factors that prompt firms to locate themselves in the central areas of large metropolitan regions. This exploration will also provide valuable insights into wage determinants and employee turnover, addressing the following question:

3. How does firm relocation impact wages and employee turnover?

Chapter 1 : A New Norm? Exploring the Shift to Working From Home in the Post-Pandemic Labor Market

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1.1 Introduction

Since the outbreak of COVID-19, Working From Home (WFH) has gained significant popularity. Prior to the pandemic, WFH was already being adopted by certain types of workers and represented 5.7% of the working population in 2019 according to the American Community Survey. However, due to concerns about the virus, governments imposed restrictions on face-to-face interactions. In order to ensure business continuity, many companies opted to implement WFH arrangements for their employees. Even after the initial outbreak subsided, WFH has continued to persist. In fact, According to [Barrero et al. \(2023\)](#), the number of full days worked at home has substantially increased from 2019 to mid 2023. That is to say, the share of remoters reached 28 percent in the US.

This increasing prevalence of WFH raises important questions regarding its impact on both labor market outcomes and the inequalities that exist between diverse labor markets. In this paper, we build a search and matching model with an original extension introducing *(i)* regional heterogeneity between urban and rural areas, *(ii)* occupational choice between fully on-site, remotely or in hybrid arrangement and *(iii)* the intensity of WFH in the hybrid set up. Using this framework, we aim to *(i)* understand this increase in the share of remote workers, *(ii)* study the effect of this shift on labor market outcomes in two heterogeneous areas (urban and rural), and *(iii)* evaluate the benefit of WFH on inequalities between these two areas.

It is important to understand how this shift in WFH will impact different labor markets using a heterogeneous intensity of WFH as the perception and adoption of remote work vary across different areas. In fact, [Dingel and Neiman \(2020\)](#) found that while 37% of jobs in the US could be fully performed from home, the prevalence of WFH differs significantly in low-income economies, where the share of remote work is generally lower. This highlights the disparities in the ability to transition to remote work based on economic factors. Moreover, studies by [Bartik et al. \(2020 a\)](#) and [Brynjolfsson et al. \(2020\)](#) provide evidence of inequality in WFH arrangements concerning industries, age groups, gender, and occupations. The adoption of remote work is not evenly distributed across these categories, indicating that certain groups may face more challenges or have less access to remote work opportunities. Furthermore, [Barrero et al. \(2023\)](#) show that the information sector, Finance, Insurance, Professional and Business Services has the highest WFH intensity while retail, hospitality, food services, transportation, and manufacturing have the lowest rates. They also show that this rate increases significantly with population density and education and is the highest for workers in their thirties.

Even during the COVID-19 outbreak, the labor market impact of the pandemic varied unequally within countries. According to evidence presented by [Adams-Prassl et al. \(2020\)](#) in the UK, US, and Germany, workers who were unable to WFH were the most likely to lose their jobs and experienced wage decreases. This further emphasizes the disparities in the labor market consequences of remote work and its impact on different segments of the workforce. In summary, the adoption of WFH varies across regions and countries, with low-income economies having a lower share of remote work. This highlights the importance of modeling two heterogeneous areas that do not equally embrace the intensity of WFH.

Moreover, as stated earlier, the SWAA indicates that the share of remote work quadruple from 2019 to mid-2023. [Barrero et al. \(2020 a\)](#) attribute it to several factors. Firstly, individuals have had better-than-expected experiences with remote working, leading to a more positive perception of its feasibility. Additionally, investments in both physical and human capital have been made to facilitate remote work. The stigma surrounding remote work has also diminished, further contributing to its widespread adoption. Furthermore, concerns regarding crowded work environments and the risk of contagion have played a significant role in the increase of remote work. Lastly, the pandemic has spurred technological innovations that support remote work, leading to its further growth and acceptance.

In this paper, we take into account three main shifts in the economy since the Pre-COVID period : *(i)* commuting costs, *(ii)* the disutility of WFH, and *(iii)* remote productivity. We study the effect of this shift on labor market outcomes in the two heterogeneous areas (urban and rural) and evaluate the benefit of WFH on inequalities between these two areas. Particularly, we will see how WFH affects inequalities in unemployment, wages, unemployed welfare, and economic wealth.

First, the Gasoline prices increased by 28.8% between 2018 and mid-2023 according to the [US Department of Energy](#) making workers less willing to commute and work on site. In fact, the relationship between commuting and labor market outcomes has been studied several times before. Some studies highlight that longer commuting time can reduce job matching efficiency and increase unemployment duration, as workers may face geographical constraints reducing the pool of potential job offers available to workers.¹

¹In the exhaustive list you can find [Berg and Gorter \(1996\)](#), [Nijkamp et al. \(2000\)](#), [Ommeren et al. \(2000\)](#), [Ommeren and Fosgerau \(2009\)](#), [Ruppert et al. \(2009\)](#), [Rouwendal \(2004\)](#), [Guglielminetti et al. \(2020\)](#).

Second, the COVID-19 pandemic has dramatically changed the perception of WFH. Before the pandemic, WFH was often seen as a convenience for some types of workers. However, with the outbreak of the pandemic and the enforced social distancing measures, the shift to remote work was mandatory to ensure business continuity. This pushed many employees who had never worked from home before to adapt to a remote work environment. This has shown that remote work can be a viable option for many types of jobs, and many workers have reported enjoying the flexibility and lack of commute associated with WFH. Hence, the negative perception of remote work has shifted.²

Finally, WFH offers numerous advantages. Firstly, it reduces commute time and costs, leading to less stress and more available time for work or other activities. Secondly, it provides greater flexibility and autonomy, allowing workers to effectively manage their time and minimize distractions. Additionally, WFH enables individuals to create more comfortable working environments, enhancing focus and concentration. Lastly, it promotes improved work-life balance, which contributes to higher job satisfaction and motivation. Several studies have demonstrated that these advantages result in increased productivity among remote workers.

[Bloom et al. \(2015\)](#) conducted a randomized controlled trial with a Chinese travel agency and found a 13% increase in productivity among remote workers compared to the control group. This increase was attributed to fewer breaks and sick days as well as a quieter working environment, resulting in more calls per minute. [Choudhury et al. \(2021\)](#) examine the effect of transitioning from a work-from-home to a work-from-anywhere program at the United States Patent and Trademark Office using a natural experiment. The findings reveal a 4.4% increase in output, indicating a positive impact on productivity. Furthermore, [Etheridge et al. \(2020\)](#) investigated the self-reported productivity of home workers during the UK lockdown. They found that jobs suitable for remote work and those that increased their WFH intensity prior to COVID reported higher productivity on average. The study also established a strong correlation between lower productivity and decreased mental welfare. Finally, [Aksoy et al. \(2022\)](#) found that most employees were favorably surprised by their WFH productivity during the pandemic. In fact, respondent were questioned on their WFH productivity relative to expectations. While 31% responded the same, 56.4% have had a better experience, the remaining being negative. On average this translates to an increase of 6.7% in productivity for all countries (8.1% for US only).

²See [Aksoy et al. \(2022\)](#), [Barrero et al. \(2020 a\)](#), [Ozimek \(2020\)](#) and [Felstead and Reuschke \(2020\)](#).

On the other hand, there are arguments suggesting a decrease in productivity among remote workers. For instance, a study conducted by [Gibbs et al. \(2021\)](#) analyzed data from an Asian IT services company and found that although the number of hours worked increased, average output declined. They estimated a productivity decrease ranging from 8% to 19% due to higher communication and coordination costs. The negative impact was found to affect certain groups more, including women, workers with children at home, and new employees who had not yet adapted to the firm's culture. Another study by [Kunn et al. \(2020\)](#) examined the effect of WFH on cognitive performance using data from chess players. They compared the quality of chess moves made by players before the COVID-19 pandemic (offline) and during the pandemic (online). The findings revealed a significant decrease in performance, suggesting that WFH can have a negative impact on productivity, particularly in jobs requiring high cognitive abilities. Last but not least, using data from a Fortune 500 firm's call centers, [Emanuel and Harrington \(2023\)](#) show that remote work has a negative impact on productivity which is mainly explained by the negative worker selection into remote work. They show that not only the number of calls per hour drop but also with it, its quality and, thus, more prevalent for less experienced workers.

Several factors may contribute to the decrease in productivity associated with remote work. Firstly, there is the challenge of separating work and personal life, which can lead to burnout or distractions. Secondly, the lack of social interaction and support in remote work environments can result in feelings of isolation and decreased motivation. Technical issues, such as slow internet speeds or incompatible software, can also hinder productivity. Additionally, difficulties in collaborating with colleagues or accessing necessary resources can slow down work processes.³ Nevertheless, we follow [Barrero et al. \(2023\)](#) and attribute this debate -on the positive or negative effect of WFH on productivity- to the concept and definition of productivity itself and focus on the effect of the time saved through not commuting. In fact, following the SWAA, we assume an increase in productivity for remote workers as respondents use the saved commuting time in 40% into extra work.

Taking into account those three main shifts we show that although the Post-COVID economy suffers from the increase in commuting costs, the decrease in the disutility in remote work and the increase in productivity of remoters offset this negative impact. Furthermore, we show that when the disutility of remote work is sufficiently low, it leads to lower unemployment and wage inequalities between the two zones. Moreover, we

³For more on the effects of WFH on productivity, studies such as [Felstead and Reuschke \(2020\)](#), [Ozimek \(2020\)](#), [Brynjolfsson et al. \(2020\)](#), and [Aksoy et al. \(2022\)](#) provide extensive insights.

conduct an analysis of the welfare of the unemployed and economic wealth. It highlights the benefits of reducing remote work disutility. In fact, results depict a win-win situation by improving the welfare of the unemployed and reducing the welfare gap between rural and urban areas while increasing at the same time the overall wealth in both economies.

Finally, we use this framework to study whether the market chooses the efficient level of vacancies and employment, as a social planner can do. Indeed, one can argue that due to the increase in remote work possibilities, unemployed individuals might not only intensively search for jobs in their local area but also explore opportunities globally, leading to externalities caused by the negative congestion effect. In this paper, we contrast the equilibrium achieved by a social planner who optimizes vacancies and employment levels for the overall societal welfare with the equilibrium achieved by the market. Our findings reveal that, despite the market not accounting for certain negative externalities, the increase in remote work does not contribute to a strong increase in these externalities.

This research article not only illuminates the detrimental impact of commuting costs on the labor market but also presents a solution to mitigate this long-standing issue. Commuting can pose various challenges, including time-consuming travel, stress associated with public transportation, delays, strikes, and the high costs of fuel. On the other hand, WFH allows individuals to evade these difficulties. However, it comes with its own set of challenges, such as potential difficulties in collaboration with colleagues, maintaining a healthy work-life balance, and technical issues. This paper aims to demonstrate the extent to which WFH can benefit the labor market while also engaging with the scope of urban and rural literature. Previous studies have already explored the connections between urban economics and labor economics.⁴ By examining these connections, we aim to gain a comprehensive understanding of how WFH can benefit both these diverse markets and contribute to reducing inequalities between them.

The remainder of this paper is organized as follows. Section [1.2](#) presents the model, and Section [1.3](#) discusses calibration, data and the model fit regarding the Pre-COVID data. Section [1.4](#) depicts the model's results due to the Post-COVID shifts. Section [1.5](#) presents the planner's problem and its solutions. Finally, Section [1.6](#) concludes.

⁴See [Zenou \(2009\)](#) for insights into urban labor economic theory.

1.2 Model

We aim to analyze, on one hand, the effect of working from home on the labor market with search and matching frictions. On the other one, we want to forecast the effect of this new trend on inequalities between two heterogeneous labor markers. To do so, the DMP model is extended to feature (i) regional heterogeneity between urban and rural areas (ii) occupational choice between fully on-site, remotely or in hybrid arrangement and (iii) working from home intensity in the hybrid set up.

1.2.1 Search

Spatial labor market and search process : The economy is divided into 2 heterogeneous spatial labor markets: urban and rural. In each spatial zone, there is a representative firm $j = \{u, r\}$. Firms in the different spatial zones produce the same good y . However, there is a heterogeneity in the productivity levels between the two areas. Each firm j post vacancies V_j . Unemployed worker n residing in area i can either match with a firm within his residential area or in the other one. Following [Lacava \(2023\)](#), an unemployed worker searches with a higher intensity $\gamma \geq 0.5$ in the region where he is residing, and with a lower intensity $1 - \gamma$ in the other one. This difference, in search intensity, can be explained as cultural and language differences. It is assumed to be exogenous to the labor market and is symmetric across regions. Once, a worker and firm meet, they discover with whom they match and decide whether the worker should work fully on-site, fully remote or in a hybrid set-up.

Matching: Unemployed worker seeking to find a job in zone j (i.e Job seekers JS_j) is the sum of a share of unemployed worker living in zone j and searching with intensity γ (i.e γU_j) and a share of unemployed worker living in zone i and searching with intensity $1 - \gamma$ (i.e $(1 - \gamma)U_i$). Those job seekers and vacancies V_j meet through a matching function. Following [Den Haan et al. \(2000\)](#), the matching function for each sector is⁵

$$M_j(JS_j, V_j) = \frac{JS_j V_j}{(JS_j^\mu + V_j^\mu)^{1/\mu}}$$

With $JS_j = \gamma U_j + (1 - \gamma)U_i$

⁵This matching function imply that the job finding and vacancy filling rate lay between $[0; 1]$.

Noting the tightness of market j as $\theta_j = \frac{V_j}{JS_j}$, the job finding rate in zone j is $f_j = \frac{M_j}{JS_j} = (1 + \theta_j^{-\mu})^{-1/\mu}$. An unemployed worker meet the firm in his own region with a probability $f_{jj} = \gamma \times f_j$ and in the other region with a probability $f_{ji} = (1 - \gamma) \times f_j$. The probability for a firm j to fill its vacancy is $q_j = \frac{M_j}{V_j} = (1 + \theta_j^\mu)^{-1/\mu}$. A vacancy meets an unemployed worker in the other region with probability $q_{ji} = q_j \times \omega_{ji}$ and in the same region with a probability $q_{jj} = q_j \times (1 - \omega_{ji})$ with $\omega_{ji} = \frac{(1-\gamma)U_i}{JS_j}$.

1.2.2 Value function of Employed and Unemployed Worker

As stated before, there are three type of workers : On site, remote and hybrid workers $c = \{o, r, h\}$ and two spatial zones : urban and rural. Each worker can work either on site, remotely or in a hybrid setting in his own residential area or in the other one. The choice between working full time on-site, remotely or in a hybrid arrangement is based on a joint decision between the firm and the worker through Nash Bargaining.

Employed Worker:

Working on-site (WOS) : When working on-site, employees might experience the challenges of commuting, including the time spent traveling, the stress associated with public transportation, potential delays in transportation services, and the inconvenience of dealing with strikes. Additionally, they need to allocate time to prepare themselves to be professionally presentable for work. All of these factors are encompassed in the disutility of WOS, denoted as $g(\tau)$. Each period, the value of τ is randomly drawn since these challenges can vary from one period to another. Since these parameters primarily relate to time, we approximate this disutility using the following $g(\tau) = c_\tau \tau$, where τ represents the commuting time and c_τ represents the commuting costs. Additionally, considering that the commuting experience varies between commuting within the same residential area or between two different areas, we assume that these commuting costs depend on the workers' residential/working areas.

Working from home (WFH) : WFH presents its own set of challenges, such as potential difficulties in collaborating with colleagues, the struggle to maintain a healthy work-life balance, and technical issues that may arise. In addition, workers may have to incur certain expenses related to WFH, such as managing a comfortable workspace or dealing with increased electricity bills. All of these factors are considered in the disutility of working from home, denoted as ζ . Similarly to the commuting costs, we acknowledge

that the WFH experience can vary between urban and rural areas, leading us to assume that this parameter is specific to the residential areas of the workers.

Working in Hybrid Arrangement (WHA) : In this set-up, workers allocate a portion λ of their working time to WFH (referred to as the intensity of WFH in WHA), while the remaining portion, $1 - \lambda$, is spent WOS. Consequently, they experience a disutility of $(1 - \lambda)g(\tau)$ associated with WOS. However, we assume that the intensity of WFH in WHA has a non-linear impact on the disutility of remote work *i.e.* ζ . This is because the disutility of WFH may increase as the amount of time spent in remote work rises, potentially leading to social isolation, compromised work-life balance, and blurred boundaries between work and personal life. Consequently, hybrid workers will also experience a disutility of $H(\lambda)\zeta$ associated with WFH. Additionally, we consider that hybrid workers incur a flexibility cost, denoted as c_h , due to the transition between different work environments. This flexibility cost could arise from the need to adjust schedules to accommodate office days or to be prepared to work with varying devices or software depending on the location. For simplicity, we assume that the flexibility cost is proportional to the degree of disutility experienced in WFH, leading to $c_h = \alpha_h\zeta$.

Therefore, denoting $L(\tau, \lambda)$ as the disutility of a worker, we have the following :

$$L(\tau, \lambda) \begin{cases} g(\tau) & \text{if working on-site} \\ \zeta & \text{if working from home} \\ (1 - \lambda)g(\tau) + H(\lambda)\zeta + c_h & \text{if working in hybrid arrangement} \end{cases}$$

With $H(\lambda) = 1 - (1 - \lambda)(1 - \log(1 - \lambda))$. This function exhibits the following characteristics: (i) as the intensity of WFH in WHA approaches zero (respectively, one), the disutility experienced by workers becomes similar to that of individuals who are fully WOS (respectively, fully WFH). Specifically, $H(0) \rightarrow 0$ and $H(1) \rightarrow 1$. (ii) When solving for the optimal intensity of WFH in WHA, denoted as λ^* , this function allows for the possibility that as the disutility of WOS approaches zero (respectively, infinity), workers choose an intensity of WFH in WHA of 0% (respectively, 100%). In other words, $\lim_{\tau \rightarrow 0} \lambda^* = 0$ and $\lim_{\tau \rightarrow +\infty} \lambda^* = 1$.⁶

⁶The maximization program leading to the determination of λ^* is solved in this section.

Occupational choice : Given that the disutility of WOS is randomly determined in each period, workers and firms make their choice by maximizing the total surplus generated by the match. If the disutility is sufficiently low, they opt for WOS. If the disutility is high enough, they choose to WFH. However, when the disutility falls within an intermediate range, workers select WHA as their preferred option.

The value function of a worker n with an occupational choice $c \in \{o, r, h\}$, working in zone $j \in \{u, r\}$ and residing in zone $i \in \{u, r\}$ is given by

$$W_{n,ji}^c(\tau) = w_{n,ji}^c(\tau) - L^c(\tau_{n,ji}, \lambda_{n,ji}) + \beta \left[s_j U_i + (1 - s_j) \int_0^{\tau^{max}} W_{n,ji}^e(\tau) dG(\tau) \right] \quad (1.1)$$

With,

$$W_{n,ji}^e = \max \{ W_{n,ji}^o; W_{n,ji}^r; W_{n,ji}^h \}$$

Unemployed Worker:

Unemployed worker, residing in zone i can find a job in his own area with a probability f_{ii} or in the other area with a probability f_{ji} . Once a worker and firm meet, they choose the optimal occupational choice c for the worker. Let U_i be the expected discounted flow of income when unemployed in zone i , hence

$$U_i = b + \beta \left[f_{ii} \int_0^{\tau^{max}} W_{n,ii}^e(\tau) dG(\tau) + f_{ji} \int_0^{\tau^{max}} W_{n,ji}^e(\tau) dG(\tau) + (1 - f_{ii} - f_{ji}) U_i \right] \quad (1.2)$$

1.2.3 Firms:

We make two assumptions regarding productivity levels: (i) **Managerial Quality:** There exists a disparity in productivity levels among firms (ii) **Quality of Labor:** Workers possess different levels of productivity. As a result, when a rural worker is employed by an urban firm, he benefits from the superior managerial quality of the firm. Conversely, when an urban worker is employed by a rural firm, the rural firm benefits from the high quality of labor provided by the urban worker. Furthermore, a worker residing and working in an urban area enjoys the advantages stemming from both. Finally, for simplicity, we make the assumption that the managerial quality and the quality of labor induce the same productivity gains. This translates as following

$$\begin{aligned}
y_{uu} &= y_{rr} \times (1 + \alpha_u)^2 \\
y_{ur} &= y_{rr} \times (1 + \alpha_u) \\
y_{ru} &= y_{rr} \times (1 + \alpha_u)
\end{aligned}$$

Value of Vacancy

Firm j posts vacancies that are filled with the endogenous probability $q(\theta_j)$. Firms cannot ex-ante discriminate between the residential areas of unemployed workers. Therefore, firms cannot post different types of vacancies for each area. Noting κ the per unit of time cost of posting a vacancy and V_j its value while unfilled, the value of an unfilled vacancy can only be written in terms of the expected value from a filled job (*i.e.* \bar{J}_j)

$$V_j = -\kappa + \beta[q_j \bar{J}_j + (1 - q_j)V_j] \quad (1.3)$$

The expression for the expected value of a filled job in firm j is given by

$$\bar{J}_j = (1 - \omega_{ji})\bar{J}_{jj} + \omega_{ji}\bar{J}_{ji} \quad (1.4)$$

With, $\bar{J}_{ji} = G(\tau_{ji}^{R_1})\tilde{J}_{ji}^o + (G(\tau_{ji}^{R_2}) - G(\tau_{ji}^{R_1}))\tilde{J}_{ji}^h + (1 - G(\tau_{ji}^{R_2}))\tilde{J}_{ji}^r$ and $\tilde{J}_{ji}^o = \frac{\int_0^{\tau_{ji}^{R_1}} J_{nji}^o(\tau)dG(\tau)}{G(\tau_{ji}^{R_1})}$,

$$\tilde{J}_{ji}^h = \frac{\int_{\tau_{ji}^{R_1}}^{\tau_{ji}^{R_2}} J_{nji}^h(\tau)dG(\tau)}{G(\tau_{ji}^{R_2}) - G(\tau_{ji}^{R_1})}.$$

Value of Job

Once a firm meets a worker, it can observe his residential area and commuting time. Hence, given the wage bargaining process specified below (leading to w_{ji}^c), a firm producing in zone j have a value of employing a worker n , residing in area i and working in the occupation c of the following:

$$J_{n,ji}^c(\tau) = y_{ji} - w_{n,ji}^c(\tau) + \beta[s_j V_j + (1 - s_j)\bar{J}_{ji}] \quad (1.5)$$

Free entry condition

The free entry condition leads to $V_j = 0$. Hence, equation [1.3](#) becomes

$$\frac{\kappa}{q_j} = \beta[(1 - \omega_{ji})\bar{J}_{jj} + \omega_{ji}\bar{J}_{ji}] \quad (1.6)$$

Law of motion of employment in firm:

Firms can employ workers residing in the same location or in the other one. The WOS disutility τ is revealed after the match. Hence the law of motion of employment for firm j employing workers from i is given by

$$N_{ji}^c = \mathcal{G}^c(\tau_{ji}^R) [(1 - s_j)[N_{ji}^o + N_{ji}^h + N_{ji}^r] + q(\theta_{ji})V_j] \quad (1.7)$$

with,

$$\begin{cases} \mathcal{G}^c(\tau_{ji}^R) = G(\tau_{ji}^{R1}) & \text{for } c = o \\ \mathcal{G}^c(\tau_{ji}^R) = G(\tau_{ji}^{R2}) - G(\tau_{ji}^{R1}) & \text{for } c = r \\ \mathcal{G}^c(\tau_{ji}^R) = 1 - G(\tau_{ji}^{R2}) & \text{for } c = h \end{cases}$$

Hence, nothing $N_{ji} = \sum^c N_{ji}^c$, $U_i = 1 - N_{ii} - N_{ji}$ and $U_j = 1 - N_{jj} - N_{ij}$ we have

$$s_j N_{ji} = f_{ji} U_i \quad (1.8)$$

1.2.4 Nash Bargaining

The match surplus generated by worker n , residing in area i , working in occupation c in firm j is $W_{n,ji}^c - U_i$ and the match surplus generated by the firm employing him is $J_{n,ji}^c - V_j$. Hence, the total surplus ($S_{n,ji}^c$) generated by this match is obtained as the sum of those two as following

$$S_{n,ji}^c = W_{n,ji}^c - U_i + J_{n,ji}^c - V_j \quad (1.9)$$

Noting η , the worker's bargaining power, wages are determined upon meeting with a simple Nash bargaining :

$$w_{n,ji}^c = \operatorname{argmax}_{w_{n,ji}^c} \{(W_{n,ji}^c - U_i)^\eta (J_{n,ji}^c - V_j)^{1-\eta}\}$$

The Nash-bargaining solution $w_{n,ij}^e$ for a problem with transferable utility satisfies

$$W_{n,ji}^c - U_i = \eta S_{n,ji}^c \quad (1.10)$$

$$J_{n,ji}^c = (1 - \eta) S_{n,ji}^c \quad (1.11)$$

Nothing $\bar{S}_{ji} = G(\tau_{ji}^{R_1}) \tilde{S}_{ji}^o + (G(\tau_{ji}^{R_2}) - G(\tau_{ji}^{R_1})) \tilde{S}_{ji}^h + (1 - G(\tau_{ji}^{R_2})) \tilde{S}_{ji}^r$ and $\tilde{S}_{ji,t}^c = \frac{\int^I S_{n,ji,t}^c(\tau) dG(\tau)}{\bar{G}^c}$, equation [1.9](#) leads to

$$(1 - \beta(1 - s_j)) \bar{S}_{ji} = y_{ji} - \bar{L}(\tau_{ji}, \lambda_{ji}) - b - \beta [f_{ji} \eta \bar{S}_{ji} + f_{ii} \eta \bar{S}_{ii}] \quad (1.12)$$

Equation [1.12](#) shows that the average surplus generated by the match of a worker residing in zone i and working in zone j is related to the outside option of this worker as he can find a job in his own residential area.

Recall the job creation condition leads to:

$$\frac{\kappa}{q_j} = \beta [(1 - \omega_{ji}) \bar{J}_{jj} + \omega_{ji} \bar{J}_{ji}]$$

Using equation [1.11](#) and [1.12](#), we have

$$\frac{\kappa}{(1 - \eta) q_j} = \beta [(1 - \omega_{ji}) \bar{S}_{jj} + \omega_{ji} \bar{S}_{ji}] \quad (1.13)$$

1.2.5 Wages

The solution of Nash program gives the following wage of a worker n residing in i and working in j

$$w_{n,ji}^c(\tau) = \eta [y_{ji} + \beta (f_{ji} \bar{J}_{ji} + f_{ii} \bar{J}_{ii})] + (1 - \eta) [L^c(\tau_{n,ji}, \lambda_{n,ji}) + b] \quad (1.14)$$

Wages can be divided into two components: (i) The first component is influenced by the firm's profitability and the tightness of the labor market. When the unemployed search for a job, they can match with a firm within their residential area or in the other one. This gives them bargaining power to negotiate wages based on this outside option. This is represented by $f_{ji}\bar{J}_{ji} + f_{ii}\bar{J}_{ii}$. (ii) The second component is determined by the disutility associated with their chosen occupation, which they also have the ability to negotiate $L^c(\tau_{n,ji}, \lambda_{n,ji})$.

1.2.6 The intensity of WFH in WHA :

The optimal intensity of WFH in WHA is given by maximising the total surplus generated by a match (i.e. $\frac{\partial S_{n,ji}^h}{\partial \lambda_{n,ji}} = 0$), leading to⁷

$$\lambda_{n,ji}^* = 1 - e^{-\frac{c_{ji,\tau}\tau_{n,ji}}{\zeta_i}} \quad (1.15)$$

1.2.7 Occupational Choice:

Worker and firm engage in Nash Bargaining and then assess the occupational choice by comparing the total surplus generated by the match for each of the three occupational choices. They weigh these values and select the thresholds that determine which occupational choice will be ultimately chosen.

Choice between On-site and Hybrid The solution is given by equalizing the total surplus generated by the match in the two occupations

$$S_{n,ji}^o - S_{n,ji}^h = W_{n,ji}^o - U_i + J_{n,ji}^o - W_{n,ji}^h - U_i + J_{n,ji}^h = 0$$

Leading to :

$$\lambda_{n,ji}^* c_{\tau,ji} \tau_{n,ji} - H(\lambda_{n,ji}^*) \zeta - c_h = 0 \quad (1.16)$$

⁷In Appendix [A.1](#) we show that this solution is the same when maximising through Nash bargaining or profits maximisation.

Choice between Hybrid and Remote

$$S_{n,ji}^r - S_{n,ji}^h = W_{n,ji}^r - U_i + J_{n,ji}^r - W_{n,ji}^h - U_i + J_{n,ji}^h = 0$$

Leading to :

$$\zeta_i - (1 - \lambda_{n,ji}^*)c_{\tau,ji}\tau_{n,ji} - H(\lambda_{n,ji}^*)\zeta - c_{h,i} = 0 \quad (1.17)$$

1.2.8 Numerical Resolution

The steady-state equilibrium cannot be determined analytically. However, it is computed by the fixed point iterative algorithm described below. Noting $\mathcal{I} = \{jj, ji, ij, ii\}$

1. The values of the reservation commuting time $\tau_{\mathcal{I}}^R$ and the intensity of WFH in WHA $\lambda_{n,\mathcal{I}}^*$ are exogenous to the model.
2. Guess the initial value of θ_j and θ_i .
3. Compute the job finding rate $f_{\mathcal{I}}$.
4. Using equation [1.8](#) solve for the employment levels $N_{\mathcal{I}}$ and hence compute $\omega_{\mathcal{I}}$.
5. Using equation [1.12](#) compute $\bar{S}_{\mathcal{I}}$.
6. Finally using equation [1.13](#) update the belief on θ_i and θ_j .

1.3 Parameters' Calibration

1.3.1 Parameters

The model parameters are calibrated on data prior to the COVID-19 crisis. Hence, the calibration is set on data before 2018 the later included. The vector of parameters to be calibrated:

$$\Psi = \{\beta, \eta, b, \kappa, \mu, c_{\tau,w}, c_{\tau,b}, \mu_{\tau}, \sigma_{\tau}, \alpha_u, \zeta_u, \zeta_r, \alpha_h, s_u, s_r, \gamma\},$$

u is for urban, r is for rural, $c_{\tau,w}$ is the commuting cost within the same area such that $c_{\tau,w} = c_{\tau,ii} = c_{\tau,jj}$ and $c_{\tau,b}$ is the commuting cost between two different areas such that $c_{\tau,b} = c_{\tau,ij} = c_{\tau,ji}$.

Usual Parameters: The time discount factor β is equal to $1/(1 + 0.0573)^{(1/12)}$.⁸ The value of bargaining power is set to the mean bargaining power found in the literature (*i.e.* $\eta = 0.5$). For the remaining parameters we summarize the data used to calibrate the model.⁹

1.3.2 Data

Since we have little data on rural and urban zone, we will use data on educational attainment for unemployment rate, job separation rate and wages. This data will be linked to the one with the level of educational attainment in those two areas to build a data specific to each zone.

Diploma

Workers in urban areas generally have higher levels of educational attainment compared to rural areas. Table 1.1 illustrates this difference, indicating that the proportion of workers with less than a high school degree or a high school degree is higher in rural areas compared to urban areas. Conversely, the share of workers with a bachelor's degree is higher in urban areas (31.9%) than in rural areas (18.5%). This observation suggests that the quality of the labor force may differ between the two areas.

	LHS	HS	Coll.	Bach.	Share of pop
Urban	13.6%	26.1%	28.4%	31.9%	84%
Rural	16%	35.9%	29.6%	18.5%	16%

Table 1.1: **Educational attainment for adults 25 and older Urban Vs Rural.**
Estimated average from 2000 to 2018

⁸This value matches the mean discount rate in a historical cross-country panel of asset prices data used in Petrosky-Nadeau et al. (2018), which is 5.37% per annum.

⁹See Appendix A.2 for the data construction and details.

Wages

Table 1.2 reveals that urban workers enjoy an 8% wage premium. This premium can be attributed not only to the higher quality of labor in urban areas but also to the presence of higher managerial quality in those areas.

	Median Wage
Urban	3373
Rural	3119

Table 1.2: Median monthly earning Urban versus rural from 2000 to 2018.

Unemployment, Job finding rate and Job separation rate

We follow Kandoussi and Langot (2021) to construct data on unemployment, and JSR but we only focus on data from 2000 to 2018. Using data on educational attainment in each zone, we obtain Table 1.3. This Table shows that unemployment rate is higher in rural areas and that it can be partly explained by the fact that workers in rural areas separate more easily than those in urban areas.

	Urban	Rural
<i>JSR</i>	0.0182	0.0200
<i>UR</i>	0.0588	0.0642

Table 1.3: Job flows Urban Versus Rural.

Worker Flow between Rural and Urban Areas

To identify the workers flow between the residing area and the working one we cross-file between two datasets¹⁰: (i) The first one indicate the Residence County to Workplace County Flows for the United States 2011-2015 5-Year ACS Commuting Flows while (ii) the second indicate the Percentage of the total population of the county represented by the urban population in 2010. We can hence build a dataset indicating the number of

¹⁰Both series are from United State Census Bureau.

flows for the four different possibilities: (i) From Urban to Urban (ii) From Urban to Rural (iii) From Rural to Urban (iv) From Rural to Rural. We can therefore summarize the information in Table 1.4. We find that the share of urban workers on total workers is 84% and that the share of workers residing in urban zone and working in rural zone is only 11% which is not counterfactual.

	p_{RU}	p_{RU}^{Tot}
Value	0.11	0.087

Table 1.4: **Workers flows from Working County to Residence County.** $p_{RU} = \frac{N_{RU}}{N_{UU}+N_{RU}}$ and $p_{RU}^{Tot} = \frac{N_{RU}}{N_{Tot}}$

Commuting parameters

As stated before, WOS disutility is primarily related to time, we approximate this disutility as $g(\tau) = c_\tau \tau$, where τ represents the commuting time and c_τ represents the commuting costs. Hence, we aim to calibrate those two parameters to match the data.¹¹

Commuting Time and Distance : Using [the American Community Survey 2018](#) we estimate that commuting time follows lognormal Pdf with $\mu_\tau = 3.3$ and $\sigma_\tau = 0.6$.

Commuting Costs : Following [The Clever Real Estate](#), to account for commuting cost, 3 variables will be taken into account : (i) fuel (ii) maintenance and (iii) opportunity. On average the total monthly commute costs adds up to $c_{total} = c_f + c_m + c_{op} = 46 + 83 + 148.4 = 277.4\$$.

Working From Home

Using the the 2017-18 Leave and Job Flexibilities Module of the American Time, [Dey et al. \(2020\)](#) estimate that the percentage of workers who are able to work and did teleworker in the non metropolitan area's is about 3.4%, while this number is around 10% in metro areas. Hence we have, $\mathcal{S}_{WFH,r} = 0.034$ and $\mathcal{S}_{WFH,u} = 0.1$. Moreover, we assume that workers in hybrid arrangement choose to WFH for 2 to 3 days a week. Hence, this lead to an average intensity of WFH in WHA of $\lambda^* = 0.5$.

¹¹See Appendix [A.2](#) for more details.

1.3.3 Identification

Direct identification : Using Table [1.3](#), we identify $s_u = 0.0182$ and $s_r = 0.02$ and from the commuting time data, we set $G \rightsquigarrow \text{LogN}(3.3, 0.6)$.

Indirect identification : To identify the remaining parameters

$$\Psi = \{b, \kappa, \mu, c_{\tau,w}, c_{\tau,b}, \alpha_u, \zeta_z, \alpha_h, \gamma\},$$

We use the following :

$$\Phi = \left\{ \frac{W_u}{W_r}, UR_{z,t}, p_{RU}, p_{RU}^{Tot}, \frac{c_{total}}{\bar{w}_z}, \mathcal{S}_{WFH,z}, \lambda \right\},$$

with $z \in \{u, r\}$, we have $\dim(\Psi) = \dim(\Phi) = 10$. We search for Ψ aiming to minimize the root mean square error for each time series in Φ . Table [1.6](#) report the results.

1.3.4 Calibration Result

Parameters	Value
Time discount factor β	0.995
Wage Bargaining power η	0.5
Job Separation rate in urban s_u	0.0182
Job Separation in rural s_r	0.0200
Productivity of workers living in rural area and working in rural area y_{rr}	1
Average commuting time μ_{τ}	3.3
Standard deviation of commuting time σ_{τ}	0.6

Table 1.5: **Parameter Using external information.**

First, it appears that the gaps between the targeted and simulated moments are overly reasonable. The value of the opportunity costs of employment b is 0.202 which is lower than the calibration found in the literature however it is within the range of 18% to 60% of the average wage. Moreover, in this framework workers are not only compensated for their outside option (unemployment) they are also compensated for their disutility related to their occupational choice. Once those two parameters are taken into account, the total benefits, that a worker can bargain for, range from 0.28 to 0.63 . The cost of opening

a vacancy is set to 0.211 which is close to the 20% of the expected present value of the lifetime wage. The elasticity of the matching function ($\mu = 0.405$) is close to the value used by [Petrosky-Nadeau and Zhang \(2017\)](#) (0.407), however, it is significantly lower than the value obtained by [Den Haan et al. \(2000\)](#) (1.27). The productivity premium in the urban area is 0.038 meaning that both managerial and labor quality are higher in urban areas.

Parameters	Value	Moments	Data	Model
The value of unemployment activities b	0.202	UR_{urban}	0.059	0.056
The fixed cost of vacancy posting κ	0.211	UR_{rural}	0.064	0.066
Elasticity of the matching function μ	0.405	$\frac{W_{urban}}{W_{rural}}$	1.083	1.070
Productivity premium for urban area α_u	0.038	p_{RU}^{Tot}	0.087	0.062
Search intensity γ	0.849	p_{RU}	0.106	0.123
Commuting costs in urban $c_{\tau,w}$	0.003	$\frac{c_{\tau,u}\bar{w}}{w_{urban}}$	0.082	0.079
Commuting costs in rural $c_{\tau,b}$	0.004	$\frac{c_{\tau,r}\bar{w}}{\bar{w}_{rural}}$	0.089	0.104
Disutility of WFH ζ_u	0.281	Share of remote workers	0.100	0.101
Disutility of WFH ζ_r	0.424	Share of remote workers	0.034	0.033
Hybrid costs α_h	0.107	Intensity of WFO in WHA	0.500	0.493

Table 1.6: **Model's Calibration, Target and Simulated Moments.**

This calibration also shows that the disutility of doing remote work is higher for rural workers than for urban ones. This reflects the fact that teleworking can be challenging for workers who do not have access to the necessary technology and equipment. In fact, urban areas tend to have more infrastructure and resources that support remote work, such as high-speed internet, coworking spaces, and other amenities that make it easier for workers to work from home or other remote locations. Moreover, rural areas tend to have more agriculture and manufacturing jobs that may require physical presence and face-to-face interactions.¹²

Finally, the search intensity is set to 0.849 which is slightly lower than the value estimated by [Lacava \(2023\)](#) to match the net migration rate (*i.e.* 0.961).

¹²This aligns with empirical research that indicates the unequal distribution of remote work across countries, regions, industries, and occupations, as mentioned in [Dingel and Neiman \(2020\)](#).

	Vacancy filling rate	Job finding rate	wages
Work Urban-live Urban	0.073	0.267	1.023
Work Rural-live Urban	0.014	0.041	1.016
Work Rural-live Rural	0.095	0.232	0.949
Work Urban-live Rural	0.015	0.047	0.982

Table 1.7: **Model's Results: VFR, JFR and Wages.**

Urban Versus Rural : The steady-state results, in table 1.7 show that urban workers are always better off whether they work in urban or rural areas compared to the rural workers. Moreover, working in the urban area is always the best option for the two types of workers as the wages are higher in this area due to the higher productivity. This will increase the job finding rate in this area making the rural one less attractive which creates a congestion effect and makes the vacancy harder to be filled in urban areas.

	\bar{W}_u	\bar{W}_r
On-site	1.0067	0.9515
Hybrid	1.0616	1.0293
Remote	1.1199	1.1108

Table 1.8: **Model's Results: Wages and Occupational choice**

On-site, Hybrid and remote : Table 1.8 presents the findings that employees who work remotely or have hybrid work arrangements tend to earn higher wages than those who work exclusively in a traditional office setting. This finding is not surprising nor is new. In fact, Gariety and Shaffer (2007) finds that WFH is associated with an overall positive wage differentials using Current Population Survey supplement on work schedules and work at home. Moreover, Dingel and Neiman (2020) show that WFH jobs pay more than job that cannot be done at home. One of the reason for this trend can be traced back to the Pre-COVID era when remote work was less prevalent and perceived as risky. Workers had concerns about the challenges and isolation that could arise from working remotely, leading to a higher perceived disutility. To compensate for this disutility, employees demanded higher wages.

1.4 Model's Implications

According to a study by [Barrero et al. \(2023\)](#), it is estimated that the number of full days worked at home quadrupled from the Pre-pandemic levels. This increase in remote work is attributed to a number of factors, including better-than-expected remote working experiences, investments in physical and human capital that facilitate remote work, reduced stigma associated with remote work, and sanitation concerns. In fact, they emphasize that for the two quarters of 2023, full days worked at home account for 28 percent of paid workdays among Americans 20-64 years old. In this section, we will *(i)* explain this 20.2 increase in the share of remote workers after the Covid-19 crisis. *(ii)* Study the effect of this shift on labor market outcomes in two heterogeneous areas (urban and rural). *(iii)* Finally, evaluate the benefit of WFH on inequalities between these two areas. Particularly, we will see how WFH impacts inequalities in unemployment, wages, unemployed welfare and economic wealth.

1.4.1 Post COVID-19 Economy

We consider three main shifts in the model : *(i)* The increase in commuting costs, *(ii)* The increase in remote workers productivity and *(iii)* the shift in the disutility of working from home.

Commuting costs : The model should take into account all the element that may influence the workers' decision to choose between WFH or WOS. Equations [1.16-1.17](#) show that for higher commuting costs, workers are less willing to commute and WOS. The change in this parameter should influence labor outcomes. In fact, Gasoline prices rose by 28.8% from 2018 to the two first quarter of 2023 according to the [US Department of Energy](#).¹³ In this model, it is equivalent to an increase of commuting cost by 5%.¹⁴ Hence, in the new economy $c'_\tau = c_\tau \times 1.05$.

¹³We take Gasoline as a reference because it is the most commonly used U.S. transportation fuel according to the U.S. Energy Information Administration

¹⁴The monthly cost of fuel will become $c_f = 59.3\$$ making the average monthly commuting costs to $c_{total} = 291$, which represent an increase of 5%.

Remote workers' productivity : There is an ongoing debate regarding whether remote workers experience an increase or decrease in productivity. While some studies suggest that remote workers benefit from reduced commuting time and costs, greater flexibility and autonomy, improved working conditions, and a better work-life balance resulting in higher job satisfaction and motivation, others argue that the difficulties in separating work and personal life, lack of social interaction and support, and challenges in collaborating with colleagues or accessing necessary resources can lead to decreased productivity while working from home.¹⁵

In this paper, we follow the 2022 Survey of Working Arrangements and Attitudes.¹⁶ We assume an increase in productivity for remote workers. In fact, in this survey, respondents use the saved commuting time in 40% into extra work, 19.7% into indoor leisure, 16.2% into chores at home and the remaining into outdoor leisure and childcare. If we establish as in the Fair Labor Standards Act that the standard workday is 8 hours (40 hours a week), and if we estimate that remote workers save approximately 1 hour in commuting per day (27 minutes per round trip), and that they use 40% of this saved hours working at home, hence this estimates that remote workers are 4.5% more productive.

The disutility of WFH : The disutility of WFH can be estimated by considering both monetary expenses and the shift in the stigma associated with WFH. Monetary expenses include technology and communication expenses (such as computers, software, and internet) as well as workspace expenses (desk, chair, office supplies, etc.). Unfortunately, there is no available data on the variation in workspace expenses between 2018 and 2023. However, due to disruptions in the supply chain and increased demand for furniture during this period, it is reasonable to assume that prices may have increased, thereby increasing the disutility of remote work. This variation could be reported as a "+x%" increase for now. For technology expenses, we can use the Bureau of Labor Statistics (BLS) data on the Consumer Price Index (CPI) for Computers, Peripherals, and Smart Home Assistants in the U.S. city average for all urban consumers. Based on the 2007=100 price index, the variation in technology expenses is approximately an 8.7% decrease between 2018 and 2023.

¹⁵See Emanuel and Harrington (2023), Bloom et al. (2015), Choudhury et al. (2021), Etheridge et al. (2020), Gibbs et al. (2021) and Kunn et al. (2020) for both sides of arguments.

¹⁶See SWAA

The psychological factor is related to the decrease in the stigma associated with WFH. Before the COVID-19 crisis, remote work was perceived as risky and less prevalent. However, with the pandemic, remote work became more widespread, and workers became accustomed to it, reducing the perceived disutility. According to a survey by [Barrero et al. \(2020 a\)](#), 6.6% of respondents reported a decrease in their perception of WFH, while 65.1% reported an increase. The remaining respondents reported no change.¹⁷ As it is challenging to precisely quantify this variation in stigma, it can be reported as a "-y%" decrease.

To incorporate these factors, we multiply the parameters ζ_1 and ζ_2 by a scaling parameter, denoted as δ , resulting in $\zeta'_1 = \delta \times \zeta_1$ and $\zeta'_2 = \delta \times \zeta_2$. The available data indicates that $\delta = 0.913 + \Delta$. Finally, Δ will be calibrated so that the share of remote workers in the Post-Covid economy is at 26.9% (*i.e* increase of 20.2 ppt compared to the Pre-Covid economy). $\Delta \geq 0$ means that the variation in work pace expenses overpowers the decrease in the psychological factor.

1.4.2 The COVID "Shocks"

Shifts in the Model's Parameters :

As stated before, we will study the impact of these three shifts on the model. Hence in the new benchmark, we have : $\zeta' = \delta \times \zeta$, $c'_\tau = c_\tau \times 1.05$ and, $y^r = y^o \times (1 + \alpha_r)$, which will change the two values of $\tau_{ji,t}^{R_1}$ and $\tau_{ji,t}^{R_2}$.¹⁸ Moreover, for simplicity, we assume that hybrid workers gain half of the increase of remote workers productivity leading to $y^h = y^o \times (1 + \frac{\alpha_r}{2})$. These shifts in the model's parameters will affect workers' and firms' decisions as now the productivity levels are different depending on the occupational choice.

¹⁷[Ozimek \(2020\)](#) also reports that 56% of hiring managers experienced a better than expected shift to WFH. [Felstead and Reuschke \(2020\)](#) report that 88.2% of workers who worked at home during the lockdown would like to continue working at home.

¹⁸ α_r is scaled by the level of heterogeneity between on-site and remote workers, denoted as δ (*i.e* $\alpha_r = 4.5\% \times \delta$). It is important to note that as δ approaches zero, the heterogeneity between these two type of workers also decreases, as every worker chooses to work remotely. Since α_r is a measure of the difference between these two states, it should decrease as the level of heterogeneity between them decreases.

Shift in the Value Functions :

Equations [1.1](#) to [1.3](#) remain unchanged. However, equation [1.5](#) becomes

$$J_{n,ji}^c(\tau) = y_{ji}^c - w_{n,ji}^c(\tau) + \beta[s_j V_j + (1 - s_j) \bar{J}_{ji}] \quad (1.18)$$

With $y_{ji}^r = y_{ji}^o \times (1 + \alpha_r)$ and $y_{ji}^h = y_{ji}^o \times (1 + \alpha_r/2)$

Nash Bargaining leads now to the following surplus function

$$(1 - \beta(1 - s_j)) \bar{S}_{ji} = \bar{y}_{ji} - \bar{L}(\tau_{ji}, \lambda_{ji}) - b - \beta [f_{ji} \eta \bar{S}_{ji} + f_{ii} \eta \bar{S}_{ii}] \quad (1.19)$$

With, $\bar{y}_{ji} = G(\tau_{ji}^{R1}) y_{ji}^o + (G(\tau_{ji}^{R2}) - G(\tau_{ji}^{R1})) y_{ji}^h + (1 - G(\tau_{ji}^{R2})) y_{ji}^r$, leading to the following wage equation

$$w_{n,ji}^c(\tau) = \eta [y_{ji}^c + f_{ji} \beta \bar{J}_{ji} + f_{ii} \beta \bar{J}_{ii}] + (1 - \eta) [L^c(\tau_{n,ji}, \lambda_{n,ji}) + b] \quad (1.20)$$

As the productivity level is not dependent on the intensity of WFH in WHA, the optimal value of the latter remains unchanged. Finally, the reservation value of commuting time leading to the choice of occupation should now be solved for

Choice between On-site and Hybrid

$$y_{ji}^h - y_{ji}^o + \lambda_{n,ji}^* c_{\tau,ji} \tau_{n,ji} - H(\lambda_{n,ji}^*) \zeta - c_{h,i} = 0 \quad (1.21)$$

Choice between Hybrid and Remote

$$y_{ji}^h - y_{ji}^r + \zeta_i - (1 - \lambda_{n,ji}^*) c_{\tau,ji} \tau_{n,ji} - H(\lambda_{n,ji}^*) \zeta - c_{h,i} = 0 \quad (1.22)$$

1.4.3 Results

We compare the labor market outcomes from the Pre-COVID crisis to the Post-COVID economy in 2023, where the commuting costs increased, the productivity of remote workers increased and the disutility of WFH decreased while assuming that there are no other exogenous factors that may impact the labor market. Table 1.9 presents the main changes in the labor market outcomes, and we investigate how each parameter shift influences the labor outcomes by allowing one parameter at a time to remain unchanged.

The analysis reveals that Δ must be equal to -0.201 to meet the 20.2ppt increase in the share of remote workers. This reveals that the confinement period decreased the stigma associated with WFH, and that this decrease overpowers the increase in the workspace expenses. This aligns with Barrero et al. (2020 a), Ozimek (2020), and Felstead and Reuschke (2020) who reported that the perception of WFH has shifted positively.

Second, we find that compared to the Pre-COVID period, the benchmark unemployment rate in both rural and urban areas has slightly decreased. This is mainly due to the fact that, although the increase in commuting costs has increased the bargained wages and made workers less profitable for firms, the large decrease of WFH stigma coupled with the increase of their productivity overpowers the negative effect on the firm's profitability. In column (3) of the table, where there is no increase in commuting costs, we observe that if the economy experiences only a shift in productivity and in the disutility of WFH, the unemployment rate would have decreased further while wages would have increased at the same time. Moreover, the increase in commuting costs explains only a small portion of the increase in the share of remote work, while the largest part of this shift is explained by the change in remote worker productivity (see column (5)).

Additionally, in column (4) of the table, where only the disutility of remote workers did not change, we find that the decrease in disutility has dampened the negative effect of the increased commuting costs on the unemployment rate. Furthermore, in column (5) of the table, where the increase in productivity of remote workers is set to 0, we observe that the drop in unemployment rate would have been slightly higher if the increase in productivity of remote workers did not occur and this, for both areas.

In conclusion, the main decrease in the unemployment rate between the Pre-COVID economy and the Post-COVID one is mainly due to the high level of productivity reinforced by the decrease in worker disutility, as a higher share of remote workers is now present in the economy with higher productivity, making them more profitable for firms. This decrease is dampened by the increase in commuting costs but is overall overpowered. Our findings

highlight the importance of considering the interplay between productivity, commuting costs, and worker disutility when analyzing the labor market outcomes in a Post-COVID economy.

	Pre-COVID	Post-COVID			
	(1)	Benchmark (2)	$\Delta c_\tau = 0$ (3)	$\Delta \zeta = 0$ (4)	$\alpha_r = 0$ (5)
U_U	0.0564	0.0561	0.0560	0.0563	0.0563
U_R	0.0657	0.0655	0.0654	0.0657	0.0657
U	0.0614	0.0612	0.0611	0.0614	0.0614
w_U	1.0221	1.0370	1.0366	1.0398	1.0219
w_R	0.9548	0.9613	0.9606	0.9598	0.9549
Share of remote	0.0673	0.2691	0.2538	0.1722	0.1642

Table 1.9: **Understanding The shift in the labor market.**

1.4.4 The effect of Remote Workers Disutility

In the benchmark economy, we have seen that the increase in commuting costs has had a negative impact on labor market outcomes, leading to a slight increase in unemployment rates in both urban and rural areas. However, this negative effect is offset by the increase in remote worker's productivity and the decrease in remote worker's disutility. Specifically, the increase in remote worker productivity has contributed to a higher share of remote workers in the economy, making them more profitable to firms and helping mitigate the negative impact of higher commuting costs on labor outcomes. Additionally, the decrease in remote worker disutility has enhanced the effect of the latter mechanism.

To analyze, further, how this WFH disutility influences the outcome of this model, we multiply ζ_u , ζ_r with a scaling parameter in the Post-COVID benchmark case and see how the model will evolve. Hence, we have now $\zeta'_u = \delta \times \zeta_u$ and $\zeta'_r = \delta \times \zeta_r$ with $\delta = [0; 1.5]$.

Figure [1.1](#) is divided into three panels. For $\delta = 0.712$, the economy is at its Post-COVID Benchmark. Panel *a* shows that the proportion of remote workers decreases as the disutility of teleworking, denoted as ζ , increases. This means that when the disutility of teleworking decreases, the relative value of WFH increases compared to WOS. At a $\zeta = 0$ level, the value of WFH (as determined by Equation [1.1](#)) depends only on the worker's wage. Meanwhile, the value of WOS becomes less appealing, as workers still incur commuting costs. Therefore, workers and firms tend to choose remote work more

frequently when the disutility of teleworking is lower. Moreover, Panel *b* of the same figure shows that the intensity of WFH in WHA, denoted as λ^* , is also a decreasing function of ζ for similar reasons as stated before. However, in Panel *c*, the total share of hybrid workers in the economy is a non-monotonic function that initially increases and then decreases, with a maximum at around $\delta = 0.33$, on average. This is because when the disutility of teleworking is low enough, workers tend to prefer fully remote work instead of a hybrid arrangement. Conversely, when the disutility of teleworking is high enough, workers tend to prefer fully on-site work instead of a hybrid arrangement. Therefore, the share of hybrid workers is the highest at an intermediate level of this disutility of.

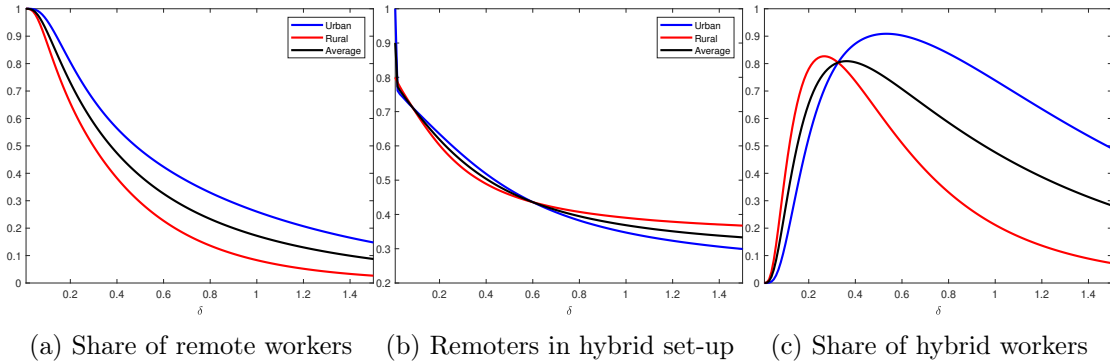


Figure 1.1: **Share of remote workers as a function of ζ**

Wages : Alexandre and Pallais (2017) conducted a large-scale randomized control trial for a national call center and found that workers are willing to accept an 8% reduction in wages to work from home. In the same spirit, Aksoy et al. (2022) show that employees value the option of working from home 2-3 days per week at 5% of pay on average. This model features the same trend. In fact, Figure 1.2 presents several interesting findings related to wages for both urban and rural workers in the benchmark economy. Panel (a) shows that, overall, wages for urban workers are higher than for rural ones. However, panel (b) shows that as δ decreases, wages for urban workers decrease more rapidly than for rural ones. Interestingly, wages for rural workers working in rural areas actually increase for intermediate values of δ in the range of 0.16 to 1, while urban wages continue to decrease. However, for values of δ below 0.16, wages for both rural and urban workers decrease. Hence, as in Alexandre and Pallais (2017) and Aksoy et al. (2022), workers are willing to accept lower wages to WFH.

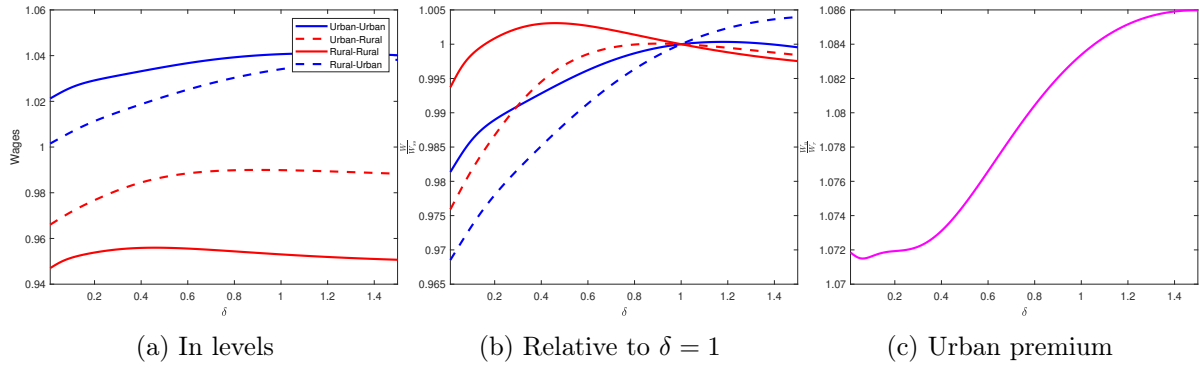


Figure 1.2: Wages as a function of ζ

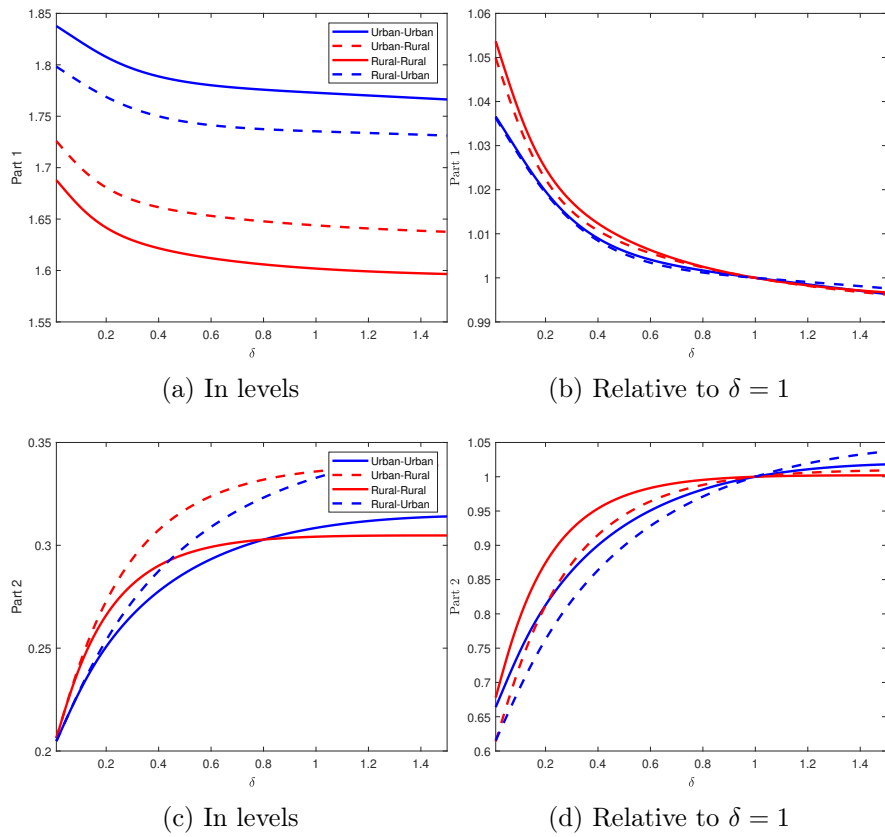


Figure 1.3: Disentangling Wages

To understand these findings, we disentangle the two parts that constitute wages in the model. The first part is driven by market tightness, while the second part depends on factors such as the disutility of remote work and job type (on-site, hybrid, or fully remote). Figure 1.3 shows that there are two contradictory mechanisms at play. On one hand, as δ decreases and workers become more profitable due to their high levels of remote productivity, the first part of wages also increases (panel (a) and (b)). On the other hand, as the disutility of remote work decreases, the second part of wages decreases (panel (c) and (d)).

The total effect on wages observed in Figure 1.2 can be explained as follows. In general, the effect of the decreased disutility in the second part of wages outweighs the increase in worker profitability, resulting in an overall decrease in wages. However, for rural workers working in rural areas, the effect is more complex. For intermediate values of δ (0.16 to 1), the effect of worker profitability dominates and wages increase. However, for values of δ below 0.16, the effect is driven by lower worker disutility, resulting in lower wages for both rural and urban workers.

Finally, in Panel c of Figure 1.2, it is shown that the wage gap between urban and rural workers decreases as δ decreases, resulting in lower inequalities.

Unemployment rate: Figure 1.4 displays that the unemployment rate increases as the disutility of teleworking, driven by δ , increases. For the lowest values of δ , unemployment rates in both urban and rural areas are at their lowest points and converge respectively toward 5.4% and 6.3%. On one hand, this is because, for low levels of disutility, workers are willing to bargain for lower wages in exchange for working remotely, (see in Figure 1.2). On the other hand, as the disutility of remote workers decreases, the share of this type of workers increases and with it the overall profitability (as the productivity of remote workers is high). The speed decline in unemployment rate through the decline of δ is more pronounced for rural workers than urban ones as they become relatively more profitable compared to the case where $\delta = 1$. This decreases the unemployment gap between both areas and hence the inequalities between these two areas.

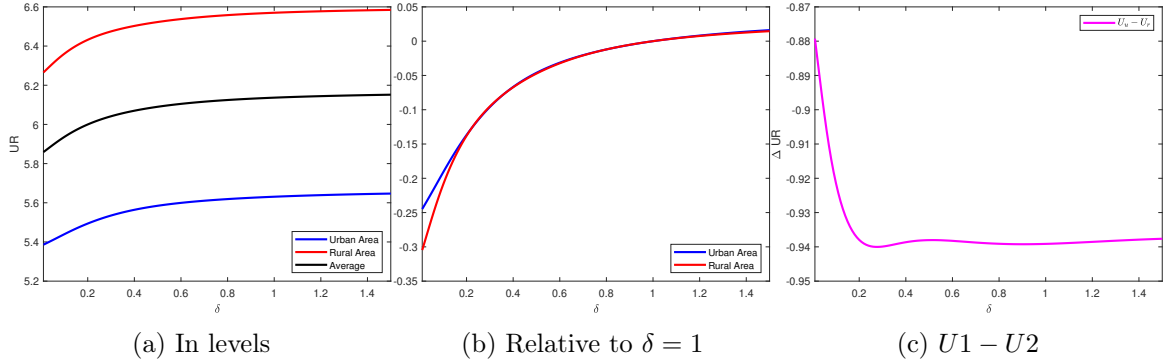


Figure 1.4: Unemployment rate as a function of ζ

1.4.5 The Impact of WFH on Welfare and Wealth

Are Unemployed Workers Better Off?

In his book [Pissarides \(2000\)](#), the author argues that measuring the welfare of society should not be based solely on economic growth or the welfare of those who are employed. Instead, he emphasizes the importance of considering the welfare of those who are unemployed. Hence, we evaluate the impact of WFH disutility on unemployed welfare and its inequalities. As depicted in Panel (a) of Figure [1.5](#), unemployed workers are better off when they are residing in the urban area. This can be attributed to the fact that rural workers experience a large gap in job finding rates, given the initial productivity differences between them and their urban counterparts (i.e., when $\delta = 1$) as shown in Figure [1.6](#). Moreover, Panel (b) of Figure [1.5](#) shows that the unemployed welfare inequality decreases with the disutility of WFH only for low values of δ . As stated before, this is because for $\delta = 1$, there are initially more remote workers in urban areas compared to rural areas, the higher remote productivity leads to increased demand for remote workers in urban areas, making them more attractive to firms. Consequently, the job-finding rate in urban areas is higher than in rural areas, leading to higher inequalities between the two zones. Nevertheless, as the value of δ decreases, not only the welfare of unemployed workers increases but also with it a decrease in the disparities between the two regions. Thus, a lower WFH disutility is beneficial, for the unemployed well-being, if this disutility is sufficiently low to attract a significant number of remote workers in both areas.

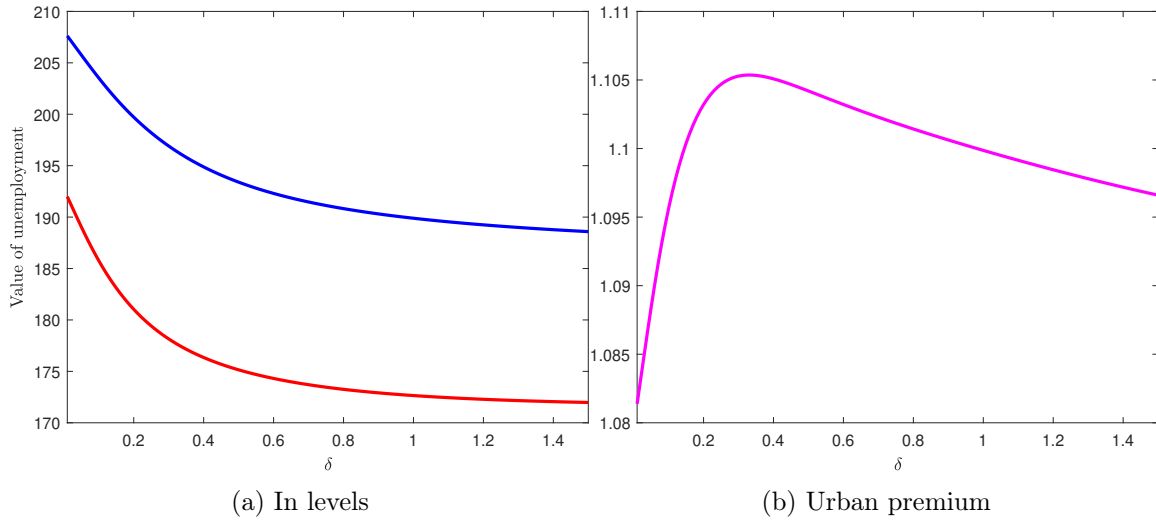


Figure 1.5: **Measuring the Welfare of Unemployed Workers.** The blue (red) line represent the urban (rural) area.

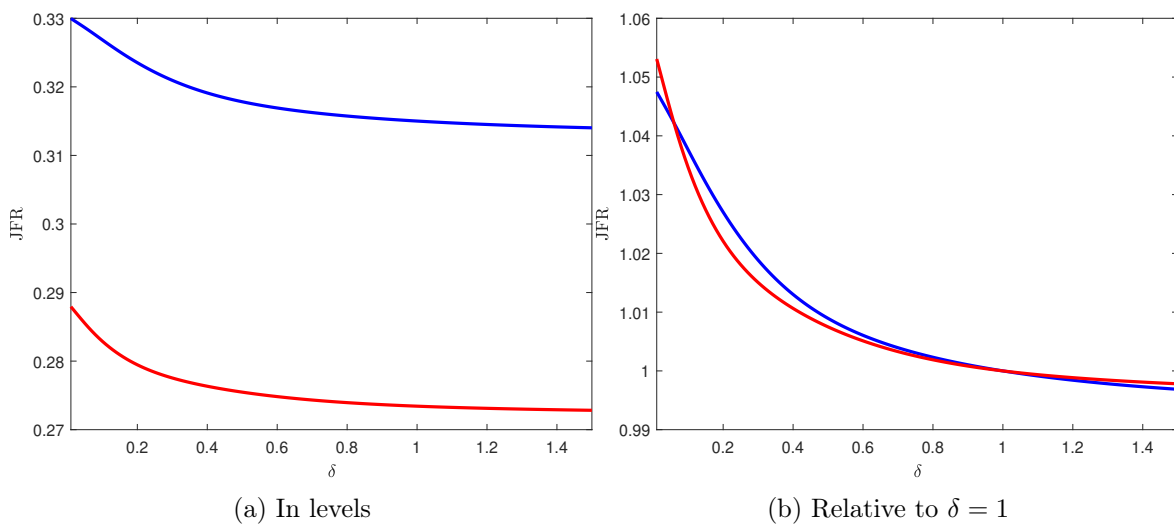


Figure 1.6: **Job Finding Rate.** The blue (red) line represent the urban (rural) area.

Measuring Economic Wealth

Although we have shown that unemployed welfare is positively impacted with lower values of WFH disutility. It is also interesting to see, how the overall economic wealth in the two areas evolves depending on the different cases. In this framework, we approximate the effect of WFH on wealth as its effect on net production (NP) in each area :

$$NP_i = \bar{y}_{ji} - \sum_J p_{ji} \bar{L}(\tau_{ji}, \lambda_{ji}) - \kappa$$

with $p_{ji} = \frac{N_{ji}}{N_{ji} + N_{ii}}$.

In Figure [1.7](#), Panel (a) demonstrates that decreasing disutility among remote workers leads to an increase in overall net production in both regions. This is due to two factors: the direct effect of the reduction of remote disutility and the indirect effect on total commuting costs in the economy. As the disutility of WFH decreases, the proportion of on-site workers decreases, resulting in fewer people commuting and incurring those costs.

However, Panel (b) of the same figure shows that for intermediate values of δ , this decrease in disutility results in greater divergence in net production, with urban zones being favored. This is because firms in urban zones benefit not only from higher managerial and labor quality but also from a higher proportion of remote workers. Therefore, both the costs of commuting and working from home decrease more rapidly in the urban economy for intermediate values of δ . Only when δ reaches very low values does the rural zone begin to catch up.

The analysis of the welfare of the unemployed and economic wealth highlights the benefits of reducing remote work disutility. It results in a win-win situation by improving the welfare of the unemployed and reducing the welfare gap between rural and urban areas. Additionally, it increases overall net production in both economies. However, the reduction in disutility only narrows the welfare and the net production gap between the two zones for low values of remote work disutility.

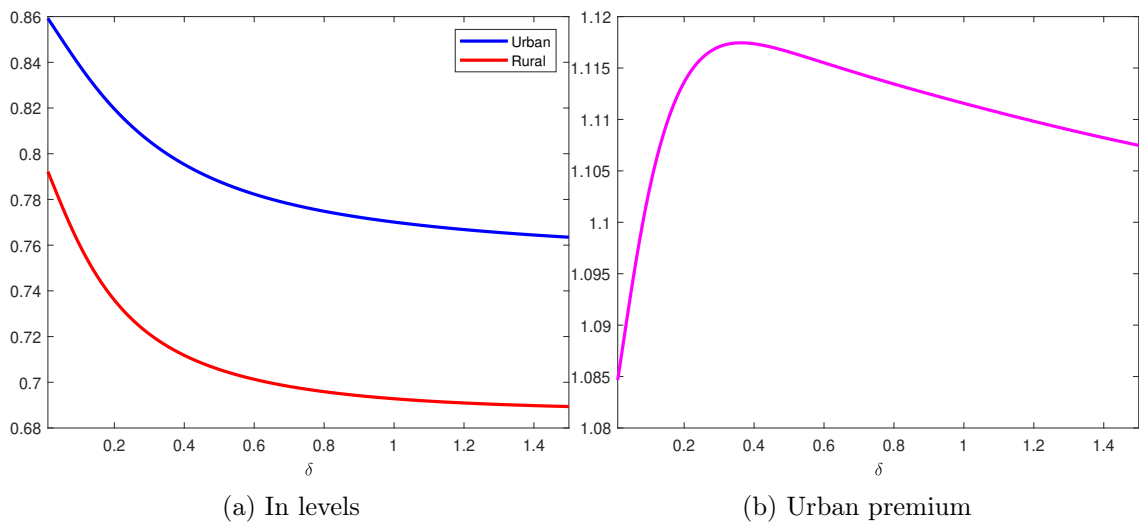


Figure 1.7: Net Production

1.5 Social Planner

Consider a social planner who, in each period, chooses a sequence of vacancies levels $V \equiv [V_i, V_j]$ and employment levels $N^c \equiv [N_{jj}^o, N_{ij}^o, N_{ji}^o, N_{ii}^o, N_{jj}^h, N_{ij}^h, N_{ji}^h, N_{ii}^h, N_{jj}^r, N_{ij}^r, N_{ji}^r, N_{ii}^r]$ in order to maximize the present discounted value of output net of vacancy costs. Hence, the planner solves the following recursive problem

$$\begin{aligned} \mathcal{V}(N_t) &= \max_{\mathcal{C}} D_t + \beta \mathcal{V}_{t+1}(N_{t+1}) \\ \text{s.t.} \quad &\begin{cases} D_t = \sum_i^I \sum_j^J \sum_c^C N_{t,ji}^c (y_{ji} - L_{ji}^c) + (2 - \sum_i^I \sum_j^J \sum_c^C N_{t,ji})b - \kappa(V_{t,j} + V_{t,i}) \\ N_{ji,t}^c = \mathcal{G}^c(\tau_{i,t}^R) \left[(1 - s_j) \sum_c^C N_{ji,t-1}^c + M_{j,t} \omega_{ji,t} \right] \\ M_{j,t} \omega_{ji,t} \geq 0 \end{cases} \quad (\lambda_{ji,t}^p) \end{aligned}$$

With $\mathcal{C} = \{N_t^c, V_t\}$

The first order condition conditional on $V_{t,j}$

Noting, $\tilde{J}_{ji}^{p,c} = \frac{\partial \mathcal{V}}{\partial N_{ji}^c}$ with $\tilde{J}_{ji}^{p,c} = \frac{\int_0^{\tau_{ij}^{max}} J_{ji}^{p,c} dG(\tau)}{\mathcal{G}^c(\tau_{ij}^R)}$ and $\bar{J}_{ji}^p = \sum_c^C \mathcal{G}^c(\tau_{ij}^R) \tilde{J}_{ji}^{p,c}$ the first order condition leads to the following, steady state relation (See Appendix [A.3.1](#))

$$\frac{\kappa}{\frac{\partial M_j(\gamma U_j + (1-\gamma)U_i, V_j)}{\partial V_j}} = \beta [(1 - \omega_{ji})\bar{J}_{jj}^p + \omega_{ji}\bar{J}_{ji}^p] \quad (1.23)$$

$$\frac{\kappa}{\frac{\partial M_i(\gamma U_i + (1-\gamma)U_j, V_i)}{\partial V_i}} = \beta [(1 - \omega_{ij})\bar{J}_{ii}^p + \omega_{ij}\bar{J}_{ij}^p] \quad (1.24)$$

Noting $\epsilon_{M|V} = \frac{\partial M}{\partial V} \frac{V}{M}$, equation [1.23](#) can be rewritten as :

$$\frac{\kappa}{\epsilon_{M_j|V_j} q_j} = \beta [(1 - \omega_{ji})\bar{J}_{jj}^p + \omega_{ji}\bar{J}_{ji}^p] \quad (1.25)$$

The first order condition conditional on $N_{t,I}^c$

At the steady state the FOC leads to (See Appendix [A.3.2](#) for more details)

$$(1 - (1 - s_j)\beta) \bar{J}_{ji}^p = y_{ji} - \bar{L}(\tau_{ji}, \lambda_{ji}) - b - \beta \left[f_{ji} \epsilon_{M_j|JS_j} \bar{J}_{ji}^p + f_{ii} \epsilon_{M_i|JS_i} \bar{J}_{ii}^p - \mathcal{E}_{ji} \right] \quad (1.26)$$

$$(1 - (1 - s_i)\beta) \bar{J}_{ii}^p = y_{ii} - \bar{L}(\tau_{ii}, \lambda_{ii}) - b - \beta \left[f_{ji} \epsilon_{M_j|JS_j} \bar{J}_{ji}^p + f_{ii} \epsilon_{M_i|JS_i} \bar{J}_{ii}^p - \mathcal{E}_{ji} \right] \quad (1.27)$$

With,

$$\mathcal{E}_{ji} = f_{ji}(1 - \omega_{ji}) [1 - \epsilon_{M_j|JS_j}] [\bar{J}_{jj}^p - \bar{J}_{ji}^p] + f_{ii}\omega_{ij} [1 - \epsilon_{M_i|JS_i}] [\bar{J}_{ij}^p - \bar{J}_{ii}^p] \quad (1.28)$$

1.5.1 Optimality

Recall, the equilibrium in the market is defined by

$$\frac{\kappa}{(1 - \eta)q_j} = \beta[(1 - \omega_{ji})\bar{S}_{jj} + \omega_{ji}\bar{S}_{ji}] \quad (1.29)$$

$$(1 - \beta(1 - s_j))\bar{S}_{ji} = y_{ji} - \bar{L}(\tau_{ji}, \lambda_{ji}) - b - \beta [f_{ji}\eta\bar{S}_{ji} + f_{ii}\eta\bar{S}_{ii}] \quad (1.30)$$

$$(1 - \beta(1 - s_i))\bar{S}_{ii} = y_{ii} - \bar{L}(\tau_{ii}, \lambda_{ii}) - b - \beta [f_{ji}\eta\bar{S}_{ji} + f_{ii}\eta\bar{S}_{ii}] \quad (1.31)$$

Proposition: If $\bar{S}_{ji} = \bar{J}_{ji}^p$, $\epsilon_{M_j|V_j} = \epsilon_{M_i|V_i} = 1 - \eta$, $\epsilon_{M_j|JS_j} = \epsilon_{M_i|JS_i} = \eta$ and $\mathcal{E}_{ji} = \mathcal{E}_{ij} = 0$, then the search externalities are "eliminated" and the market decisions are optimal.

For the sake of simplicity let $M(JS, V) = V^\alpha JS^{1-\alpha}$, in this case, $\epsilon_{M_j|V_j} = \epsilon_{M_i|V_i} = \alpha$ and $\epsilon_{M_j|JS_j} = \epsilon_{M_i|JS_i} = 1 - \alpha$. This leads to $\eta = 1 - \alpha$ which is the original Hosios condition. In appendix [A.3.3](#), we show that $\mathcal{E}_{ji} = \mathcal{E}_{ij} = 0$ leads to $\gamma = \{0, \frac{1}{2}, 1\}$. Therefore, the market has the optimal level as the planner if the latter chooses a level of search intensity such that $\gamma = \{0, \frac{1}{2}, 1\}$ and that the share of workers (firms) in the surplus of a match is equal to the elasticity of the matching function with respect to the corresponding search input.

This shows, that the market allocation is not optimal. However, the source of externality is not due to WFH itself but from the search of unemployed workers in the two markets. Market can reach optimality in a Hosios sens if and only if the bargaining power of a worker is equal to the elasticity of the matching function with respect to JS and that unemployed workers either search equally in both markets or focus 100% of their search on one market. Therefore, it is interesting to see how this externality influences the equilibrium.

1.5.2 Numerical Resolution of the Planner's Problem

As in the Market equilibrium, the steady-state equilibrium cannot be determined analytically. However, it is computed by the fixed point iterative algorithm described below. Noting $\mathcal{I} = \{jj, ji, ij, ii\}$

1. The values of the reservation commuting time $\tau_{\mathcal{I}}^R$ and the intensity of WFH in WHA $\lambda_{n,\mathcal{I}}^*$ are exogenous to the model.¹⁹
2. Guess the initial value of θ_j and θ_i .
3. Compute the job finding rate $f_{\mathcal{I}}$ and the matching elasticities $\epsilon_{M|JS}$ and $\epsilon_{M|V}$.
4. Using the law of motion of employment solve for the employment levels $N_{\mathcal{I}}$ and hence compute $\omega_{\mathcal{I}}$.
5. Using equation 1.26 compute $\bar{J}_{\mathcal{I}}^p$.
6. Finally using equation 1.25 update the belief on θ_i and θ_j .

1.5.3 Results

To study the effect of this search externality we focus on the case where $\gamma = 0.5$. In fact, the corner solutions $\gamma = \{0, 1\}$ are not interesting, as they lead to an equilibrium of two separate markets with no interactions. Therefore, we start by computing the planner solution with $\gamma = 0.5$. This gives us, the optimal bargaining power for workers *i.e* $\epsilon_{M_j|JS_j} = \eta_j$. In Appendix A.3.6 we show that $\epsilon_{M_j|JS_j} = \epsilon_{M_j|JS_j}(\theta_j)$ is specific to each area. We export this η_j to the market equilibrium and compute the optimal level in the market in the Pre and the Post-COVID economy.²⁰ We then shutdown the condition that the share of workers in the surplus of a match is equal to the elasticity of the matching function (*i.e* $\eta \neq \epsilon_{M|JS}$) and see how it impacts the equilibrium. Finally, We compare those two results with the benchmark economy where neither of those conditions, leading to optimality, are respected (*i.e* $\eta \neq \epsilon_{M|JS}$ and $\gamma \neq 0.5$).

¹⁹In Appendix A.3.4 and A.3.5 we show that the planner solution is similar to the market solution.

²⁰Note that when both conditions are respected (*i.e* $\epsilon_{M_j|JS_j} = \eta_j$ and $\gamma = 0.5$) the equilibrium is similar in the market and for the social planner.

Table [1.10](#) shows that whether the economy is in the Pre or Post-COVID economy the optimal solution leads not only to a higher level of unemployment rate but also to similar levels in both areas. First, when workers take into account the externality that one unemployed worker put, by searching in both areas, on other unemployed workers and internalize it in his bargaining power, this leads to higher levels of bargained wages, hence to lower levels of profitability leading to higher levels of unemployment (See column (2) and (5) in the table). Second, when $\gamma = 0.5$, unemployed workers search equivalently in both areas leading to a similar probability of finding a job within the same area. This does not mean that the tightness in both markets are similar (*i.e* $\theta_u \neq \theta_r$) but that unemployed workers have equal chances to access the job (*i.e* $f_{uu} = f_{ur}$) and that the low levels of productivity of rural workers are compensated with lower wages ($w_{uu} \geq w_{ur}$). Columns (3) and (6) of the table show that when both those conditions are not met, not only the unemployment levels are lower but also the urban area is advantaged compared to the rural one. In fact, unemployment levels are lower at the same time wages are higher leading to a higher gap between those two areas.

	Pre-COVID			Post-COVID		
	Optimum (1)	$\eta \neq \epsilon_{M JS}$ (2)	(2) + $\gamma \neq 0.5$ (3)	Optimum (4)	$\eta \neq \epsilon_{M JS}$ (5)	(5) + $\gamma \neq 0.5$ (6)
U_U	0.0695	0.0618	0.0564	0.0692	0.0615	0.0561
U_R	0.0695	0.0618	0.0657	0.0692	0.0615	0.0655
U	0.0695	0.0618	0.0614	0.0692	0.0615	0.0612
w_U	1.0088	1.0080	1.0221	1.0251	1.0230	1.0370
w_R	0.9797	0.9727	0.9548	0.9871	0.9806	0.9613

Table 1.10: **The Effect of Optimality Conditions.** In column (2) and (5) we take the benchmark level of the worker's bargaining power $\eta = 0.5$. In column (3) and (6) we take the benchmark search intensity levels $\gamma = 0.849$.

Comparison between the Pre-COVID and Post-COVID effect of those optimality conditions shows that the differences in unemployment rate between the optimal level and the benchmark cases are similar and did not evolve with the changes that occurred in the economy between these two periods. Although it is out of the scope of our model, one can directly see that with the decrease in the disutility of remote work, it is easier for workers to search in other areas than the one where they reside in. In this case, the search intensity γ is a decreasing but asymptotic function of WFH. Hence, with the shift that

happened in the economy between the two periods (*i.e.* the increase in commuting costs, increase in remote worker's productivity and the decrease in the disutility of remote work) workers may be willing to search more intensely in other areas, as remote work is more widespread, leading to a closer solution to the optimal one.

To have an insight on the matter, we simulate the Post-COVID economy as in section 1.4.4 (*i.e.* $\zeta' = \delta \times \zeta$). However, in this case, we impose that the search intensity within the same residential area is positively correlated with this disutility. That is to say, when the level of WFH disutility is at its Pre-COVID levels so does the search intensity. However, when this WFH disutility is at its lowest levels, the search intensity reaches the 50% levels, leading to an equal search in both areas. Figure 1.8 shows that when the level of the disutility reaches zero, the unemployment rates are at 6.7%, and this for both areas. Although Panel (a) of this figure shows that this market equilibrium is not optimal for higher values of δ , Panel (b) of this same figure shows that the decrease of WFH disutility makes the equilibrium reaches its optimum at a faster pace.

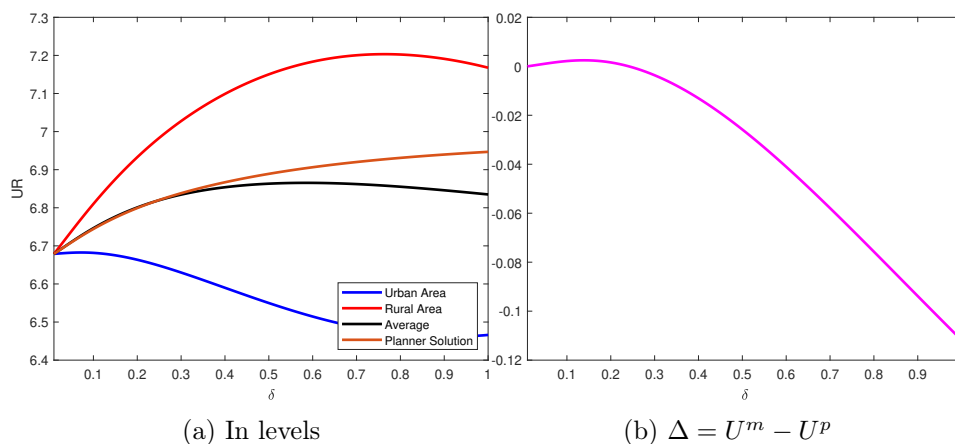


Figure 1.8: Unemployment Rate when Search Intensity depends on WFH levels.

1.6 Conclusion

This study examines the impact of the new WFH trend on labor market outcomes. Using a structural model we explain the 20ppt increase in the share of remote workers after the Covid-19 crisis and its effect on labor market outcomes in two heterogeneous areas. More precisely, we show that the increase in commuting costs has led to a slight increase in the unemployment rate in both urban and rural areas, which has been offset by the increase in remote workers' productivity and the decrease in worker disutility. Moreover, we evaluate the benefit of WFH on inequalities between these two areas. We find that reducing remote work disutility results in a win-win situation by improving the welfare of the unemployed, narrowing the welfare gap between rural and urban areas, and increasing overall wealth in both economies.

In this paper, our primary focus has been on examining the direct impact of WFH on the labor market and inequalities between two specific areas. However, it is important to recognize that WFH can have broader implications for the economy, leading us to highlight a few key areas that warrant further exploration in the near future. Firstly, it would be valuable to extend the model to encompass several regions that are not easily accessible through commuting, where WFH becomes the primary option for employment matching. For instance, we anticipate that permitting workers to reside in Bali while working for firms in France could have a more pronounced effect on labor markets, highlighting the importance of considering a wider geographic scope. Furthermore, as WFH becomes more prevalent, firms can potentially reduce costs associated with office space. A decrease in those costs may influence firms' employment decisions. To incentivize WFH, companies may choose to allocate a portion of their saved office rent towards WFH expenses and utilities for their employees. This approach not only enhances productivity but also helps alleviate concerns employees may have about WFH. Lastly, this study also raises interesting possibilities regarding the potential of WFH or working anywhere in mitigating rural-urban migration patterns while improving labor market outcomes. Exploring this aspect in future research, using an expanded version of this structural model, could provide valuable insights into the dynamics at play.

Chapter 2 : On the heterogeneous impacts of the COVID-19 lockdown on unemployment

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2.1 Introduction

The COVID-19 crisis has led to severe lockdown measures, on account of heightened health and sanitation concerns. These sanitation measures have generated an unprecedented increase in US unemployment. Moreover, these measures did not affect all workers in the same way. In fact, as depicted in Figure 2.1, the impact is the highest for workers with less than a high school diploma.¹ Furthermore, the two last crises have induced very different changes in workers' flows. In fact, while the COVID-19 crisis induced a brutal and high, in magnitude, response of unemployment and its flows, the subprime crisis impact was lower in magnitude but much higher in persistence (see Figure 2.2). This makes it harder to identify a parsimonious model able to explain this particular succession of crises.²

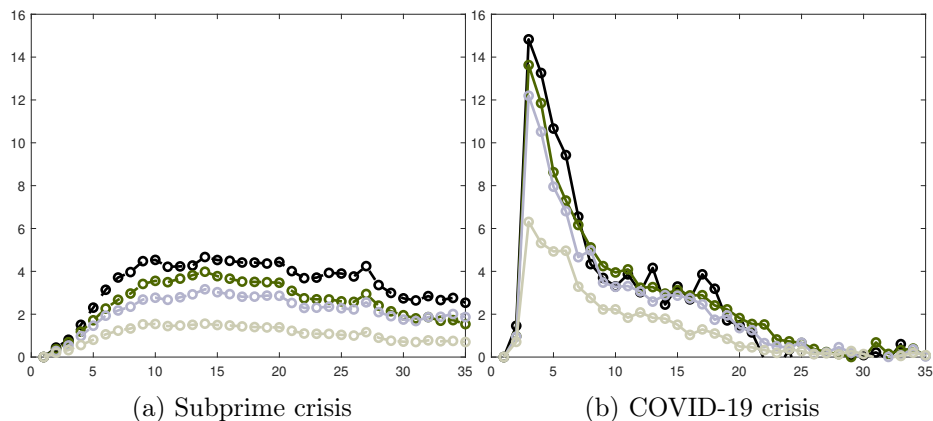


Figure 2.1: **Rises in monthly unemployment rates by diploma after Subprime and COVID-19 crises.** Increases in percentage points relative to the pre-crisis levels. Black: Less than High School diploma. Khaki: High School diploma. Gray: College degree. Camel: Bachelor and more degree. Panel a: COVID-19 crisis. Panel b: Subprime crisis.

One of the important factors explaining the differences between those two crises is the large increase in temporary separations, during the COVID-19 crisis, leading to a higher use of recalls. In fact, Hall and Kudlyak (2022) explain that the subprime crisis leads to a higher number of "jobless" unemployed workers (*i.e.* not temporally furloughed) causing

¹See also Lee et al. (2021) and Falk et al. (2021) for detailed analysis of the unequal unemployment rise during the COVID-19 crisis.

²Note that the COVID-19 crisis has strongly raised the non-participation rate (-3.2 pp from February to April 2020). However, we observe that the speed at which the unemployment and the non-employment (unemployed and non-participants) come back to their pre-crisis level are the same (see Appendix B.1 for more details on these data). This leads us to focus on only unemployment adjustments in the following.

a highly persistent unemployment rate. On the other hand, the number of unemployed workers with jobs (*i.e* temporally furloughed) has increased largely during the COVID-19 crisis which led to a less time-consuming search and matching process and hence to a more rapid recovery of the unemployment rate.

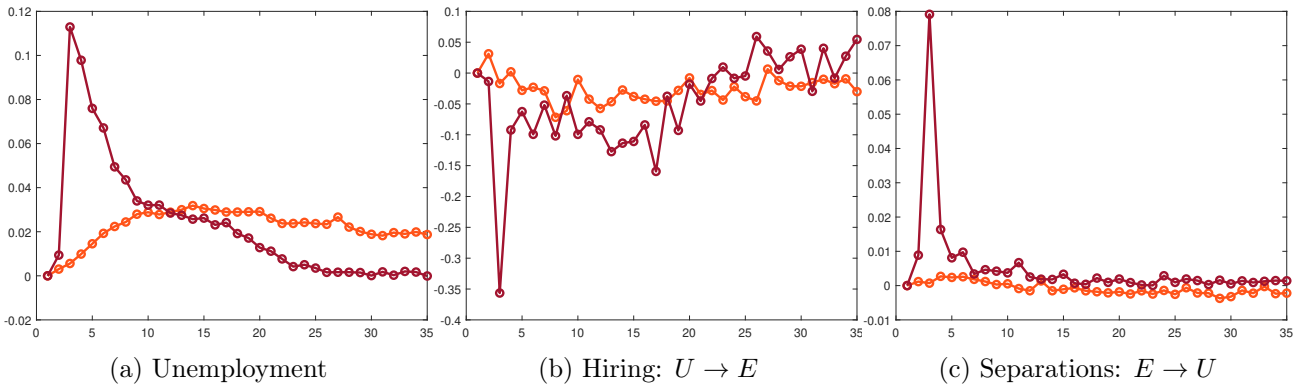


Figure 2.2: **Dynamics of monthly workers flows and stock after Subprime and COVID-19 crises.** Red: COVID-19 crisis. Orange: Subprime crisis. Increases in percentage points relative to the pre-crisis levels.

In the current study, we develop a general equilibrium model with matching frictions that reproduces the impact of the lockdown on heterogeneous workers in the United States (U.S.).³ We propose an original extension of the DMP model, which introduces (*H1*) worker heterogeneity, (*H2*) time-varying microeconomic risks over the business cycle, (*H3*) congestion externalities in the hiring costs, and (*H4*) real-wage rigidity. This model is calibrated to reproduce the impact of the 2008 subprime crisis on unemployment and workers' flows. Using this calibrated model, we reveal the COVID-19 shocks, specific to each type of job, that allow it to fit the monthly labor market data since March 2020. The constraints on market exchanges induced by the lockdown are modeled as reductions in Total Factor Productivity (TFP). We introduce two measures of the Coronavirus Aid, Relief, and Economic Security (CARES) Act. On one hand, unemployed workers benefit from an important increase in unemployment benefits.⁴ On the other, the CARES act provides incentives for firms to hold back their workers through the Paycheck Protection

³Our work thus pursues those of Petrosky-Nadeau and Zhang (2021), Hall (2017) and Hall and Kudlyak (2020), which shows how the DMP model can explain previous crises.

⁴Government add \$600 in weekly benefits for all eligible unemployed workers during the first wave and \$300 during the second wave.

Program (PPP).⁵ There were two rounds of PPP, the first begins in April 2020 and ends in August 2020 and the second takes place in January 2021 and ends by May 2021. Taking advantage of our structural approach, we estimate the lockdown induced constraints for different jobs, as well as the effectiveness of the CARES act to dampen the impact of this recession on the unemployment risk of different workers.

The main challenge consists of extending the DMP model such that it explains large crises. First, the unemployment rate more than doubled within one month of the COVID-19 crisis. Second, the unemployment rate has never experienced a rapid decline suggesting that the nature of the crisis and its related public intervention may explain the non-persistence of unemployment compared to the previous crisis.⁶ Third, the increase in unemployment risk during the crisis depends highly on the worker type (i.e., heterogeneity matters).^{7,8} Finally, not only specific to the COVID-19, the distribution of job productivity for each job varies during the business cycle, with heterogeneity increasing during times of recession.⁹

To explain the impact of various crises on US unemployment, an extended version of the DMP model including assumptions $(H1)-(H4)$ is developed for an economy where workers have heterogeneous educational attainments.¹⁰ We start by showing that our model can

⁵The PPP of the CARES provides loans to firms. These loans become subsidies if covered operating costs exceed the loan amount and the borrower maintains headcount. A large majority of firms have asked for loan forgiveness by holding their workforce. See section 2.4 and Baker et al. (2020) for more details.

⁶Hall and Kudlyak (2020) show that, during periods of recovery over the past 70 years, we can see a 0.5-percentage-point reduction in unemployment per year, which suggests that the COVID-19 crisis would be resolved within 15 years.

⁷Robin (2011) and Lise and Robin (2017) show that heterogeneity matters in accounting for aggregate labor dynamics. See also Ferraro (2018) & (2000) and Adjemian et al. (2021).

⁸Empirical investigations of Adams-Prassl et al. (2020) show that, for some occupations, workers' ability to undertake a large percentage of their tasks from home (i.e., "telework") is limited; this is especially true for low-income professions. Using the European Union labor force survey, Fana et al. (2020) show that most of the negative effects of the lockdown measures are concentrated on less-skilled workers. Indeed, the sectors forcefully closed by decree of their decomposition are characterized by low wages and high separation rates. These findings suggest that worker heterogeneity matters in the evaluation of the lockdown impacts on unemployment.

⁹This fact has been underscored by Bloom (2009) and put in light again for the COVID crisis in Bloom et al. (2020).

¹⁰Heterogeneity in educational attainment is fixed over time so as it is consistent with a model that lacks mobility among submarkets. This distinguishes our modeling strategy from that of Gregory et al. (2020), who define three worker groups on the basis of their "performance" with respect to labor market transitions. Heterogeneity by education level seems to be well suited to predicting workers' type-specific effects of the lockdown measures, and their heterogeneous effects (see Adams-Prassl et al. (2020), Fana et al. (2020), Lee et al. (2021) or Falk et al. (2021)).

reproduce the impact of the 2008 subprime crisis. Although this crisis is not similar to the COVID-19 one, having a model that reproduces the observed asymmetric adjustments of the US labor market (i.e., rapid increase and slow recovery), and the unemployment risk inequalities (i.e., the least educated are strongly impacted), is essential to forecast the impact of the COVID-19 crisis.

Using this calibrated model, we identify the size of the shocks needed to reproduce the COVID-19 crisis. We show that the “direct” impact of the lockdown measures significantly differs across educational levels: in April 2020, workers without a high school diploma suffered from a 35% drop in their TFP, while those holding a bachelor degree or more saw their TFP decreased by only 3%. The negative impact of the lockdown on worker TFP thus lies between these two extreme cases for the two other worker types (i.e., -22% and -12.5% for those with a high school diploma and college diploma, respectively). When the second wave of restrictions ended in June 2021, productivity levels returned to their pre-crisis levels.

Moreover, although we do not directly distinguish in our model between temporary layoffs and jobless unemployed workers, we take into account the effect of this historical increase in temporary layoffs during the COVID-19 crisis on the (non)-persistence of the unemployment rate. To do so, we assume that the costs of job vacancies are inversely related to the increase in temporary layoffs. In fact, as the firm-worker match is preserved, the use of recalls exempts firms from paying the usual costs associated with hiring a jobless unemployed worker. The decrease in those costs will, hence, boost the job finding rate and help employment gain its pre-crisis levels more rapidly.¹¹

We also show that the CARES act helps the economy by stimulating job findings and lowering separations. In fact, the CARES act through its large employment subsidies damps significantly the unemployment increase by braking the separation dynamics and kicking the hirings: without the CARES act, the unemployment rate would be higher by 18.4 pp in August 2020, 8.5 pp in January 2021, and 4 pp in June 2021. By assuming that the wage bargaining process, as all social activity, has been shutdown during the lockdown, the increase of unemployment benefits has only a moderate effect on unemployment dynamics. This wage rigidity assumption during the lockdown period is supported by [Cortes and Forsythe \(2020\)](#) who show that conditional on remaining employed, earnings changes during the pandemic were not atypical on average, suggesting that the time-limited increase in unemployment benefits has not affected the wages.

¹¹See [Gertler et al. \(2022\)](#) for a framework with both temporary layoff and jobless unemployment.

Furthermore, this crisis had also an unprecedented impact on the French labor market. The unemployment rate went from 7.7% in February 2020 to 23.7% in April 2020 when including individuals on short-time work as part of the unemployed population. After reaching this peak in just two months, the subsequent decline in unemployment was also unprecedented. By September, the unemployment rate, including those on short-time work, had dropped to 10.65%. As for the US case, these adjustments differed greatly from those observed in previous crises. However, the government intervention was different in those countries. While in the US the CARES act carried the economy through unemployment benefits and the PPP program, in France, the government allowed companies to separate from certain employees without breaking their contracts through partial unemployment. This enables a faster resumption of work, as it is less costly. Hence, we use the same conceptual framework recalibrated and adjusted to the French experience and compare the consequences of those different public policies.

There is already a significant literature studying the impact of the COVID-19 crisis on the US labor market. Numerous empirical studies, including [Gallant et al. \(2020\)](#), [Barrero et al. \(2020 b\)](#), [Bartik et al. \(2020 b\)](#), [Sahin et al. \(2021\)](#) among others, attest to the unprecedented amplitude of the drop in hirings and the increase in separations, both leading to the spike in US unemployment. Other works based on structural approaches improve our understanding of the propagation mechanisms of this crisis, such as [Gregory et al. \(2020\)](#), [Hall and Kudlyak \(2020\)](#) or [Bernstein et al. \(2020\)](#).¹² Our paper complements these previous studies by determining the most parsimonious structural model making it possible to quantitatively account for the impact of the COVID-19 crisis on the US labor market, in terms of its amplitude, its persistence, and the resulting inequalities.

The remainder of this paper is organized as follows. Section [2.2](#) presents the model, and Section [2.3](#) discusses calibration and model-fits regarding the 2008 subprime crisis data. Section [2.4](#) presents projections for the impact of COVID-19 on the US labor market and the effect of the CARES act followed by the analysis of the French experience in section [2.5](#). Finally, Section [2.6](#) concludes.

¹²[Kapicka and Rupert \(2020\)](#) and [Birinci et al. \(2020\)](#) integrate DMP type models into epidemiological models in order to better analyze the interplay between public health policies and economic efficiency. [Bianchi et al. \(2021\)](#) provide empirical support on links between unemployment changes and health outcomes. This very interesting normative approach is beyond the scope of the present paper.

2.2 Model

We aim to analyze the effect of aggregated and disaggregated shocks within a general equilibrium model with Search and Matching frictions.¹³ We add two important externalities with respect to the canonical DMP model —both of which aim to account for the greatest difficulties in times of crisis. First, the units' recruitment costs increase when unemployment rises, thus magnifying the congestion externality on hirings. Second, the dispersion of idiosyncratic productivities (microeconomic uncertainty) is countercyclical. The consumption choices generate interactions among different labor markets through the endogenous relative prices of goods.¹⁴ Only a mass $1 - \varphi$ of the population has access to financial markets and can finance firms wishing to reopen after activity cessations.¹⁵ We make the assumption that in the financial market, the capitalists can either use their savings to accumulate a storable good or to finance the opening of new jobs.

2.2.1 Consumers

The labor market for each skill s is segmented, and we assume that each skill s can produce only one type of product j (perfect correspondence between s and j). The mass of workers of each skill (educational attainment) is ω_s . The preferences are defined over goods $j \in \mathcal{J}_t \Leftrightarrow s \in \mathcal{S}_t$. When all markets are open, \mathcal{S}_t is $s = 1, \dots, S$, where S is the maximal number of varieties (skills). Otherwise, $\dim(\mathcal{S}_t) = S_t < S$.

Financially unconstrained agents: the capitalist. The capitalists aim to maximize the sum of their discounted utility, which is given by

$$\sum_{t=0}^{\infty} \beta_t^t \left(\frac{(C_t^K)^{1-\nu}}{1-\nu} + A_b B_t \right) \quad \text{with } C_t^K = S_t^{\frac{1}{1-\sigma}} \left(\sum_{s \in \mathcal{S}_t} (C_{s,t}^K)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where C_t^K denotes the basket of consumption goods and B_t the composite storable goods that provide utility. The consumer price index (CPI) is defined by $p_t = \left(\frac{1}{S_t} \sum_{s \in \mathcal{S}_t} p_{s,t}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$

¹³We make abusive use of the term "shock" because we will perform deterministic simulations of unanticipated sequences of exogenous variables.

¹⁴This strategy allows to account for substitution between goods that can be affected differently by the lockdown (see [Krueger et al. \(2020\)](#)).

¹⁵These financial markets are necessary for the borrowing of firms wishing to reenter the market after periods of closure.

and is normalized to unity ($p_t = 1, \forall t$). Storable goods accumulate as follows:

$$B_{t+1} = (1 - \delta)B_t + S_t^{\frac{1}{1-\sigma}} \left(\sum_{s \in \mathcal{S}_t} (I_{s,t}^K)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} - \frac{\varphi}{1-\varphi} \sum_{s \notin \mathcal{S}_t} \omega_s \psi_s \kappa_{s,t} V_{s,t},$$

If a firm chooses to open a vacancy at time t (i.e $V_{s,t}$), it will pay related costs $\kappa_{s,t}$.¹⁶ Hence, we assume that a capitalist finances the firm's reopening costs (i.e., the last term of the last equation). Because markets $s \notin \mathcal{S}_t$ are not open at this period t , the unit cost of each transaction between the capitalist and a reopening firm is ψ_s . The budgetary constraint of this representative agent is

$$\begin{aligned} C_t^K + I_t^K &= \frac{\varphi}{1-\varphi} \left(\sum_{s \in \mathcal{S}_t} \omega_s D_{s,t} - \sum_{s \notin \mathcal{S}_t} \omega_s \psi_s \kappa_{s,t} V_{s,t} \right) - T_{s,t} \equiv \mathcal{R}_t - T_{s,t} \\ \Rightarrow B_{t+1} &= (1 - \delta)B_t + \mathcal{R}_t - T_{s,t} - C_t^K, \end{aligned}$$

where $D_{s,t}$ and $T_{s,t}$ are, respectively, the dividends earned collected from the firms of sectors $s = 1, \dots, S$ and the taxes. When $s \in \mathcal{S}_t$, this dividend is positive, whereas when $s \notin \mathcal{S}_t$, this dividend is negative and equal to $\kappa_{s,t} V_{s,t}$ for each firm planning to reopen in the next period. The Euler equation defines the discount factor $\tilde{\beta}_t = \beta_t \left(\frac{C_{t+1}^K}{C_t^K} \right)^{-\nu}$, where β_t is the discount factor shocks.

In the following, we assume that $B_t > 0, \forall t$.¹⁷ This assumption is sustainable because the pricing of the vacancy costs prior to reopening (ψ_s) can be arbitrarily low. The particular assumptions made with regard to the capitalist's preferences drive consumption to be autonomous; this property implies that all the income fluctuations of the capitalist are absorbed by changes to their inventories B_{t+1} .¹⁸

Financially constrained agents: the workers. Workers are risk-neutral and are characterized by their skill $q = 1, \dots, S$. The preferences of each agent i with the skill q are defined as follows:

$$C_{i,q,t}^L = S_{n,t}^{\frac{1}{1-\sigma}} \left(\sum_{s \in \mathcal{S}_t} (C_{i,q,s,t}^L)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

Their resource constraint is given by

$$I_{i,q,t} = \sum_{s \in \mathcal{S}_t} p_{s,t} C_{i,q,s,t}^L = C_{i,q,t}^L \quad \text{for} \quad I_{i,q,t} = \{w_{i,q,t}(\alpha), b_{i,q,t}\} \quad \forall q = 1, \dots, S,$$

¹⁶See the firms' problem below for more details on $\kappa_{s,t}$

¹⁷Indeed, we must have $B_t \geq 0, \forall t$. When this constraint is binding, this implies that the capitalist cannot finance the reopening costs of the firms; this leads them to close, regardless of anticipated profits.

¹⁸With the solution for the consumption $C_t^K = \left(\frac{\tilde{\beta}_t A_b}{1 - \beta_t(1-\delta)} \right)^{\frac{-1}{\nu}}$, we have $B_{t+1} - (1 - \delta)B_t = \mathcal{R}_t - C_t^K$.

where $w_{i,t}(\alpha)$ denotes the real wage of the employed worker and $b_{i,t}$ is the real unemployment benefit of the unemployed worker.

The value functions of each worker are

$$\begin{aligned} W_{i,q,t}(\alpha) &= w_{i,q,t}(\alpha) + \tilde{\beta}_t \left[(1 - s_{q,t+1}) \int_{\alpha_{q,t+1}^r}^{\infty} W_{i,q,t} \frac{dG(\alpha)}{1 - G(\alpha_{q,t+1}^r)} + s_{q,t+1} U_{i,q,t+1} \right] \\ U_{i,q,t} &= b_{i,q,t} + \tilde{\beta}_t \left[f_{q,t+1} (1 - s_{q,t+1}) \int_{\alpha_{q,t+1}^r}^{\infty} W_{i,q,t} \frac{dG(\alpha)}{1 - G(\alpha_{q,t+1}^r)} + (1 - f_{q,t+1} (1 - s_{q,t+1})) U_{i,q,t+1} \right], \end{aligned}$$

where $\tilde{\beta}_t$ is the discount factor and depends on time t because it is a function of the discount factor shocks. $s_{q,t}$ is the endogenous job-separation rate, and $f_{q,t}$ is the meeting rate between an unemployed job seeker and a vacant job position.

2.2.2 Labor market flows

As in the DMP model, a matching function generates meetings, whereas separations result from the selection of workers that are more productive than an endogenous threshold. Workers and firms direct their search efforts in one submarket corresponding to a skill $s = 1, \dots, S$. Following [Den Haan et al. \(2000\)](#), the matching function for each sector is

$$M_s(U_{s,t}, V_{s,t}) = \frac{U_{s,t} V_{s,t}}{(U_{s,t}^\tau + V_{s,t}^\tau)^{1/\tau}},$$

ensuring that the probabilities of an unemployed worker finding a job per unit of time $f_s(\theta_{s,t}) = \frac{M(U_{s,t}, V_{s,t})}{U_{s,t}} = (1 + \theta_{s,t}^{-\tau})^{-1/\tau}$ and the vacancy to be filled $q_s(\theta_{s,t}) = \frac{M(U_{s,t}, V_{s,t})}{V_{s,t}} = (1 + \theta_{s,t}^\tau)^{-1/\tau}$ are in the interval $[0; 1]$.

At the beginning of each period t , the number of workers inside the firm is the sum of the hirings in the previous period ($q_{s,t-1} V_{s,t-1}$) and the previous employment stock ($N_{s,t-1}$). Then, in each firm i of sector s , an idiosyncratic shock takes place and the productivity of worker ($\alpha_{i,s,t}$) is discovered. There are separations if $\alpha < \alpha_{i,s,t}^r$. This threshold provides the mass of endogenous separations. Note that the pool of separation includes old and new matches. The microeconomic shock α is drawn in the time-varying distribution $G_{s,t}(\alpha)$, which is a log-normal distribution with a mean μ_G and a variation $\sigma_{s,t}$. To account for the increase in microeconomic risk in a recession, we assume that

$$\sigma_{s,t} = \sigma_G \left(\frac{U_t}{U} \right)^{\xi_s}, \quad (2.1)$$

where the current unemployment rate level U_t and its long-term value U are taken as given at the level of the firm i on the labor market segment s . We choose $\frac{U_t}{U}$ to be an indicator

of the crisis. The higher the unemployment rate is far from its steady level, the deeper the economy is in the crisis and the higher the microeconomic risk. Moreover, the parameter ξ controls the impact of the recession on σ_t .¹⁹ Once the information on productivity is revealed, the stock of employment available for production can be determined; from there, wage-bargaining can occur and, finally, production takes place. It is only at the end of period t that the stocks of unemployment ($U_{s,t}$) and employment ($N_{s,t}$) are given, allowing one to determine new matches that occur through the choice of $V_{s,t}$, based on $q_{s,t}$.

The law of motion of employment is

$$N_{s,t} = (1 - s_s)(1 - G_{s,t}(\alpha_{s,t}^r))(N_{s,t-1} + q(\theta_{s,t-1})V_{s,t-1}), \quad (2.2)$$

where $0 < s_s < 1$ is the exogenous probability of job destruction. The job-separation rate is defined by $JSR_t \equiv s_{s,t} = s_s + (1 - s_s)G_{s,t}(\alpha_{s,t}^r)$, and it gives the INs to unemployment, given the information of the period t . The job-finding rate is defined by $JFR_t \equiv f_{s,t} = (1 - s_{s,t+1})f_s(\theta_{s,t})$, and it gives the OUTs to unemployment, taking into account not only the information of period t but also that of period $t + 1$. Finally, the normalization of the population size to unity leads to $\varphi \sum_{s=1}^S \omega_s(U_{s,t} + N_{s,t}) + (1 - \varphi) = 1$.

2.2.3 Firms

For firm i from sector s , hirings result from a search process that consists of posting the number of vacancies $V_{i,s,t}$ that will be matched with unemployed workers with a probability $q_{s,t}$; this is not controlled by the firm. The unit cost, in production units, of each vacancy is given by

$$\kappa_{i,s,t} = \kappa_{s,t} = \kappa_s \left(\frac{U_{s,t}}{U_s} \right)^{\gamma_s} \quad \forall j, \quad (2.3)$$

where both the current unemployment rate level $U_{s,t}$ and its long-term value U_s are taken as given at the level of the firm i on the labor market segment s ; this leads one to interpret the time-varying component of the vacancy cost as a congestion externality.²⁰ Given that γ_s depends on s , this congestion externality is sector-specific. Unit costs are higher during a recession because at such a time, each vacant job (which is scarce in such a period) receives a very large number of applications (and the number of unemployed

¹⁹The countercyclicality of firm-level microeconomic risk is documented by Bloom (2009) and Bloom et al. (2018) and put in light again for the COVID crisis in Bloom et al. (2020).

²⁰We choose the same functional form as Hall and Kudlyak (2020), but we introduce a sector-specific parameter γ_s that induces a sector-specific congestion externality.

individuals is important). Therefore, recessions increase the cost of treatment for each application.²¹

Denoting $\tilde{\alpha}_{s,t} = \frac{\int_{\alpha_{s,t}^r}^{+\infty} \alpha dG_{s,t}(\alpha)}{1-G_{s,t}(\alpha_{s,t}^r)}$, the production function is²² $Y_{s,t} = A_{s,t}A_t\tilde{\alpha}_{s,t}N_{s,t}$, where $A_{s,t}$ and A_t are the skill-specific and aggregate productivity, respectively. Denoting $\tilde{w}_{s,t} = \frac{\int_{\alpha_{s,t}^r}^{+\infty} w_{s,t}(\alpha)dG_{s,t}(\alpha)}{1-G_{s,t}(\alpha_{s,t}^r)}$, and $s_{s,t}^w$ wage subsidies that a firm may receive, the firm's objective is to maximize its discounted profits:

$$\max \sum_{\tau=0}^{+\infty} \tilde{\beta}_t^\tau D_{s,t+\tau} = \max \sum_{\tau=0}^{+\infty} \tilde{\beta}_t^\tau \{p_{s,t+\tau}Y_{s,t+\tau} - (1-s_{s,t+\tau}^w)\tilde{w}_{s,t+\tau}N_{s,t+\tau} - \kappa_{s,t+\tau}V_{s,t+\tau}\},$$

subject to Equation (2.2) and the Kuhn–Tucker conditions, given by²³

$$q_s(\theta_{s,t})V_{s,t} \geq 0, \quad \lambda_{s,t} \geq 0, \quad \text{and} \quad \lambda_{s,t}q_s(\theta_{s,t})V_{s,t} = 0.$$

Regime 1. If the expectation of the average job value is sufficiently large to lead $V_{s,t} > 0$, then $\lambda_{s,t} = 0$. In this case, the dynamics are given by

$$\begin{aligned} 0 &= p_{s,t}A_{s,t}A_t\alpha_{s,t}^r - (1-s_{s,t}^w)w_{s,t}(\alpha_{s,t}^r) + \frac{p_{s,t}\kappa_{s,t}}{q(\theta_{s,t})} \\ \frac{p_{s,t}\kappa_{s,t}}{q_s(\theta_{s,t})} &= \tilde{\beta}_t \left[(1-s_{s,t+1}) \left(p_{s,t+1}A_{s,t+1}A_{t+1}\tilde{\alpha}_{s,t+1} - (1-s_{s,t+1}^w)\tilde{w}_{s,t+1} + \frac{p_{s,t+1}\kappa_{s,t+1}}{q_s(\theta_{s,t+1})} - \lambda_{s,t+1} \right) \right] \end{aligned}$$

Note that when the firm cannot sell today (i.e., $p_{s,t}$ does not exist) but expects a recovery, it can borrow resources from the capitalist and then restart its activity, even after activity cessation in period t .

²¹Blanchard and Diamond (1994) were the first to elucidate the foundations of these countercyclical unit costs, based on the existence of exchange externalities: they show that in a labor market where entrepreneurs prefer hiring short-term unemployed workers, recessions lead to an increase in the share of long-term unemployed workers who then congest the hiring process. Hall and Kudlyak (2020) show why this congestion effect matters if the DMP model is to reproduce the observed persistence of unemployment after a recession. Moreover, Engbom (2019) and Molavi (2018) suggest that countercyclical hiring unit costs are supported by the data.

²²In the following, we omit for simplicity the index i , which denotes firm i in each sector s because the equilibrium is symmetrical within sectors.

²³See Appendix B.2 for more details on the firm's problem solutions.

Regime 2. If the expectation of the average job value is sufficiently low leading to $V_{s,t} = 0$, then $\lambda_{s,t} > 0$. When $V_{s,t} = 0$, we have $\theta_{s,t} = 0 \Leftrightarrow q(\theta_{s,t}) \rightarrow 1$. Therefore, the dynamics are given by

$$\begin{aligned} 0 &= p_{s,t}A_{s,t}A_t\alpha_{s,t}^r - (1 - s_{s,t}^w)w_{s,t}(\alpha_{s,t}^r) + (p_{s,t}\kappa_{s,t} - \lambda_{s,t}) \\ \lambda_{s,t} &= p_{s,t}\kappa_{s,t} - \tilde{\beta}_t \left[(1 - s_{s,t+1}) \left(p_{s,t+1}A_{s,t+1}A_{t+1}\tilde{\alpha}_{s,t+1} - (1 - s_{s,t+1}^w)\tilde{w}_{s,t+1} + \frac{p_{s,t+1}\kappa_{s,t+1}}{q_s(\theta_{s,t+1})} - \lambda_{s,t+1} \right) \right] \end{aligned}$$

When the solution is constrained at $\theta_{s,t} = 0$, then we have $N_{s,t} = (1 - s_s)(1 - G_{s,t}(\alpha_{s,t}^r))N_{s,t-1}$ until $\theta_{s,t+n} > 0$ in n periods. Note that it is possible to reach $N_{s,t} = 0$ if $\alpha_{s,t}^r$ leads to $G_{s,t}(\alpha_{s,t}^r) = 1$.

2.2.4 Wages

To determine the equilibrium wage, we use a sharing rule of a generalized Nash bargaining process between the worker and the firm where $\eta_s \in (0, 1)$ is the heterogeneous workers' relative bargaining weight and $b_{s,t}$ is the heterogeneous workers' flow value of unemployment activities. Moreover, as usual in quantitative evaluation of standard DMP models, it is relevant to introduce real wage rigidities²⁴ — recently reaffirmed by the studies of Kurmann and McEntarfer (2019) and Jardim et al. (2019)²⁵ and put back in the spotlight by Cortes and Forsythe (2020) using the COVID-19 crisis experience²⁶. There are several ways to introduce real wage rigidities in DMP models: (i) an alternating offer bargaining game as in Hall and Milgrom (2008) or (ii) the incorporation of a wage norm or social consensus as in Hall (2005). Following Blanchard and Gali (2010) or Leduc and Liu (2019), we adopt the second modeling strategy, knowing that its implications are quite similar to the first one. Therefore, the real wage is a weighted average of the Nash bargaining wage and the steady state wage:

$$w_{s,t}(\alpha) = \varrho_s \left[\frac{\eta_s}{1 - s_{s,t}^w} (p_{s,t}\alpha A_s A_t + p_{s,t}\kappa_{s,t}\theta_{s,t}) + (1 - \eta_s)b_{s,t} \right] + (1 - \varrho_s)w_s, \quad (2.4)$$

²⁴See, among others, Blanchard and Gali (2010), Christiano et al. (2016), Leduc and Liu (2019), Petrosky-Nadeau and Zhang (2021). These papers show that DSGE models with a labor market *à la* DMP must introduce real wage rigidities to fit the observed characteristics of the US business cycle.

²⁵These studies show that roughly 20% of job stayers experienced nominal wage cuts during the recession, while less than 10% had their earnings frozen. See also the survey of Elsby and Solon (2019).

²⁶They show that earnings changes for workers who remain employed during the COVID-19 crisis are not atypical during this time period.

The free parameter $\varrho_s \in [0, 1]$ measures the skill specific wage rigidity, and w_s the steady-state average wage for each s -type worker. Following [Daly et al. \(2012\)](#) empirical study²⁷, we assume that wage rigidity decreases with educational level. Hence, we assume that $\varrho_s = a_\varrho x + b_\varrho$ where $a_\varrho < 0$.

2.2.5 General equilibrium

In the following, we normalize the CPI $p_t = 1, \forall t$.

Demand. Given that the baskets of consumption and inventories are described by the same constant elasticity substitution functions, the aggregate demand for each sector ($Y_{s,t}^D$) is given by

$$Y_{s,t}^D = p_{s,t}^{-\sigma} \left(\frac{\varphi \sum_{j \in \mathcal{S}_t} \omega_j C_{j,t}^L + (1 - \varphi) (C_t^K + I_t^K)}{S_t} \right),$$

implying that the aggregate demand is $Y_t^D = \sum_{s \in \mathcal{S}_t} p_{s,t} Y_{s,t}^D$.

Supply. In each goods market, the aggregate supply $Y_{s,t}^S$ is given by

$$Y_{s,t}^S = \omega_s (Y_{s,t} - \kappa_{s,t} V_{s,t}),$$

implying that the aggregate supply is $Y_t^S = \sum_{s \in \mathcal{S}_t} p_{s,t} Y_{s,t}^S$.

Government. The budgetary constraint of the government is

$$(1 - \varphi) T_{s,t} = \varphi (b_{s,t} (1 - N_{s,t}) + s_{s,t}^w w_{s,t} N_{s,t}).$$

Equilibrium. Given that $Y_{s,t}^D = Y_{s,t}^S \equiv Y_{s,t}^*$ at the equilibrium, $\forall s$ —which implies $Y_t^D = Y_t^S \equiv Y_t^*$ —the equilibrium prices are deduced from

$$p_{s,t} = \left(\frac{1}{S_t} \frac{Y_t^*}{Y_{s,t}^*} \right)^{\frac{1}{\sigma}} \quad \forall s \in \mathcal{S}_t.$$

Labor market. Using the wage equation (Equation [\(2.4\)](#)), we obtain the job-destruction condition (reservation productivity), and the job-creation condition (hirings)²⁸:

$$\alpha_{s,t}^r = \max \left\{ 0; \frac{1}{(1 - \eta_s \varrho_s) p_{s,t} A_{s,t} A_t} \left(\begin{array}{l} \varrho_s (1 - \eta_s) (1 - s_{s,t}^w) b_{s,t} + \varrho_s \eta_s p_{s,t} \kappa_{s,t} \theta_{s,t} \\ + (1 - \varrho_s) (1 - s_{s,t}^w) w_s - \left(\frac{p_{s,t} \kappa_{s,t}}{q(\theta_{s,t})} - \lambda_{s,t} \right) \end{array} \right) \right\} \quad (2.5)$$

$$\frac{p_{s,t} \kappa_{s,t}}{q_s(\theta_{s,t})} - \lambda_{s,t} = \tilde{\beta}_t \left[(1 - s_{s,t+1}) \left(\begin{array}{l} p_{s,t+1} A_{s,t+1} A_{t+1} \tilde{\alpha}_{s,t+1} - (1 - s_{s,t+1}^w) \tilde{w}_{s,t+1} \\ + \left(\frac{p_{s,t+1} \kappa_{s,t+1}}{q_s(\theta_{s,t+1})} - \lambda_{s,t+1} \right) \end{array} \right) \right] \quad (2.6)$$

²⁷See [frbsf website](#) for updated data until 2020

²⁸The job-creation condition is obtained by regrouping Equations [\(B.4\)](#)–[\(B.7\)](#) of Appendix [B.2](#)

Closure and reopening of a business sector. A recession can lead one sector s to close ($N_{s,t} = 0$) or be unable to sell ($Y_{s,t} < \kappa_{s,t}V_{s,t}$) in period t . If this is the case, then the number of exchanged varieties is lower than its maximal number (i.e., $\dim(\mathcal{S}_t) < S$). At the same time, the entrepreneur's expectations can lead them to reopen in $t + 1$. Therefore, it is necessary to borrow in t from the capitalist an amount of their storable goods to post vacancies at period t in order to restart the activity in $t + 1$. Given that this sector s has a "negative" net supply ($Y_{s,t}^S = \omega_s (Y_{s,t} - \kappa_{s,t}V_{s,t}) < 0$), there are no sales for sector s in period t . Without any information on the relative price of these goods s in t , this transaction is valued at the price ψ_s in the budget constraint of the capitalist.²⁹ If the capitalist does not exist, firms cannot reopen after a period without sales.

Note that we choose to focus on sectors that match the educational attainment. Hence, neither this crisis nor the previous ones have resulted in a total shutdown of the production of one of those sectors. Nevertheless, COVID-19 led to a total shutdown of some industries (non-food retail, restaurants, hotels, or leisure services). Hence, if the model aims to replicate the impact on industries rather than education, we would need to address the scenario of "closure and reopening of a business sector". Therefore, in Appendix B.3, we run a simulation where the economy is hit by a shock high enough to result in the closure of some sectors. This sheds light on the importance of this formulation of the capitalist.

2.3 Calibration based on the subprime crisis experience

This section presents our calibration strategy. We use worker flows by education level to identify the parameters allowing the model to explain the 2008 subprime crisis, driven by a common shock in each labor market segment.

2.3.1 Parameters based on external information

The model is calibrated at a monthly rate. Thus, the average value for $\tilde{\beta} = 1/(1 + 0.0573)^{1/12}$.³⁰ For the capitalist's preference parameters, we set $\delta = 0.025/12$ following Harding et al. (2007); we also set $\nu = 1.7$, which is in the range of the estimation of Attanasio and Vissing-Jorgensen (2003). We calibrate the share of this population to represent 2% of the overall population, with a saving rate of 10% (See Saez and Zucman

²⁹This shadow price ψ_s is calibrated such that the storable goods of the capitalist always respect $B_t > 0$.

³⁰This value matches the mean discount rate in a historical cross-country panel of asset prices data used in Petrosky-Nadeau et al. (2018), which is 5.37% per annum.

(2014)). This allows us to deduce the steady-state values for C^K and B^K and identify A_b . For the workers, we normalize the average of the aggregate productivity component to unity ($A = 1$). Each “sector” represents the production of a worker type, which is identified by their educational attainment.³¹ We restrict the log-normal distributions of α to be the same for each subpopulation, with a zero mean and a standard deviation equal to 0.12, as in Krause and Lubik (2007).

2.3.2 Parameters based on first-order moments restrictions

Using data from Cairo and Cajner (2016), we derive worker flows based on Current Population Survey (CPS) data (January 1976–January 2014). To use a larger sample, we rescale these data to be coherent with aggregate worker flows calculated from US Bureau of Labor Statistics (BLS) data (1947–2020).³² The first-order moments of worker flows used to identify the model parameters are shown in Table 2.1, where all job-finding rates (JFR) are the same, as they are not significantly different from the average. At the steady state, these moments are linked by the restrictions $UR_s = \frac{JSR_s}{JSR_s + JFR_s}$. Assuming,

	LHS	HS	Coll.	Bach.
JFR	0.408	0.408	0.408	0.408
JSR	0.051	0.029	0.024	0.013
UR	0.112	0.066	0.056	0.030
Population shares	9.480%	31.976%	31.166%	27.378%

Table 2.1: **Worker flows and stocks.** Data came from Cairo and Cajner (2016) and cover the 1976–2014 period; we rescaled these data. For population shares, the data came from the BLS and cover the 2000–2020 period. The educational attainment typologies are as follows: less than high school diploma (LHS), high school diploma (HS), college diploma (Coll.) and bachelor degree or more (Bach.).

as in Den Haan et al. (2000) or Krause and Lubik (2007), that 68% of the separations are exogenous, the job-separation rates by skill (JSR_s) give the equilibrium values of the productivity reservation threshold (α_s^r). Using the job-finding rates by skill (JFR_s), we deduce the equilibrium value of the skill specific unemployment rate (θ_s). Applying the definitions of the skill specific unemployment rate (UR_s), we can then deduce vacancies (V_s) at the steady state. Finally, with the log-normal distribution of α , we deduce the

³¹As this characteristic practically does not change after entering the labor market, this segmentation justifies the absence of mobility between “sectors” assumed in our model.

³²See Appendix B.4 for more details on the data.

	LHS	HS	Coll.	Bach.
Endogenous separation rate s_s^{endo}	0.0171	0.0094	0.0078	0.0041
Exogenous separation rate s_s^{exo}	0.0350	0.0196	0.0163	0.0086
Average worker's productivity $\tilde{\alpha}_s$	1.0118	1.0099	1.0095	1.0085
Bargaining power η_s	0.4247	0.4849	0.4999	0.5410
Ratio of home production to production in business $\tilde{b}_s/\tilde{\alpha}_s$	0.9467	0.9418	0.9401	0.9342
Skill-specific firm productivity A_s	0.5145	3.4297	4.6644	8.5056

Table 2.2: **Results of the calibration using labor market restrictions.**

mean productivity of each skill ($\tilde{\alpha}_s$). Using Equations (2.5)–(2.6) taken at the steady state and assuming that κ_s is proportional to A_s , s.t. $\kappa_s = kA_s$, we identify η_s and $\tilde{b}_s \equiv b_s/(p_s A_s)$, which are thus skill-specific. The value of k is chosen such that the average bargaining power over all skills is equal to 1/2.³³

Moreover, we restrict the set of parameters to minimize the distance between the skill-specific relative wage in the model and its empirical counterpart.³⁴ Hence we restrict the values of $\{A_s\}_{s=1}^S$ such that the model matches the average wages by education level, as observed in the United States:

$$\frac{w_s^{data}}{\text{mean}(w_s^{data})} = \frac{p_s A_s \Gamma_s}{\sum_{s=1}^S \tilde{\omega}_s p_s A_s \Gamma_s} \quad \text{with } \Gamma_s = \eta_s(\tilde{\alpha}_s + k\theta_s) + (1 - \eta_s)\tilde{b}_s,$$

where empirical data are denoted as w_s^{data} . Nevertheless, this restriction depends on the equilibrium prices p_s . Therefore, this identifying system is solved using all the general equilibrium restrictions:

$$p_s = \left(\frac{1}{S} \frac{\sum_{s=1}^S p_s \omega_s (Y_s - \kappa_s V_s)}{\omega_s (Y_s - \kappa_s V_s)} \right)^{\frac{1}{\sigma}} \quad \text{with } Y_{s,t} = A_s N_s \tilde{\alpha}_s,$$

which give the consistent relative prices p_s , $\forall s$. This procedure obtains a unique solution if we add the normalization $\sum_s \omega_s p_s A_s = 1$ (i.e., the average productivity is equal to unity). The results of this calibration procedure are reported in Table 2.2

2.3.3 Parameters based on out-of-steady state model implications

To generate a financial crisis, we introduce a common financial shock—which is to say, one that strikes all economic players uniformly—to reproduce the depression and recovery

³³See Appendix B.5 for more details.

³⁴The wage statistics derive from weekly and hourly earnings data from the CPS, over the 2000 Q1 to 2020 Q1 period.

observed in the US labor market. Following [Hall \(2017\)](#), we model this financial shock as a drop in the discount rate, as if this rate included variations in the risk premium.^{[35](#),[36](#)} Given that the DMP model is an asset-pricing model, expectations in the risk premium are important for valuating jobs, and so they have a direct impact on hiring and separation decisions. By reducing the discount factor, the financial crisis reduces the discounted value of expected profits, then instantaneously reduces (increases) hirings (separations). We assume that the sequence of β_t is given by the following process:

$$\beta_t = \rho_b \beta_{t-1} + (1 - \rho_b) \beta - \frac{\epsilon_{b,0}}{\vartheta_b^{(t/\mu_b)}},$$

Which is closed to an ARMA(1,1) process, where the AR component is driven by the parameter ρ_b , and the MA component is given by, $\frac{\epsilon_{b,0}}{\vartheta_b^{(t/\mu_b)}}$ (the parameters μ_b determines the hump-shape of MA component)^{[37](#)} To identify the remaining parameters

$$\Psi = \{\sigma, \tau, \{\xi\}_{s=1}^S, \{\gamma_s\}_{s=1}^S, a_\varrho, b_\varrho, \rho_\beta, \epsilon_{\beta,0}, \vartheta_\beta, \mu_\beta\},$$

with $\dim(\Psi) = 8 + 2 \times S$ and $S = 4$, we choose moments that describe the worker flows during the 2008 subprime crisis (i.e., the most recent crisis, prior to COVID-19). This allows the model to reveal under which restrictions it can generate a deep crisis.^{[38](#)}

We identify Ψ using

$$\Phi = \left\{ \left\{ \{JSR_{s,t}\}_{t=t_0}^{t_1}, \{JFR_{s,t}\}_{t=t_0}^{t_1} \right\}_{s=1}^S \right\},$$

where t_0 corresponds to September 2008 and t_1 to December 2013. Given that $\dim(\Phi) = 64 \times 4 \times 2 = 512 > \dim(\Psi) = 16$, this strategy can be interpreted as an informal test

³⁵Indeed, the risk premium data exhibited a prominent spike in 2008–2009, when it exceeded its historical average during this Great Recession: the difference between the yield on a risky bond (given by the 5-Year High Quality Market (HQM) Corporate Bond Spot Rate) and the yield on a Treasury bond of equivalent maturity rose from 0.6 points in January 2007 to 5.45 points in October 2008. In 2008, the expectations of an increase in risk led to an increase in the risk premium and thus induced a drop in the discount factor. Since the risk premium measures expectations of credit risk and default in the economy, it serves as an important measure by which to monitor markets and ascertain whether a downturn is expected in the near future.

³⁶In [Martellini et al. \(2020\)](#), a discount rate decrease- by reducing the expected profits- cuts incentives to open vacancies, but also the job-to-job mobilities and thus job separations, given that agents can search on-the-job. Hence, the impact of discount rate changes on unemployment is ambiguous. This is not the case in our model where the reduction of the expected profits cuts the job finding rates and raises job separation rates leading unambiguously to unemployment increases.

³⁷See Appendix [B.6](#) for the figure of β_t .

³⁸We assume that the economy is initially at the steady state. At date t_0 , the aggregate shock makes the economy deviate from its steady path. At the final date t_* , the economy converges back to its steady state. We set $T = t_* - t_0 = 120$, which means that 10 years after the shock, the economy has reverted to its steady state.

of the model³⁹ We search Ψ , which minimizes the root mean square error for each time series in Φ . Table 2.3 reports the value of the identified parameters.

Common Parameters		σ	τ	a_ϱ	b_ϱ
		2	1.5	-0.14	0.57
		ρ_b	$\epsilon_{b,0}$	ϑ_b	μ_b
		0.1	0.085	1.17	2.6
		LHS	HS	Coll.	Bach.
Specific Parameters	ξ_s	0.6	0.55	0.5	0.35
	γ_s	0.9	0.6	0.5	0.3
Equilibrium values	p_s	4.68	0.96	0.83	0.65
	$p_s A_s$	2.41	3.30	3.88	5.51
	$\frac{w_s}{\sum_s \omega_s w_s}$	0.61	0.83	0.96	1.36

Table 2.3: **Results of the calibration.**

With these parameters, our model appears to reproduce the magnitude and persistence of the impact of this crisis, as well as these contrasted impacts on heterogeneous workers (see the Figures in Appendix B.6). The peak in unemployment for those with a diploma, lower than those issued in high schools, saw a four points increase in the unemployment rate compared to the 2008 summer level. This increase was by only 3.3 points for those who graduated from a high school, 3 points for those with a diploma issued by a college, and 1.7 points for those having a bachelor degree or more. The model succeeds in reproducing this heterogeneity in the labor market. Consistent with the work of Cairo and Cajner (2016), these differences in the adjustment of unemployment rates are due to the greater amplitudes of separations according to educational attainment: less-educated graduates lose their jobs more easily than more-educated ones, while for all types of graduates the chances of finding a job decrease in the same proportions. Therefore, endogenous separations are crucial for explaining heterogeneity in unemployment dynamics.

³⁹In accordance with the model where the participation rate is constant and mobility across submarket is nil, the job finding and separation rates ($JFR_{s,t}$, $JSR_{s,t}$) give the unemployment rate ($UR_{s,t}$), $\forall s, t$.

Our model generates a large endogenous persistence: unemployment reverts to its initial value after seven years. Hence, it appears to reproduce the magnitude and the persistence of a crisis, as well as the contrasted impacts on heterogeneous workers.⁴⁰ For these reasons, this model can be used to predict economic fallout dovetailing from the COVID-19 crisis.

2.4 Explaining the impact of COVID-19

We model the lockdown as restrictions on transactions that change supply as if the TFP has been reduced. To damp the impact of these restrictions, government has implemented a new policy: the CARES act.

2.4.1 Modelling the CARES acts

We consider the CARES acts in two ways: (i) The Pandemic unemployment programs and (ii) The Paycheck Protection Program.

The Pandemic unemployment programs. Government launched a \$439 Billion Federal Pandemic Unemployment Compensation (FPUC) program in two rounds. The first round (r1) adds \$600 in weekly benefits for all eligible unemployed workers from April through the end of July while the second (r2) adds \$300 from December through September. Nevertheless, all claimers did not perceive these benefits: only a half (49.3% exactly) of initial claimers received it between March 2020 and July 2021 (see the Unemployment Insurance Data Dashboard of [The Century Foundation](#)). This leads us to increase the UI by only \$300 and \$150 respectively in the first and second rounds of the FPUC.⁴¹ Moreover, although, the FPUC was approved to last until September, almost half of states chose to end it by June, leading us to weight this benefit increase by a probability from June onward (see Table [2.4](#)). Despite this imperfect coverage, the FPUC pushed up the average unemployment benefits close to the average wage for workers with the lowest educational attainment.

⁴⁰Note that during this crisis all four sectors remained open (*i.e* $S=4 \forall t$ during the crisis)

⁴¹[Ganong et al. \(2020\)](#) show that the median statutory replacement rate was 145%. This is significantly larger than the largest replacement rate -taking into account the percentage of claimers who have received this benefit- in our calibration. We restrict the model to the case where employment is the dominant strategy for the workers, otherwise, no equilibrium can be found.

	LHS	HS	Coll.	Bach.
Basic UI program				
w (\$ per week)	592	746.8	856	1368
$UI = \min\{\tau \times w; UI^{max}\}$ (\$ per week)	266	336	385	500
FPUC round 1 (r1)				
UI_{r1} , April-July 2020 (\$ per week)	566	636	685	800
UI_{r1}/UI	2.13	1.89	1.78	1.6
FPUC round 2 (r2)				
$UI_{r,0}$, December 2020-May 2021 (\$ per week)	416	486	535	650
$UI_{r2,0}/UI$	1.56	1.44	1.39	1.3
$UI_{r2,1}$, June 2021 (\$ per week)	347	417	466	581
$UI_{r2,1}/UI$	1.30	1.24	1.21	1.16
$UI_{r2,2}$, July-August 2021 (\$ per week)	338	406	454	570
$UI_{r2,2}/UI$	1.27	1.21	1.18	1.14

Table 2.4: **The Pandemic unemployment programs.** w are the average 2019 wages from [BLS](#). $\tau = 0.45$ is the homogeneous replacement rate from the [US Department Of Labor: UI Replacement Rates](#) and the maximum of UI is set to $UI^{max} = 500$. The eligibility rate: As 23 States interrupted the program in June 2021, and 3 additional in July, the probability of a US unemployed worker to benefit from the program goes from 1 to $1 - 23/50 = 0.54$ in June and $1 - 26/50 = 0.48$ from July.

The Paycheck Protection Program. CARES act also provides incentives for firms to hold back their workers through the Paycheck Protection Program (PPP). Firms that borrowed from the government through the Paycheck Protection Program (PPP), may be eligible for loan forgiveness if (i) employee and compensation levels are maintained, (ii) the loan proceeds are spent on payroll costs and other eligible expenses, and (iii) at least 60% of the proceeds are spent on payroll costs.⁴² There were two draws of PPP, the first begins in April 2020 and ends by August 2020 and the second takes place from January 2021 to May 2021. Each firm can claim up to 2.5 times its average monthly payroll costs during the first round and up to 3.5 for the second. Borrowers can ask for a loan during the first, the second or both draws. Small Business Administration (see [SBA](#)) provides information on the number of loans granted and the amount of these loans (see Table [B.2](#) in Appendix [B.7](#)). We transform these loans into employment subsidies, assuming for

⁴²Up to January 2, 2022, 80% of the loans were forgiven according to Small Business Administration see [the Forgiveness reports](#).

simplicity that 100% of the PPP are subsidies. This due to the fact that in October 2021, 73% of the PPP loans are actually transformed to subsidies, 25% of the PPP are loans for which firms ask a transformation to a subsidy, and only 2% are loans (source: [Small Business Administration](#)).

Let's denote the average transfer T_{PPP} received one time by a representative firm during the period going from April to July 2020 (this transfer is given by the total amount of loan divided by the total number of borrowers). If all US jobs were covered by these loans, then the total payroll (wN) subsidized would be $T_{PPP}/(wN)$. Nevertheless, only 84% of jobs were covered by a PPP loan in July, thus leading to actual subsidies for a representative job to be $0.84 \times T_{PPP}/(wN) \approx 0.41$ over these 4 months.⁴³ Using the stock of the total amount of loans and of the total number of borrowers observed in August, we can estimate that 90% of jobs were covered by the PPP over these first 5 months. This leads to an average subsidy for each firm of 44% of its monthly payroll. We have smoothed this transfer over these 5 months by assuming that the larger amount of it is used at the beginning of the crisis when the restrictive measures of the lockdown are stricter. We assume that $s_{s,t}^w = \iota_s^w(a_{w1} \times t + b_{w1,s})$, with $a_w < 0$. We introduce the parameter ι_s^w which depends on the distribution of educational attainment by industry and thus accounts that the job subsidies are heterogeneous among workers' types (see Table [B.1](#) in Appendix [B.7](#)). The 5 parameters $\{a_{w1}, \{b_{w1,s}\}_{s=1}^4\}$ will be estimated through the model but are restricted to satisfy $\sum_s \sum_{t=1}^5 \omega_s s_{s,t}^w = 0.44$, which is the target for the PPP loans actually distributed during the first draw. For the second PPP round (between January 2021 to May 2021), we use the same strategy to calibrate the payroll subsidies (a_{w2} and $b_{w2,s}$), except that the covered employment is only 47% (52% of the covered employment of the first round, i.e. 90%) as the total amount of loans in this round represents 52% of the first one. Hence, over these last 5 months, the average subsidy for each firm is 9.4% of its monthly payroll.

Lockdown restrictions: TFP and wage bargaining. Using the COVID-19 Stringency Index^{44,45}, we determine the relevant lockdown months. We assume that lockdown also blocks the wage bargaining processes. Therefore, wages keep their February 2020 level until July 2020 (March 2021) during the first (second) lockdown. After this period, we assume that the bargaining processes take place progressively as the other activities.

⁴³We calibrate $w = 962,81$ and $N = 50$ based on [BLS: Employment by size of establishment](#).

⁴⁴The stringency index is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest). If policies vary at the subnational level, the index shows the response level of the strictest subregion.

⁴⁵Data is available from [the Oxford COVID-19 Government Response Tracker](#)

Hence, an "intermediate" wage rigidity is implemented until it converges toward its pre-crisis level. With these assumptions, the large increases in the UB do not affect the workers' wages. This absence of wage reaction to changes in UB has some empirical support. First, Cortes and Forsythe (2020) showed that conditional on remaining employed, earnings changes during the pandemic were not atypical on average. Second, given the insignificant number of hires during the lockdown, we can not observe re-employment wages. These two points support our assumption of a zero-elasticity of wages to UB during these periods.

	Wave 1	Wave 2
TFP shocks		
Lockdown	March to September 2020 Period $T1$	November 2020 to May 2021 Period $T2$
Wage Bargaining		
Blocked ($\varrho_{s,t} = 0$)	April to July 2020 Period T^{w1}	November 2020 to March 2021 Period T^{w2}
Intermediate wage rigidity ($0 < \varrho_{s,t} < \varrho_s$)	August to September 2020 Period $T3$	April 2020 to August 2021 Period $T4$

Table 2.5: **Lockdown Timing.**

Recalls. Figure 2.3 illustrates that during the COVID-19 crisis, there was a significant rise in temporary separations, indicating a higher utilization of recalls. This option reduces the expenses associated with hiring during the recovery period since recalled workers do not need to go through the same interviewing process as unemployed individuals.⁴⁶ Therefore, we assume that the costs of job vacancies is inversely related to the occurrence of temporary layoffs. In other words, if the proportion of permanent layoffs decreases from the pre-crisis level observed in February, the costs associated with job vacancies will decrease accordingly. Moreover, we assume that a reduction in permanent layoffs during period t will lead to a decrease in vacancy costs in the subsequent period $t + 1$ as they will be recalled in future periods. To express this relationship more formally, let's denote the data on permanent layoff levels as PL. Consequently, we assume that the unit cost of a vacancy ($\tilde{\kappa}_{s,t}$) is given by:

$$\tilde{\kappa}_{s,t} = \left(\frac{PL_{t-1}}{PL_{February}} \right)^{v_\kappa} \times \kappa_{s,t}$$

⁴⁶This point has been already suggested by Gregory et al. (2020) and supported by empirical analysis provided by Chodorow-Reich and Coglianese (2021).

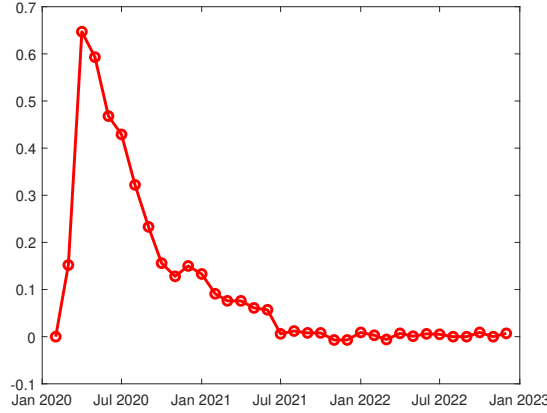


Figure 2.3: **Temporary Layoffs.**

Model calibration. The empirical studies of [Adams-Prassl et al. \(2020\)](#) and [Fana et al. \(2020\)](#) have also shown that the lockdown measures have unequal impacts on workers. This suggests that the lockdown shocks are worker-skill-specific. Assuming that the structure of the US economy has not changed, we use our model, calibrated on the subprime crisis, to reveal the monthly sequences of shocks that have hit each type of job since March 2020. We find these sequences of skill-specific shocks by minimizing the distance between data and simulated data. Hence, we aim to identify the following parameters

$$\Gamma = \left\{ \{A_{s,t}\}_{t \in T1 \cup T2}, \{\varrho_{s,t}\}_{t \in T3 \cup T4}, a_{w1}, b_{w1,s}, a_{w2}, b_{w2,s}, v_{\kappa} \right\}_{s=1}^S \quad \dim(\Gamma) = 95$$

that allow the model to match the following moments:

$$\Upsilon = \left\{ \{UR_{s,t}\}_{s=1}^{S-1}, JFR_t, JSR_t \right\}_{t=\text{March 2020}}^{\text{December 2022}}.$$

Given that $\dim(\Upsilon) = 34 \times 5 = 170 > \dim(\Gamma)$, this strategy can be interpreted as an informal test of the model. Beyond revealing the unequal impact of the lockdown shocks on each specific occupation, we can also use the model to predict the persistence of the crisis and the effect of the CARES act.

2.4.2 Explaining unemployment during the pandemic crisis

Identifying economic counterparts of restrictive measures. Figure [2.4](#) shows the sequences of TFP shocks that allow the model to match the disaggregate unemployment rate, as well as the aggregate job-finding and separation rates (Υ). This figure highlights the large unequal impact of lockdown measures, as suggested by [Adams-Prassl et al. \(2020\)](#), [Fana et al. \(2020\)](#), [Lee et al. \(2021\)](#) and [Falk et al. \(2021\)](#). In March 2020, the

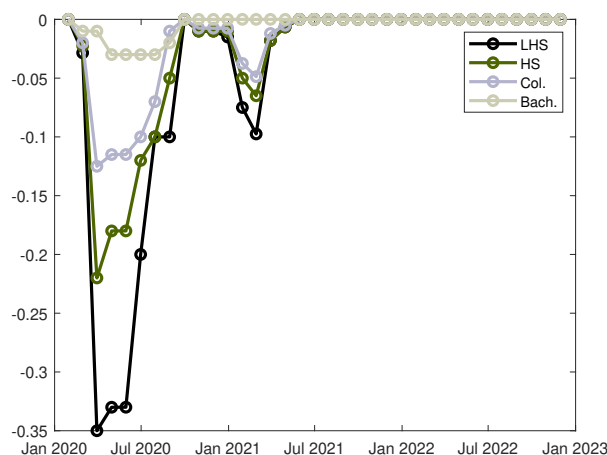


Figure 2.4: **The economic counterparts of restrictive measures: TFP changes.**

lockdown measures had a negative but moderate impact, estimated between -1% and -2.85% of TFP. In April, the impact of the lockdown was much greater and very unequal. For those with less than a high school diploma, the lockdown reduced workers' productivity by 35%, while those who hold a bachelor degree or more saw their productivity decrease by only 3%. For the two other worker types, the negative impact of the lockdown on TFP was between these two extremes (i.e., -22% for those with a high school diploma and -12.5% for those with a college diploma). Subsequently—which is to say, from June 2021, the month in which the severe restrictions ended—productivity returned to its pre-crisis levels, suggesting that economic efficiency is no longer reduced by these restrictive measures. During the second wave, the restrictions were less strict and induced a decrease in the workers' productivity from -4.88% for workers holding a College degree to -9.75% for those with less than a high school diploma (see Figure 2.4). Note that the larger price increase of goods produced by the more restricted activities mitigates the negative impact of the reductions in TFP (modeling the sales' restrictions).⁴⁷ This makes an echo to Krueger et al. (2020)'s results showing that endogenous shifts in private consumption behavior across sectors of the economy can dampen the impact of a lockdown episode. But, given the observed skill-specific unemployment dynamics, price adjustments are dominated by the TFP declines.

Identifying the CARES act shock. For the government subventions on wages, the estimated impact of the CARES act are reductions from 25% for Less than High School workers to 10.2% for those with a Bachelor and more. These cost reductions linearly decline at the same speed for all workers until becoming nil by the end of August 2020

⁴⁷See Appendix B.8 for the prices dynamics.

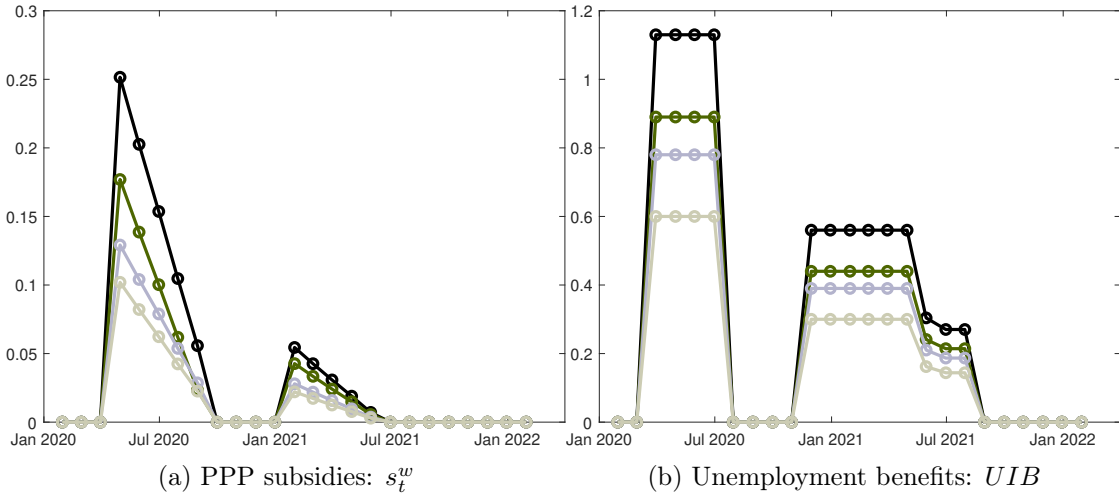


Figure 2.5: CARES act shocks.

for the first round and by the end of May 2021 for the second one (see panel (a) of Figure 2.5). Finally, for the UIB, the estimated impact of the CARES act are increases up to 113% for less than high school workers and up to 60% for those having a Bachelor or more (see panel (b) of Figure 2.5). This underlines the unequal effect of COVID-19 on different worker types.

Model fit. Figure 2.6 shows that (i) data includes a turning point directly by the end of the lockdown and (ii) the recovery observed after this date is, at this time, largely more rapid than those seen in previous crises. This suggests that the shock was brutal and stronger than in previous crises. However, the smaller persistence suggests that the large incentives for holding back workers offered by the CARES act have changed the hiring and separation behaviors. Note that, these supportive results for the CARES acts depend on the absence of wage bargaining during the lockdowns which largely dampens the potentially negative impact of the UI rise on employment.

Unemployment peak. With the calibrated shocks, the model reproduces the 11-percentage-point increase in US unemployment (see Panel (c) of Figure 2.6). The shock sequences that allow the model to match the disaggregated unemployment rates must hit workers unequally, because the increase in unemployment rate among those with less than a high school diploma was by 14.8 percentage points, whereas for those with a bachelor degree or more was by only 6.3 percentage points (see Figure 2.7). This sharp rise in unemployment is largely due to the impressive rise in layoffs (see Panel (b) of Figure 2.6). Panel (d) of Figure 2.6 shows the contributions of separations and findings in unemployment dynamics. The initial increase in unemployment is mainly due to separations (84% of the initial jump

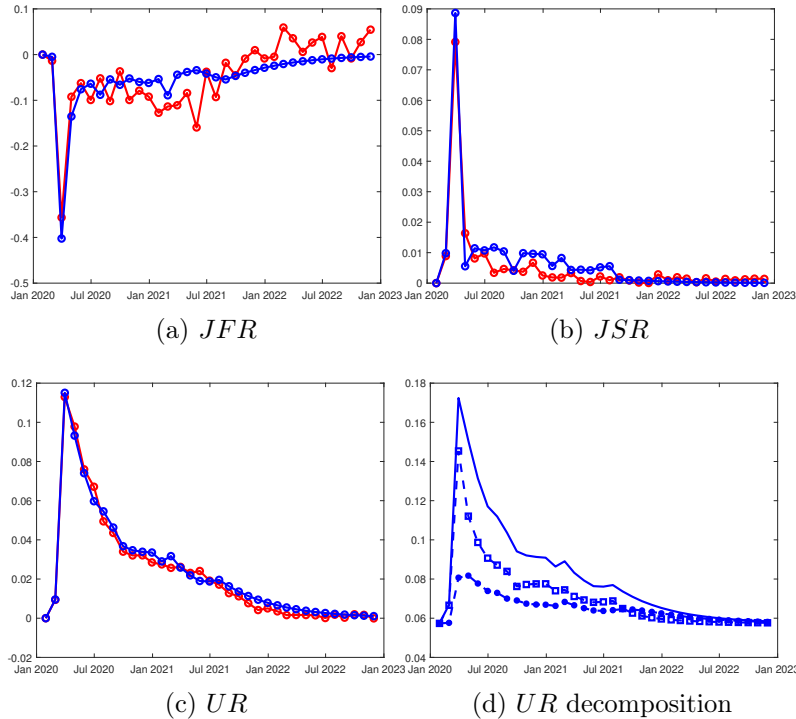


Figure 2.6: **Aggregate outcomes.** Panels (a)–(c). Red lines: data; Blue lines: model. Panel (d). Line: benchmark case; Dotted line with circles: unemployment rates when JSR are at their steady-state levels; Dotted line with squares: unemployment rates when JFR are at their steady-state levels.

in the unemployment rate); however, after three months, unemployment rate adjustments are driven by both separations and the job-finding rate.⁴⁸

Unemployment persistence. The rapid decline in unemployment is observed for all worker types: in the four labor markets, the fall in unemployment in June had already absorbed nearly half of the increase recorded in April, at the peak of the crisis. Therefore, this very strong recovery requires a very sudden shock sequence for some submarkets, but very little persistence for all. This explains the shapes of the TFP drops. At the same time, the high speed of unemployment decline, which has never been observed in the previous crisis, requires a significant government intervention explained by the generous wage subventions (see panel (a) of Figure 2.5). This allows the model to match a lower unemployment persistence compared to the previous crises.⁴⁹

⁴⁸See Appendix B.8 for more details on labor market indicators by education level.

⁴⁹The model underestimates the power of the recovery. Greig et al. (2021) examine the path of liquid balances during the pandemic for different income levels and family structure. They show that the economic stimulus has led to elevated balances, especially for lower-income families and also families with kids (those with high marginal propensities to consume). This suggests that some demand shocks, not taken into account in our model, would be useful to better model the recovery.

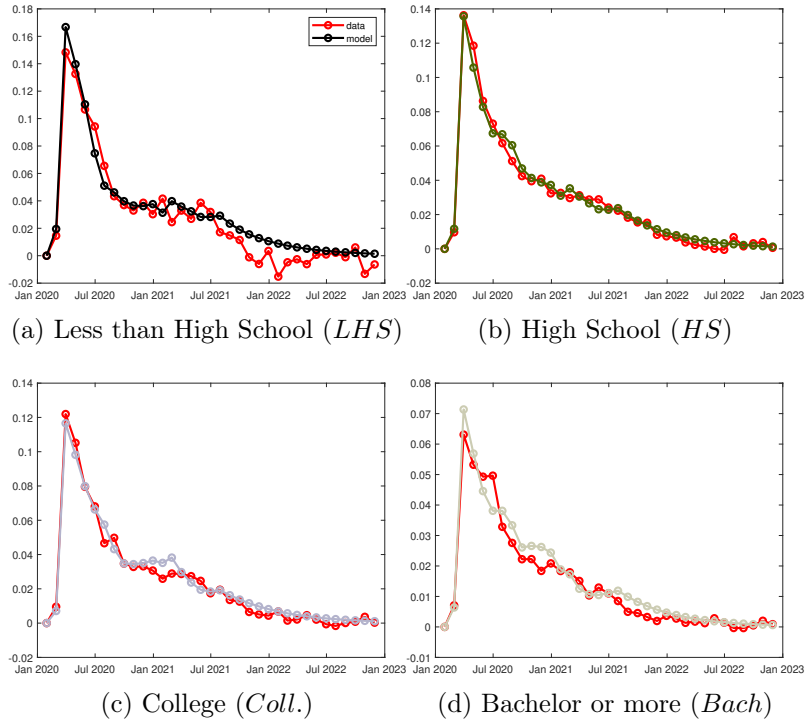


Figure 2.7: Disaggregate unemployment rate.

2.4.3 Disentangling the impact of the CARES act

To isolate the impact of the CARES act, we build the counterfactual simulation where the labor market institutions are stable: *(i)* the PPP subsidies are not introduced and *(ii)* there is no change in UB nor in wage rigidity. Without the CARES act, simulation results show that the unemployment rate would be higher by 18.4 pp in August 2020, 8.5 pp in January 2021, and 4 pp in June 2021. More precisely, Figure 2.8 shows that without any government intervention, separations (respectively findings) are persistently above (respectively below) their pre-crisis level. Hence, this not only induces high levels of unemployment but also a long persistent effect over time.

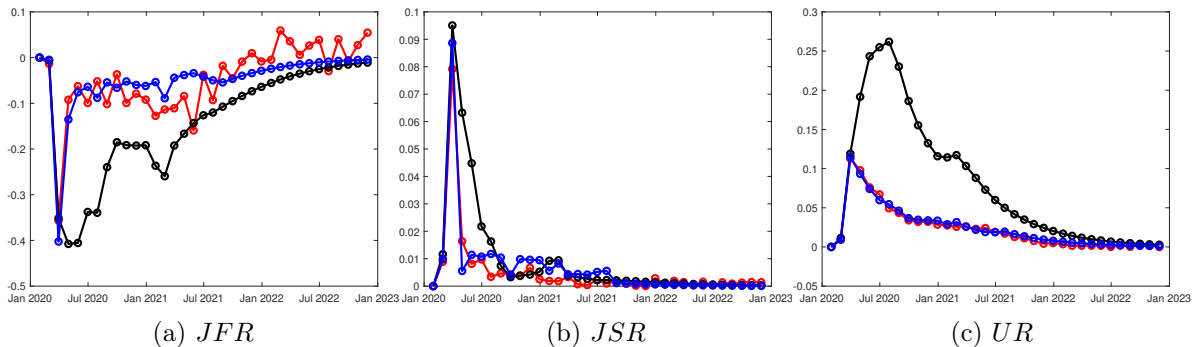


Figure 2.8: **Aggregate outcomes.** Panels (a)–(c). Red lines : data. Blue lines: benchmark model. Black lines: model without any government intervention.

There are two potential opposite effects that can affect the labor market through the CARES act: on one hand, employment subsidies encourage labor hoarding and therefore reduce the rise in unemployment, and on the other hand, unemployment benefits increase reservation wages and therefore unemployment. Our model shows that the experience of removing all CARES act measures implies that the effect leading to lower labor costs is dominant. In fact, even if the UB increase encourages separation, the total effect of the CARES act helps the economy to overcome the persistent recovery (see Figure 2.8). Finally, the CARES act makes it possible to significantly reduce the average duration of unemployment, which was one of its priority objectives.

2.4.4 Contributions of each extension

In this section, we analyze the contribution of (i) the *hiring cost* function that accounts for congestion effects varying with unemployment and (iii) *varying risk*, which accounts for the increase in microeconomic uncertainty in recession.

We then shut off one of these extensions and re-calibrate the $T \times S = 136$ -specific shocks, thus allowing the model to match the 136 unemployment rates moments by education level, observed from March 2020 to December 2022. We assume that the government spending induced by the CARES act is the same as in the benchmark model.⁵⁰ For March 2020, the identified shocks, nearly, all remain the same, irrespective of the model’s restrictions: this can be attributed to the small impact of the crisis during that month. For April and later on, the shocks identification largely depends on restriction introduced in the model, emphasizing the importance of each extension of our DMP model. When

⁵⁰Figure B.11 and B.12 in Appendix B.11 reports the estimated sequences of the productivity shocks.

the hiring costs are constant—as in the basic DMP model—then the amplitude of the April shock must be smaller, irrespective of education level. However, they must be more persistently higher onward: indeed, without the externality on hiring cost, the internal persistence of the DMP model is very low and must therefore be "replaced" by a persistently high negative shocks, so that the model reproduces the observed data. A constant microeconomic risk (which is countercyclical in our benchmark model) drives some estimated shocks to become larger than the one in our benchmark model. Moreover, in the second wave, some shocks need to be positive to match the data which is counterfactual.

One can also determine the importance of each of the aforementioned extensions by measuring gaps relative to data. Indeed, our calibration strategy constraints the model to match the monthly unemployment rate by diploma but leaves free the worker flows (JFR and JSR) observed at the aggregate level from March 2020 to December 2022. The large differences between the constrained models and the JFR and JSR data show that each extension makes a significant contribution (see Figures 2.9 and 2.10).

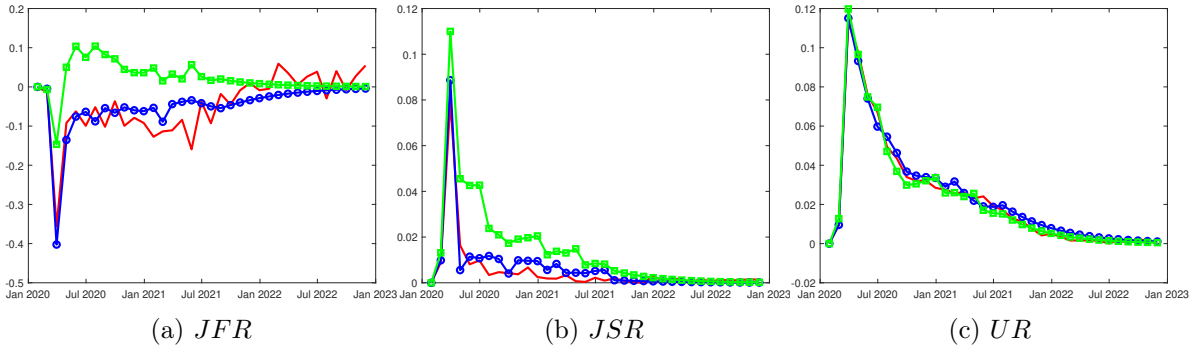


Figure 2.9: **Hiring cost.** Red: data; Blue: benchmark model; Green: models with $\gamma_s = 0$.

When the externality in the hiring cost is suppressed, we re-encounter the usual drawback of the DMP model: the persistence in the job-finding rate below its pre-crisis value is largely underestimated (Panel (a) of Figure 2.9): without congestion externality on unit hiring costs, the larger number of unemployed workers in a recession facilitates hiring. To counterbalance this shortcoming, the negative TFP changes for LHS, HS and Coll. workers needed to mimic unemployment rates are more persistent, and thus lead to an overestimation of the job-separation rates (Panel (b) of Figure 2.9).

When the time-varying risk of microeconomic shocks is removed ($\sigma_{s,t} = \sigma_G, \forall s, t$), both the JSR and JFR are biased, despite the good fit of unemployment. During a recession, the increase in $\sigma_{s,t}$ (with the average of the distribution remaining constant) expands the weight of both excellent and very bad draws. Since the distribution that matters for

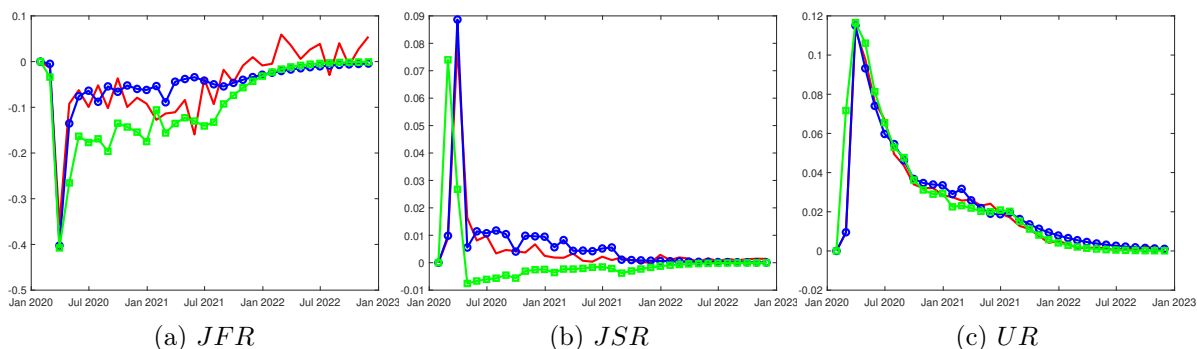


Figure 2.10: **Varying risk.** Red: data; Blue: benchmark model; Green: models with $\xi = 0$.

evaluating expected profits is cut to the left by reservation productivity, an increase in variance raises the expected profits, which in turn boosts hires. Panel (a) of Figure 2.10 shows that without this effect, the expected profits would be lower, which would lead to fewer hires. For separations, this effect also acts to reduce JSR but is overcompensated by (i) the increase in labor market tightness, which increases wages, and (ii) the thickening of the left-tail distribution, which pushes up the mass of firings. Hence, an increase in the variance of the distribution implies an increase in the mass of low-productive jobs at the profitability limit.⁵¹ Therefore, in the absence of this effect, there would be fewer separations (see Panel (c) of Figure 2.10).

2.5 COVID-19 in France

As for the US case, we model the lockdown as restrictions on transactions that change supply as if the TFP has been reduced. However, to dampen the impact of these restrictions, the French government has implemented a different policy : Partial Unemployment. Moreover, the French lockdown was done in three waves compared to two waves in the US (see table 2.6 for more details).

	Wave 1	Wave 2	Wave 3
TFP shocks			
Lockdown	March to May 2020 Total and strict	November 2020 Partial	January 2021 to April 2021 National curfew

Table 2.6: **Lockdown Timing in France.**

⁵¹See [Pissarides \(2000\)](#), ch.2, for analytical derivations of these results.

2.5.1 Explaining unemployment during the pandemic crisis

Partial Unemployment. Partial unemployment allows companies to retain a portion of their employees who are unable to work while still providing them with compensation. It is a transfer initiated by the government that covers the costs of a workforce that is unable to produce due to confinement-related constraints. Beyond ensuring compensation for those affected by activity restrictions, the distinction between partial unemployment and traditional unemployment arises during the phase of deconfinement and the return of activity. The return to work of those on partial unemployment, who have remained under contract, is less costly. Appendix [B.9](#) describes the choices made by the company when it selects, for each period, the fraction of its workforce on partial unemployment whose costs are covered by the government. This alters labor productivity and hiring costs, without modifying other behaviors. In particular, we showed that $\kappa_{s,t}$ is reduced proportionally to the number of employees on partial unemployment work in each segment of the labor market, as long as the government finances this measure.

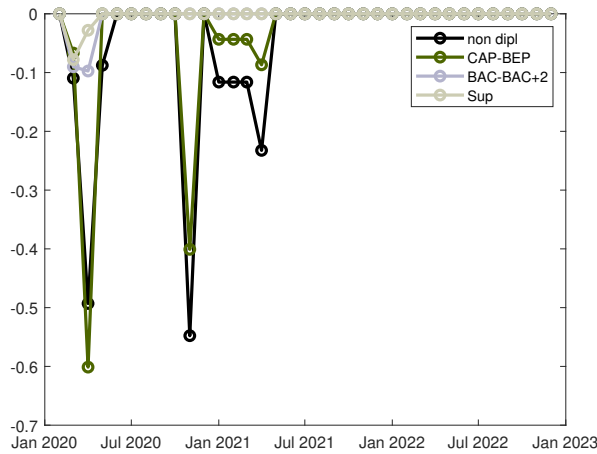


Figure 2.11: **Impact of the lockdowns from March 2020 to December 2022 on productivity.**

Identifying economic counterparts of restrictive measures. Figure [2.11](#) represents the negative variations in TFP, interpreted as the restrictions induced by the lockdown. The decrease in TFP reached 50% in April for non-graduates. This decrease is larger than the one in the US (35%) and is explained, on one hand, by the stricter restrictions in France. On the other one, it is also explained by the fact that, in the French case, the unemployment rate also included partially unemployed workers. Similarly, individuals with a diploma higher than a Bachelor's degree experienced an almost negligible loss.

Unemployment Panel (a) of Figure 2.12 demonstrates that the calibration of this extended DMP model enables us to replicate the monthly dynamics of the French unemployment rate since March 2020. Panel (b) shows that the unequal amplitudes of unemployment increases based on education levels are also accurately reproduced by the model: including partial unemployment, the rise is 25 percentage points in April 2020 for individuals without a diploma and around 8 percentage points for those with at least a Bac+2 qualification.

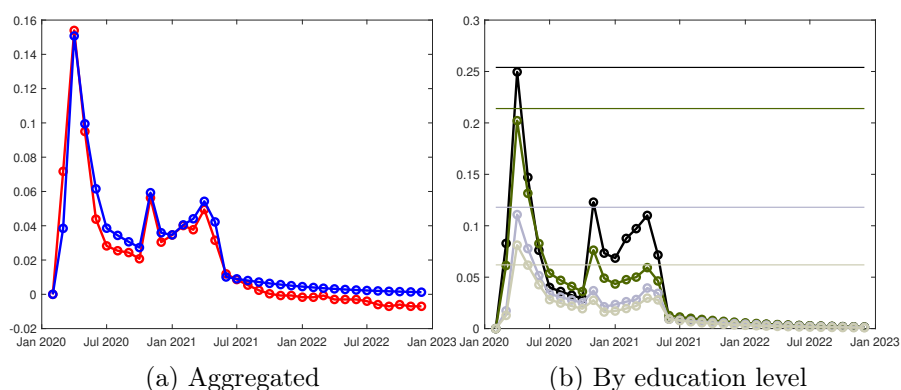


Figure 2.12: **Impact of the lockdowns from March 2020 to December 2022 on the unemployment rate.** Panel (a): Red lines : data; Blue lines: model. Panel (b): Black : non-graduates; Khaki: CAP-BEP; Gray: Bac-Bac+2; Camel: higher education. All series are shown as deviations from their pre-crisis values, i.e., those of February 2020. In Panel (b): Solid lines indicate the observed unemployment rates by education level in April 2020.

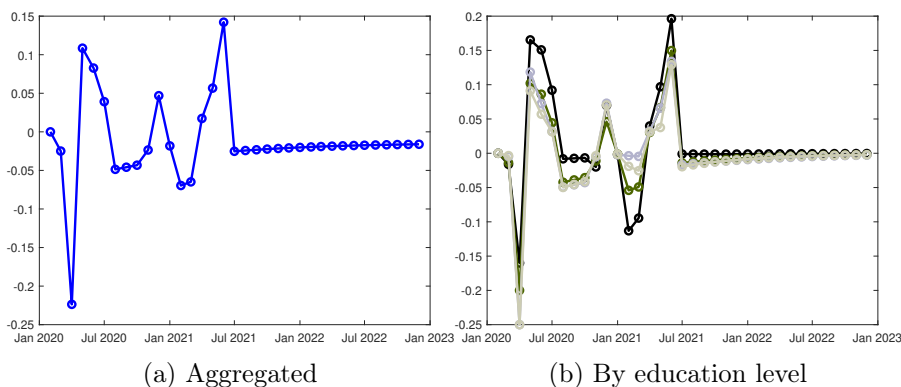


Figure 2.13: **Impact of the lockdowns from March 2020 to December 2022 on the Job Finding Rate.**

Figures 2.13 and 2.14 illustrate the evolutions of the worker flows that generate these stock dynamics. For the first wave of the lockdown, Panel (a) in Figure 2.13 indicates a 22 percentage point decrease in hiring, reaching zero hiring in April, then, peaking in May, remaining above pre-crisis levels in June and July, and then falling below the reference level from August 2020. Thus, after three months of strong job recoveries from May to July 2020, largely explained by the return to work of employees on partial unemployment, the hiring rate remains below its reference value. After the end of the third lockdown, it can be observed that hiring gradually converges towards its initial level while remaining slightly below its long-term level. Panel (b) of Figure 2.13 indicates that all types of employment are affected by the halt in hiring in April, and job recoveries are very strong for all education levels.

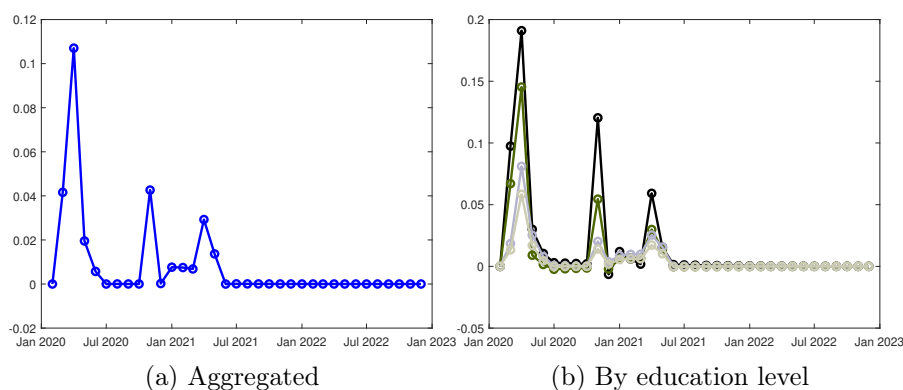


Figure 2.14: **Impact of the lockdowns from March 2020 to December 2022 on the separation rate.**

Panel (a) of Figure 2.14 shows that the separation rate increased by 10.7 percentage points between February and April. This combination of zero hirings in April and a significant increase in separations explains the peak in unemployment in April 2020. By July 2021, the separation rate had returned to its pre-crisis level. Panel (b) of this Figure demonstrates that all types of employment were affected by these major waves of activity cessation, although they impacted lower-educated individuals more.

2.5.2 Disentangling the impact of Partial Unemployment

The impact of partial unemployment measures, which help mitigate the costs associated with hiring during the recovery period, can also be revealed by our model. This temporary moderation of costs during the deconfinement phase can be interpreted as the efficiency

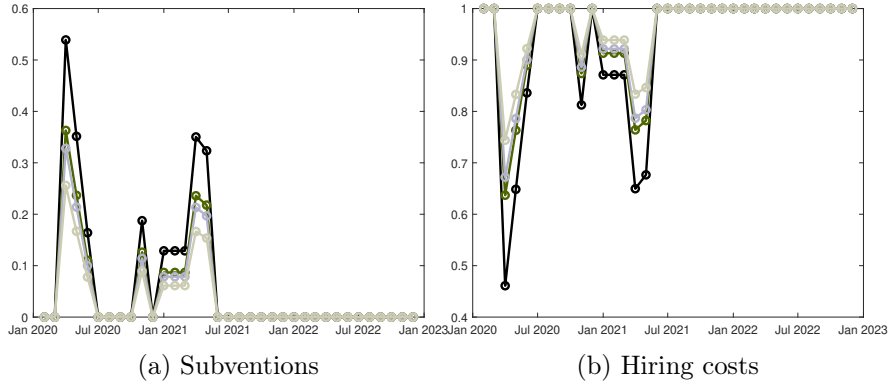


Figure 2.15: **Impact of partial unemployment on hiring costs.**

of partial unemployment measures⁵²

Panel (a) of Figure 2.15 shows the magnitude of the cost reduction ($\Upsilon \times P_s$), while Panel (b) illustrates the resulting evolution of the unit cost of hiring, i.e., $(1 - \Upsilon \times P_s)\kappa_{s,t}$ ⁵³. To account for the rapid reduction in unemployment levels observed during the deconfinement phase, we estimate that partial unemployment reduces the unit costs of resuming employment by 54% for positions employing non-graduates and by 26% for individuals with at least a Bachelor's degree. These adjustments also occur during subsequent periods of restrictions.

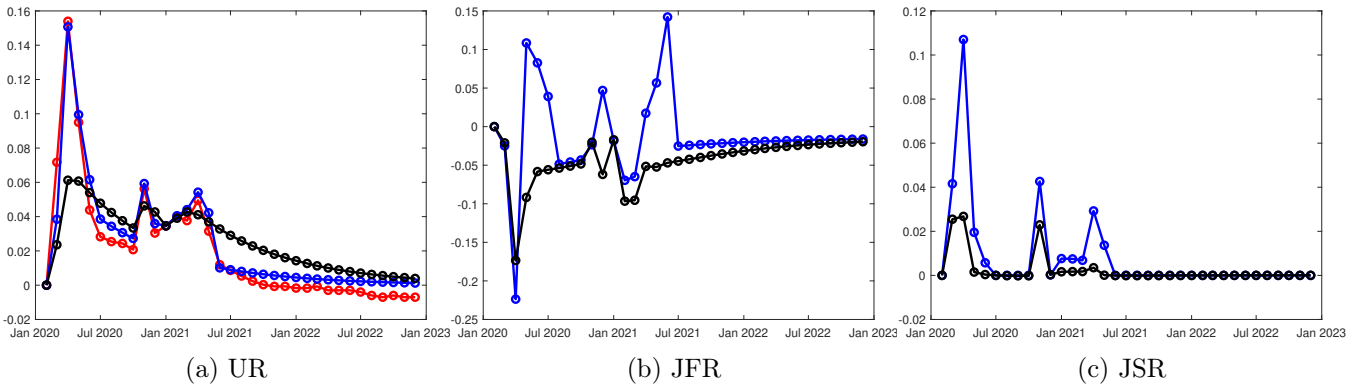


Figure 2.16: **Impact of partial unemployment on total unemployment.** Red : data. Blue: benchmark model. Black: model without partial unemployment

⁵²It is important to note that our model assumes neutrality towards risk for economic agents, so we focus solely on the employment gains rather than evaluating the welfare surplus associated with consumption smoothing facilitated by partial unemployment insurance.

⁵³ $\mathcal{P}_{s,t}$ is the fraction of job that can operate. See Appendix B.9 to understand $\Upsilon \times P_s$

Figure [2.16](#) compares the reference simulation with a scenario without the reduction in costs associated with the resumption of employment for individuals on partial unemployment. The model predicts that the aggregate unemployment rate would be 2 percentage points higher in July 2021 without the partial unemployment measures, highlighting the positive effects of partial unemployment on job recovery. Beyond these long-term effects, the counterfactual simulation also shows that partial unemployment facilitates and therefore amplifies layoffs: as employers anticipate that re-employment will be less costly, they are more likely to separate from their employees more easily. The strategy known as workforce retention is less valued. However, these significant upward adjustments in unemployment are offset by the strong recovery in activity right from the start of the deconfinement period, which supports the case for these measures.

Comparison US Vs France: We have shown that the CARES Act serves to encourage labor hoarding, thereby mitigating the increase in unemployment. Moreover, the standard recall system implemented in the United States contributes to a robust recovery. In the case of France, the utilization of partial unemployment help also in the long-term recovery.

2.6 Conclusion

This study evaluates the impact of the COVID-19 crisis on the US labor market. This is done using an extension of the Diamond–Mortensen–Pissarides model in a general equilibrium setup. We introduce several extensions: *(i)* heterogeneity of workers by education level, making it possible to combine heterogeneous adjustments in labor markets; *(ii)* endogenous separations, accounting for sharp increases in unemployment and business closures; *(iii)* time-varying microeconomic risks over the economic cycle; *(iv)* congestion externalities explaining the persistence of unemployment during recovery; and *(v)* wage rigidity, allowing the model to account for job separations even after the lockdown.

The model makes it possible to identify the size of the shocks needed to reproduce the observed first months of the crisis. These shocks induced by lockdown are identified conditionally to policy changes due to the CARES act. Given the large changes in labor market policies, the economic impact of the lockdown is very large, in particular for workers without university degrees. We show that the CARES act allows to significantly dampen the impact of the lockdown. In particular, it reduces significantly unemployment persistence. Finally, counterfactual simulations, in which one of the above extensions is shut down, stress the importance of each one in explaining labor market dynamics.

Chapter 3 : Will You Follow me to the Suburbs? The Consequences of Establishments' Relocation in a large Metro Area

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3.1 Introduction

One of a firm's most important decisions is choosing its establishments' locations. A large empirical literature in urban economics has highlighted that firms locate in large metro areas despite their more expensive rents because agglomeration economies increase their productivity (Combes and Gobillon (2015)). Such higher levels of productivity partly reflect the fact that the labor supply to a firm varies dramatically with its location. Being in a large agglomeration might improve both the quantity and quality of matches between firms and workers (Duranton and Puga (2004, 2020)).

As suggested by standard urban economics models (see Zenou (2009) for an overview), similar considerations might influence the location choice of firms *within* metro areas. Nonmonetary job characteristics, such as a shorter commuting time or a more pleasant work environment, have long been regarded as important factors influencing workers' utility and, thus, labor supply. As jobs more distant from the worker's residency are less attractive because they are associated with longer commuting time (Manning and Petrongolo (2017)), and high-skilled workers are increasingly segregated within metro areas (Musterd et al. (2017)), the location of establishments within a metro area might influence not only the quantity but also the quality of the labor supply to the establishment. In the largest metro areas such as New York, London, or Paris, where the most productive workers are living (Combes et al. (2008), Card et al. (2021)), establishments located in the expensive center have access to a unique pool of workers attracted by low commuting times by public transportation and an abundance of leisure amenities offered by the concentration of shops and restaurants (Carlino and Saiz (2019)).

In recent years, however, in response to a dramatic increase in renting costs in the center, the share of jobs in the suburbs has grown rapidly (Hill and Brennan (2005), Glaeser et al. (2001)). By moving to the suburbs where rents are cheaper, firms can rent more space at a lower cost. However, being far from the center also induces longer commuting times by public transportation for most metro area workers and is often associated with a less pleasant environment in the neighborhood of the establishment. If workers from the center cannot be easily substituted by workers living closer in the suburbs, and a longer commuting time and less prestigious location affect the utility of workers, firms in more remote locations might have to pay higher wages in compensation to attract workers.

Despite the importance of these questions, credible evidence on how locating an establishment to the suburbs instead of the center affects the composition of its employment and wages remains scarce. One empirical challenge is that firms and workers located in the suburbs and the center are systematically different in terms of sector or composition of employment. As a result, naive comparisons between wages paid by establishments located in the center and the suburbs cannot be used to draw any robust conclusion regarding how the establishment's location affects the labor supply to the firm.

To assess the relative costs and benefits of being in the center relative to the suburbs, we exploit establishments' relocation within the Paris metro area in France. Using these relocations, we first assess how local establishments are hiring within the metro area by comparing the geographical origins of workers hired before and after the location. Second, to understand the costs of locating in less central locations which tend to induce a longer commuting time for most workers in the metro area, we use increases in commuting time associated with the relocation in different parts of the metro area to estimate how they affect job separation and wages. We investigate, in particular, whether similar commuting time increases affect these outcomes differently when an establishment relocates from the center to the suburbs relative to an establishment relocating from the suburbs to the center.

To guide our empirical investigation, we first discuss a simple non-competitive model in which due to search frictions, wages are determined by Nash bargaining. We assume firms and workers renegotiate wages after the relocation to take into account the effects on utility of both changes in commuting time and differences in consumption amenities next to the neighborhood of the establishment. We highlight that if wages are downward rigid and firms do not reduce the wages of workers for whom commuting time decreases, consistent with our empirical evidence and the literature pointing to an aversion to wage cuts (Kahneman et al. (1986)), the within-establishment correlation between changes in wages and changes in commuting time depends on how differences in local amenities affect the utility of the worker. The model predicts, in particular, a stronger correlation between changes in wages and commuting time when the relocation is also associated with a decline in amenities, as for a relocation from the center to the suburbs. In this case, even workers for whom commuting time declines might need to be compensated for remaining in the firm. In contrast, when the change in amenities associated with the relocation increases the utility of workers, such as might be the case for relocations from the suburbs to the center, workers might not even need to be compensated for preserving the match as the positive effects on their utility due to the change in amenities might

compensate the negative consequences of the increase in commuting time.

We also highlight that the firm's incentives to preserve the match might also depend on the labor supply in the new location. In particular, firms moving into the center, which is easily accessible from most parts of the metro area, might have fewer incentives to preserve the match, as hiring a worker with a lower commuting time might be easier for them. When workers can be easily replaced, an increase in commuting time associated with the relocation should affect the separation probability. However, it should not affect wages, as predicted by frictionless urban economics models à la [Fujita et al. \(1997\)](#).

The consequences of commuting time increases associated with the relocation might also depend on the workers' residency. In particular, workers living in the center might be more difficult to retain for establishments moving to the suburbs as they might be more able to find another employer offering a shorter commuting time after the relocation. As a result, we expect to find stronger effects of relocation to the suburbs on job separation probability for workers living in the center of Paris.

The Paris metro area is an ideal setting to study these questions, and we believe general lessons could be drawn from understanding the functioning of the labor market in such a large metro area. With more than 6 million workers and 12 million inhabitants, it is the largest metro area in Europe after London and accounts for 23% of French employment. As in most metro areas, many establishments relocated to the suburbs in recent decades ([Aguilera \(2005\)](#), [Guillain et al. \(2006\)](#)), a process facilitated by the expansion of rapid transit suburban transportation lines ([Mayer and Trevien \(2017\)](#)). Large metro areas such as Paris also concentrate the most paid workers and higher-paying establishments ([Behrens et al. \(2014\)](#)), and understanding the organization of these large labor markets is of prime interest.

As a result of the large size of the Paris metro area and because we have access to exhaustive administrative data, we can exploit the relocation of more than 4 400 establishments between 2003 and 2018 that had more than 20 employees before the relocation. Such a large sample allows us to document how the effects of an increase in commuting time depend on the establishment's destination within the metro area and to capture differences across workers by skill levels or depending on their residency in the metro area.

Our empirical approach allows us to deal with some of the limitations affecting previous works that have attempted to understand how the location of an establishment affects its labor supply. By following the same establishments and workers over time, our estimates are unaffected by systematic differences between firms and workers in different parts of

the metro area. Our models also include establishment fixed effects that absorb any systematic establishment level increases in wages or separation probability associated with the relocation. We also include occupation fixed effects at the three-digit level to account for any systematic correlation between commuting time increase and occupations which might be driven by the fact that skilled workers are concentrated in the center of the metro area. Our key identification hypothesis is that, conditional on including these fixed effects, within establishments' differences in commuting time following the relocation are not correlated with preexisting wage trends or higher risks of job separation. Using changes in commuting time exogenous to the workers' decision ensures that our estimates are not affected by unobserved worker levels shock.

Empirically, we find that establishments relocate relatively far from their initial location as there is a 7 km average distance between the old and the new locations. As, within establishments, workers tend to live in many different parts of the metro area, the effects of relocations on their commuting time vary dramatically across workers. The effects also depend strongly on where the establishments relocate. Relocations from the center to the suburbs, in particular, are associated with a large and persistent increase in commuting time by public transportation. In this case, the average commuting time by public transportation of employees in the establishment increases dramatically by 20% (8 minutes), corresponding to a third of the standard deviation. Symmetrically, relocations from the suburbs to the center decrease by 16% (7 minutes) average commuting time by public transportation.

Despite these significant effects on commuting time, the relocations do not strongly affect where recently hired workers live in the metro area, thus suggesting remarkable stability in the geographical perimeters within the metro area where the firm is hiring. Even if workers hired after the relocation tend to live closer to the new location than those hired before, their geographical origins are very similar. In addition, there is no evidence of a dramatic turnover in which workers affected by the largest increase in commuting time are replaced by workers living much closer to the firm's new location.

To understand these results, we turn to our within-establishment estimates of the consequences of commuting time increases on job separation and wages. Across all types of relocations, we find that the risks of job separation increase after the relocation for workers affected by an increase in commuting time by public transportation. Interestingly, the consequences of commuting time increases vary dramatically depending on where the establishment relocates, with point estimates that are twice as large for relocations from the center to the suburbs. However, the effects tend to be small as they range between

a 7.5 and 4 p.p. increase in the job separation probability in response to a one-hour increase in commuting time two years after the relocation. In addition, consistent with the hypothesis that workers in the center might have more employment opportunities, we find stronger effects of relocations on job separation probability for workers living in the center of Paris.

A possible explanation for these relatively moderate effects of commuting time increases on job separation is that firms compensate workers for the increase in commuting time to preserve the match. Consistent with this explanation, we find that, for establishments relocating from the center into the suburbs, one hour increase in commuting time in public transportation is associated with a 4,6% larger wage increase in the first year after the relocation. On the other hand, we find no evidence that firms are cutting the wages of those experiencing a decrease in commuting time.

As expected, if, in addition to commuting time, amenities in the neighborhood of the establishment also affect the utility of workers, the adjustment of wages to commuting time also depends dramatically on the destination of the establishment following the relocation. For establishments relocating between different parts of the suburbs, for which local amenities might not be so affected by the relocation, the adjustment of wages to commuting time increases tends to be twice as low. Importantly, we find no evidence of any wage increase associated with increased commuting time for firms relocating to the center. Given the fact that commuting time increases are also associated with a lower but significant increase in job separation in these cases, such lack of wage adjustment suggests that establishments relocating into the center might have fewer incentives to preserve the match as they are more able to replace workers that might leave the establishment in response to an increase in their commuting time.

Whether firms adjust wages to an idiosyncratic increase in commuting time also depends strongly on the skill levels of the workers, consistent with the evidence that skilled workers might be more costly to replace. Using occupations to classify workers in three broad skill groups, we only find a significant wage adjustment to longer commuting time for high- and medium-skilled workers, with larger effects for high-skilled workers. For low-skill workers, on the other hand, even though their risk of job separation increases dramatically in response to commuting time increases, we find little evidence that their wages also adjust to an increase in commuting time.

Our results are robust to alternative specifications of the empirical model. Within each relocation type, our estimates are broadly similar across sectors, thus suggesting that sectoral differences in the composition of establishments that relocate in different parts of the metro area do not drive the previous differences. Our results are also robust to including fixed effects for the municipality of residency, which absorb any systematic correlation between commuting time increases and specific wage trends for workers living in the same municipality of the metro area. We also find similar estimates when we restrict the sample to workers hired three years before the relocation, thus suggesting that our results are not affected by any differential hiring of workers just before the relocation.

Related literature— We contribute to several strands of the literature. Our work is first related to the literature relating commuting time to wages and labor supply, which includes [Zax \(1991\)](#), [Gronberg and Reed \(1994\)](#), [Callee and Winston \(1998\)](#), [Van Ommeren et al. \(2000\)](#) and more recently [Manning and Petrongolo \(2017\)](#) and [Le Barbanchon et al. \(2021\)](#). As the earlier literature used cross-sectional data, omitted variable biases might affect these estimates as suggested by panel data estimates using voluntary changes in commuting time reported by [Manning \(2003\)](#). However, even if they control for time-invariant worker unobserved heterogeneity, panel data estimates using voluntary changes might be problematic as they might be associated with unobserved shocks at the worker level. In contrast, by using changes in commuting time driven by the relocation of an establishment, we exploit variations that are more likely to be uncorrelated to unobserved worker-specific shock. One key additional advantage of using within-establishment variations associated with relocations is that it allows us to control for any permanent establishment-specific differences in workers’ or establishments’ characteristics between the center and the suburbs.

Such an empirical approach is similar to [Zax and Kain \(1996\)](#), who document how the relocation of a large firm from the center to the suburbs in Detroit increased the job separation probability of black workers who tend to live in the center relative to white workers, that tend to live in the suburbs. This approach was also recently followed more systematically by [Mulalic et al. \(2014\)](#) who estimate compensating wage differentials for commuting time using firms relocation in Denmark. However, our work differs in several important ways. First, we concentrate on a large metro area in which relocations tend to have a large effect on commuting time by public transportation, and differences in local amenities or the characteristics of labor supply across parts of the metro area are

important. As our time span is larger¹ and the population of the metro area of Paris is more than double the population of Denmark, our sample size is 50 times larger. Such a larger size allows us to capture differences in wage adjustment across relocation types and workers. Second, while [Mulalic et al. \(2014\)](#) approximate changes in commuting time using the distance in km, we underline the empirical importance in the context of a large metro area of using specific measures of commuting time by public transportation and by car, as these two measures tend to differ widely between the center and the suburbs of such a large metro area, as we document below.

Finally, our work is also related to the literature exploring the determinants of spatial wage disparities following [Combes et al. \(2008\)](#) and more recently [Card et al. \(2021\)](#). While these papers describe the sorting of establishments and workers across local labor markets, we investigate the consequences on the employment composition of the establishments' location within a large metro area.

The remainder of this paper is organized as follows. Section [3.2](#) presents the conceptual framework, and Section [3.3](#) presents the data used for this research. Section [3.4](#) discusses the main characteristics of the Paris Metro Area followed by Section [3.5](#) which explains the empirical approach and the econometric models used. In section [3.6](#) we present the results of the estimation to analyze the consequences of establishments' relocations on the composition of employment and on wages paid to workers that remained in the establishment. Section [3.7](#) presents the robustness tests for our results. Finally, Section [3.8](#) concludes.

¹We can consider establishments' relocation over 13 years while they consider relocations over four years.

3.2 Conceptual framework

Differences in rental costs for firms within metro areas are enormous. In the Paris Metro area, office rents per square meter are six times higher in the center relative to the inner ring (BNP Real Estate (2022)). Spatial equilibrium models, as in Roback (1982), suggest that despite these differences, firms find it profitable to pay these expensive rents because they are more productive by doing so. One potential source of these productivity differences might be agglomeration economies driven by the fact that the concentration of firms from the same sector increases their productivity (Ellison et al. (2010)) or the fact that higher density levels permit more direct interactions between workers with positive effects on productivity (Combes and Gobillon (2015)).

A second class of explanations, on which we concentrate here, is that locating in the center affects the labor supply to the firm, particularly by allowing firms to offer shorter commuting times by public transportation to most workers in the metro area. Existing evidence suggests that commuting time is one of the most important characteristics of a job for a worker.² As documented in detail below, given the centralization of the mass rapid transit network and despite the increase in the share of workers living in the suburbs, being located in the suburbs instead of the center is associated with a substantial increase in average commuting time by public transportation for the employees.

Another advantage of being located in the center is that similar to other monocentric metro areas such as New York or London (Brueckner et al. (1999)), it offers exceptional amenities through the concentration of leisure amenities offered by shops and restaurants and picturesque locations (Carlino and Saiz (2019)). These amenities might be crucial to attracting the most talented workers living in the center of the metro area, similar to other metro areas in Europe (Pareja-Eastaway et al. (2010)) or the US (Couture and Handbury (2020)) and, if they affect the utility of workers, they might decrease their reservation wages.

To formalize how using shocks to commuting time associated with establishments' relocation can help us to understand the importance of commuting time and local amenities in the labor supply to the firm, we sketch a simple non-competitive model in which a worker and the firm renegotiate wages after the relocation of the establishment to adjust to an

²According to Kahneman et al. (2004), commuting generates the lowest level of positive affect and high levels of negative affect among all other daily activities. Stutzer and Frey (2008) finds that longer commuting times are associated with lower subjective well-being.

idiosyncratic change in commuting time to a different part of the metro area.³

Workers are assumed to be hand-to-mouth and consume all their income at each period. Following Manning (2003), we assume that the instantaneous (indirect) utility of worker i is linear in log wage, commuting time, and amenities such that $U(w_i, \tau_i, a) = w_i - c\tau_i + a$ where c is the unit cost of commuting, τ_i is the time spent on commuting and a is the effect of the local level of amenities associated with the location of the establishment on utility. These amenities, valued similarly across workers in the establishment, capture the fact that working in different parts of the metro area might affect utility through the prestige associated with a given location or its proximity to leisure amenities. Denoting by b_i the reservation utility of the worker, workers stay in the establishment if their utility is superior to their reservation utility, that is $U(w_i, \tau_i, a) \geq b_i$.

For firms, the profit of a match is given by $J = y_i - w_i$ in which y_i is the real output of the worker. We assume that, in each period, workers and establishments that previously matched renegotiate to decide whether they find it profitable to preserve the match. Suppose they find it profitable to preserve the match. In that case, wages are determined according to the Nash solution to a bargaining problem with bargaining power η , such that, if the match is preserved, wages are given at each period by $w_i = \eta y_i + (1 - \eta)(c\tau_i - a + b_i)$.

An exogenous relocation of the establishment affects commuting time by $\Delta\tau_i = \tau'_i - \tau_i$ with τ'_i denoting the new commuting time, which can be longer or shorter. For expositional simplicity, we assume that $\Delta y_i = 0$ such that there is no change in worker's productivity as a consequence of the relocation.⁴ However, the relocation changes the amenities associated with the neighborhood of the establishment by $\Delta a = a' - a$. This term can be positive when the new location has better amenities or negative otherwise.

If the firm and the worker find it profitable to preserve the match after the relocation, the change in wage is given by:

$$\Delta w_i = -(1 - \eta)\Delta a + (1 - \eta)c\Delta\tau_i \quad (3.1)$$

³We focus on the case in which the residential choice of the workers is exogenous and fixed. As shown empirically, we find no evidence that workers relocate their residency as a consequence of the relocation of their establishment.

⁴We could alternatively assume that we could decompose Δy_i by a change in productivity affecting similarly to all workers in the establishment, and that could be absorbed by establishment fixed effects, and a share idiosyncratic to the worker but uncorrelated with the increase in commuting time.

The previous equation implies that using data on wage and commuting time changes associated with establishments' relocation, the parameters $(1 - \eta)c$ that determine the impact of commuting time on wages can be easily estimated with a linear regression of changes in wage on changes in commuting time including establishment fixed effects to absorb the establishment specific changes in amenities $-(1 - \eta)\Delta a$ that affects the wages of all workers similarly.⁵

The assumption of symmetrical Nash bargaining implies that any positive or negative change in commuting time will affect wages. Net of the effect of amenities, this assumption implies that while the wages of workers observed as remaining in the establishment and experiencing an increase in commuting time should increase, the wages of workers that benefit from a *decrease* in commuting time should symmetrically decrease. In practice, as demonstrated below, and consistent with a large literature on downward nominal wage rigidity (Altonji and Devereux (2000)), we find little evidence of wage cuts associated with a decrease in commuting time. If wages are downward rigid, then it is straightforward to see that the empirical correlation between wages and changes in commuting time will also depend on the change in amenities. To see this, notice that if there are no wage cuts, then there exists a threshold in the change in commuting time Δt_i denoted $\Delta t_i^* = \Delta a/c$, and which thus directly depends on the change in amenities Δa , such that $\Delta w_i = 0$ when $\Delta t_i \leq \Delta a/c$ while Δw_i remains determined by Eq 3.1 when instead $\Delta t_i > \Delta a/c$.

As demonstrated formally in the appendix, this implies that relative to the case in which wages adjust fully to any positive or negative change in the utility of workers, the coefficient of the regression of the changes in wages on change in commuting time will be attenuated the larger Δa . This is due to the fact that the correlation now depends directly on the share of workers that needs to be compensated which is given by $\gamma = Pr(\Delta t_i > \Delta a/c)$. It is only when Δa is sufficiently negative such that $\gamma = 1$ and all workers in the establishment need to be compensated, as when wages are not downward rigid, that a linear regression of changes in wages on changes in commuting time within establishments recovers the structural parameters $(1 - \eta)c$. In contrast, when Δa is positive and sufficiently large such that $\gamma = 0$, even workers for whom the increase in commuting time is the largest see their utility increase as the consequence of the change in amenities, then there is no correlation between changes in commuting time and changes in wage.

⁵Formally, let j denote the establishment and $\overline{\Delta w_j}$ and $\overline{\Delta t_j}$ be the establishment average change in wage and commuting time, and by $\widetilde{\Delta w_i} = \Delta w_i - \overline{\Delta w_k}$ and $\widetilde{\Delta t_i} = \Delta t_i - \overline{\Delta t_j}$, the coefficient of a linear regression of $\widetilde{\Delta w_i}$ on $\widetilde{\Delta t_i}$ is the sample equivalent of $\text{cov}(\widetilde{\Delta w_i}, \widetilde{\Delta t_i})/\text{var}(\widetilde{\Delta t_i})$.

Until here, we have focused on the effect of the relocation on wage change for workers who have remained employed and thus for whom continuing the match was profitable for the worker and the firm. However, the relocation also affects the maximum commuting time required for the match to be preserved given by $\tau^* = (y_i + a' - b_i)/c$, and this threshold increases with the level of amenities a' in the new location. The probability of job destruction associated with the constraint of profitability of the match is given by $P(\tau' > (y_i + a' - b_i)/c)$. It depends positively on the worker's productivity in the establishment and the new amenities.

Even if the match remains profitable, there might be situations in which firms might not be willing to preserve it. This is the case when they can find, after the relocation, a worker with a similar level of productivity who lives closer to the firm and will thus accept lower wages. To formalize this intuition, assume that, even if preserving the match is profitable, firms can also decide to find another worker. However, they can only receive one application per period and cannot be sure whether they will find a worker with whom it is possible to find a profitable match. Assuming the firm is risk neutral and the profits are zero if they match with a worker with a commuting time superior to τ^* , the expected profit from searching for a new match is $J_{new} = y_i - w_{new} = \int_0^{\tau^*} (1 - \eta)(y_i - c\tau_{new} + a' - b)dG(\tau)$ where $G(\cdot)$ denotes the cumulative distribution function of the distribution of commuting time in the new location. Denoting by J_{old} the profits from the existing match, the firm prefers to destroy the match and search for another worker after the relocation if: $J_{new} \geq J_{old}$ which simplifies to $c\left(\tau'_i - \int_0^{\tau^*} \tau_{new}dG(\tau)\right) \geq (1 - G(\tau^*))(y_i + a' - b)$. The previous expression indicates that the firm will search for another worker if the expected wage reduction associated with a lower commuting time for the new worker is superior to the reduction in expected profit associated with the uncertainty of finding a worker with whom the match might be profitable. When $G(\tau^*)$ is close to one, which implies that most matches are profitable, the previous condition only depends on whether the actual commuting time of the worker in the existing match is superior to the expected commuting time from the matching with a new worker.

Symmetrically, workers might also prefer to leave the match to find another firm offering lower commuting time. In that case, the effect of relocation might vary across workers in the same establishment and depend on the density of firms next to the worker's residency. Such a case can be easily modeled by assuming that the reservation wage of the worker, b_i , which captures what the worker would expect to earn if she decides to search for another firm, depends on the residency of the worker as it would determine the probability to match with a firm offering a certain level of commuting time and amenities. Given the

concentration of employment in the center, it implies that workers in the center might have a higher b_i , as they might be more able to find an establishment with lower commuting time and higher amenities.

While simple, our theoretical framework allows us to derive three empirically testable hypotheses to analyze how wages should adjust to an exogenous commuting time change depending on where the establishment relocates within the metro area. First, our model predicts that if wages do not decrease for workers for whom commuting time decreases, then differences in local amenities will influence the correlation between commuting time increase, the adjustment of wages, and the separation probability.

Second, at the firm level, the probability of a firm being willing to preserve the match might depend on its ability to replace workers with long commuting time with workers with low commuting time. Suppose workers are quickly replaced by workers leaving closer, as might be the case for a firm relocating into the center. In that case, increases in commuting time might have a strong effect on job separation but little effect on wages.

Third, for workers, the probability of leaving the match might also depend on the density of establishments close to them. We might thus expect that workers who live in the center, close to a large number of establishments, are more likely to leave the match.

We assess the empirical relevance of these three hypotheses in the rest of the paper.

3.3 The data

To investigate the consequences of relocations on commuting time, job separation, and wages, we combine employer-employee longitudinal administrative data that contains information on establishments' locations and workers' residencies within the metro area with publicly available commuting time data.

Longitudinal Employer-employee data — We use administrative data at the worker level for each French establishment of the Paris metro area from the DADS (*Déclaration administrative des données sociale*) over 2003-2018. The DADS is a compulsory annual declaration that needs to be filled by employers for all of their employees.⁶ We exploit the wage earner files (*DADS salarié*) that report information about the main job held by

⁶We accessed these data from the French Secure Access Data (CASD). We do not use data from before 2002 as they do not contain information allowing us to follow workers over time.

the worker in a given year. As a result, our sample only contains workers for whom the establishment was their main employer during the year.

The data contain a separate administrative identifier for each firm and its establishments. Each identifier is associated with a unique address of the establishment. Thus, as discussed below, establishments' relocations are easy to identify empirically, as when an establishment relocates, the administration issues a new identifier.

The original files do not contain an identifier allowing tracking workers across years.⁷ However, workers can be matched easily over time as each yearly file contains variables not only for the current year but also retrospective information for the past year (Babet et al. (2022)).⁸ Using programs from Babet et al. (2022), we can assign a pseudo-identifier to 98% of the workers in our sample.⁹

Sample restriction — Our sample includes all standard private sector jobs for men and women from the Paris metro area. We focus on standard employment relationships and exclude subsidized contracts for young workers, interns, and apprenticeships (4% of observations). The data report information on annual earnings, number of hours, days, the industry code, and occupation.¹⁰ We use hourly wages as our main measure of earnings that we calculate using information on the annual number of hours and annual total earnings. In the supplementary Appendix C.4, in accordance with recent results from Lachowska et al. (2022 a) for the US, we provide evidence corroborating the quality of the hours' information. In particular, in Figure C.1 in the Supplementary Appendix, we show that the share of jobs paid less than the hourly minimum wage is very small across years (inferior to 1%). Following Babet et al. (2022), we exclude jobs with an hourly wage inferior to 80% of the legal minimum hourly wage for the corresponding year (0.1%) or above 100 times the minimum hourly wage (0.01%).

⁷No identifier was included to reinforce confidentiality even though the files included the entire population of employees. These constraints have been recently relaxed, and the French Statistical Institute has authorized researchers to match workers over time using the procedure described here.

⁸For year t , the file report information on establishment ID, gender, number of hours, job duration in days, start and end dates of the job, municipality of work and residence, earnings and age for both year t and $t - 1$.

⁹A limitation of this procedure is that, as it exploits annual retrospective information, a worker can only be matched between two years if she is observed to work during at least one day of work per year. As a result, workers not observed in the panel during an entire year because they did not work a single day of that year or became self-employed cannot be matched. If they reenter the sample later, the algorithm will assign them another identifier.

¹⁰No information on education is reported, so we approximate workers' skill levels using the occupation.

Geographical definitions— Consistent with the organization of the local public transportation networks, the Paris metro area, displayed in Panel A of Figure 3.1, is defined using the boundaries of the Île-de-France region.¹¹ Following the common practice, the center of the metro area is defined using the municipality of Paris, and the inner and outer rings of the metro area are defined using the boundaries of the eight departments of the region.¹² As illustrated in Panel A of Figure 3.1, the inner ring includes the three densest departments that are just next to the municipality of Paris, and the departments at the edge of the metro area are included in the outer ring.

Our sample includes all workers living and working in the Paris metro area. However, to study establishment relocation, we restrict our sample to establishments relocating between the center and the inner suburbs, where the composition of economic activities is the most similar relative to the outer ring. As discussed below, one additional advantage of focusing on such a geographical zone is that most commuting to work occurs by public transportation in these zones, as most employers cannot offer a parking space. Since most establishments concentrate there, these relocations account for more than 90% of the relocations identified in our sample. Thus, except when indicated otherwise, throughout the rest of the paper, the term relocations to the ‘suburbs’ is thus used to refer to relocations into the inner suburbs of Paris.

Establishment selection — We focus on establishments with more than 20 employees to ensure there is enough variation in the change in commuting time across employees associated with the relocation of the establishment.¹³ We also focus on establishments from the service industries that are not selling their production locally and thus for which the location of the establishment does not directly affect the demand to the firm.¹⁴ Among these industries, we distinguish four one-digit sectors: Information and Communication,

¹¹An alternative would have been to use the urban area (*aire urbaine*) of Paris which is based on daily commuting patterns. In practice, using the region or the urban area would have little empirical consequences as the region includes 97% of the population of the urban area. See [McAvay and Verdugo \(2021\)](#) for a more detailed discussion.

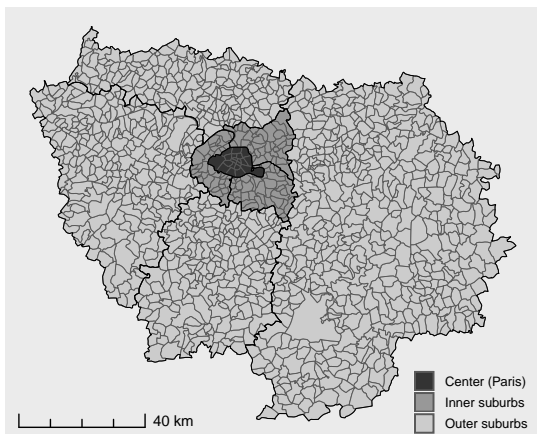
¹²The French departments are an administrative division equivalent to a US or UK county.

¹³We also have eliminated two very large establishments with more than 2 500 workers in our relocation sample in which all workers were erroneously declared as working in the head office instead of being declared separately in each establishment.

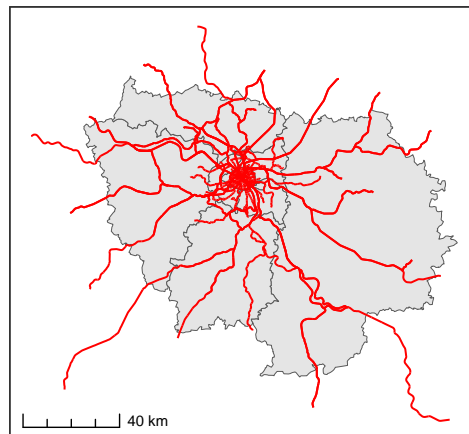
¹⁴Establishments from the Construction or Transportation sector are excluded as their workers do not necessarily work where the establishment is located. We also exclude establishments from agricultural and manufacturing sectors, very rare nowadays in the Paris metro area, and industries from wholesale and retail trade, which sells goods locally and for which the establishments’ location directly influences consumer demand.

Finance and Insurance, Professional, Scientific and Technical Services, and Administrative and Support Services. These industries include 50% of private sector employment in the metro area and up to 65% in the center.

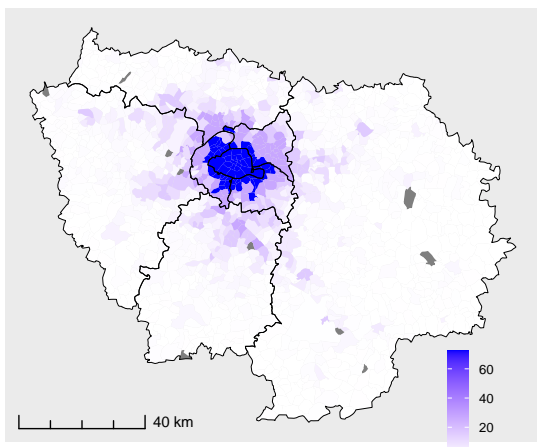
A. Municipalities and arrondissements of Paris



B. Mass rapid transit: Metro and suburban trains



C. Residential density



D. Average Wage by Municipality of Residency

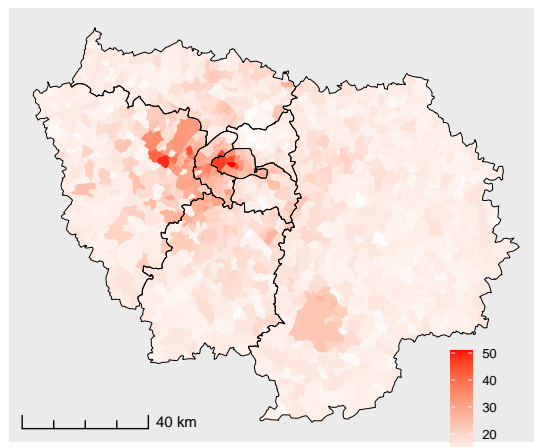


Figure 3.1: **Paris Metro Area.** *Sources:* Maps from Geofla and DADS Data. *Notes:* Panel A reports the limits of the municipalities in the Paris Metro areas. The limits of the 20 *arrondissements* are also reported for the municipality of Paris in the center. Panel B reports in red the lines of metros and suburban trains. Panels C and D describe differences in residential density and average hourly wages by the municipality of residency across municipalities.

Commuting time data— We estimate commuting time to work using the municipality of residency of the worker as the data does not contain the detailed street-level addresses of workers’ residencies. While the exact address would be preferable, municipalities are small in practice, and the differences will likely be limited. Panel A in Figure 3.1 shows that the Paris metro area is fragmented between 1 268 different municipalities. With an average population of 7 900 inhabitants, the average population size of these municipalities is only slightly larger than a US census tract. Importantly, for the larger municipality of Paris in the center, the data also report the establishment’s location and residency of workers at the detailed level of the 20 *arrondissements* that divide Paris and are also represented in Figure 3.1.

Commuting times by public transportation are obtained from the itinerary calculator *Navitia.io*, developed by a French National Railways company subsidiary. This calculator exploits data from all alternative public transportation modes, including the metro, suburban train, tramways, and buses, to calculate the fastest itinerary possible by combining different transportation modes. The same data is used by popular commercial distance planners such as Google Maps or Mappy, and we have checked that our commuting data match closely the results from a request on these websites.

Commuting time by car and distance by road in km are obtained from the Metric database developed by the French statistical institute. While the mode of calculation differs, these commuting times by car are very similar to those obtained from a request on a commercial navigation app. Appendix C.2 provides further details on these datasets.

For each worker and transportation mode, we use as a departure point the official coordinate of the municipalities of residency and, as an arrival point, the municipality of the establishment.¹⁵ For public transportation, we request commuting time for itineraries starting on Monday at 8 a.m. For commuting time by car, we use travel time during peak hours, which are the most relevant commuting times for those commuting to work.

3.4 Main Characteristics of the Paris Metro Area

To understand the consequences of the relocation of establishments between the center and the suburbs, we describe in this section the main characteristics of the metro area, particularly between the center and the suburbs. Overall, relative to the suburbs, the

¹⁵In most cases, this corresponds to the town hall’s location, which tends to be in the center of the municipality.

center of Paris is characterized by an exceptional concentration of transportation network and high-paying establishments associated with a high density of high-wage workers living there. We also show that most of the higher wages paid to workers who live or work in the center reflect primarily differences in worker heterogeneity more than in establishment pay.

Public transport organization— Road congestion and a lack of parking spaces imply that commuting by car is very rare for workers living in the center and, albeit to a lower extent, for those living in the inner suburbs.¹⁶ As most establishments in the center and the inner suburbs cannot offer a parking space to their workers, an important factor influencing the location choice of firms might thus be how many workers can access rapidly the establishment by public transportation. To assess these differences, Panel B of Figure 3.1 describes the mass rapid transit network of the metro area. As in most metro areas, the transportation network follows a hub and spoke structure, and, as a result, the network’s density decreases rapidly with distance from the center. The network is particularly concentrated in the center of Paris, which includes 244 out of 303 subway stations from 14 metro lines. These metro lines are connected with 15 suburban train lines that allow them to reach the inner and outer suburbs rapidly. As we document below, when we study the consequences of relocation to the suburbs, such concentration of the transportation network in the center implies that a firm located in the center can be easily reached by workers from different parts of the metro area while average commuting times by public transportation increase dramatically in the suburbs relative to the center.

Density differences— The share of workers living in different parts of the metro areas also varies dramatically. Like most European metro areas, the residential density of the center of Paris remains very high as 17% of the population live in the center of Paris, which remains one of the densest in the world. Panel C of Figure 3.1 shows that residential density declines rapidly in the inner ring and, to a larger extent, in the outer ring, which is much less dense. The differences in residential density broadly mirror those of employment concentration. Employment is even more concentrated in the center as 31% of the employment of the metro area is in the municipality of Paris, and 38% is in the inner suburbs.

¹⁶Less than 9% of workers living in the center of Paris and only a third of those living in the inner suburbs commute to work by car. In contrast, in the outer suburbs, 58% of workers are commuting by car (Acs and Laurent (2021)). For comparison, 74% of French workers are commuting to work by car, and only 16% are taking public transportation (Brutel and Pages (2021)).

Spatial wage differences— Panel D of Figure 3.1 documents differences in the characteristics of workers across the commuting zone using the average wage of inhabitants for each municipality. Workers living in the center are paid higher wages, particularly those living in the Western part of Paris. In comparison, workers living in the suburbs are paid lower wages, particularly those living in the Eastern suburbs.¹⁷

To summarize these differences, Table 3.1 reports the residual log wage gap between workers living in the center and the suburbs, adjusted for age differences using a third-order polynomial in age. Average residual wage differences between residents living in the center and the suburbs are large, close to 22 log points. In Panel B, we consider the gap by place of work instead of by residency: the wage gap between the center and the suburbs is divided by two but remains large. In Panel C, we restrict the sample to workers living and working either in the center or within the suburbs to focus on workers with lower commuting time. In this case, the wage gap is similar to the wage gap by place of residency, thus suggesting that workers receiving the highest wages in the metro area are more likely to live and work in the center of the metro area.

Role of workers and firm’s heterogeneity in the suburbs/center wage gap—

While the previous evidence suggests that workers living in the center receive higher wages than those in the suburbs, these differences might not necessarily reflect that these workers are more productive. Another possibility might be that workers in the center receive higher wages because firms located in the center pay higher wages to all of their workers. Indeed, recent literature has documented the importance of establishment-specific premia in explaining wage inequality (Card et al. (2013)), and more recently, their role in explaining spatial wage disparities (Card et al. (2021)).

To separate the contribution of differences in workers or establishment characteristics in explaining wage differences between the center and the suburbs, we follow Abowd et al. (1999) and use the mobility of workers across establishments to separate the contribution of unobserved workers and firms’ heterogeneity. We estimate a two-way fixed effects AKM model given by $y_{it} = X'_{it}\beta + \alpha_i + \psi_{j(i,t)} + \epsilon_{it}$ where y_{it} is the log-earnings of worker i in period t and X'_{it} is a third-order polynomial in age, that we interact with an unrestricted set of year and gender dummies as in Card et al. (2018). The worker effect α_i can be interpreted as capturing the combination of observable and unobservable worker skills that are rewarded equally across employers. The term $\psi_{j(i,t)}$ is a constant over time additive

¹⁷Heblich et al. (2021) documents that such relative deprivation in the Eastern part of the metro area characterizes many industrial cities.

wage premium associated with establishment $j(i, t)$, which denotes the establishment where worker i works at period t . This term captures proportional pay premiums paid by the establishment to all its employees.¹⁸

	Difference in mean residual log wage	Difference in mean person effect	Difference in mean establishment effect	Remainder
Difference in average residual wage Center / Suburbs				
A. Live in Center – Live in Suburbs				
Difference	0.228	0.196	0.031	0.000
<i>Share of total</i>	<i>100.0</i>	<i>86.2</i>	<i>13.7</i>	<i>0.0</i>
B. Work in Center – Work in Suburbs				
Difference	0.114	0.097	0.017	0.001
<i>Share of total</i>	<i>100.0</i>	<i>85.1</i>	<i>15.2</i>	<i>-0.3</i>
C. Live and work in Center – Live and work in Suburbs				
Difference	0.241	0.211	0.032	-0.001
<i>Share of total</i>	<i>100.0</i>	<i>87.2</i>	<i>13.2</i>	<i>-0.4</i>

Table 3.1: **Wage differences between the center and inner suburbs.** Source: DADS data 2010-2015. Note: Column 1 in the table reports the average differences in residual log wages between the center and the suburbs of the Paris metro area. Wages are residualized using a third-order polynomial in age estimated separately per year and gender. Columns 2-4 report the results from a decomposition using the AKM model with person and establishment effect. Column 2 reports differences in average worker effect, column 3 in establishment effects, and column 4 is the residual. Panel A reports these differences by place of residency between workers living in the center and the suburbs. Panel B reports these differences by place of work between workers working in the center and the suburbs. Panel C reports these differences for workers that live and work in the center and the suburbs. (**) and (***) denote statistical significance at 5% and 1% level.

The AKM model can be directly used to assess the importance of worker and establishment heterogeneity to wage differences between the center and the suburbs. Conditional on the worker working or residing in location $L_i = l$, either the center or the suburbs, the mean residual wage can be decomposed as: $E_l [y_{it} - X'_{it}\beta] = E_l [\alpha_i] + E_l [\psi_{j(i,t)}]$ where $E_l [\cdot] = E [\cdot | L_i = l]$. In such decomposition, the first term captures the contribution of

¹⁸Ordinary least squares (OLS) estimates of the previous model are unbiased under the conditional ‘exogenous mobility’ assumption. Such an assumption requires there should be no correlation between the error term ϵ_{it} and the assignment of workers to employers across years. Even if formal tests often reject such a strong hypothesis (Abowd et al. (2019), Bonhomme et al. (2019)), recent work by Card et al. (2018) suggests that it constitutes a reasonable approximation.

average person effects in the center or the suburbs, while the second term captures the contribution of the average establishment effect.

The results of this decomposition are reported in columns 2 to 3 of Table [3.1](#).¹⁹ The figure confirms that establishments in the center pay higher wages than those in the suburbs. However, the importance of establishment-specific premia is limited as they only account for 15% of the residual wage gap. In practice, most of the difference in average residual wage gaps between the center and the suburbs reflects differences in workers' characteristics which account for 85% of the overall difference.

3.5 Empirical approach

In this section, we present our econometric models designed to understand the consequences for firms relocating an establishment in different parts of the metro area. Next, we describe how we identify establishments' relocation in the data.

3.5.1 Econometric models

To assess how much an idiosyncratic increase in commuting time associated with the relocation affects the probability of job separation, we consider the following linear-probability model:

$$y_{ij,t} = \beta_0 + \beta_1 \Delta CTime_{ij} + \eta_j + u_{ij} \quad (3.2)$$

where $y_{ij,t} = 1$ is a dummy variable equals to one if worker i is not observed in establishment j in t years after the relocation, η_j is an establishment fixed effect, while u_{ij} is an error term. The variable $\Delta CTime_{ij}$ measures the change in commuting time by public transportation, defined in hours, associated with the relocation between the residency of the worker in year $t = -1$, before the relocation, and the new establishment' location in $t = 0$.²⁰ In our baseline model, this variable can be negative or positive, depending on whether the establishment is closer or farther away from the worker's residency after

¹⁹Models are estimated using a five years period on the connected sets of firms and workers as, even if establishments fixed effects appear persistent over time ([Lachowska et al. \(2022 b\)](#)), assuming time-invariant heterogeneity of workers over longer periods may not be appropriate. In any case, our results are robust to considering alternative periods or windows of estimation.

²⁰To take into account the fact that workers could endogenously change residency to get closer to the establishment after the relocation, a hypothesis we explore empirically below, changes in commuting time are always calculated by fixing the municipality of residency to the one observed before the relocation.

the relocation. Estimates of β_1 should be different from zero if commuting time increases affect workers' utility and firms do not perfectly adjust workers' wages in compensation.

To capture the consequences on wages of changes in commuting time across workers associated with the relocation of an establishment, we estimate linear models of the form:

$$\Delta w_{ij,t} = \gamma_0 + \gamma_1 \Delta CTime_{ij} + \eta_j + u_{ij,t} \quad (3.3)$$

where $\Delta w_{ij,t} = w_{ij,t} - w_{ij,-1}$ is the change in log hourly wages for worker i observed in the establishment j in period t after the relocation relative to $t = -1$, the year before the relocation, with $t = 0$ denoting the year in which the relocation occurred. As for job separations, η_j is an establishment fixed effect, while u_{ij} is an error term.

Using first differences, we eliminate unobserved individual or firm-specific determinants of log wages that are constant over time. Our coefficient of interest is γ_1 which captures the effects of a change in commuting time on the change in log wages. Estimates of γ_1 significantly different from zero would be consistent with non-competitive models of wage formation in which firms differentially compensate workers for an idiosyncratic increase in commuting time after the relocation to preserve the match.

As discussed before, an increase and a decrease in commuting time might not have the same effects, as firms might not want to cut the wages of those experiencing a decrease in commuting time if workers have an aversion to wage losses. We directly test this hypothesis by estimating models allowing for a different effect of an increase and a decrease in commuting time.

In both models, the inclusion of establishments' fixed effects η_j captures all establishment-level changes in wages or job separation affecting all workers in the establishment similarly. Their inclusion implies that our parameters of interest are identified using within-establishment differences across workers in job separation and wage changes.

A concern for our estimates is that workers living in some municipalities are also more likely to work in specific occupations due to spatial segregation by residency within the metro area. As illustrated earlier in Figure [3.1](#), the highest-paid workers are more likely to live in the center and the West, while the lowest-paid workers are more likely to live in the suburbs and the East. Our results might thus be biased if, due to spatial segregation, different occupation groups systematically experience longer or lower commuting time increases following a relocation. To address this concern, our estimates systematically include occupation fixed effects at the three-digit level, which absorb systematic differences in job separation probability and wage changes for about 404 occupations. We also include municipality and arrondissement of residency fixed effects that capture systematic

wage trends or job separation across workers living in one of the 1 268 municipalities or arrondissements of the Paris metro area.

Composition of sample— Our baseline sample includes all workers observed in the establishment at least one year before the relocation (i.e., in year $t = -1$). A concern with this restriction is that firms might have anticipated the consequences of relocation in their hiring decision before the relocation by hiring workers with a lower disutility of commuting time in case the relocation increases dramatically their commuting time. If it is empirically important, such selective hiring should bias our results towards zero. To investigate whether any selective hiring before the relocation affects our results, we document in the robustness section that our main results are very similar if we restrict the sample to workers present earlier in the establishment, three years before the relocation, and who were less likely to anticipate the relocation when they were hired.

Commuting time measure— A limitation of our data is that it does not contain the commuting mode of the worker, which could also respond endogenously to the relocation. As a result, we cannot assess any effect of the relocation on the commuting mode of the worker. Our estimates might thus be biased if workers shift endogenously to commuting by car when their commuting time by public transportation increases. However, in practice, the probability of commuting by car is very small when the establishment is located in the center of Paris or when the worker lives in the center of Paris. In contrast, while not frequent, commuting by car might be less exceptional for workers living in the inner suburbs and commuting into an establishment in the inner suburbs, even if it is rare for an employer to supply parking space to its employees in these zones. To assess whether empirically commuting time by public transportation is the most relevant commuting time measure, we also report estimates controlling simultaneously for commuting time by car and by public transportation.

3.5.2 Identification of establishments' relocation

We identify relocation events when at least 50% of workers observed in an establishment in year $t-1$ are working in year t in a new establishment located in a different municipality or arrondissement of Paris.²¹ To test for potential anticipation, we restrict our sample to establishments observed for at least two years before the relocation. As the wage responses

²¹We show in the robustness section that our results are not sensitive to this 50% threshold.

to the relocation may differ in the medium run (Mulalic et al. (2014)), we additionally restrict our sample to establishments observed at least three years after the relocation.

A second important restriction is that, as discussed earlier, to minimize concerns about mismeasurement of commuting time changes due to the possibility of commuting by car, we focus on relocations between the center and the inner suburbs, where commuting by public transportation is the dominant commuting mode. However, our sample includes all workers living in the Paris metro area, including those living in the large ring.

Characteristics of relocation— In Table 3.2, we describe the main characteristics of our sample of establishments identified as relocating within the metro area. Using this definition, we identify 4 492 relocations of establishments in the Paris metro area between the (inner) suburbs and the center. Relocations from suburbs to suburbs, which account for 72% of the identified relocations, are the most common. However, relocations from center to suburbs or suburbs to center are not rare as they account for 18% and 9% of relocations in our sample, respectively.

A significant result from Table 3.2 is that most employees remain in the establishment after the relocation. Although we only require 50% of workers from the former establishment to be observed in the new establishment, we observe in practice about 83% of workers from the previous establishment in the new establishment. That most workers remain in the establishment after the relocation diminishes the risk that the relocations are associated with changes in activities within the establishments. Relocations are also associated with an increase in employment of the establishment, in particular for establishments relocating from the center to the suburbs, thus suggesting that relocations are associated with an expansion of the activities of the establishments.

Panel B in Table 3.2 documents differences in the sectoral compositions of establishments across different types of relocation. We find little differences across all types of relocations, which suggests that differences in the sectoral composition of establishments will not explain differences in our estimates across relocation types. The only noticeable exception is observed for establishments from the Information and Communication sector, which accounts for a larger share of relocations from the suburbs to the center.

Type of relocation	All	Center to suburbs	Suburbs to center	Suburbs to suburbs	Center to Center
A. Characteristics of establishment relocation					
Number of establishments	4,385	818	398	1755	1414
Share of all relocation	100%	18.6	9.1	40.0	32.2
Average share of employees in new establishment after relocation	83.5%	83.1	85.0	84.6	81.5
Median number of employees before relocation	139	175	126	159	102
Median number of employees after relocation	172	208	200	197	99
B. Sectoral Composition					
Information and communication	21.4	19.0	31.6	21.4	19.5
Finance and Insurance	22.3	24.8	22.2	15.4	30.7
Professional, Scientific, and Technical Services	41.6	39.9	39.5	47.0	35.8
Administrative and Support Services	14.7	16.3	6.7	16.2	14.0

Table 3.2: **Characteristics of relocations.** *Source:* DADS data 2010-2015, Navitia and Metric. *Note:* Panel A reports the characteristics of establishments identified as relocating within the Paris metro area. Each column reports these characteristics separately for firms that relocate from the center to the suburbs, suburbs to the suburbs, suburbs to the suburbs, and center to the center. Panel B reports the establishments' sectoral distribution for each relocation type.

3.6 Results

In this section, we analyze the consequences of establishments' relocations on the composition of employment and on wages paid to workers who remained in the establishment. Our goal is to answer two key questions: First, do relocations affect the distribution of commuting time in the establishment? Conversely, do we observe instead a large turnover from employees, in which those that experience an increase in commuting time are replaced by workers living closer, leaving the distribution of commuting time unchanged as a result? Second, do the relocations affect the geographical origins of recently hired workers within the metro area? In particular, how much closer are workers hired after the relocation relative to the new location? In order to answer these questions, we first describe how relocations affect commuting time distribution within the establishment. Next, to understand the previous aggregate patterns, we assess whether firms compensate workers for an increase in commuting time by estimating at the worker level the consequences of idiosyncratic changes in commuting time on job separation and wages.

3.6.1 Effect of relocations on the distribution of commuting time

We start by describing in Panel A of Table [3.3](#) how far firms relocate their establishment by reporting the distance and the commuting time between the two locations. We find that firms relocate their establishment relatively far, at 7 km away on average from the initial location, with distances longer by 2 km for relocation from the center to the suburbs. Due to the density of the Paris metro area, such distances are associated with 35 to 42 minutes of commuting by public transportation and from 25 to 36 minutes of commuting by car between the new and old locations of the establishment.

Given these non-negligible distances, Panel B in Table [3.3](#) documents that relocations between the center and the suburb have a substantial effect on average commuting time in the establishment as they are associated with an 8 minute increase in commuting time, which corresponds to an 18% increase relative to the pre-relocation average. In contrast, relocations from the suburbs into the center are associated with a 7 minute *decrease* in commuting time by public transportation.

Even when the effects of relocations on average commuting time are close to zero, such as for relocation within the center or suburbs, the fact that most establishments employ workers from different parts of the metro area implies that within-establishment differences across workers in the effects of relocation on commuting time are substantial. To document these differences, Table [3.4](#) reports the distribution of changes in commuting time for workers present in the establishment both before and after the relocation. The table shows that the consequences of relocations are quite heterogeneous within establishments as the standard deviation of the change in commuting time is comprised between 27 to 40 minutes across these different types of relocation. Even for relocation within the center or the suburbs, for which the average change is close to zero, commuting time by public transportation increases for more than half of the workers. For at least 10% of them, the increase is superior to 20 minutes. We exploit such within-establishment diversity in our individual-level estimates.

Table [3.3](#) also illustrates that these relocations tend to have a very different effect on commuting time by car, which suggests it might be empirically crucial to distinguish between these two alternative measures of commuting time. For relocations between the center and the suburbs, given the traffic congestion and centralization of the transportation network in the center, the sign of the effect is even reversed as they are associated with a 2-minute decrease in average commuting time by car. In comparison, relocations from the suburbs to the center are associated with a 3-minute increase in commuting time by

car. However, as emphasized earlier, commuting by car might not be a relevant option for most workers as most employers in the center or inner suburbs cannot offer a parking space.

Type of relocation	All	Center to suburbs	Suburbs to center	Suburbs to suburbs	Center to Center
A. Average distance between the old and new location of the establishment					
Distance in km	7.3	8.8	10.5	8.0	3.3
Distance by public transportation (in min)	37.1	39.2	42.4	41.6	25.0
Distance by car (in min)	27.7	36.4	37.3	25.4	20.2
B. Average change in commuting time for employees					
Δ Distance in km	0.7	2.3	-1.3	0.6	0.1
Δ Commuting time by public transportation (in min)	1.7	8.1	-6.8	1.4	-0.1
Δ Commuting time by car (in min)	0.4	-1.0	2.9	0.4	0.6

Table 3.3: **Commuting time of relocation.** *Source:* DADS data 2010-2015, Navitia and Metric. *Note:* Panel A reports the distance in km and by public transportation and car between the old and new locations of establishments that relocate for each different type of relocation. Panel B reports how each relocation has affected the average distance and commuting time by public transportation and car of workers within the establishment.

	Δ Commuting time by public transportation (in min)						
	Share (Δ Commuting Time) >0	Standard deviation	P10	Q1	P50	Q3	P90
Center to suburbs	67.2	34.1	-14.9	-0.7	8.7	20.0	30.4
Suburbs to center	30.8	39.4	-32.8	-21.0	-8.0	4.7	22.3
Suburbs to suburbs	49.4	37.9	-23.0	-9.1	0.0	12.2	26.7
Center to center	47.1	27.5	-18.7	-7.7	0.0	8.3	17.8

Table 3.4: **Distribution of commuting time change.** *Source:* DADS data 2010-2015, Navitia and Metric. *Note:* The Table reports the distribution of change in commuting time by public transportation. Each line reports this distribution for alternative types of relocation. The first column shows the share of workers with increased commuting time. Other columns report the distribution's standard deviation, the first decile, first quartile, median, third quartile, and last decile.

Trends in commuting time— Given the significant increase in commuting time associated with the relocation for some workers, particularly for relocations to the suburbs, an important question is whether establishments anticipate the relocation by hiring workers living closer to the future location prior to the relocation event, and hence separating from workers living farther away. To visualize any anticipatory change in commuting time, Figure 3.2 represents the evolution of average commuting time from 2 years before to 2 years after the relocation. Despite the large effects of the relocation, we find little evidence of pre-trends in commuting time in the years before. Figure C.2 in the supplementary Appendix C.5 shows that such a conclusion is unchanged when using establishments observed at least three years before the relocation.

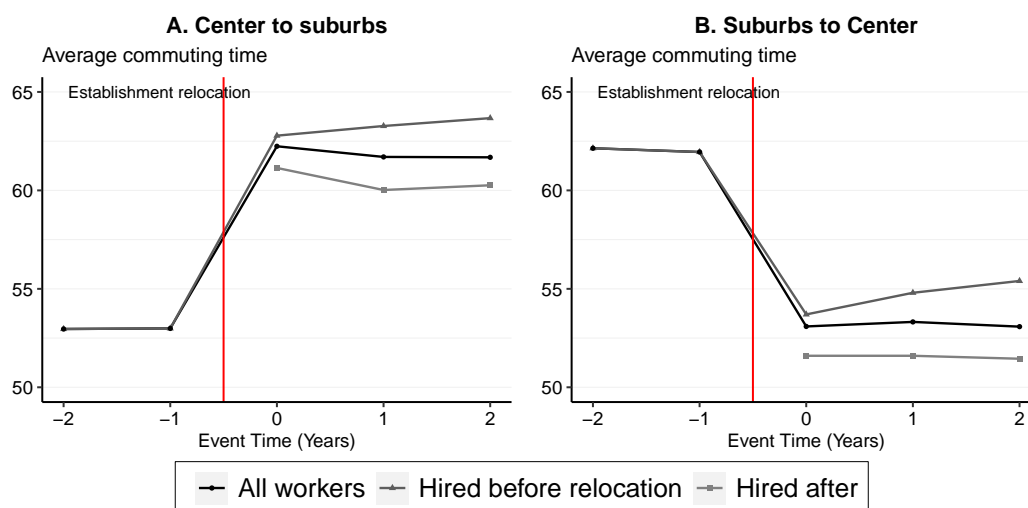


Figure 3.2: **Commuting time before and after relocation.** *Sources:* DADS Data and Navitia. *Notes:* The panels report the average commuting time across establishments that relocate in event time $t = 0$. Commuting times are calculated using the municipality of residency and the municipality of the establishment. After the relocation year, we report separately the commuting time of workers observed in the establishment before the relocation and the commuting time of workers hired after the relocation.

Another significant result from Figures 3.2 and C.2 is that, after the relocation, average commuting times do not return to their pre-relocation levels, even three years after, thus suggesting that the relocation permanently shifted the distribution of commuting time in these establishments. To understand how much this increase reflects the contribution of workers hired before relative to workers hired after the relocation, Figure 3.2 and C.2 report their average commuting time separately. While recently hired workers tend to live closer and have a shorter commute, the differences are small as they are inferior

to 3 to 4 minutes, corresponding to a 6% difference. Overall, while workers hired after the relocation tend to live closer than workers hired before and who remained in the establishment, differences in average commuting time between workers hired before and after the relocation are moderate, thus suggesting no dramatic change in the geographical origins of workers after the relocation.

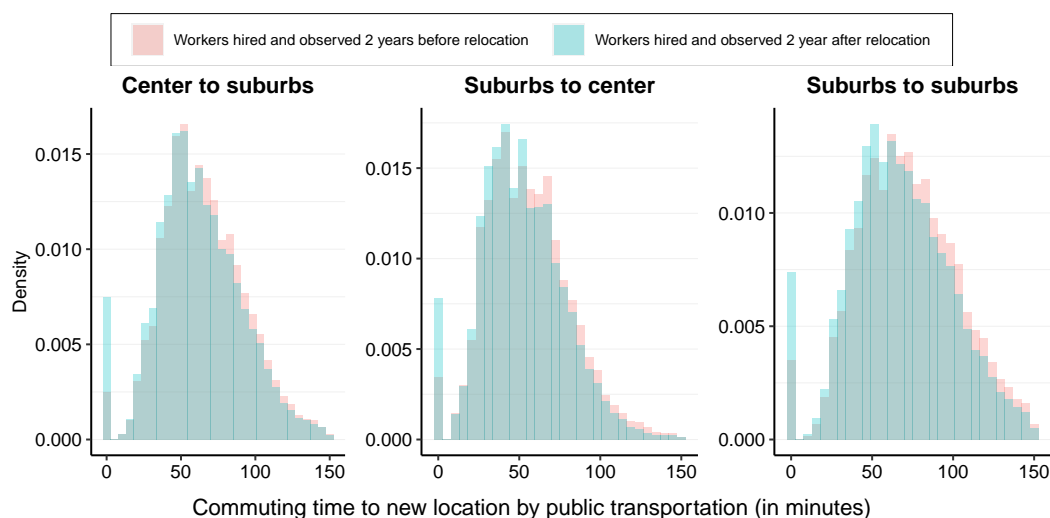


Figure 3.3: **Distribution of commuting time to new location 2 years before and after the relocation.** *Sources:* DADS Data and Navitia. *Notes:* The paper shows the overlay histograms of the distribution of commuting time for workers in the establishment 2 years before the relocation and 2 years after the relocation for workers hired after the relocation. Each histogram from left to right considers relocation from center to suburb, suburb to center, and suburb to suburb.

An issue with interpreting these results is that such small differences might reflect that workers with the longest commute have left the establishment after the relocation. To understand more systematically how the relocations affect where workers hired by the establishment live in the metro area, we compare in Figure 3.3 the distribution of commuting time to the new location between workers observed two years before the relocation, and that did not necessarily stay in the new establishment after the relocation, relative to workers hired after the relocation and observed two years after the relocation. While workers hired after the relocation tend to have a lower commuting time to the new location, a striking result is that the two distributions largely overlap, as confirmed by standard estimators for distributional overlap (Anderson et al. (2009)), which are comprised between 88% and 90% for relocation from suburbs to center and from center to suburbs, respectively, thus suggesting that most of them tend to live in the same pool of

municipalities. Overall, even if employees hired after the relocation tend to live closer, these small differences in commuting time between workers employed before and after the relocation suggest that, despite the distance between the two locations, the geographical origins of workers hired by the establishment remained very similar.

3.6.2 Commuting time, job separation and wages

The previous results suggest that, even when they increase the commuting time of most workers, as for relocation from the center to the suburbs, the effects of relocations on average commuting time appear persistent. Relocations are not associated with a large turnover of workers in which workers living far from the new location are replaced by workers living closer. This result implies that if increased commuting time diminishes workers' utility, firms need to compensate workers experiencing an increase in commuting time to preserve the match. To assess these possibilities, we turn now to individual-level estimates of the impact of commuting time changes on job separation probability and on the wages of workers that remained in the establishment.

Validity of the empirical strategy— We start by providing evidence regarding the validity of our empirical strategy designed to capture a causal effect of a change in commuting time on job separation and wages. Our key identification hypothesis is that changes in commuting time following the relocation do not affect workers in a way correlated with preexisting wage trends. A first important threat to this hypothesis would be that firms optimize their relocations such that they affect less the commuting time of workers that, even without the relocation, would have experienced specific wage trends or would have been less likely to separate. While including occupation fixed effects might moderate these concerns, any remaining correlation between changes in commuting time and unobserved wage determinants might affect our results. Another possibility is that workers might anticipate the consequences of the relocation by leaving the firm before the relocation, or firms might increase their wages before the relocation to retain them. If these effects are empirically important, we should find that wage increases or job separation probabilities before the relocation are associated with future increases in commuting time. To assess these possibilities empirically, the first two columns of Table [3.5](#) report estimates in which we test whether changes in separation probability in Panel A or in log wages in Panel B that occurred one and two years before the relocation are affected by future changes in commuting time due to the relocation. Overall, for both outcomes and years, the estimated coefficients are precisely estimated zeros, and there is little evidence

that preexisting changes in wages or job separation are associated with future changes in commuting time associated with the relocation.

Outcome	A. Separation probability				
Event year	Two years before relocation	One year before relocation	One year after relocation		
Δ Commuting time by public transportation	-0.001	0.001	0.014***	0.012***	
	(0.003)	(0.004)	(0.002)	(0.003)	
Δ Commuting time by car				0.004	0.004
				(0.004)	(0.004)
Δ Commuting time by public transportation > 0					0.038***
					(0.004)
Δ Commuting time by public transportation < 0					0.005***
					(0.002)
N	222,037	222,037	259,370	259,370	259,370
Outcome	B. Change in wage				
Δ Commuting time by public transportation	0.004	-0.003	0.011***	0.012***	
	(0.002)	(0.001)	(0.002)	(0.002)	
Δ Commuting time by car				-0.001	-0.001
				(0.003)	(0.003)
Δ Commuting time by public transportation > 0					0.028***
					(0.003)
Δ Commuting time by public transportation < 0					-0.005
					(0.004)
N	163,035	217,779	257,127	257,127	257,127

Table 3.5: The effects of changes in commuting time on wages and separation probability. *Source:* DADS data 2010-2015. *Note:* The Table shows the results of regressions in which the dependent variable is the separation probability in Panel A and the change in wage relative to before relocation in Panel B. The main variables of interest are various measures of changes in commuting time by car and public transportation. Columns 1 and 2 show placebo regression in which we regress separation probability and change in wage occurring two and one year before the relocation. Columns 3 to 5 report the effect after the relocation. All regressions include establishment and occupation fixed effects. Standard errors are clustered at the establishment level. (**) and (***) denote statistical significance at 5% and 1% level.

Baseline estimates— Column 3 in Table 3.5 reports the baseline estimates of our model assessing the effects of commuting time changes on job separation in Panel A and on wages in Panel B. Overall, we find strong evidence that idiosyncratic commuting time changes affect the risks of job separation and wages. However, the effects are economically small as the estimates suggest that a one-hour increase in commuting time, which corresponds to about two standard deviations according to Table 3.4, is associated with 1.4% increase in job separation probability and a 1.1% increase in wage.

Taking into account commuting time by car— As discussed earlier, a limitation of our data is that we do not observe the actual commuting mode of the worker. As a result, the relatively small effects estimated previously might be explained by the fact that commuting time by car and not by public transportation is the relevant measure for some workers. To test this hypothesis, we report in column 4 of Table 3.5 estimates of specifications that additionally control for changes in commuting time by car. Consistent with the fact that most commuting to work in the center and the inner suburbs use public transportation, the coefficients associated with changes in commuting time by car are both economically very small and statistically insignificant. In addition, their inclusion barely affects the estimated coefficient of commuting time by public transportation.

While unlikely for workers living in the center, a possibility is that commuting by car might be a relevant alternative for workers living in the suburbs, particularly if they have to commute to an establishment in the inner suburbs. To explore this possibility, the supplementary Appendix Table C.2 reports additional estimates in which we include an interaction term between the change in commuting time by car and the probability of living in the suburbs. We also estimate the model separately for establishments that relocate to the inner suburbs, as commuting by car is more likely to be a relevant alternative in that case. Consistent with the previous evidence, we find little effect of adding commuting time by car for these workers.

Testing for symmetrical effects— Commuting time increases and decreases might not have a symmetric effect on wages, particularly if workers have an aversion to wage cuts. If this hypothesis is true, this could explain why we found small effects of commuting time changes on job separation and wages. To investigate this hypothesis, we report estimates in column 4 in Table 3.5 that allow the effects of commuting time decreases and increases

to differ.²²

Overall, the estimates strongly reject the hypothesis of symmetric effects, as the differences between commuting time increases and decreases are large and statistically significant for both outcomes. For the job separation probability, while commuting time decreases are associated with a small decrease in the probability of separation, the effects of an increase in commuting time are seven times larger, indicating that the job separation probability would increase by 4 p.p. in response to one hour of additional commuting time.

For wages, the differences are even more striking. On the one hand, we find little evidence that firms cut the wages of employees benefiting from a decline in commuting time as the coefficient associated with a decrease in commuting time is economically small and not statistically significant. In contrast, the coefficients associated with increased commuting time are large and measured precisely, indicating an hourly wage increase of 3 log points associated with one hour of additional commuting time.

As a consequence of these significant differences, and to save space, we only report the estimates of coefficients associated with increased commuting time in the rest of the paper.

3.6.3 Differences across relocation types

As discussed earlier, relocations might also change the amenities associated with working in a given establishment. If these amenities also affect workers' utility, commuting time increases might have a stronger effect on both job separation probabilities and wages. We expect, in particular, to find a stronger effect of commuting time increases on workers from establishments that relocate from the center into the suburbs relative to those that relocate into the prestigious center of Paris. Another possibility is that differences in the characteristics of the new location also affect the ability of establishments to replace workers. Establishments that relocate into the center might have less incentive to preserve the match if they can easily replace workers. If this hypothesis is true, we should find no effects of commuting time increases on wages in this case, even if they affect the probability of job separation.

To assess the empirical relevance of these two hypotheses, we report in Table 3.6 and 3.7 separate estimates of the effects of commuting time increases on the job separation probability and wages, respectively, across different types of relocation from the relocation

²²While not reported here, we also tested for asymmetric effects of increases or decreases in commuting time by car and found no effects.

year up to 2 years after. The Tables also report separate placebo estimates up to 2 years before the relocation, allowing for testing for pretends.

Event year	Annual job separation probability		Separation probability relative to before relocation		
	-2	-1	0	1	2
	A. Center to Suburbs				
Δ Commuting by public transportation > 0	0.002	-0.001	0.052***	0.061***	0.075***
	(0.002)	(0.001)	(0.007)	(0.008)	(0.008)
N	46,489	46,489	56,386	56,386	56,386
	B. Suburbs to center				
Δ Commuting by public transportation > 0	-0.001	-0.001	0.022**	0.042***	0.039***
	(0.001)	(0.001)	(0.011)	(0.013)	(0.014)
N	22,606	22,606	24,656	24,656	24,656
	C. Suburbs to suburbs				
Δ Commuting by public transportation > 0	0.002	-0.001	0.031***	0.047***	0.048***
	(0.001)	(0.00004)	(0.005)	(0.006)	(0.006)
N	100,075	100,075	116,385	116,385	116,385
	D. Center to Center				
Δ Commuting by public transportation > 0	0.005	0.001	0.022**	0.041***	0.044***
	(0.002)	(0.002)	(0.010)	(0.011)	(0.012)
N	52,867	52,867	62,943	62,943	61,943

Table 3.6: **Effects of relocation on job separation probability.** *Source:* DADS data 2010-2015. *Note:* The Table shows the results of regressions in which the dependent variable is the separation probability. Columns 1 and 2 show placebo regression in which we regress separation probability two and one year before the relocation. Columns 3 to 5 report the effects one, two, and three years after the relocation. Panel A, B, C, and D consider a different type of relocation depending on the origin and destination of the establishment that relocates. All regressions include establishment and occupation fixed effects. Standard errors are clustered at the establishment level. (**) and (***) denote statistical significance at 5% and 1% level.

Event year	Two-year change in wage		Change in wage relative to before relocation		
	-2	-1	0	1	2
	A. Center to suburbs				
Δ Commuting by public transportation > 0	0.004	-0.007	0.046***	0.036***	0.043***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)
N	34,184	45,063	55,806	48,263	41,434
	B. Suburbs to center				
Δ Commuting by public transportation > 0	0.009	0.004	-0.004	-0.003	0.006
	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
N	16,445	21,030	24,434	20,978	18,521
	C. Suburbs to Suburbs				
Δ Commuting by public transportation > 0	0.005	0.005	0.021***	0.014***	0.017***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)
N	74,764	96,684	115,605	99,005	88,242
	D. Center to Center				
Δ Commuting by public transportation > 0	0.011	0.001	0.024***	0.015**	0.026***
	(0.006)	(0.005)	(0.007)	(0.007)	(0.009)
N	38,013	55,747	61,730	52,095	46,250

Table 3.7: **Effects of relocation on wages.** *Source:* DADS data 2010-2015. *Note:* The Table shows the results of regressions in which the dependent variable is the change in wage. Columns 1 and 2 show placebo regression in which we regress the change in wage two and one year before the relocation. Columns 3 to 5 report the effects one, two, and three years after the relocation. Panel A, B, C, and D consider alternative types of relocation depending on the origin and destination of the establishment that relocates. The explanatory variable is the commuting time increase by public transportation associated with the relocation measured in hours. All regressions include establishment and occupation fixed effects. Standard errors are clustered at the establishment level. (**) and (***) denote statistical significance at 5% and 1% level.

Overall, the results strongly confirm that the effects of commuting time increases vary dramatically across different types of relocation. For the job separation probability in Table 3.6, the point estimates have the same sign and are highly statistically significant across relocation types. However, the estimated coefficients tend to be 25% larger for relocations to the suburbs, for which we find that, after two years, a one-hour increase in commuting time is associated with a 7 p.p. increase in the job separation probability against 4 to 5 p.p. for other types of relocation. Table 3.7 shows that relocations to the suburbs are also associated with a 4 log points increase in hourly wages for each additional hour of commuting time, which is more than twice as large relative to the estimated effects for relocation within the suburbs.

In contrast, the effects of commuting time increase on wages are dramatically different for establishments that relocate from the suburbs into the center. Even though commuting time increases associated with these relocations increase the probability of job separation, there is little evidence that establishments that relocate from the suburbs into the center adjust their workers' wages proportionally, as the estimated coefficients on the wage regression are close to zero in this specification.

Overall, our results are consistent with the hypothesis that commuting time increases associated with relocations to the suburbs are more costly for establishments as they are associated with higher increases in job separation probabilities and wages. In contrast, the fact that we find no wage adjustment for relocation to the center despite the increasing risks of job separation is consistent with the hypothesis that preserving the match has less value for establishments relocating to the center.

Placebo regression on workers hired after the relocation— A concern with the previous estimates is that the relocation affected differentially the productivity and, thus, the wages of workers in a way correlated with their residency. If this is the case, part of the previous results might reflect differential productivity trends across workers affecting wages and correlated with their residency. Assuming such trends persist over time, they should also be observed in workers hired after the relocation. In order to assess this hypothesis, we report in Table 3.8 regression estimates in which we compare our baseline estimates with estimates on workers hired after the relocation for whom we impute a placebo change in commuting time had they been in the firm before the relocation. For both the job separation probability in Panel A and wages in Panel B, the results confirm that the previously estimated effects appear specific to workers hired before the relocation, as no differential risks of job separation or changes in wages are observed on workers hired

after the relocation.

	A. Job separation probability					
	All relocation		Center to suburbs		Suburbs to center	
Δ Commuting by public transportation >0	0.035***	0.006	0.052***	0.022	0.022**	-0.023
	(0.003)	(0.008)	(0.007)	(0.013)	(0.011)	(0.027)
N	259,370	109,791	53,386	25,093	24,656	9,733
Type of worker	Hired before	Hired after	Hired before	Hired after	Hired before	Hired after
	B. Change in wage					
Δ Commuting by public transportation >0	0.026***	-0.001	0.046***	0.001	-0.004	0.022
	(0.003)	(0.005)	(0.005)	(0.009)	(0.008)	(0.017)
N	257,127	94,290	55,806	22,218	24,434	8,534
Type of worker	Hired before	Hired after	Hired before	Hired after	Hired before	Hired after

Table 3.8: **Placebo regression on workers hired after the relocation** *Source:* DADS data 2010-2015. *Note:* The Table shows the results of regressions in which the dependent variable is the job separation probability in Panel A and the change in wage in Panel B for different types of establishment relocation. Within each group, we report separate regression for workers hired before and after the relocation on the commuting time change. The explanatory variable is the commuting time increase by public transportation associated with the relocation measured in hours. All regressions include establishment and occupation fixed effects. Standard errors are clustered at the establishment level. (**) and (***) denote statistical significance at 5% and 1% level.

3.6.4 Differences by workers' residency

Another possibility is that relocation's consequences vary with the workers' residencies. Workers living in the center of the Paris metro area might have access to more or better job opportunities for a low commuting time relative to those living in the suburbs. To assess this possibility, Table 3.9 reports regressions in which the coefficient of commuting time increase is allowed to differ depending on whether the worker's residency is in the center of the Paris metro area or the suburbs.

The results confirm that commuting time increases tend to have a larger effect on workers living in the center of the Paris metro area, particularly for the probability of job separation. The additional risks of job separation appear particularly large as the estimates imply that the effects of commuting time increase appear to be three times larger on job

separations. The differences are more moderate for wages, but the estimated effects are nevertheless 50% larger for workers living in the center of Paris relative to workers in the suburbs.

Type of relocation	All relocation	Center to suburbs	Suburbs to center	Suburbs to suburbs	Center to Center
	A. Separation probability relative to before relocation				
Δ Commuting by public transportation > 0	0.025***	0.032***	0.021***	0.028***	-0.005
	(0.004)	(0.008)	(0.011)	(0.005)	(0.011)
Δ Commuting by public transportation > 0 x Workers live Center	0.067***	0.063***	0.038	0.067***	0.085***
	(0.007)	(0.011)	(0.062)	(0.014)	(0.017)
N	259,370	56,386	24,656	116,385	61,943
	B. Change in wage relative to before relocation				
Δ Commuting by public transportation > 0	0.023***	0.044***	-0.001	0.020***	0.018**
	(0.003)	(0.003)	(0.008)	(0.003)	(0.008)
Δ Commuting by public transportation > 0 x Workers live Center	0.015***	0.007	-0.103	0.017**	0.017**
	(0.006)	(0.006)	(0.056)	(0.006)	(0.006)
N	257,127	55,806	24,434	115,605	61,282

Table 3.9: **Effects of relocation on workers living in center relative to suburbs.**

Source: DADS data 2010-2015. *Note:* The Table shows the results of regressions in which the dependent variable is the separation probability one year after the relocation in Panel A and the change in wage one year after relative to the year before the relocation in Panel B. Each column report separate estimates for a different type of establishment relocation. The explanatory variables are the increase in commuting time by public transportation measured in hours associated with the relocation and the interaction between this variable and a variable equal to one if the worker lives in the center of Paris. All regressions include establishment and occupation fixed effects. Standard errors are clustered at the establishment level. (**) and (***) denote statistical significance at 5% and 1% level.

3.6.5 Heterogeneity by skills and gender

The consequences of commuting time increases might also differ across workers by skill levels. As skilled workers are more costly to replace (Blatter et al. (2012)), firms might be more willing to increase their wages to preserve the match. To test this hypothesis, as education is not reported in the data, we use the workers' occupations to distinguish between three broad skill groups high, medium, and low-skill occupations defined using the

French occupational classification codes.²³ Results of these separate estimates reported in Table 3.10 for relocations to the suburbs point to large differences in the adjustment to commuting time increases across these groups. While commuting time increases substantially affect job separation probability for low-skill workers, we find they have little effect on their wages, in contrast to high- and medium-skill workers. For relocations to the center, the estimation results are once again very different as we find no effects of commuting time increase on wages in any of these groups, thus suggesting that differences in the composition of employment by skills across establishments do not explain the differences between these two types of relocations.

Gender differences in the effects of commuting time increase might also be important as commuting time might have a larger disutility for women than men (Le Barbanchon et al. (2021)). To test this hypothesis, the last two columns of Table 3.10 report separate estimates by gender. Consistent with this hypothesis, we find a larger and more precise effect of commuting time increases on the job separation probability for women associated with a relocation to the center. On the other hand, the coefficients are very similar for relocation to the suburbs while, for wages, the adjustment to commuting time increases appear rather similar for men and women.

3.6.6 Differences across sectors

As emphasized earlier in Table 3.2 the distribution of establishments across sectors is broadly similar across our different categories of relocation with the important exception of the share of establishments from the Information and Communication sector, which tends to be slightly larger among relocations to the center. If the consequences of relocations are heterogeneous across sectors, these differences in sectoral compositions might explain some of the differences between relocations from the center to the suburbs and relocations from the suburbs to the center. To investigate this hypothesis, Table 3.11 reports separate estimates across sectors for these two types of relocation.

Overall, the estimates reported in Table 3.11 are inconsistent with the hypothesis that differences in the sectoral composition of establishments explain differences between relocations. Overall, we find relatively few differences in estimates across sectors relative to differences between each type of relocation as, within sectors, relocations to the suburbs tend to have a systematically larger and statistically significant effect on wages and job separation relative to relocation from the suburbs to the center. A notable exception is

²³See appendix for details on the match.

the Administrative and Support Services sector, for which we find no effect of commuting time change on wages for any relocation.

	High Skill	Medium Skill	Low Skill	Men	Women
	A Job separation probability after relocation				
	A1. Center to suburbs				
Δ Commuting by public transportation > 0	0.056***	0.121***	0.058***	0.069***	0.055***
	(0.015)	(0.029)	(0.015)	(0.012)	(0.012)
N	16,983	4,810	16,115	30,132	26,254
	A2. Suburbs to Center				
Δ Commuting by public transportation > 0	0.025	0.036	0.067***	0.029	0.050***
	(0.028)	(0.041)	(0.023)	(0.019)	(0.018)
N	7,416	2,394	6,972	12,991	11,665
	B Change in wage relative to before relocation				
	B1. Center to suburbs				
Δ Commuting by public transportation > 0	0.051***	0.039**	0.012	0.038***	0.036***
	(0.011)	(0.018)	(0.009)	(0.008)	(0.009)
N	15,395	3,931	12,378	25,640	22,623
	B2. Suburbs to Center				
Δ Commuting by public transportation > 0	-0.025	0.009	0.006	-0.011	-0.002
	(0.020)	(0.024)	(0.009)	(0.012)	(0.010)
N	6,470	1,947	5,727	11,056	9,922

Table 3.10: **Differences in effects of commuting time increases by occupation groups and gender.** *Source:* DADS data 2010-2015. *Note:* The Table shows the results of regressions in which the dependent variable is the separation probability in Panel A and the change in wage in Panel B. Panels A1 and B1 consider relocation from the center to the suburbs. Panels A2 and B2 consider relocation from the suburbs to the center. Columns 1, 2, and 3 show estimates for High-skill, medium-skill, and low-skill workers. Columns 4 and 5 show results for men and women. The explanatory variable is the commuting time increase by public transportation associated with the relocation measured in hours. All regressions include establishment and occupation fixed effects. Standard errors are clustered at the establishment level. (**) and (***) denote statistical significance at 5% and 1% level.

	A Job separation probability after relocation			
	Information and communication	Finance and Insurance	Professional, Scientific, and Technical Services	Administrative and Support Services
	A1 Center to suburbs			
Δ Commuting by public transportation > 0	0.071***	0.052***	0.062***	0.069***
	(0.021)	(0.017)	(0.015)	(0.023)
N	9,746	11,488	17,985	6,890
	A2 Suburbs to Center			
Δ Commuting by public transportation > 0	0.039	0.042	0.043**	0.069
	(0.032)	(0.027)	(0.020)	(0.052)
N	6,331	4,822	7,676	2,304
	B Change in wage relative to before relocation			
	B1 Center to suburbs			
Δ Commuting by public transportation > 0	0.065***	0.044***	0.046***	-0.015
	(0.013)	(0.012)	(0.013)	(0.010)
N	9,512	10,487	12,724	6,948
	B2 Suburbs to Center			
Δ Commuting by public transportation > 0	0.032	-0.010	-0.011	-0.016
	(0.022)	(0.020)	(0.010)	(0.016)
N	5,462	4,726	5,513	2,399

Table 3.11: **Differences across sectors.** *Source:* DADS data 2010-2015. *Note:* The Table shows the results of regressions in which the dependent variable is the separation probability in Panel A and the change in wage in Panel B. Each column show estimates for establishments in a different sector. Panels A1 and B1 consider relocation from the center to the suburbs, while Panels A2 and B2 consider relocation from the suburbs to the center. The explanatory variable is the commuting time increase by public transportation associated with the relocation measured in hours. All regressions include establishment and occupation fixed effects. Standard errors are clustered at the establishment level. (**) and (***) denote statistical significance at 5% and 1% level.

3.7 Robustness

We assess the robustness of our main results in Table [3.12](#). For reference, our baseline results are reported in column 1. As discussed earlier, a first threat to the interpretation of our results is that firms might have anticipated the relocation by hiring workers just before the relocation for whom an increase in commuting time has a lower effect on their utility. If this hypothesis is true, the estimates should differ when performed on a sample of workers hired much before the relocation, and that thus were less likely to anticipate the change. To investigate this hypothesis, column 2 reports results using only workers observed in the establishment three years before the relocation. While such restriction significantly decreases the sample size, the results appear unchanged relative to our main results.

Another threat to the interpretation of our results is that the relocation of an establishment might be associated with a change in the activities performed in the establishment. These changes in activities might affect our results if they affect the wages or job separation probability of workers differentially in a way correlated with the increase in commuting time. To assess the importance of this issue, we report results in column 3, estimated using establishments in which more than 80% of workers observed in the previous establishment are also observed in the new establishment, while only a share of 50% was required in our baseline sample. Focusing on establishments in which the composition of workers relative to the past establishment remained unchanged should decrease the risk that the relocation is associated with a change in the activities of the establishment affecting workers. While such restriction also significantly decreases the sample size, it has little qualitative effect on our point estimates.

In column 4, we assess the robustness of our results to the inclusion of municipality and, for the municipality of Paris, arrondissements fixed effects associated with the worker's residency. Including these fixed effects should absorb any correlation between change in commuting time and change in wages common to workers living in the same municipality or arrondissement. Reassuringly, our results are unaffected by their inclusion.

	(1)	(2)	(3)	(4)
Specification	Baseline	Only workers hired 3 years before relocation	More than 80% of workers in the new establishment	Municipality fixed effects
	A. Job separation probability after relocation			
Δ Commuting by public transportation > 0	0.034***	0.038***	0.032***	0.038***
	(0.004)	(0.005)	(0.005)	(0.004)
N	259,370	160,652	192,990	259,370
	B. Change in wage relative to before relocation			
Δ Commuting by public transportation > 0	0.028***	0.027***	0.028***	0.029***
	(0.003)	(0.004)	(0.004)	(0.003)
N	257,127	159,808	191,354	257,127

Table 3.12: **Robustness of the main results.** *Source:* DADS data 2010-2015. *Note:* The Table shows the results of regressions in which the dependent variable is the separation probability in Panel A and the change in wage in Panel B. The explanatory variable is the commuting time increase by public transportation associated with the relocation measured in hours. Column 1 reproduces the baseline estimates from Table 3.5. Column 2 reports estimates using only workers observed in the establishment at least three years before the relocations. Column 3 reports estimates using a sample of establishments in which more than 80% of the workers from the initial establishment are also observed in the new establishment. Column 4 reproduces results from a specification including municipality and, for the municipality of Paris, arrondissement fixed effects. All regressions include establishments and occupation fixed effects. Standard errors are clustered at the establishment level. (**) and (***) denote statistical significance at 5% and 1% level.

3.8 Conclusion

To understand the trade-offs firms face when choosing an establishment's location in a large metro area, we investigated the consequences of establishments' relocation across different parts of the Paris metro area, particularly between the center and the suburbs. We first documented that relocations significantly affect commuting time by public transportation within establishments. The effects appear particularly large for relocations from the center into the suburbs, which are associated with a persistent increase in commuting time by public transportation for most workers from the establishment. Despite this increase, there is a significant overlap in the geographical origins within the metro area between workers hired before and after the relocation. Even if workers hired after the

relocation tend to live closer to the establishment, workers hired after the relocation live in the same parts of the metro area as those hired before.

To explain these patterns, we investigate how differences in increases in commuting time associated with the relocations affect the job separation probabilities and wages across workers within the establishment. We find that increases in commuting time increase the risks of job separation, but their effects are, on average small. Importantly, consistent with the hypothesis that differences in amenities across parts of the metro area also influence workers' utility, the effects of similar commuting time increases differ dramatically depending on which part of the establishment relocates. In particular, we find that increases in job separation risk tend to be twice as large for relocations to the suburbs. The effects on job separation appear also larger for workers living in the center of Paris, who might have access to more job opportunities for a low commuting time relative to workers in the suburbs.

We find evidence that one explanation for the relatively moderate effects of commuting time increases on the job separation probability is that establishments increase the wage of workers in compensation differently, consistent with a non-competitive model of wage formation. We find particularly large wage increases for relocations from the center to the suburbs, particularly for workers living in the center of Paris. In contrast, we find no evidence that establishments relocating to the center also adjust workers' wages to commuting time increases, consistent with the hypothesis that they have less incentive to preserve the match and can more easily replace workers in the center. We also find no wage cut for workers benefiting from a *decrease* in commuting time on wage, thus suggesting that these workers benefit from an increase in their share of the surplus from the match.

Overall, our results are consistent with the hypothesis that relocations to the suburbs are more costly for firms as they appear associated with both lower levels of amenities, which increases the risk of separation and longer commuting time for a larger share of workers in the metro area, in particular for workers living in the center which tend to react more strongly to increases in commuting-time. These results are consistent with extensive urban economics literature emphasizing the role of commuting time on workers' labor supply to the firm. For skilled workers, these results are also consistent with non-competitive models of the labor market in which firms can increase wages to preserve the match when a change in the working environment affects the workers' utility.

An important limitation of our results is that, given the data requirements, our results are specific to a single metro area, Paris, as we do not have access to data that would allow

us to replicate our study in other large metro areas in which there remains a substantial concentration of employment in the center, such as London or New York. Further studies should also investigate the trade-off of firms in polycentric metro areas, such as Los Angeles or Dallas, characterized by a lower density of the public transportation network and where most commuting to work occurs by car.

Conclusion

Through this doctoral thesis, I aim to gain new insight into the labor market. To do so, I use both theoretical search and matching model and econometric methods. This thesis consists of three chapters, each providing a response to the following questions. : (1) How does the emerging trend of remote work influence labor market outcomes and inequalities within two distinct spatial zones? (2) How did COVID-19 impact unemployment for different types of workers, and how did public interventions mitigate its negative effects? And (3) How does firm relocation impact wages and employee turnover?

Chapter 1 focuses on the first question by examining the impact of working from home on labor market outcomes using an extension of the search and matching model. This chapter not only reveals the shifts that occurred, in the economy, due to the COVID-19 pandemic but also addresses the data gap to (i) explain the increase in the share of remote workers following the COVID-19 crisis; (ii) investigate the effects of this shift on labor market outcomes in two distinct areas; and (iii) assess the potential benefits of working from home in reducing inequalities between urban and rural regions.

In this chapter, we show that the increase in commuting costs has a negative impact on the unemployment rate in both urban and rural areas. However, this negative impact is offset by the increase in remote workers' productivity and the decrease in WFH disutility. Furthermore, we find that reducing remote work disutility results in a win-win situation by improving the welfare of the unemployed, narrowing the welfare gap between rural and urban areas, and increasing overall wealth in both economies emphasizing its positive impact on the economy.

Chapter 2 brings an answer to the second question through a general equilibrium model that incorporates matching frictions to analyze the impact of the COVID-19 lockdown on unemployment. In this chapter, we show that the economic impact of the lockdown is very large, in particular for workers without a university degree. Nevertheless, the study

finds that both the CARES Act (in the US) and partial unemployment (in France) play a significant role in helping the labor market absorb the COVID-19 shock. In fact, we show that the CARES Act serves to encourage labor hoarding. Moreover, the recall system implemented in the United States contributes to a robust recovery. Finally, we show that in France, the utilization of partial unemployment help also in the long-term recovery. A key message of this chapter is that, although the subprime and the COVID-19 crises are in nature different, the remarkable public interventions during the latter crisis have facilitated an unprecedented speed of economic recovery.

Finally, Chapter 3 focuses on understanding the decision-making process of firms when selecting the locations for their establishments. Particularly, through this chapter, we aim to gain insight into the effect of relocation on wages and employee turnover. The findings indicate that an increase in commuting time due to a relocation leads to a higher probability of job separation. Hence, in order to maintain the employment relationship, establishments that move to the suburbs tend to increase the wages for skilled workers, particularly those residing in the city center. The study also shows that these findings are not similar for every relocation. Particularly, we show that there are no wage adjustments for establishments relocating to the center. Finally, the study rejects the hypothesis of wage cuts for workers for whom commuting time decreases as a result of the relocation of their establishment.

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Appendix A

A.1 The intensity of WFH in WHA

A.1.1 By surplus maximisation

Recall, $S_{n,ji}^h = W_{n,ji}^h - U_i + J_{n,ji}^h$

Hence, by differentiating

$$\frac{\partial S_{n,ji}^h}{\partial \lambda_{n,ji}} = \frac{\partial (W_{n,ji}^h - U_i)}{\partial \lambda_{n,ji}} + \frac{\partial J_{n,ji}^h}{\partial \lambda_{n,ji}} = 0 \quad (\text{A.1})$$

Using equation [1.1](#), [1.2](#), [1.5](#) and the free entry condition, we have

$$\frac{\partial (W_{n,ji}^h - U_i)}{\partial \lambda_{n,ji}} = \frac{\partial w_{n,ji}^h(\tau)}{\partial \lambda_{n,ji}} - \frac{\partial L^h(\tau_{n,ji}, \lambda_{n,ji})}{\partial \lambda_{n,ji}} \quad (\text{A.2})$$

$$\frac{\partial J_{n,ji}^h(\tau)}{\partial \lambda_{n,ji}} = - \frac{\partial w_{n,ji}^h(\tau)}{\partial \lambda_{n,ji}} \quad (\text{A.3})$$

Putting [A.3](#) and [A.2](#) in [A.1](#)

$$\frac{\partial w_{n,ji}^h(\tau)}{\partial \lambda_{n,ji}} - \frac{\partial L^h(\tau_{n,ji}, \lambda_{n,ji})}{\partial \lambda_{n,ji}} - \frac{\partial w_{n,ji}^h(\tau)}{\partial \lambda_{n,ji}} = 0$$

$$\frac{\partial L^h(\tau_{n,ji}, \lambda_{n,ji})}{\partial \lambda_{n,ji}} = 0$$

Leading to

$$\lambda_{n,ji}^* = 1 - e^{-\frac{c_{\tau,ji}\tau_{n,ji}}{\zeta_i}}$$

A.1.2 Through Nash Bargaining

$$w_{n,ji}^h = \operatorname{argmax}_{w_{n,ji}^h; \lambda_{n,ji}} \{(W_{n,ji}^h - U_i)^\eta (J_{n,ji}^h)^{1-\eta}\}$$

$$\eta \frac{\partial W_{n,ji}^h(\tau) - U_i}{\partial \lambda_{n,ji}} J_{n,ji}^h = -(1 - \eta) \frac{\partial J_{n,ji}^h}{\partial \lambda_{n,ji}} (W_{n,ji}^h - U_i)$$

$$\frac{\partial w_{n,ji}^h(\tau) - L^h(\tau_{n,ji}, \lambda_{n,ji})}{\partial \lambda_{n,ji}} \eta J_{n,ji}^h = \frac{\partial w_{n,ji}^h(\tau)}{\partial \lambda_{n,ji}} (1 - \eta) (W_{n,ji}^h - U_i)$$

From wage bargaining we find: $(1 - \eta)(W_{n,ji}^c - U_i) = \eta J_{n,ji}^c$ leading to

$$\frac{\partial w_{n,ji}^h(\tau) - L^h(\tau_{n,ji}, \lambda_{n,ji})}{\partial \lambda_{n,ji}} = \frac{\partial w_{n,ji}^h(\tau)}{\partial \lambda_{n,ji}}$$

Which is the same solution as directly maximizing the total surplus.

$$\frac{\partial L^h(\tau_{n,ji}, \lambda_{n,ji})}{\partial \lambda_{n,ji}} = 0$$

A.1.3 Through profit maximisation

Equation [1.5](#), shows that maximizing, the marginal value of a worker $\frac{\partial J_{n,ji}^h(\tau)}{\partial \lambda_{n,ji}}$ is equivalent to maximizing directly his wage $\frac{\partial w_{n,ji}^h(\tau)}{\partial \lambda_{n,ji}} = 0$

From equation [1.14](#) we can easily show that

$$\frac{\partial w_{n,ji}^h(\tau)}{\partial \lambda_{n,ji}} = \frac{\partial (1 - \eta) L^h(\tau_{n,ji}, \lambda_{n,ji})}{\partial \lambda_{n,ji}} = 0$$

Which is the same solution as directly maximizing the total surplus.

A.2 Data

A.2.1 Diploma

The data on educational attainment is obtained from [USDA](#), which compiles information by combining multiple data files. This includes data on county metro-non-metro status based on the Office of Management and Budget’s metropolitan area definitions, as well as the American Community Survey 5-year period estimates. However, we only have data available for the years 2000, 2015, 2016, and 2019. To address this limitation, we included data from 2019 as an estimate for 2018, assuming that during the first year of the COVID-19 pandemic, the economy was largely stagnant and educational changes were not a central focus. Additionally, based on the data from 2015 and 2016, which showed minimal to no change between consecutive years, we used the average of the four-year data to compute the educational attainment shares in both rural and urban areas from 2000 to 2018.

A.2.2 Wages

The quarterly wage data is obtained from [the Bureau of Labor Statistics \(BLS\)](#). However, since the model is calibrated using monthly data, we convert the quarterly data into monthly data.

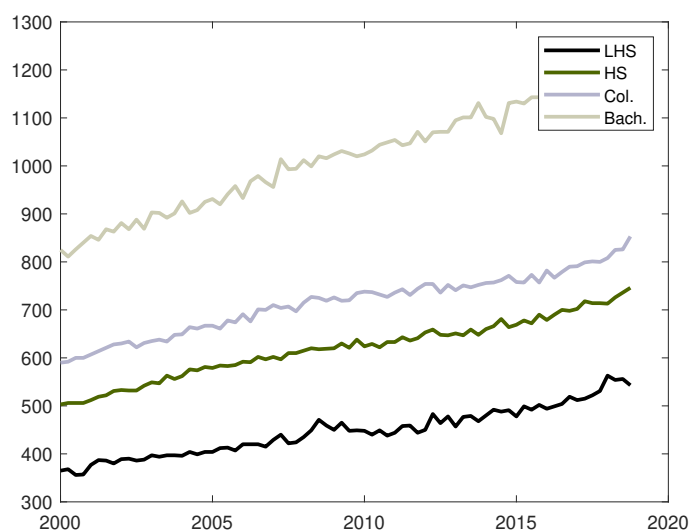


Figure A.1: Quarterly Weekly Wages

	LHS	HS	Coll.	Bach.
Median Wage	2009	2786	3209	4578

Table A.1: **Median earning by educational attainment from 2000 to 2018.** Source : Weekly and hourly earnings data from the Current Population Survey [BLS](#)

A.2.3 Flows

Unemployment, Job finding rate and Job separation rate

- **Aggregate data:** The macro-level unemployment rate and job-separation rate data that we use are constructed from BLS data, from 2000 to 2018. Data pertaining to monthly employment and unemployment levels for all people aged 16 and over are seasonally adjusted. To construct worker flows following [Adjemian et al. \(2019\)](#), we use the number of unemployed workers who have been unemployed for less than five weeks. After dividing the unemployment levels in each month by the sum of unemployment and employment, we obtain monthly series for U_m (where m refers to the monthly frequency). We also have data on individuals unemployed for less than five weeks U_m^5 . We can then construct, the worker flows which is given by $JSR_m = \frac{U_{m+1} - U_m^5}{E_m}$.
- **Data by educational attainment:** Using data from [Cairo and Cajner \(2016\)](#) and BLS data on the aggregated Unemployment and Job separation rate, we derive worker flows based on educational attainment (January 2000–January 2018)¹. The first-order moments of worker flows used to identify the model parameters are shown in Table [A.2](#).

	LHS	HS	Coll.	Bach.	Aggregate
JSR	0.0367	0.0204	0.0169	0.0095	0.0184
UR	0.1059	0.0677	0.0566	0.0333	0.0600
Share of population	0.11	0.33	0.31	0.25	1

Table A.2: **Worker flows and stocks.** Data came from [Cairo and Cajner \(2016\)](#) and cover the 2000–2014 period; we rescaled these data. For population shares, the data came from the BLS and cover the 2000–2018 period. The educational attainment typologies are as follows: less than high school diploma (LHS), high school diploma (HS), college diploma (Coll.) and bachelor degree or more (Bach.).

¹See [Kandoussi and Langot \(2021\)](#) for the rescaling method

A.2.4 Commuting Time and Distance

Using [the American Community Survey 2018](#) for workers 16 years and over who did not work at home, we can produce the data on the daily commuting time in US. We then estimate the parameters and the law that fits this data. Figure [A.2](#) plots the estimation of a lognormal Pdf with $\mu_\tau = 3.3$ and $\sigma_\tau = 0.6$ which will be the calibration of the log normal law in the model.

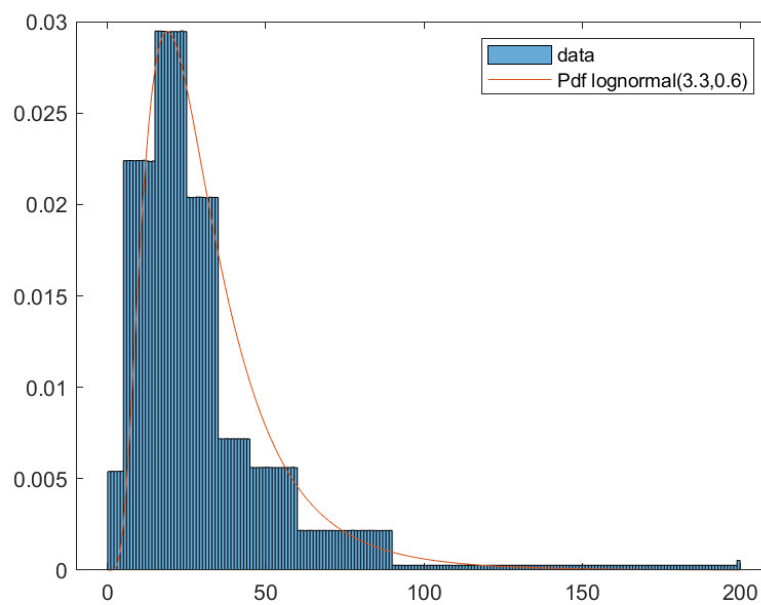


Figure A.2: Commuting time estimation in US.

A.2.5 Commuting Costs:

Following [The Clever Real Estate](#), to account for commuting cost, 3 variables will be taken into account :

- Fuel: The monthly cost of fuel is estimated by dividing the distance to work (*i.e* d per day which represent 42 miles²) by the average miles per gallon (50 to 60mpg). This will be multiplied by the number of business days in a month (19-22 business days) and then by the average gas price per gallon (the average cost of gas in 2018: 2.74 \$ a gallon). In this case : $c_f = \frac{42}{55} \times 22 \times 2.74 = 46\$$.
- Maintenance: The monthly cost of maintenance is the average cost of maintenance per mile (9 cents) multiplied by the average number of miles to work: $c_m = 0.09 \times 42 \times 22 = 83\$$.
- Opportunity: We estimated the monthly opportunity cost of a person's time as the amount of money they could have earned had they been working instead of commuting by multiplying the median hourly wages in 2018 (14.99\$) by the number of hours spent commuting to work. However, we make the assumption that this opportunity cost applies to only 1 way trip as workers will usually use the extra time in the morning to rest and do home chores meaning³ : $c_{op} = 22 \times 14.99 \times 27/60 = 148, 4\$$

²Assuming that typical car speed on residential roads or busy city roads is 50km/h and that the speed of vehicles on the main road, traveling reasonably fast is between 80 and 90km/h. We take an average of speed of 75km/h. Then we can assume that the distance is $\bar{d} = 75 \times \tau \times \frac{2}{60} = 67.5km$

³This aligns with [Aksoy et al. \(2023\)](#)

A.3 Social Planner

A.3.1 The first order condition conditional on $V_{t,j}$

$$\frac{\partial \mathcal{V}_t}{\partial V_{t,j}} = 0$$

$$\begin{aligned} & \beta \left[\mathcal{G}^o(\tau_{t+1,jj}^R) \frac{\partial \mathcal{V}_{t+1}}{\partial N_{t+1,jj}^o} + \mathcal{G}^h(\tau_{t+1,jj}^R) \frac{\partial \mathcal{V}_{t+1}}{\partial N_{t+1,jj}^h} + \mathcal{G}^r(\tau_{t+1,jj}^R) \frac{\partial \mathcal{V}_{t+1}}{\partial N_{t+1,jj}^r} \right] \frac{\partial M_{t,j}(\gamma U_j + (1-\gamma)U_i, V_j)}{\partial V_{i,j}} (1 - \omega_{ji,t}) \\ & + \beta \left[\mathcal{G}^o(\tau_{t+1,ji}^R) \frac{\partial \mathcal{V}_{t+1}}{\partial N_{t+1,ji}^o} + \mathcal{G}^h(\tau_{t+1,ji}^R) \frac{\partial \mathcal{V}_{t+1}}{\partial N_{t+1,ji}^h} + \mathcal{G}^r(\tau_{t+1,ji}^R) \frac{\partial \mathcal{V}_{t+1}}{\partial N_{t+1,ji}^r} \right] \frac{\partial M_{t,j}(\gamma U_j + (1-\gamma)U_i, V_j)}{\partial V_{t,j}} \omega_{ji,t} = \kappa \\ & + (\lambda_{jj,t}^p (1 - \omega_{ji,t}) + \lambda_{ji,t}^p \omega_{ji,t}) \frac{\partial M_{t,j}(\gamma U_j + (1-\gamma)U_i, V_j)}{\partial V_{t,j}} \end{aligned}$$

Noting, $\tilde{J}_{t,ji}^{p,c} = \frac{\partial \mathcal{V}_t}{\partial N_{t,ji}^c}$ with $\tilde{J}_{t,ji}^{p,c} = \frac{\int_0^{\tau_{t,ji}^{max}} J_{t,ji}^{p,c} dG(\tau)}{\mathcal{G}^c(\tau_{t,ji}^R)}$ and $\bar{J}_{t,ji}^p = \sum_c \mathcal{G}^c(\tau_{t,ji}^R) \tilde{J}_{t,ji}^{p,c}$, this leads to:

$$\begin{aligned} \frac{\kappa}{\frac{\partial M_j(\gamma U_j + (1-\gamma)U_i, V_j)}{\partial V_j}} &= \beta [(1 - \omega_{ji}) \bar{J}_{jj}^p + \omega_{ji} \bar{J}_{ji}^p] \\ \frac{\kappa}{\frac{\partial M_i(\gamma U_i + (1-\gamma)U_j, V_i)}{\partial V_i}} &= \beta [(1 - \omega_{ij}) \bar{J}_{ii}^p + \omega_{ij} \bar{J}_{ij}^p] \end{aligned}$$

A.3.2 The first order condition conditional on $N_{t,I}^c$

$$\begin{aligned} \frac{\partial \mathcal{V}}{\partial N_{t,ji}^o} &= 0 \\ \frac{\partial \mathcal{V}}{\partial N_{t,ji}^h} &= 0 \\ \frac{\partial \mathcal{V}}{\partial N_{t,ji}^r} &= 0 \\ \frac{\partial \mathcal{V}}{\partial N_{t,ii}^o} &= 0 \\ \frac{\partial \mathcal{V}}{\partial N_{t,ii}^h} &= 0 \\ \frac{\partial \mathcal{V}}{\partial N_{t,ii}^r} &= 0 \end{aligned}$$

As $\frac{\partial M_{t,j}}{\partial N_{t,ji}^c} = \frac{\partial M_{t,j}}{\partial N_{t,ii}^c}$ and $\frac{\partial 1-\omega_{ji}}{\partial N_{t,ji}^c} = \frac{\partial 1-\omega_{ii}}{\partial N_{t,ii}^c}$, the derivative that are needed are the following

$$\begin{aligned} I &= \frac{\partial M_{t,j}}{\partial N_{t,ji}^c}(1 - \omega_{ji}) + M_{t,j} \frac{\partial 1 - \omega_{ji}}{\partial N_{t,ji}^c} \\ J &= \frac{\partial M_{t,i}}{\partial N_{t,ji}^c} \omega_{ij} + M_{t,i} \frac{\partial \omega_{ij}}{\partial N_{t,ji}^c} \\ K &= \frac{\partial M_{t,j}}{\partial N_{t,ji}^c} \omega_{ji} + M_{t,j} \frac{\partial \omega_{ji}}{\partial N_{t,ji}^c} \\ L &= \frac{\partial M_{t,i}}{\partial N_{t,ji}^c}(1 - \omega_{ij}) + M_{t,i} \frac{\partial 1 - \omega_{ij}}{\partial N_{t,ji}^c} \end{aligned}$$

Using, $\bar{J}_{t,ji}^p = \sum_c^C \mathcal{G}^c(\tau_{t,ij}^R) \bar{J}_{t,ji}^{p,c}$ we have

$$\begin{aligned} (1 - (1 - s_j)\beta) \bar{J}_{t,ji}^p &= y_{ji} - \bar{L}_{ji}(\tau_{t,ji}, \lambda_{t,ji}) - b + \beta \begin{bmatrix} (1 - \omega_{ji})f_{ji} [1 - \epsilon_{M_j|JS_j}] \bar{J}_{t+1,jj}^p \\ + \omega_{ij}f_{ii} [1 - \epsilon_{M_i|JS_i}] \bar{J}_{t+1,ij}^p \\ - f_{ji} [\epsilon_{M_j|JS_j}\omega_{ji} + (1 - \omega_{ji})] \bar{J}_{t+1,ji}^p \\ - f_{ii} [\epsilon_{M_i|JS_i}(1 - \omega_{ij}) + \omega_{ij}] \bar{J}_{t+1,ii}^p \end{bmatrix} \\ (1 - (1 - s_i)\beta) \bar{J}_{t,ii}^p &= y_{ii} - \bar{L}_{ii}(\tau_{t,ii}, \lambda_{t,ii}) - b + \beta \begin{bmatrix} (1 - \omega_{ji})f_{ji} [1 - \epsilon_{M_j|JS_j}] \bar{J}_{t+1,jj}^p \\ + \omega_{ij}f_{ii} [1 - \epsilon_{M_i|JS_i}] \bar{J}_{t+1,ij}^p \\ - f_{ji} [\epsilon_{M_j|JS_j}\omega_{ji} + (1 - \omega_{ji})] \bar{J}_{t+1,ji}^p \\ - f_{ii} [\epsilon_{M_i|JS_i}(1 - \omega_{ij}) + \omega_{ij}] \bar{J}_{t+1,ii}^p \end{bmatrix} \end{aligned}$$

Noting :

$$\mathcal{P}_{ji} = \begin{aligned} &(1 - \omega_{ji})f_{ji} [1 - \epsilon_{M_j|JS_j}] \bar{J}_{t+1,jj}^p + \omega_{ij}f_{ii} [1 - \epsilon_{M_i|JS_i}] \bar{J}_{t+1,ij}^p \\ &- f_{ji} [\epsilon_{M_j|JS_j}\omega_{ji} + (1 - \omega_{ji})] \bar{J}_{t+1,ji}^p - f_{ii} [\epsilon_{M_i|JS_i}(1 - \omega_{ij}) + \omega_{ij}] \bar{J}_{t+1,ii}^p \end{aligned}$$

This leads

$$\mathcal{P}_{ji} = \begin{aligned} &-f_{ji}\epsilon_{M_j|JS_j} \bar{J}_{t+1,ji}^p - f_{ii}\epsilon_{M_i|JS_i} \bar{J}_{t+1,ii}^p \\ &+ f_{ji}(1 - \omega_{ji}) [1 - \epsilon_{M_j|JS_j}] [\bar{J}_{t+1,jj}^p - \bar{J}_{t+1,ji}^p] + f_{ii}\omega_{ij} [1 - \epsilon_{M_i|JS_i}] [\bar{J}_{t+1,ij}^p - \bar{J}_{t+1,ii}^p] \end{aligned}$$

Hence,

$$\begin{aligned} (1 - (1 - s_j)\beta) \bar{J}_{t,ji}^p &= y_{ji} - \bar{L}_{ji}(\tau_{t,ji}, \lambda_{t,ji}) - b - \beta \begin{bmatrix} + f_{ji}\epsilon_{M_j|JS_j} \bar{J}_{t+1,ji}^p + f_{ii}\epsilon_{M_i|JS_i} \bar{J}_{t+1,ii}^p \\ - f_{ji}(1 - \omega_{ji}) [1 - \epsilon_{M_j|JS_j}] [\bar{J}_{t+1,jj}^p - \bar{J}_{t+1,ji}^p] \\ - f_{ii}\omega_{ij} [1 - \epsilon_{M_i|JS_i}] [\bar{J}_{t+1,ij}^p - \bar{J}_{t+1,ii}^p] \end{bmatrix} \\ (1 - (1 - s_i)\beta) \bar{J}_{t,ii}^p &= y_{ii} - \bar{L}_{ii}(\tau_{t,ii}, \lambda_{t,ii}) - b + \beta \begin{bmatrix} + f_{ji}\epsilon_{M_j|JS_j} \bar{J}_{t+1,ji}^p + f_{ii}\epsilon_{M_i|JS_i} \bar{J}_{t+1,ii}^p \\ - f_{ji}(1 - \omega_{ji}) [1 - \epsilon_{M_j|JS_j}] [\bar{J}_{t+1,jj}^p - \bar{J}_{t+1,ji}^p] \\ - f_{ii}\omega_{ij} [1 - \epsilon_{M_i|JS_i}] [\bar{J}_{t+1,ij}^p - \bar{J}_{t+1,ii}^p] \end{bmatrix} \end{aligned}$$

A.3.3 Condition to optimality

We have

$$\begin{aligned}\mathcal{E}_{ji} &= f_{ji}(1 - \omega_{ji}) [1 - \epsilon_{M_j|JS_j}] [\bar{J}_{jj}^p - \bar{J}_{ji}^p] + f_{ii}\omega_{ij} [1 - \epsilon_{M_i|JS_i}] [\bar{J}_{ij}^p - \bar{J}_{ii}^p] \\ \mathcal{E}_{ij} &= f_{ij}(1 - \omega_{ij}) [1 - \epsilon_{M_i|JS_i}] [\bar{J}_{ii}^p - \bar{J}_{ij}^p] + f_{jj}\omega_{ji} [1 - \epsilon_{M_j|JS_j}] [\bar{J}_{ji}^p - \bar{J}_{jj}^p]\end{aligned}$$

Hence, $\mathcal{E}_{ji} = \mathcal{E}_{ij} = 0$ leads to

$$\begin{aligned}f_{ji}(1 - \omega_{ji}) [1 - \epsilon_{M_j|JS_j}] [\bar{J}_{jj}^p - \bar{J}_{ji}^p] &= f_{ii}\omega_{ij} [1 - \epsilon_{M_i|JS_i}] [\bar{J}_{ii}^p - \bar{J}_{ij}^p] \\ f_{jj}\omega_{ji} [1 - \epsilon_{M_j|JS_j}] [\bar{J}_{ji}^p - \bar{J}_{jj}^p] &= f_{ij}(1 - \omega_{ij}) [1 - \epsilon_{M_i|JS_i}] [\bar{J}_{ii}^p - \bar{J}_{ij}^p]\end{aligned}$$

By dividing term by term the two equality

$$\frac{f_{ji}(1 - \omega_{ji}) [1 - \epsilon_{M_j|JS_j}] [\bar{J}_{jj}^p - \bar{J}_{ji}^p]}{f_{jj}\omega_{ji} [1 - \epsilon_{M_j|JS_j}] [\bar{J}_{ji}^p - \bar{J}_{jj}^p]} = \frac{f_{ii}\omega_{ij} [1 - \epsilon_{M_i|JS_i}] [\bar{J}_{ii}^p - \bar{J}_{ij}^p]}{f_{ij}(1 - \omega_{ij}) [1 - \epsilon_{M_i|JS_i}] [\bar{J}_{ii}^p - \bar{J}_{ij}^p]}$$

Leading to

$$\begin{aligned}\frac{f_{ji}(1 - \omega_{ji})}{f_{jj}\omega_{ji}} &= \frac{f_{ii}\omega_{ij}}{f_{ij}(1 - \omega_{ij})} \\ \frac{f_j(1 - \gamma)(1 - \omega_{ji})}{f_j\gamma\omega_{ji}} &= \frac{f_i\gamma\omega_{ij}}{f_i(1 - \gamma)(1 - \omega_{ij})} \\ \frac{(1 - \gamma)(1 - \omega_{ji})}{\gamma\omega_{ji}} &= \frac{\gamma\omega_{ij}}{(1 - \gamma)(1 - \omega_{ij})}\end{aligned}$$

3 solutions can be deduced

- If $\gamma = 0.5$ then $JS_i = JS_j = JS$ leading to $1 - \omega_{ji} = \omega_{ij}$. Hence, the solution to optimality is given by $\gamma = 0.5$.
- $\gamma = 1$
- $\gamma = 0$

A.3.4 The intensity of WFH in WHA for the Planner

We have shown that

$$J_{t,n,ji}^{p,h} = y_{ji} - L_{ji}^h(\tau_{t,ji}, \lambda_{t,n,ji}) - b + \beta \begin{bmatrix} I \times \bar{J}_{t+1,jj}^p \\ + J \times \bar{J}_{t+1,ij}^p \\ + K \times \bar{J}_{t+1,ji}^p + (1 - s_j) \bar{J}_{t+1,ji}^p \\ + L \times \bar{J}_{t+1,ii}^p \end{bmatrix}$$

Hence,

$$\frac{\partial J_{t,n,ji}^{p,h}}{\partial \lambda_{t,n,ji}} = 0$$

Leading to

$$\frac{\partial L_{t,n,ji}^h(\tau_{t,n,ji}, \lambda_{t,n,ji})}{\partial \lambda_{t,n,ji}} = 0$$

At the steady state, this leads to:

$$\lambda_{n,ji}^* = 1 - e^{-\frac{c_{\tau,ji} \tau_{n,ji}}{\zeta_i}}$$

$$\lambda_{n,ii}^* = 1 - e^{-\frac{c_{\tau,ii} \tau_{n,ii}}{\zeta_i}}$$

A.3.5 Occupational Choice for the Planner

We have shown that

$$\begin{aligned}
 J_{t,n,ji}^{p,o} &= y_{ji} - L_{ji}^o(\tau_{t,n,ji}, \lambda_{t,n,ji}) - b + \beta \left[\begin{array}{l} I \times \bar{J}_{t+1,jj}^p \\ + J \times \bar{J}_{t+1,ij}^p \\ + K \times \bar{J}_{t+1,ji}^p + (1 - s_j) \bar{J}_{t+1,ji}^p \\ + L \times \bar{J}_{t+1,ii}^p \end{array} \right] \\
 J_{t,n,ji}^{p,h} &= y_{ji} - L_{ji}^h(\tau_{t,n,ji}, \lambda_{t,n,ji}) - b + \beta \left[\begin{array}{l} I \times \bar{J}_{t+1,jj}^p \\ + J \times \bar{J}_{t+1,ij}^p \\ + K \times \bar{J}_{t+1,ji}^p + (1 - s_j) \bar{J}_{t+1,ji}^p \\ + L \times \bar{J}_{t+1,ii}^p \end{array} \right] \\
 J_{t,n,ji}^{p,r} &= y_{ji} - L_{ji}^r(\tau_{t,n,ji}, \lambda_{t,n,ji}) - b + \beta \left[\begin{array}{l} I \times \bar{J}_{t+1,jj}^p \\ + J \times \bar{J}_{t+1,ij}^p \\ + K \times \bar{J}_{t+1,ji}^p + (1 - s_j) \bar{J}_{t+1,ji}^p \\ + L \times \bar{J}_{t+1,ii}^p \end{array} \right]
 \end{aligned}$$

Choice between On-site and Hybrid

$$J_{t,n,ji}^{p,o} - J_{t,n,ji}^{p,h} = -L_{ji}^o(\tau_{t,n,ji}, \lambda_{t,n,ji}^*) + L_{ji}^h(\tau_{t,n,ji}, \lambda_{t,n,ji}^*)$$

Hence at the steady state, the choice is given by :

$$L_{ji}^o(\tau_{n,ji}, \lambda_{n,ji}^*) - L_{ji}^h(\tau_{n,ji}, \lambda_{n,ji}^*) = 0$$

Choice between Hybrid and Remote

Similary we find :

$$L_{ji}^r(\tau_{n,ji}, \lambda_{n,ji}^*) - L_{ji}^h(\tau_{n,ji}, \lambda_{n,ji}^*) = 0$$

A.3.6 Derivative of the matching function

Recall,

$$M_j(JS_j, V_j) = \frac{JS_j V_j}{(JS_j^\mu + V_j^\mu)^{1/\mu}}$$

With $JS_j = \gamma U_j + (1 - \gamma)U_i$

Subject to Vacancies

$$\frac{\partial M}{\partial V} = \frac{M}{V} \frac{1}{1 + \theta^\mu}$$

Hence,

$$\epsilon_{M|V} = \frac{\partial M}{\partial V} \frac{V}{M} = \frac{1}{1 + \theta^\mu}$$

Subject to Job Seekers

$$\frac{\partial M}{\partial JS} = \frac{M}{JS} \frac{\theta^\mu}{1 + \theta^\mu}$$

Hence,

$$\epsilon_{M|JS} = \frac{\partial M}{\partial JS} \frac{JS}{M} = \frac{\theta^\mu}{1 + \theta^\mu}$$

Link between $\epsilon_{M|V}$ and $\epsilon_{M|JS}$

$$\begin{aligned} 1 - \epsilon_{M|JS} &= 1 - \frac{\theta^\mu}{1 + \theta^\mu} \\ &= \frac{1}{1 + \theta^\mu} \\ &= \epsilon_{M|V} \end{aligned}$$

Appendix B

B.1 Non-Employment

To construct Non-employment data, we use three set of data : *(i)* Civilian Labor Force Levels (CLF) which includes Employed and Unemployed workers, *(ii)* Participation rate (PR) and *(iii)* Unemployed levels (U). Using, *(i)* and *(ii)* we construct Total Civilian Population (TCP), including non-participants as $TCP = \frac{CLF}{PR}$. This allows us to compute non-participant levels as: $NP = TCP - CLF$. Finally, we compute the Non-Employment Rate (NER) as follows: $NER = \frac{U+NP}{TCP}$.

Figure [B.1](#) illustrates the changes in the unemployment rate (UR) and the non-employment rate (NER). This graph demonstrates that both rates exhibit a similar speed in returning to their pre-crisis levels.

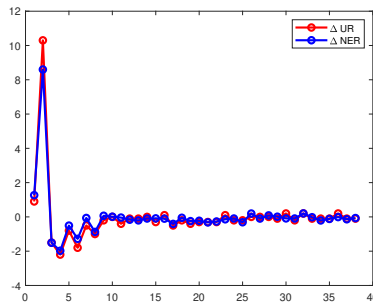


Figure B.1: **Convergence Speed of Unemployment rate and Non-employment rates.** $\Delta UR = UR_t - UR_{t-1}$ and $\Delta NER = NER_t - NER_{t-1}$.

B.2 The first-order conditions of the firm's problem

Denoting $\tilde{\alpha}_{s,t} = \frac{\int_{\alpha_{s,t}^r}^{+\infty} \alpha dG_{s,t}(\alpha)}{1 - G_{s,t}(\alpha_{s,t}^r)}$, the production function is

$$Y_{s,t} = A_{s,t} A_t N_{s,t} \frac{1}{1 - G_{s,t}(\alpha_{s,t}^r)} \int_{\alpha_{s,t}^r}^{+\infty} \alpha dG_{s,t}(\alpha) = A_{s,t} A_t \tilde{\alpha}_{s,t} N_{s,t},$$

where $A_{s,t}$ and A_t are the skill-specific and aggregate productivity, respectively. Denoting $\tilde{w}_{s,t} = \frac{\int_{\alpha_{s,t}^r}^{+\infty} w_{s,t}(\alpha) dG_{s,t}(\alpha)}{1 - G_{s,t}(\alpha_{s,t}^r)}$, the firm maximizes the following problem:

$$\begin{aligned} \mathcal{V}_{s,t}(N_{s,t}, A_t) &= \max_{V_{s,t}, N_{s,t}, \alpha_{s,t}^r} D_{s,t} + \tilde{\beta}_t \mathcal{V}_{s,t+1}(N_{s,t+1}, A_{t+1}) \\ \text{s.t.} &\begin{cases} D_{s,t} &= N_{s,t} (p_{s,t} A_s A_t \tilde{\alpha}_{s,t} - (1 - s_{s,t}^w) \tilde{w}_{s,t}) - p_{s,t} \kappa_{s,t} V_{s,t} \\ N_{s,t+1} &= (1 - s_{s,t+1})(N_{s,t} + q(\theta_{s,t}) V_{s,t}) \\ V_{s,t} &\geq 0 \end{cases} \quad (\lambda_{s,t}) \end{aligned}$$

The first-order conditions (FOCs) are

$$0 = -p_{s,t} \kappa_{s,t} + q(\theta_{s,t}) \tilde{\beta}_t (1 - s_{s,t+1}) \frac{\partial \mathcal{V}_{s,t+1}}{\partial N_{s,t+1}} + \lambda_{s,t} q(\theta_{s,t}) \quad (\text{B.1})$$

$$\begin{aligned} 0 &= \frac{\partial N_{s,t}}{\partial \alpha_{s,t}^r} (p_{s,t} A_s A_t \tilde{\alpha}_{s,t} - (1 - s_{s,t}^w) \tilde{w}_{s,t}) + N_{s,t} \left(p_{s,t} A_s A_t \frac{\partial \tilde{\alpha}_{s,t}}{\partial \alpha_{s,t}^r} - (1 - s_{s,t}^w) \frac{\partial \tilde{w}_{s,t}}{\partial \alpha_{s,t}^r} \right) \\ &\quad + \tilde{\beta}_t \frac{\partial \mathcal{V}_{s,t+1}}{\partial N_{s,t+1}} \frac{\partial N_{s,t+1}}{\partial N_{s,t}} \frac{\partial N_{s,t}}{\partial \alpha_{s,t}^r} \end{aligned} \quad (\text{B.2})$$

$$\frac{\partial \mathcal{V}_{s,t}}{\partial N_{s,t}} = p_{s,t} A_s A_t \tilde{\alpha}_{s,t} - (1 - s_{s,t}^w) \tilde{w}_{s,t} + \tilde{\beta}_t (1 - s_{s,t+1}) \frac{\partial \mathcal{V}_{s,t+1}}{\partial N_{s,t+1}} \quad (\text{B.3})$$

. The Kuhn–Tucker conditions are given by

$$q_s(\theta_{s,t}) V_{s,t} \geq 0, \quad \lambda_{s,t} \geq 0, \quad \text{and} \quad \lambda_{s,t} q_s(\theta_{s,t}) V_{s,t} = 0.$$

Knowing that $1 - s_{s,t} = (1 - s_s)(1 - G_s(\alpha_{s,t}^r))$ and using

$$\begin{aligned} \frac{\partial N_{s,t}}{\partial \alpha_{s,t}^r} &= -(1 - s_s)(N_{s,t-1} + q(\theta_{s,t-1}) V_{s,t-1}) dG_s(\alpha_{s,t}^r) = -(1 - s_s) \frac{N_{s,t}}{1 - s_{s,t}} dG_s(\alpha_{s,t}^r) \\ \frac{\partial \tilde{\alpha}_{s,t}}{\partial \alpha_{s,t}^r} &= \frac{dG_s(\alpha_{s,t}^r)}{1 - G_s(\alpha_{s,t}^r)} (\tilde{\alpha}_{s,t} - \alpha_{s,t}^r) \\ \frac{\partial \tilde{w}_{s,t}}{\partial \alpha_{s,t}^r} &= \frac{dG_s(\alpha_{s,t}^r)}{1 - G_s(\alpha_{s,t}^r)} (\tilde{w}_{s,t} - w_{s,t}(\alpha_{s,t}^r)), \end{aligned}$$

the equation [\(B.2\)](#) can be rewritten as follows.

$$0 = p_{s,t} A_s A_t \alpha_{s,t}^r - (1 - s_{s,t}^w) w_{s,t}(\alpha_{s,t}^r) + \left(\frac{p_{s,t} \kappa_{s,t}}{q(\theta_{s,t})} - \lambda_{s,t} \right)$$

These FOCs of the firm's program lead to the following intertemporal job-destruction and job-creation conditions:

$$J_{s,t}(\alpha_{s,t}) = p_{s,t}A_{s,t}A_t\alpha_{s,t} - (1 - s_{s,t}^w)w(\alpha_{s,t}) + \tilde{\beta}_t(1 - s_{s,t+1})J_{s,t+1} \quad \forall \alpha_{s,t} \geq \alpha_{s,t}^r \quad (\text{B.4})$$

$$J_{s,t}(\alpha_{s,t}^r) = 0 \quad (\text{B.5})$$

$$J_{s,t} = p_{s,t}A_{s,t}A_t\tilde{\alpha}_{s,t} - (1 - s_{s,t}^w)\tilde{w}_{s,t} + \tilde{\beta}_t(1 - s_{s,t+1})J_{s,t+1} \quad (\text{B.6})$$

$$\frac{p_{s,t}\kappa_{s,t}}{q(\theta_{s,t})} - \lambda_{s,t} = \tilde{\beta}_t(1 - s_{s,t+1})J_{s,t+1}, \quad (\text{B.7})$$

where $J_{s,t} = \frac{\partial \mathcal{V}_{s,t}}{\partial N_{s,t}}$ is the marginal value of employment, which can also be defined as $J_{s,t} \equiv \frac{\int_{\alpha_{s,t}^r}^{+\infty} J_{s,t}(\alpha) dG_{s,t}(\alpha)}{1 - G_{s,t}(\alpha_{s,t}^r)}$, where $J_{s,t}(\alpha)$ is the marginal value of a job after the realization of the idiosyncratic productivity α . Because $J_{s,t}(\alpha) \geq 0$, $\forall \alpha \geq \alpha_{s,t}^r$, the average job value, defined by $J_{s,t}$, is necessarily positive. The intertemporal job-destruction condition indicates that the current losses ($p_{s,t}A_{s,t}A_t\alpha_{s,t}^r - (1 - s_{s,t}^w)w_{s,t}(\alpha_{s,t}^r)$) must be compensated by the expected future gains generated by the job. The intertemporal job-creation condition equalizes the marginal costs of hiring at time t to the firm's marginal value of hiring, which is represented by the marginal benefits of hiring at time $t + 1$ discounted to t with the stochastic discount factor β . Hirings are based on the expectations of this average value of a job $J_{s,t+1}$, as α is revealed after the contact.

Using the wage equation, and given that $\alpha \in [0, +\infty)$ when the distribution is log-normal, the equilibrium reservation productivity is

$$\alpha_{s,t}^r = \max \left\{ 0; \frac{1}{(1 - \eta_s \varrho_s) p_{s,t} A_{s,t} A_t} \left(\begin{array}{l} \varrho_s (1 - \eta_s) (1 - s_{s,t}^w) b_{s,t} + \varrho_s \eta_s p_{s,t} \kappa_{s,t} \theta_{s,t} \\ + (1 - \varrho_s) (1 - s_{s,t}^w) w_s - \left(\frac{p_{s,t} \kappa_{s,t}}{q(\theta_{s,t})} - \lambda_{s,t} \right) \end{array} \right) \right\}$$

The FOCs of the firm's program lead to the following intertemporal job-creation condition:

$$\frac{p_{s,t}\kappa_{s,t}}{q_s(\theta_{s,t})} - \lambda_{s,t} = \tilde{\beta}_t \left[(1 - s_{s,t+1}) \left(\begin{array}{l} p_{s,t+1} A_{s,t+1} A_{t+1} \tilde{\alpha}_{s,t+1} \\ - (1 - s_{s,t+1}^w) \tilde{w}_{s,t+1} + \frac{p_{s,t+1} \kappa_{s,t+1}}{q_s(\theta_{s,t+1})} - \lambda_{s,t+1} \end{array} \right) \right]$$

The Kuhn–Tucker conditions are given by

$$q_s(\theta_{s,t})V_{s,t} \geq 0, \quad \lambda_{s,t} \geq 0, \quad \text{and} \quad \lambda_{s,t}q_s(\theta_{s,t})V_{s,t} = 0.$$

When $\lambda_{s,t} = 0$, the equilibrium paths are the same as in the DMP model. When $\lambda_t > 0$, we have $V_{s,t} = 0$, and the solution is constrained with $\theta_{s,t} = 0$ and $N_t = (1 - s)(1 - G_s(\alpha_{s,t}^r))N_{s,t-1}$.

B.3 Sector Closure

For the sake of simplicity, we conduct an economic simulation where a heterogeneous two-period TFP shock affects both sectors 1 and 2 significantly (see Figure B.2). The abruptness of this shock results in the complete closure of these sectors, leading to a 100% unemployment rate (see in Figure B.3). This closure is due to a complete separation between firms and workers (see Panel (c) of Figure B.4).

In Panel (d) of Figure B.4, we observe that sectors 1 and 2 do not engage in any sales or production for two consecutive periods. However, three months after the shock, these sectors gradually reopen. To achieve this, they begin posting job vacancies and incurring the associated costs one month before reopening, even though they generate no revenue during this period (since their sales remain at zero). They are able to manage this by borrowing a quantity of storable goods from the capitalist to cover the expenses of posting these vacancies. Figure B.5 illustrates that the dividends received by the capitalist decrease during these closure periods, resulting in a balanced budget constraint for the capitalist as they borrow the reopening costs incurred by the firms.

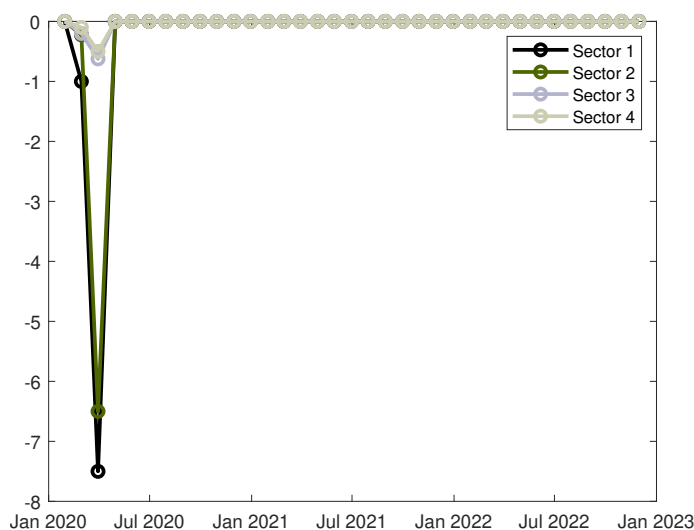


Figure B.2: Case with Sector Closure: TFP Shock.

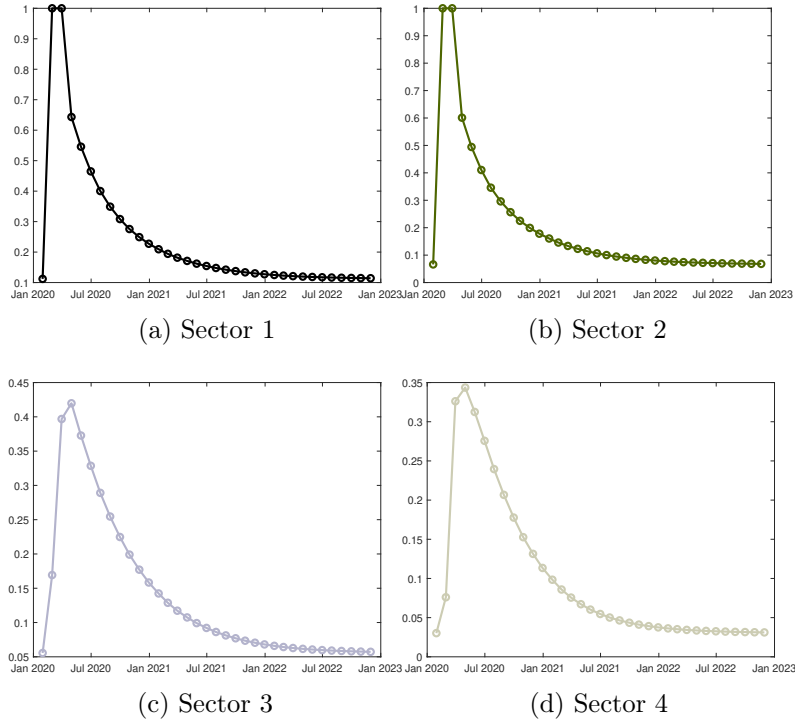


Figure B.3: Case with Sector Closure: Disaggregate unemployment rate.

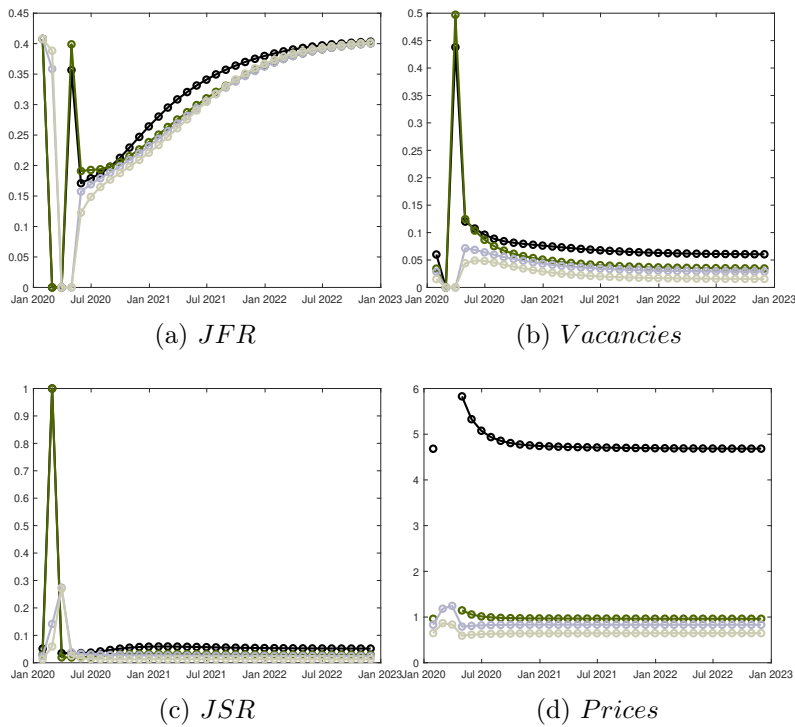


Figure B.4: Case with Sector Closure: Disaggregate Flows and Prices.

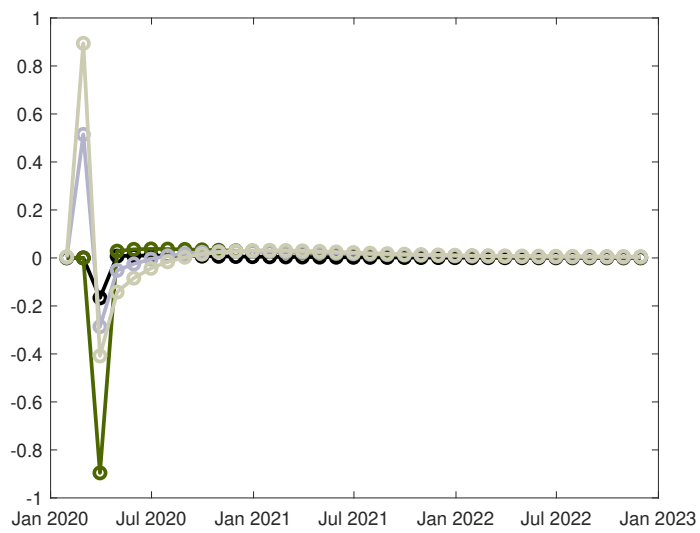


Figure B.5: Case with Sector Closure: The Capitalist.

B.4 Data

Aggregate data. The macro-level unemployment rate, job-finding rate, and job-separation rate data that we use are constructed from BLS data, from 1948 to the present. Data pertaining to monthly employment and unemployment levels for all people aged 16 and over are seasonally adjusted. To construct worker flows following [Adjemian et al. \(2019\)](#), we use the number of unemployed workers who have been unemployed for more than five weeks. After dividing the unemployment levels in each month by the sum of unemployment and employment, we obtain monthly series for U_m and U_m^5 (where m refers to the monthly frequency); these correspond to the proportion of unemployed individuals and the proportion of individuals unemployed for more than five weeks, respectively. The worker flows are given by $JSR_m = \frac{U_{m+1} - U_m^5}{E_m}$ and $JFR_m = \frac{U_m - U_{m+1}^5}{U_m}$.

Data by skill. We use constructed data from [Cairo and Cajner \(2016\)](#), which are based on CPS basic monthly data from January 1976 to January 2014. They construct the number of short-term unemployed individuals (i.e., unemployed for fewer than five weeks) for each education group; doing so allowed them to calculate the heterogeneous job-finding and separation rates.

Rescaling method. To use both data sets, we first need to rescale them. We assume our aggregate data would remain unchanged.

First, we construct the artificial macro-level unemployment rate (bur_t , $bjsr_t$, and $bjfr_t$) by using micro data ($ur_{s,t}$, $jsr_{s,t}$, and $jfr_{s,t}$) and the weight of each skill in the economy ω_s : $bur_t = \sum_{s=1}^S \omega_s ur_{s,t}$, $bjsr_t = \sum_{s=1}^S \omega_s jsr_{s,t}$, and $bjfr_t = \sum_{s=1}^S \omega_s jfr_{s,t}$. We then calculate the coefficient of rescaling x^i such that $x_{s,t}^1 = jfr_{s,t}/bjfr_t$, $x_{s,t}^2 = ur_{s,t}/bur_t$, and $x_{s,t}^3 = jsr_{s,t}/bjsr_t$.

Second, we reconstruct the micro data to match the macro data (UR , JFR , and JSR): $hjsr_{s,t} = x_{s,t}^1 JFR_t$, $hur_{s,t} = x_{s,t}^2 UR_t$, and $hjsr_{s,t} = x_{s,t}^3 JSR_t$.

Finally, to test our estimation, we calculate the macro data using the rescaled micro data: $hbur_t = \sum_{s=1}^S \omega_s hur_{s,t}$, $hbjfr_t = \sum_{s=1}^S \omega_s hjsr_{s,t}$, and $hbjsr_t = \sum_{s=1}^S \omega_s hjsr_{s,t}$; we then compare these data to the original data (UR , JFR , and JSR). We find that the rescaling matches the data well.

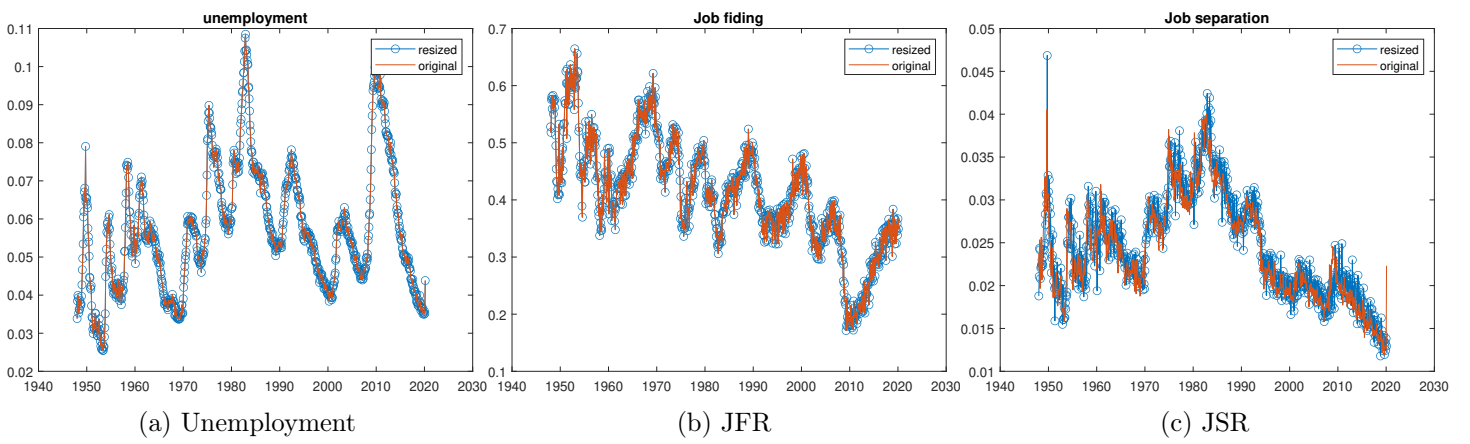


Figure B.6: **Fit of the rescaled data.**

B.5 Steady-state restrictions identifying η_s and b_s

We use the two FOCs of the firm's program with respect to $\theta_{s,t}$ and $\alpha_{s,t}^r$ to identify two parameters in each sector. We choose to identify η_s and $\tilde{b}_s \equiv b_s/(p_s A_s)$, which are thus skill-specific. If we assume that the steady-state value of κ_s is proportional to A_s , s.t. $\kappa_s = k A_s$, then we identify η_s as follows.

$$\eta_s = 1 - \frac{k}{q_s(\theta_s)\beta(1 - j s r_s)(\tilde{\alpha}_s - \alpha_s^r)},$$

where k is chosen s.t. $\frac{\sum_s \omega_s N_s \eta_s}{\sum_s \omega_s N_s} = 0.5$, leading to $k = 0.103$. The other FOC allows us to identify $\tilde{b}_s = \frac{b_s}{p_s A_s}$:

$$\tilde{b}_s = \alpha_s^r - \frac{\eta_s}{1 - \eta_s} k \theta_s + \frac{1}{1 - \eta_s} \frac{k}{q(\theta_s)},$$

which leads to a ratio of home production to production in business of $\tilde{b}_s/\tilde{\alpha}_s$.

B.6 The fit of the 2008 crisis

Figure [B.7](#) shows that, although the persistence of the AR process is low, the speed resumption of the initial shock (through ϑ_b and μ_b) makes the shock persistent enough to be able to reproduce the crisis.

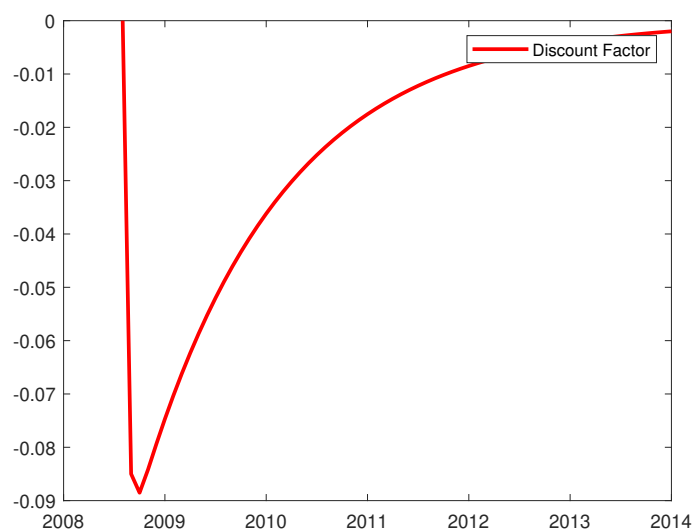


Figure B.7: Discount factor shock during the subprime crisis.

Figure B.8 presents the results and shows that the model can match the dynamics of the four labor markets (LHS, HS, Coll., and Bach. or more).

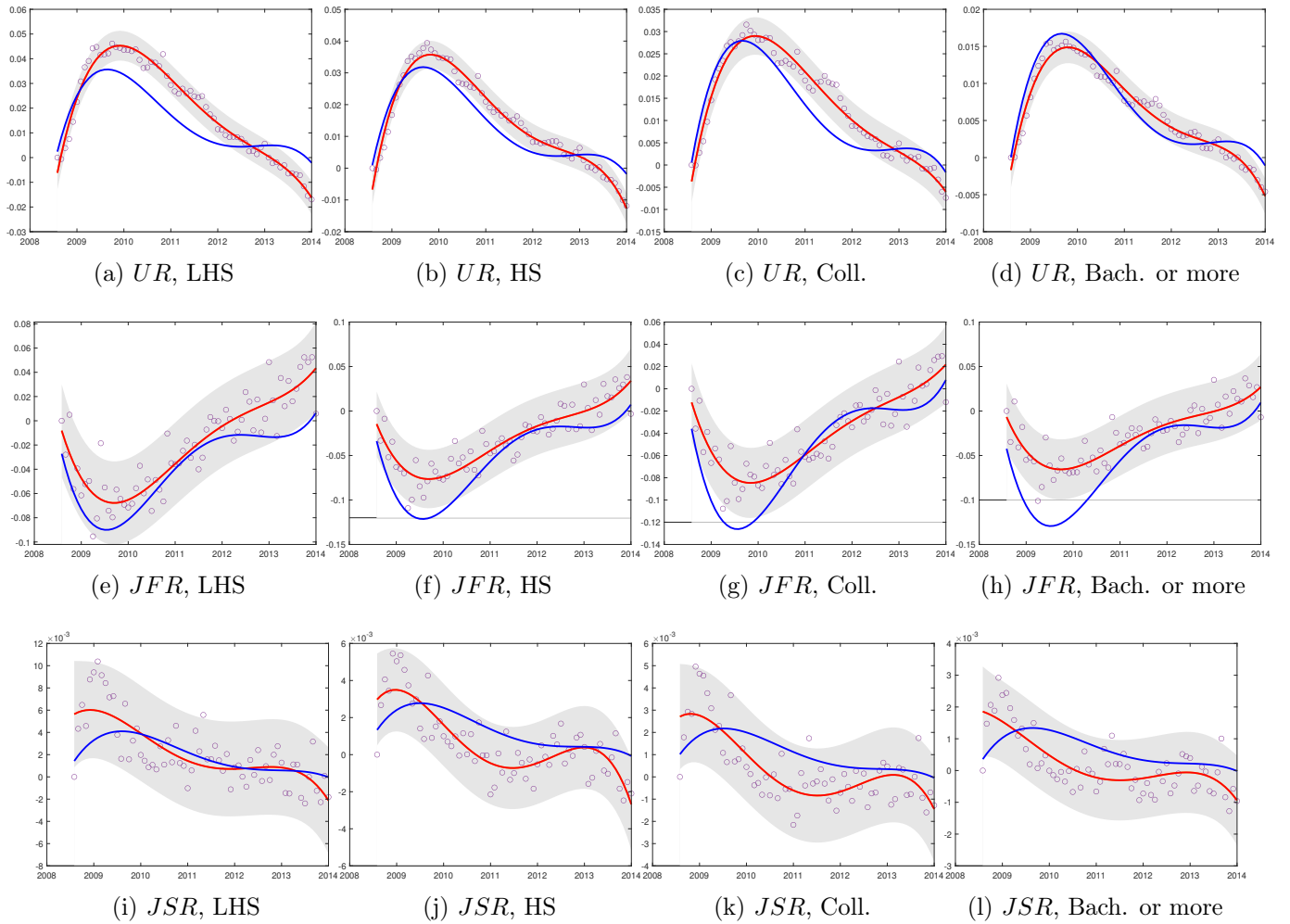


Figure B.8: **Worker flows and stock by education level.** The circles represent the raw monthly data leading to smoothed polynomials (in red), with confidence bands (95%) (in gray). The blue lines represent smoothed polynomials generated by the model.

B.7 Calibration of the COVID-19 crisis

	Loan Count	Net Dollars	% of Amount.
<hr/>			
Bachelor and more higher than 40%			
Educational Services	101,773	\$ 5,122,704,390	2%
Professional, Scientific, and Technical Services	657,326	\$28,559,859,211	10%
Arts, Entertainment, and Recreation	223,882	\$ 7,452,355,755	3%
Management of Companies and Enterprises	6,812	\$ 464,310,239	0%
Public Administration	18,359	\$ 784,812,141	0%
<hr/>			
Bachelor and more between 25% and 40%			
Health Care and Social Assistance	485,698	\$28,820,477,425	10%
Finance and Insurance	127,088	\$ 3,423,154,208	1%
Real Estate and Rental and Leasing	262,928	\$ 7,335,291,000	3%
Information	75,128	\$ 4,123,673,365	1%
Wholesale Trade	187,490	\$10,379,776,487	4%
<hr/>			
Bachelor and more lower than 25% and High school and less lower than 40%			
Manufacturing	221,216	\$ 22,148,692,329	8%
Retail Trade	468,043	\$ 15,263,246,977	5%
Utilities	5,827	\$ 392,258,537	0%
Transportation and Warehousing	763,810	\$ 15,772,271,550	6%
Other Services (except Public Administration)	1,107,768	\$27,345,366,128	10%
<hr/>			
Bachelor and more lower than 25% and High school and less higher than 40%			
Construction	558,180	\$ 33,443,602,502	12%
Mining	21,676	\$ 2,383,826,599	1%
Agriculture, Forestry, Fishing and Hunting	532,884	\$ 10,022,835,191	4%
Adm., Waste and Remediation Services	393,563	\$ 12,955,372,474	5%
Accommodation and Food Services	462,478	\$ 41,506,221,571	15%

Table B.1: **The PPP by Industry**. Data source: [US Small Business Administration](#).

Shares of educational attainment by industry: [Oregon Office of Economic Analysis](#).

	Number of loans	Value of loan	Subsidy.
Round 1	5,212,128	\$525,012,201,124	0.44
Round 2	6,611,466	\$274,820,665,396	0.094

Table B.2: **The PPP spendings.**

B.8 Labor market indicators of the benchmark model

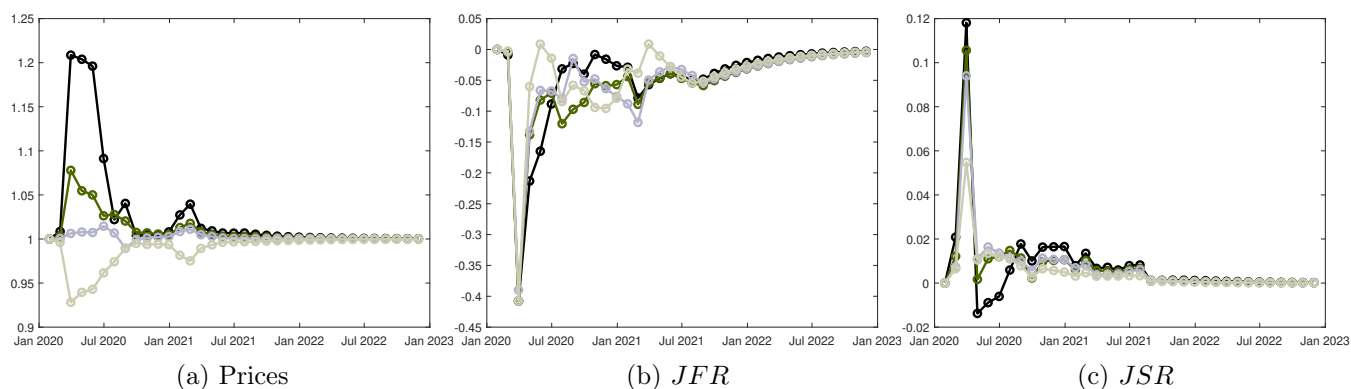


Figure B.9: **Outcomes by education level for US.** Panels (a)–(c): Black lines for the less than high school diploma (LHS); Khaki lines for the for the high school diploma (HS); Gray lines for the college diploma (Coll.); Camel lines for the bachelor degree or more (Bach.).

Panel (c) of Figure [B.9](#) shows that the CARES act, targeted on low skilled workers, allows firms to reduce separations after the lockdown episode: the *JSR* of LHS and HS workers are below their steady state levels from May to September 2020. This policy favors labor hoarding, however, congestion externalities explain why these subsidies are not sufficient to incentive firm to hire more of these low skilled workers (see Panel (b) of Figure [B.9](#)).

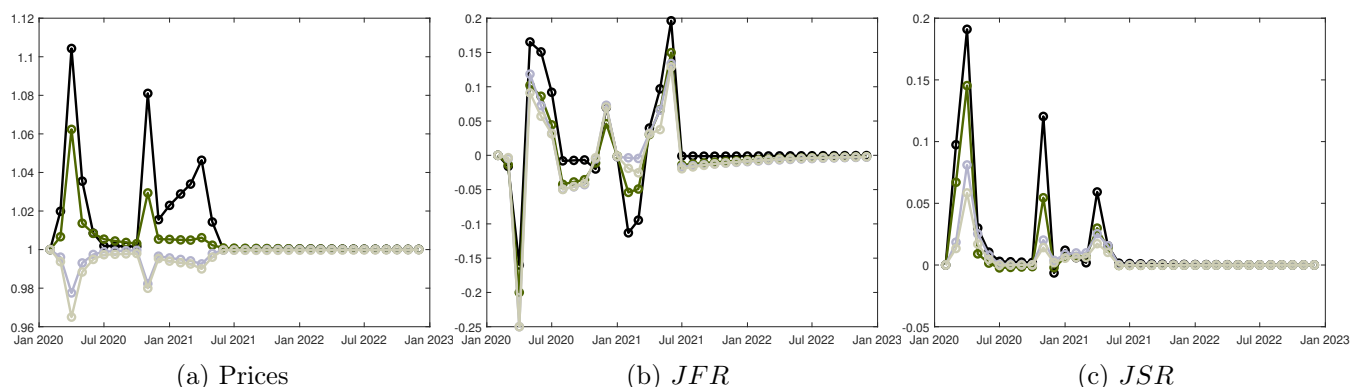


Figure B.10: **Outcomes by education level for France.** Panels (a)–(c): Black lines for Non-graduates; Khaki lines for Vocational training diploma (CAP-BEP); Gray lines for High school diploma up to two years of higher education (Bac-Bac+2); Camel lines for Higher education (sup.).

B.9 French Model

B.9.1 Partial unemployment plan implemented by the government.

Assumptions. Sanitation restrictions introduce constraints: within each firm, only a fraction $\mathcal{P}_{s,t}$ of each type of job s can operate. The portion of jobs that can remain active is determined by the government (as explained below) when deciding the extent of the restrictions. To accompany these new constraints, the government implements an insurance plan that benefits the non-operational positions: partial unemployment, which involves transferring funds to companies for positions that cannot operate but still bear (partial) labor costs.

For Firms In exchange for preserving employment, the government commits to compensating companies: the $(1 - \mathcal{P}_{s,t})$ non-operational positions receive a compensation $B_{s,t}$ if the employees retain their jobs.¹ The expected gross operating surplus² ($EBE_{s,t}$) can be expressed as follows:

$$EBE_{s,t} = \mathcal{P}_{s,t} (p_{s,t} \bar{A}_{s,t} \tilde{\alpha}_{s,t} N_{s,t} - \tilde{w}_{s,t} N_{s,t}) + (1 - \mathcal{P}_{s,t}) (-\tilde{w}_{s,t}^c N_{s,t} + B_{s,t}),$$

with $Y_{s,t} = \bar{A}_{s,t} \tilde{\alpha}_{s,t} N_{s,t}$ and $\tilde{w}_{s,t}^c = \tilde{w}_{s,t} - \chi_{s,t}$ is the compensation received by employees in the case of partial unemployment, i.e., $\chi_{s,t} \geq 0$ is the reduced salary amount in the event of partial compensation.

The government opts for full insurance, which results in full compensation of the amount.

$$B_{s,t} = (p_{s,t} \bar{A}_{s,t} \tilde{\alpha}_{s,t} - \chi_{s,t}) N_{s,t}.$$

Ex-post, i.e. once the government's decision rules are taken into account, the gross operating surplus (EBE) is.

$$EBE_{s,t} = (p_{s,t} (1 - c_{s,t} (1 - \mathcal{P}_{s,t})) \bar{A}_{s,t} \tilde{\alpha}_{s,t} - \tilde{w}_{s,t}) N_{s,t},$$

¹It should be noted that employees on partial unemployment in period t may still be part of the active workforce in period $t + 1$ with the same probability as if they had worked in period t

²The gross operating surplus does not include hiring costs, which remain less observable during this period for the government.

Assuming $\chi_{s,t} = c_{s,t}p_{s,t}\bar{A}_{s,t}\tilde{\alpha}_{s,t}$, with $0 \leq c_{s,t} < 1$. For what follows we note

$$A_{s,t} = (1 - c_{s,t}(1 - \mathcal{P}_{s,t}))\bar{A}_{s,t}.$$

This expression indicates that the TFP is reduced by the introduction of the partial unemployment program. $\partial A_{s,t}/\partial \mathcal{P}_{s,t} > 0$ and $\partial A_{s,t}/\partial c_{s,t} < 0$. This decrease in TFP offsets the incomplete wage coverage ($c_{s,t}$ % of productivity) for the $(1 - \mathcal{P}_{s,t})$ employees on partial unemployment.

For workers. This partial unemployment program implies that, in each period, the expected earnings of an employee become

$$\mathcal{P}_{s,t}\tilde{w}_{s,t} + (1 - \mathcal{P}_{s,t})\tilde{w}_{s,t}^c = \tilde{w}_{s,t} - (1 - \mathcal{P}_{s,t})\chi_{s,t},$$

and the surplus obtained upon signing an employment contract is (with $j = s$).

$$\begin{aligned} W_{i,s,t}(\alpha) - U_{i,s,t} &= w_{i,s,t}(\alpha) - b_{i,s} - (1 - \mathcal{P}_{s,t})\chi_{s,t} \\ &+ \beta \left[(1 - s_{s,t+1}) \int_{\alpha_{s,t+1}^r}^{\infty} W_{i,s,t} \frac{dG(\alpha)}{1 - G(\alpha_{s,t+1}^r)} + s_{s,t+1}U_{i,s,t+1} \right] \\ &- \beta \left[f_{s,t+1}(1 - s_{s,t+1}) \int_{\alpha_{s,t+1}^r}^{\infty} W_{i,s,t} \frac{dG(\alpha)}{1 - G(\alpha_{s,t+1}^r)} + (1 - f_{s,t+1}(1 - s_{s,t+1}))U_{i,s,t+1} \right], \end{aligned}$$

where the opportunity cost of employment in the presence of partial unemployment is increased and given by $\tilde{b}_{i,s,t} = b_{i,s} + (1 - \mathcal{P}_{s,t})\chi_{s,t}$.

Government's trade-off. The government chooses the magnitude of the constraint imposed by the lockdown measures by minimizing the following cost function:

$$\min_{\mathcal{P}_{s,t}} \left\{ (1 - \mathcal{P}_{s,t})B_{s,t} + \frac{\Phi_t}{2}\mathcal{P}_{s,t}^2 \right\} \Rightarrow \mathcal{P}_{s,t} = \frac{1}{\Phi_t}B_{s,t}$$

where the budget allocations for each segment s are assumed to be independent of each other. The first part of the cost function $((1 - \mathcal{P}_{s,t})B_{s,t})$ represents the costs of partial unemployment compensation³, while the second part $(\frac{\Phi_t}{2}\mathcal{P}_{s,t}^2)$ represents the organizational and other costs associated with the implementation and management of such a program.

For simplification, we assume $\Phi_t = \phi_t B_{s,t}$: The scale parameter defining the management costs (Φ_t) is proportional to the value of compensation ($B_{s,t}$). The solution to the cost

³Once this amount $B_{s,t}$ is transferred to the companies, they are responsible for paying their employees on partial unemployment.

minimization program is: $\mathcal{P}_{s,t} = \frac{1}{\phi_t}$, with $\phi_t \geq 1$, as $0 \leq \mathcal{P}_{s,t} \leq 1$. $\mathcal{P}_{s,t}$ decreases when ϕ_t increases, i.e. The number of active participants is lower when the insurance program expands.

Impact on the matching functions. There are $U_{s,t} + (1 - \mathcal{P}_{s,t})N_{s,t}$ individuals who are not working on each labor market, i.e., individuals without an employment contract ($U_{s,t} = 1 - N_{s,t}$) and those on partial unemployment ($(1 - \mathcal{P}_{s,t})N_{s,t}$). In the matching function, we assume that the job search efforts of these two types of agents are different: $a_{u,t}$ for individuals without a contract and $a_{p,t}$ for those on partial unemployment. Similarly, we assume that the effectiveness of a vacant job in finding an employee, denoted as $a_{v,t}$, is affected by the lockdown. The matching function then becomes:

$$M_s(a_{u,t}U_{s,t} + a_{p,t}(1 - \mathcal{P}_{s,t})N_{s,t}, a_{v,t}V_{s,t}) = \frac{(a_{u,t}U_{s,t} + a_{p,t}(1 - \mathcal{P}_{s,t})N_{s,t})a_{v,t}V_{s,t}}{((a_{u,t}U_{s,t} + a_{p,t}(1 - \mathcal{P}_{s,t})N_{s,t})^{\tau_s} + (a_{v,t}V_{s,t})^{\tau_s})^{1/\tau_s}}$$

We assume that (i) $a_{p,t} = 0$, meaning that individuals on partial unemployment cannot change jobs during the periods of partial unemployment benefits, and (ii) $a_{u,t} = a_{v,t} \equiv a_{uv,t}$, indicating that the partial unemployment program equally affects the search efficiencies of both unemployed individuals and firms. Under these assumptions, we obtain:

$$M_s(a_{uv,t}U_{s,t}, a_{uv,t}V_{s,t}) = a_{uv,t} \frac{U_{s,t}V_{s,t}}{(U_{s,t}^{\tau_s} + V_{s,t}^{\tau_s})^{1/\tau_s}}$$

where, implicitly, $a_{uv,t}$ depend on $\phi_{s,t}$, i.e. $a_{uv,t} = a_{uv}(\phi_{s,t})$. The probability of an unemployed individual finding a job is given by: $f_s(\theta_{s,t}) = a_{uv}(\phi_{s,t})(1 + \theta_{s,t}^{-\tau_s})^{-1/\tau_s}$ and the probability of a job vacancy being filled is given by: $q_s(\theta_{s,t}) = a_{uv}(\phi_{s,t})(1 + \theta_{s,t}^{\tau_s})^{-1/\tau_s}$.

B.9.2 Firm's problem

As previously we have

$$Y_{s,t} = A_{s,t}N_{s,t} \frac{1}{1 - G_{s,t}(\alpha_t^r)} \int_{\alpha_{s,t}^r}^{+\infty} \alpha dG_{s,t}(\alpha) = A_{s,t}\tilde{\alpha}_{s,t}N_{s,t}, \quad (\text{B.8})$$

And the firm problem is given by

$$\begin{aligned} \mathcal{V}_{s,t}(N_{s,t}, A_{s,t}) &= \max_{V_{s,t}, N_{s,t}, \alpha_{s,t}^r} D_{s,t} + \beta_t \mathcal{V}_{s,t+1}(N_{s,t+1}, A_{s,t+1}) \\ \text{s.t.} &\begin{cases} D_{s,t} &= p_{s,t}A_{s,t}\tilde{\alpha}_{s,t}N_{s,t} - \tilde{w}_{s,t}N_{s,t} - p_{s,t}\bar{\kappa}_{s,t}\mathcal{P}_{s,t}V_{s,t} \\ N_{s,t+1} &= (1 - s_{s,t+1})(N_{s,t} + q(\theta_{s,t})V_{s,t}) \\ V_{s,t} &\geq 0 \end{cases} \quad (\lambda_{s,t}) \end{aligned}$$

where $A_{s,t}$ incorporates the changes related to the restrictions of the lockdown measures and the policy of partial unemployment. It should be noted that the costs associated with recruitment decrease proportionally to the magnitude of the partial unemployment program ($\mathcal{P}_{s,t} = \frac{1}{\phi_t}$) because hiring can only take place for active positions.

Optimality conditions The CPO give

$$0 = -p_{s,t}\bar{\kappa}_{s,t}\frac{1}{\phi_{s,t}} + q(\theta_{s,t})\beta_t(1 - s_{s,t+1})\frac{\partial\mathcal{V}_{s,t+1}}{\partial N_{s,t+1}} + \lambda_{s,t}q(\theta_{s,t})$$

$$\Leftrightarrow 0 = -p_{s,t}\bar{\kappa}_{s,t}\frac{1}{a_{uv}(\phi_{s,t})\phi_{s,t}} + (1 + \theta_{s,t}^{\tau_s})^{-1/\tau_s}\beta_t(1 - s_{s,t+1})\frac{\partial\mathcal{V}_{s,t+1}}{\partial N_{s,t+1}} + \lambda_{s,t}(1 + \theta_{s,t}^{\tau_s})^{-1/\tau_s} \quad (\text{B.9})$$

where

$$\kappa_{s,t} \equiv \bar{\kappa}_{s,t}\frac{1}{a_{uv}(\phi_{s,t})\phi_{s,t}}.$$

Therefore, the partial unemployment policy affects hiring if $a_{uv}(\cdot)$ is not proportional to $1/\phi_{s,t}$. The variations in the function $\kappa_{s,t}$ will be identified in such a way that the model replicates the data.

The remaining of the firms' problem is the same as previously.

B.9.3 Identification

The solution of the model allows us to identify the sequences of $A_{s,t}$ and $\kappa_{s,t}$ that are affected by:

- The confinement measures, as $A_{s,t}$ can directly be reduced due to the inability to produce or exchange goods (variations in $\bar{A}_{s,t}$).
- Partial unemployment program, as ϕ_t causes variations in $A_{s,t}$ and the corresponding $\kappa_{s,t}$.

B.10 Calibration

Parameters based on external information As in US case.

Parameters based on first-order moments restrictions The data used in the model refer to the year 2016. The population shares (ω_s) and the specific unemployment rates by education level (U_s) are constructed following Beck and Vidalenc (2017).

The hiring rates by education level (JFR_s) are obtained from the work of Fontaine et al. (2020). In the steady state, these moments are related by the following restriction: $UR_s = \frac{JSR_s}{JSR_s + JFR_s}$, which gives us consistent values for the separation rates (JSR_s). Since the data from Fontaine et al. (2020) are only available for three education levels, aggregating all individuals with education beyond high school, we assume that the hiring rate for individuals with a university degree is the same as that for individuals with a Bachelor’s or Associate’s degree. ⁴ Table B.3 summarizes all of these moments.

	non dipl	CAP-BEP	Bac-Bac+2	Sup	Total
JFR	16 %	20 %	25 %	25 %	22 %
JSR	3.5 %	2.4 %	2.3 %	1.5 %	2.35 %
UR	17.9 %	10.8 %	8.42 %	5.7 %	10.03 %
Part de la population	17 %	25 %	36 %	22 %	100 %

Table B.3: **Worker flows and stocks.**

We use the same strategy of identification as in the US case. All results obtained through these steady-state restrictions are presented in Table B.4

		non dipl	CAP-BEP	Bac-Bac+2	Sup
Parameters	A_s	2.3063	2.9690	4.5065	6.2296
specific	η_s	0.4827	0.5031	0.4923	0.5205
	\tilde{b}_s	0.9814	0.9759	0.9700	0.9676
	$p_s A_s$	2.9895	3.2120	3.9844	5.7020
Equilibrium Values	$\frac{w_s}{\sum_s \omega_s w_s}$	0.7406	0.7961	0.9874	1.4136

Table B.4: **Results of the calibration using labor market restrictions**

Calibrations based on the COVID-19 crisis. To measure unemployment, we use the series of the number of unemployed provided by the OECD, to which we add the number of full-time equivalent (FTE) workers actually placed on partial employment⁵

⁴This assumption (equal hiring rates between individuals with higher education and those with a Bachelor’s or Associate’s degree) does not seem to be rejected by data on employment outcomes: the 2018 survey on the professional integration of university graduates indicates that the employment rate 30 months after graduation for the 2016 cohort is 92% for students with a DUT degree, 93% for those with a professional Bachelor’s degree, and between 92% and 98% for those with a Master’s degree. See Menard (2019).

⁵See DARES (2020) for a description of the data used.

The time series of the TFP shocks (i.e., the magnitude of confinement-related restrictions) by type of employment, as well as the reductions in the cost of resuming salaried activity due to partial employment, are calibrated so that the model reproduces the observed inequality in unemployment by education during the first lockdown⁶:

$$\Psi = \left\{ \{UR_t\}_{t=\text{December 2020}}^{\text{March 2022}}, \{UR_{s,\text{April 2020}}\}_{s=1}^S \right\} \quad \text{with } \dim(\Psi) = 34 + 3 = 37$$

where $UR_{s,\text{April 2020}}$ is derived from the unemployment rate data by occupational category (CSP), which is only available for the month of April 2020.

Regarding the fraction of individuals on partial unemployment, denoted as $1 - \mathcal{P}$, information by occupational category (CSP)⁷ allows us to deduce that 53.9% of the non-graduates, 36.3% of those with a vocational certificate (BEP-CAP), 32.8% of those with a high school diploma (Bac-Bac+2), and 25.6% of those with a higher education degree would have been on partial unemployment in April 2020. Compared to April 2020, but now at the aggregate level, we observe a decrease of 34% in the number of people on partial unemployment in May 2020, 64% in November 2020, and 76% in January 2021. Thus, we extrapolate the partial unemployment data from April 2020 using the following formula $\mathcal{P}_{s,t} = (\mathcal{P}_t / \mathcal{P}_{\text{April 2020}}) \times \mathcal{P}_{s,\text{April 2020}}$. Therefore, we have four observations of $\mathcal{P}_{s,t}$, which allows us to calibrate the decrease in hiring costs by segment of the labor market based on the magnitude of specific partial unemployment in each sub-market. To do this, we assume that the decrease in costs per job reintegration will be greater as the number of people on partial unemployment is larger. We then have $\kappa_{s,t}$ becoming $(1 - \Upsilon_s \times \mathcal{P}_{s,t})\kappa_{s,t}$, where the proportionality factor Υ_s remains to be determined, along with the variations in TFP ($A_{s,t}$) induced by the confinement.

As Ψ contains 37 moments, we can only identify 37 unknown parameters. Therefore, we need to impose restrictions. To do so, we set $\Upsilon_s = \Upsilon$ for all segments, and $A_{t,s} = 0$ for all months and labor market segments that are not listed in Table 2.6. The absence of a decrease in TFP in December 2020 assumes that the additional activity during the holiday season compensates for the restrictions imposed on certain activities during the

⁶Since we do not have data by education level, we approximate the statistic by education level using the one by occupational category that includes the most individuals with that education level. Thus, the non-graduates are approximated by manual workers, individuals with a vocational degree (BEP-CAP) by employees, those with a high school diploma or a two-year degree (Bac-Bac+2) by intermediate occupations, and finally, individuals with a degree higher than a two-year degree by managers. See Givord and Silhol (2020) for a description of the data used.

⁷The link between CSP and education level is the same as for the unemployment by education level in April 2020.

same month. Finally, we restrict the impact of the second partial lockdown (November 2020) and the curfew (January 2021) to the labor market segments of non-graduates and those with a Vocational Cert because according to Insee-Deep-Cereq-Dares-SIES (2018), sectors experiencing the strongest restrictions (accommodation, restaurants, etc.) employ a higher proportion of non-graduates and individuals with a Vocational Cert.

The parameters to be determined are:

$$\Phi = \left\{ \left\{ \left\{ A_{s,t} \right\}_{s=1}^S \right\}_{t=\text{March } 2020}^{\text{April } 2020}, A_{1,\text{May } 2020}, \left\{ A_{s,\text{November } 2020} \right\}_{s=1}^2, \left\{ \left\{ A_s \right\}_{s=1}^2 \right\}_{\text{January } 2021}^{\text{April } 2021}, \Upsilon \right\}$$

with $\dim(\Phi) = 20$ and therefore $\dim(\Phi) \leq \dim(\Psi)$.

B.11 Model fit when one extension is removed

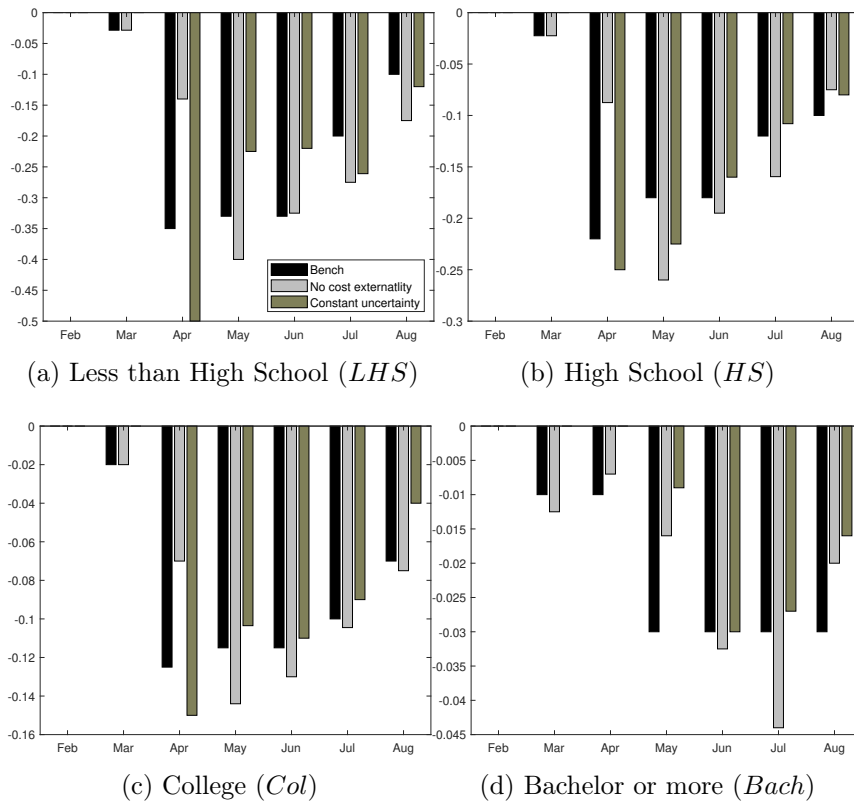


Figure B.11: **TFP changes First lockdown.** Black: Benchmark model. Dark gray: Model without wage rigidity. Khaki: Model without congestion effect on hiring costs. Gray: Model without microeconomic uncertainty. For each scenario, each bar reports the gap relative to the steady-state values.

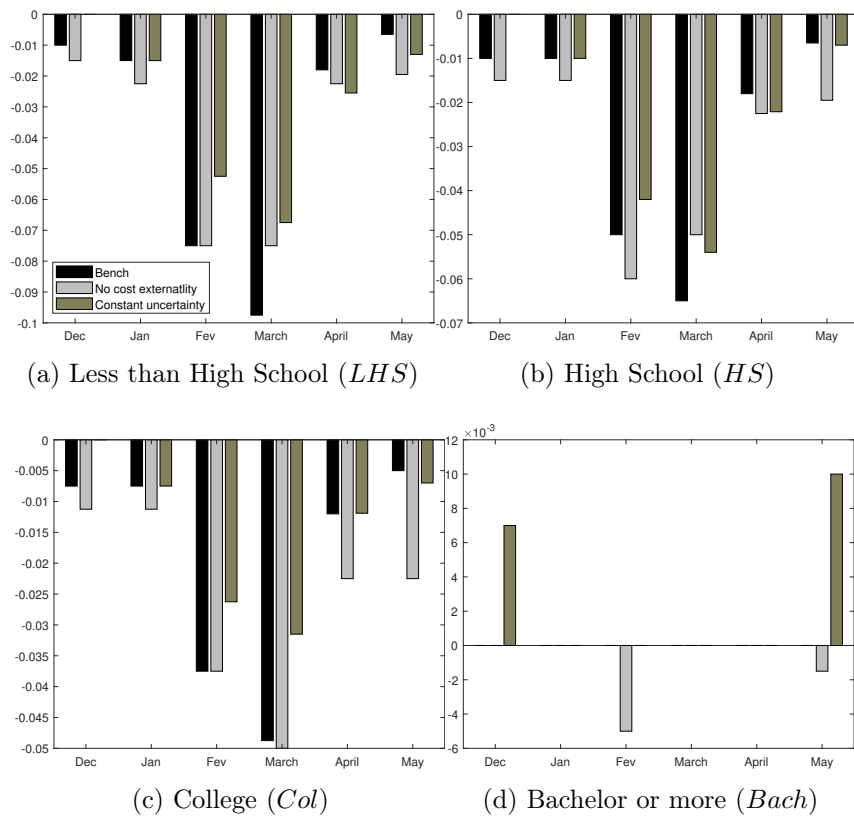


Figure B.12: **TFP changes Second lockdown.** Black: Benchmark model. Dark gray: Model without wage rigidity. Khaki: Model without congestion effect on hiring costs. Gray: Model without microeconomic uncertainty. For each scenario, each bar reports the gap relative to the steady-state values.

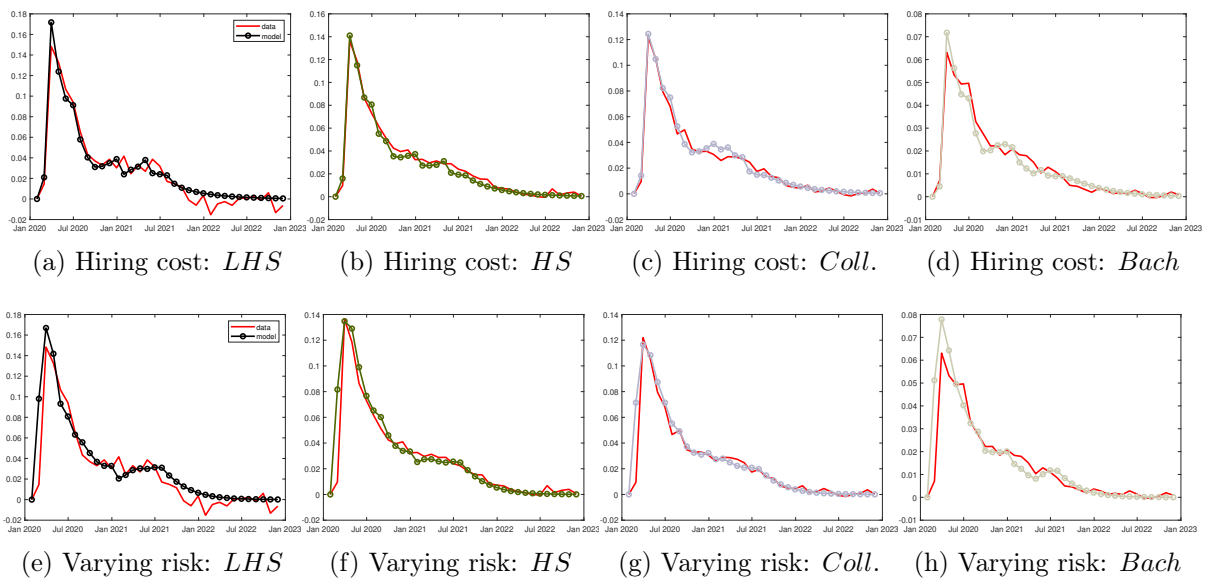


Figure B.13: **Unemployment rate by education level.** In Panels (a)–(l), the red lines represent the data.

Appendix C

C.1 Theoretical Appendix

Denote by γ , the share of workers that experience a wage increase $\Delta w_i > 0$ such that $\gamma = Pr(c\Delta t_i - \Delta a > 0) = Pr(\Delta t_i > \Delta a/c)$. Denoting the threshold as $t^* = \Delta a/c$, the law of total covariance implies that:

$$\begin{aligned} \text{cov}(\Delta w_i, \Delta t_i) = & (1 - \gamma)\text{cov}(\Delta w_i, \Delta t_i | \Delta t_i \leq t^*) + \gamma\text{cov}(\Delta w_i, \Delta t_i | \Delta t_i > t^*) + \\ & (1 - \gamma)(E(\Delta w_i | t_i \leq t^*) - E(\Delta w_i))(E(\Delta t_i | t_i \leq t^*) - E(\Delta t_i)) + \\ & \gamma(E(\Delta w_i | t_i > t^*) - E(\Delta w_i))(E(\Delta t_i | t_i > t^*) - E(\Delta t_i)) \end{aligned}$$

If wages are downward rigid, then for workers with $t_i > \Delta a/c$, $\Delta w_i = (1 - \eta)(c\Delta t_i - \Delta a)$, while for those with $t_i < \Delta a/c$, we have $\Delta w_i = 0$. This implies that $\text{cov}(\Delta w_i, \Delta t_i | \Delta t_i \leq t^*) = 0$ and $E(\Delta w_i | t_i \leq t^*) = 0$. Rearranging the previous expression and simplifying, we get:

$$\begin{aligned} \text{cov}_{\text{WR}}(\Delta w_i, \Delta t_i) = & \gamma(1 - \eta)c \times \text{var}(\Delta t_i | \Delta t_i > t^*) + \\ & \gamma E(\Delta w_i | t_i > t^*)(E(\Delta t_i | t_i > t^*) - E(\Delta t_i)) \end{aligned}$$

where cov_{WR} denote the covariance under wage rigidity. The difference between the two gives:

$$\begin{aligned} \text{cov}(\Delta w_i, \Delta t_i) - \text{cov}_{\text{WR}}(\Delta w_i, \Delta t_i) = & \\ & (1 - \gamma)\text{cov}(\Delta w_i, \Delta t_i | \Delta t_i \leq t^*) + \\ & (1 - \gamma)(E(\Delta w_i | t_i \leq t^*) - E(\Delta w_i))(E(\Delta t_i | t_i \leq t^*) - E(\Delta t_i)) \end{aligned}$$

The first term is equal to $(1 - \gamma)(1 - \eta)c \times \text{var}(\Delta t_i | \Delta t_i \leq t^*)$ and is thus positive. As Δw_i is a linear function of Δt_i , it is easy to see that $E(\Delta w_i | t_i \leq t^*) < E(\Delta w_i)$ and $E(\Delta t_i | t_i \leq t^*) < E(\Delta t_i)$ and thus that the second term is also positive.

C.2 Data Appendix

Skill group classification We use one digit codes of the occupational classification to group workers into three skill groups. *Low skill workers* correspond to Agricultural Workers, Craft and Related Trades Workers, Plant and Machine Operators and Assemblers, Elementary Occupations. *Medium skill workers* correspond to Technicians and Associate Professionals, Clerical Support Workers, Services and Sales Workers. *High skilled workers* correspond to Managers and Professionals.

C.3 Estimation of the AKM model

To separate the contribution of establishments and workers heterogeneity, we use the mobility of workers across establishments to estimate a two-way fixed effects AKM model of wage determination of the form:

$$y_{it} = X'_{it}\beta + \alpha_i + \psi_{j(i,t)} + \epsilon_{it} \quad (\text{C.1})$$

where y_{it} is the log-earnings of worker i in period t and X'_{it} is a vector of time-varying exogenous covariates. Our parameters of interests are α_i , the unobserved worker effect, and $\psi_{j(i,t)}$ a constant over time additive wage premium associated with establishment $j(i,t)$ which denotes the establishment where worker i works at period t . Following [Card et al. \(2018\)](#), we include in X'_{it} a third-order polynomial in age restricted to be flat at age 40, that we interact with an unrestricted set of year and gender dummies. In our decomposition, we concentrate on differences in average ‘residual’ wages, defined as $y_{it} - X'_{it}\beta$, net of the effect of age.

The model is estimated using 5 years period over 2010-2015 on the connected sets of firms. Two sets of firms are disconnected if no worker in the sample worked for a firm in each group. A connected set then includes all workers who ever worked in the set’s firms.

C.4 Validity of work hours in DADS data

Following Lachowska et al. (2022), we report two empirical tests regarding the quality of hours of work in the DADS data: (i) First, we study the correlation between annual changes in log earnings and annual changes in the log of paid hours between two consecutive years. (ii) Second, we study how the distribution of hourly wages is affected by annual increases of the minimum wage.

C.4.1 A regression-based test of signal-to-noise in hours data

To capture the correlation between annual changes in log earnings on changes in log hours for workers, we estimate the following linear model on a sample of workers did not change employers:

$$\Delta \log(\text{earn}_{it}) = \beta_0 + \beta_1 \Delta \log(\text{hours}_{it}) + \epsilon_{it} \quad (\text{C.2})$$

where $\Delta \log(\text{earn}_{it})$ is the annual change in log annual earnings for individual i in period t , $\Delta \log(\text{hours}_{it})$ is the annual change in log hours and ϵ_{it} is an error term.

As discussed extensively by Lachowska et al. (2022), if hours are measured accurately, and all workers are paid by the hour, the coefficient β_1 should be close to 1. However, in practice, the sample also includes workers with a fixed number of hours or who are not paid hourly which should attenuate the coefficient.

Estimation results are reported in Table [C.1](#) using workers employed by the same employer in 2013 and 2012. Our baseline model is reported in column 1, column 2 reports regression with establishment fixed effects, and column 3 reports estimates using clustered standard errors at the establishment level instead of robust standard error. Across these specifications, the estimated slope coefficients are equal to 0.86, which is very similar to the estimate of 0.8 reported by Lachowska et al. (2022) using administrative data from the State of Washington in the US. Finally, while the results presented here are obtained only using the year 2013, the results are very similar across all years in the sample.

C.4.2 Minimum wage and the hourly wage distributions in the DADS data

Since 2010, the French minimum wage has been indexed annually in January on the past annual increase in the consumer price index and half of the real annual increase of a wage index published quarterly, the base hourly wage rate of blue-collar workers. A straightforward way to capture whether our data on hours is of good quality is to assess whether the distribution of hourly wages exhibits a peak at the minimum wage and how this peak varies across years following minimum wage increases. To investigate this issue, we report the annual distribution of hourly wage rates from 2010 to 2018, defined as the ratio between annual earnings and annual hours worked. We concentrate on years after 2010 as, before that year, the annual adjustment of the minimum wage occurred in July instead of January, and within a single calendar year, there were thus two different minimum wages. The minimum wage can also be updated during the year if the annual increase in CPI observed in the monthly series is superior to 2%, which only happened twice in December 2011 and in July 2012. For these two years, the graphs report the lowest value of the minimum wage.

The hourly wage distributions for different years are reported in Figure [C.1](#) for workers paid less than 16 euros per hour, using a vertical bar to indicate the hourly wage rate of the French minimum wage. Consistent with the hypothesis that the hours data is of good quality, the distribution of hourly wages exhibits a distinct peak at the minimum wage, which shifts annually following the minimum wage increases. In addition, in most years, the share of workers with hourly wages lower than the minimum wage is very small, typically inferior to 2%, except in 2011 and 2012, in which this share is slightly higher due to the within-year increase in the minimum wage.

C.5 Additional Figures

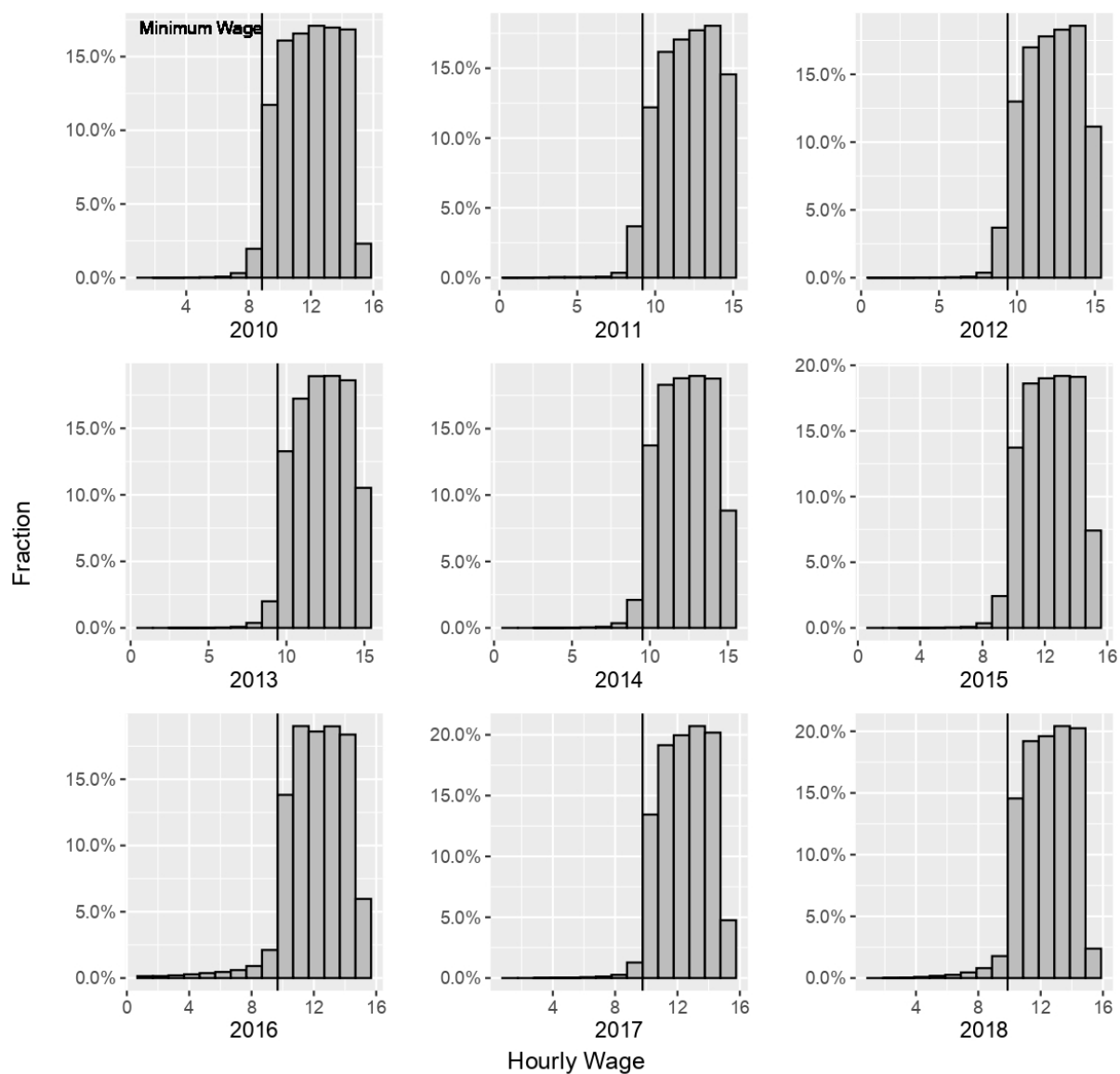


Figure C.1: **Hourly wage rate distributions and the national minimum wage, 2010-2018.** Source: DADS. Note: Each figure represents the distribution of hourly wage rates in the indicated calendar year restricted to hourly wages inferior to 16 euros. Each black vertical line denotes the value of national minimum wage in that year.



Figure C.2: **Commuting time before and after relocation over 7 year** *Sources:* DADS Data and Navitia. *Notes:* The panels report the average commuting time across establishments that relocate in event time $t = 0$. The sample is restricted to establishments observed over a 7 year period. Commuting times are calculated using the municipality of residency and the municipality of the establishment. After the relocation year, we report separately the commuting time of workers observed in the establishment before the relocation and the commuting time of workers hired after the relocation.

C.6 Additional Tables

<i>Dependent variable: Change in Log Annual Earnings</i>			
	(1)	(2)	(3)
Change in log hours	0.86*** (0.0003)	0.86*** (0.0004)	0.86*** (0.00067)
Employer fixed effects	No	Yes	No
Standard errors	Robust	Robust	Clustered
Adjusted R^2	0.760	0.783	0.760

Table C.1: **Regression estimates of the change in log annual earnings on the change of log hours in the DADS (year 2013).** *Source:* DADS data 2013-2012. *Note:* The Table shows the regression results of the log annual earnings change on the log annual hours using workers that stayed in the same employer in both years. Columns 1 and 2 report heteroscedastic robust standard errors, while Column 3 reports standard errors clustered at the establishment level.

Relocation type	A. Separation probability relative to before relocation		B. Change in wage	
	All relocation	Suburbs to suburbs	All relocation	Suburbs to suburbs
Δ Commuting time by public transportation	0.012*** (0.003)	0.011*** (0.004)	0.012*** (0.002)	0.007** (0.003)
Δ Commuting time by car	0.003 (0.004)	0.006 (0.007)	-0.001 (0.003)	0.005 (0.005)
Δ Commuting time by car x (Live in outer ring)	0.002 (0.006)	-0.003 (0.009)	-0.001 (0.003)	0.005 (0.007)
N	259,370	116,385	257,127	115,605

Table C.2: **Does commuting time by car matter for workers living in the suburbs?** *Source:* DADS data 2010-2015. *Note:* The Table shows regression results on job separation probability one year after the relocation in Panel A and on wage changes relative to before the relocation. Within each panel, we report results for all relocations and relocations from the center to the suburbs in the second column. The explanatory variables are changes in commuting time by public transportation and car associated with the relocation, measured in hours, and the interaction between changes in commuting time by car and living in the suburbs for the worker. All regressions include establishment and occupation fixed effects. Standard errors are clustered at the establishment level. (**) and (***) denote statistical significance at 5% and 1% level.

A Separation probability relative to before relocation				
	Center to suburbs	Suburbs to center	Suburbs to suburbs	Center to Center
All workers				
Δ Commuting by public transportation > 0	0.052***	0.022**	0.031***	0.022**
	(0.007)	(0.011)	(0.005)	(0.010)
N	56,386	24,656	116,386	61,943
Workers present 3 years before				
Δ Commuting by public transportation > 0	0.045***	0.030**	0.034***	0.026**
	(0.009)	(0.013)	(0.006)	(0.012)
N	34,368	14,833	74,452	36,999
B Change in wage relative to before relocation				
	Center to suburbs	Suburbs to center	Suburbs to suburbs	Center to Center
All workers				
Δ Commuting by public transportation > 0	0.036***	-0.003	0.014***	0.015*
	(0.006)	(0.008)	(0.004)	(0.008)
N	48,263	20,978	99,005	51,658
Workers present 3 years before				
Δ Commuting by public transportation > 0	0.033***	-0.001	0.014***	0.005
	(0.007)	(0.009)	(0.006)	(0.010)
N	30,578	13,290	65,893	32,213

Table C.3: Does using only workers hired three years before affect the results?

Source: DADS data 2010-2015. *Note:* The Table shows the regression results on job separation probability one year after the relocation in Panel A and on the wage changes relative to before the relocation. Across columns, results are reported for different types of relocations. The explanatory variables are changes in commuting time by public transportation and car associated with the relocation, measured in hours, and the interaction between changes in commuting time by public transportation and living in the suburbs for the worker. Within each panel, we compare our baseline results using workers observed at least one year before the relocation to estimation results using only workers observed at least three years before the relocation. All regressions include establishment and occupation fixed effects. Standard errors are clustered at the establishment level. (**) and (***) denote statistical significance at 5% and 1% level.