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

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Abstract

This paper focuses on examining the impact of working from home on labor market outcomes using an extension of the search and matching model. 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. We show that although the Post-COVID economy suffers from the increase in commuting costs, both the decrease in the disutility in remote work and the increase in productivity of remoters offset this negative impact. We also show that when the disutility of remote work is sufficiently low, it lowers unemployment and wage inequalities between the urban and rural areas. Finally, we analyze the welfare of unemployed workers and economic wealth. It highlights the benefits of reducing remote work disutility.

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]

[1]In 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).

[2]See 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

[3]For 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 2 presents the model, and Section 3 discusses calibration, data and the model fit regarding the Pre-COVID data. Section 4 depicts the model's results due to the Post-COVID shifts. Section 5 presents the planner's problem and its solutions. Finally, Section 6 concludes.

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

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.

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 is[5]

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

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

[5] This 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 $\omega_{ji} = \frac{(1-\gamma)U_i}{JS_j}$.

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.

2.2.1 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 :

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

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, $H(0) \to 0$ and $H(1) \to 1$. *(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, $lim_{\tau \to 0} \lambda^* = 0$ and $lim_{\tau \to +\infty} \lambda^* = 1$.[6]

[6]The 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

$$W^c_{n,ji}(\tau) \quad = \quad w^c_{n,ji}(\tau) - L^c(\tau_{n,ji}, \lambda_{n,ji}) + \beta \left[\; s_j U_i + (1 - s_j) \int_0^{\tau^{max}} W^e_{n,ji}(\tau) dG(\tau) \; \right] \qquad (1)$$

With,

$$W^e_{n,ji} = max \left\{ W^o_{n,ji}; W^r_{n,ji}; W^h_{n,ji} \right\}$$

2.2.2 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

$$U_i \quad = \quad b + \beta \left[\; f_{ii} \int_0^{\tau^{max}_{ii}} W^e_{n,ii}(\tau) dG(\tau) + f_{ji} \int_0^{\tau^{max}_{ji}} W^e_{n,ji}(\tau) dG(\tau) + (1 - f_{ii} - f_{ji}) U_i \; \right] \qquad (2)$$

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

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

2.3.1 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* $\bar{J}_j$)

$$V_j = -\kappa + \beta[q_j \bar{J}_j + (1-q_j)V_j] \tag{3}$$

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

$$\bar{J}_j = (1-\omega_{ji})\bar{J}_{jj} + \omega_{ji}\bar{J}_{ji} \tag{4}$$

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

2.3.2 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:

$$J_{n,ji}^{c}(\tau) = y_{ji} - w_{n,ji}^{c}(\tau) + \beta[s_j V_j + (1-s_j)\bar{J}_{ji}] \tag{5}$$

2.3.3 Free entry condition

The free entry condition leads to $V_j = 0$. Hence, equation 3 becomes

$$\frac{\kappa}{q_j} = \beta[(1-\omega_{ji})\bar{J}_{jj} + \omega_{ji}\bar{J}_{ji}] \tag{6}$$

2.3.4 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

$$N^c_{ji} \;=\; \mathcal{G}^c(\tau^R_{ji})\left[(1-s_j)[N^o_{ji} + N^h_{ji} + N^r_{ji}] + q(\theta_{ji})V_j\right] \tag{7}$$

with,

$$\begin{cases} \mathcal{G}^c(\tau^R_{ji}) = G(\tau^{R_1}_{ji}) & \text{for} \quad c = o \\ \mathcal{G}^c(\tau^R_{ji}) = G(\tau^{R_2}_{ji}) - G(\tau^{R_1}_{ji}) & \text{for} \quad c = r \\ \mathcal{G}^c(\tau^R_{ji}) = 1 - G(\tau^{R_2}_{ji}) & \text{for} \quad c = h \end{cases}$$

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

$$s_j N_{ji} = f_{ji} U_i \tag{8}$$

2.4 Nash Bargaining

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

$$S^c_{n,ji} = W^c_{n,ji} - U_i + J^c_{n,ji} - V_j \tag{9}$$

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

$$w^c_{n,ji} = argmax_{w^c_{n,ji}}\{(W^c_{n,ji} - U_i)^\eta (J^c_{n,ji} - V_j)^{1-\eta}\}$$

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

$$W^c_{n,ji} - U_i = \eta S^c_{n,ji} \tag{10}$$

$$J^c_{n,ji} = (1-\eta) S^c_{n,ji} \tag{11}$$

Nothing $\bar{S}_{ji} = G(\tau^{R_1}_{ji})\widetilde{S}^o_{ji} + \left(G(\tau^{R_2}_{ji}) - G(\tau^{R_1}_{ji})\right)\widetilde{S}^h_{ji} + \left(1 - G(\tau^{R_2}_{ji})\right)\widetilde{S}^r_{ji}$ and $\widetilde{S}^c_{ji,t} = \frac{\int^I S^c_{nji,t}(\tau)dG(\tau)}{\mathcal{G}^c}$, equation 9 leads to

$$(1-\beta(1-s_j))\bar{S}_{ji} \quad = \quad y_{ji} - \bar{L}(\tau_{ji}, \lambda_{ji}) - b - \beta\left[f_{ji}\eta\bar{S}_{ji} + f_{ii}\eta\bar{S}_{ii}\right] \tag{12}$$

Equation 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 11 and 12, we have

$$\frac{\kappa}{(1-\eta)q_j} = \beta[(1-\omega_{ji})\bar{S}_{jj} + \omega_{ji}\bar{S}_{ji}] \tag{13}$$

2.5 Wages

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

$$w^c_{n,ji}(\tau) = \eta\left[y_{ji} + \beta\left(f_{ji}\bar{J}_{ji} + f_{ii}\bar{J}_{ii}\right)\right] + (1-\eta)[L^c(\tau_{n,ji}, \lambda_{n,ji}) + b] \tag{14}$$

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 they 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 $L^c(\tau_{n,ji}, \lambda_{n,ji})$.

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 ($i.e$ $\frac{\partial S^h_{n,ji}}{\partial \lambda_{n,ji}} = 0$), leading to[7]

$$\lambda^*_{n,ji} = 1 - e^{-\frac{c_{ji,\tau}\tau_{n,ji}}{\zeta_i}} \tag{15}$$

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

$$S^o_{n,ji} - S^h_{n,ji} = W^o_{n,ji} - U_i + J^o_{n,ji} - \left(W^h_{n,ji} - U_i + J^h_{n,ji}\right) = 0$$

Leading to :

$$\lambda^*_{n,ji} c_{\tau,ji}\tau_{n,ji} - H(\lambda^*_{n,ji})\zeta - c_h = 0 \tag{16}$$

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

Choice between Hybrid and Remote

$$S^r_{n,ji} - S^h_{n,ji} = W^r_{n,ji} - U_i + J^r_{n,ji} - \left(W^h_{n,ji} - U_i + J^h_{n,ji}\right) = 0$$

Leading to :

$$\zeta_i - (1 - \lambda^*_{n,ji}) c_{\tau,ji} \tau_{n,ji} - H(\lambda^*_{n,ji})\zeta - c_{h,i} = 0 \tag{17}$$

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 $\tau^R_{\mathcal{I}}$ 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 8 solve for the employment levels $N_{\mathcal{I}}$ and hence compute $\omega_{\mathcal{I}}$.
5. Using equation 12 compute $\bar{S}_{\mathcal{I}}$.
6. Finally using equation 13 update the belief on θ_i and θ_j.

3 Parameters' Calibration

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]

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.

3.2.1 Diploma

Workers in urban areas generally have higher levels of educational attainment compared to rural areas. Table 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: **Educational attainment for adults 25 and older Urban Vs Rural.** Estimated average from 2000 to 2018

[8] This 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.

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

3.2.2 Wages

Table 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 2: **Median monthly earning Urban versus rural from 2000 to 2018.**

3.2.3 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 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
JSR	0.0182	0.0200
UR	0.0588	0.0642

Table 3: **Job flows Urban Versus Rural.**

3.2.4 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 datasets[10]: *(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

[10]Both 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 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 4: **Workers flows from Working County to Residence County.** $p_{RU} = \frac{N_{RU}}{N_{UU}+N_{RU}}$ and $p_{RU}^{Tot} = \frac{N_{RU}}{N_{Tot}}$

3.2.5 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 $c_{total} = c_f + c_m + c_{op} = 46 + 83 + 148.4 = 277.4$\$.

3.2.6 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 $\lambda^* = 0.5$.

[11] See Appendix A.2 for more details.

3.3 Identification

Direct identification : Using Table 3, we identify $s_u = 0.0182$ and $s_r = 0.02$ and from the commuting time data, we set $G \rightsquigarrow LogN(3.3, 0.6)$.

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 6 report the results.

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 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 within areas $c_{\tau,w}$	0.003	$\frac{c_{\tau,u}\bar{\tau}}{\bar{w}_{urban}}$	0.082	0.079
Commuting costs between ares $c_{\tau,b}$	0.004	$\frac{c_{\tau,r}\bar{\tau}}{\bar{w}_{rural}}$	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 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).

[12]This 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 7: **Model's Results: VFR, JFR and Wages.**

Urban Versus Rural : The steady-state results, in table 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 8: **Model's Results: Wages and Occupational choice**

On-site, Hybrid and remote : Table 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.

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.

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 16-17 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 $c_\tau^{'} = c_\tau \times 1.05$.

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

[14]The 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.

[15] See 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.

[16] See 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.

4.2 The COVID "Shocks"

4.2.1 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.

4.2.2 Shift in the Value Functions :

Equations 1 to 3 remain unchanged. However, equation 5 becomes

$$J^c_{n,ji}(\tau) = y^c_{ji} - w^c_{n,ji}(\tau) + \beta[s_j V_j + (1 - s_j)\bar{J}_{ji}] \tag{18}$$

With $y^r_{ji} = y^o_{ji} \times (1 + \alpha_r)$ and $y^h_{ji} = y^o_{ji} \times (1 + \alpha_r/2)$

Nash Bargaining leads now to the following surplus function

$$(1 - \beta(1 - s_j))\bar{S}_{ji} \quad = \quad \bar{y}_{ji} - \bar{L}(\tau_{ji}, \lambda_{ji}) - b - \beta\left[f_{ji}\eta\bar{S}_{ji} + f_{ii}\eta\bar{S}_{ii}\right] \tag{19}$$

With, $\bar{y}_{ji} = G(\tau^{R_1}_{ji})y^o_{ji} + \left(G(\tau^{R_2}_{ji}) - G(\tau^{R_1}_{ji})\right) y^h_{ji} + \left(1 - G(\tau^{R_2}_{ji})\right) y^r_{ji}$, leading to the following wage equation

$$w^c_{n,ji}(\tau) = \eta\left[y^c_{ji} + f_{ji}\beta\bar{J}_{ji} + f_{ii}\beta\bar{J}_{ii}\right] + (1 - \eta)[L^c(\tau_{n,ji}, \lambda_{n,ji}) + b] \tag{20}$$

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

$$y^h_{ji} - y^o_{ji} + \lambda^*_{n,ji}c_{\tau,ji}\tau_{n,ji} - H(\lambda^*_{n,ji})\zeta - c_{h,i} = 0 \tag{21}$$

Choice between Hybrid and Remote

$$y^h_{ji} - y^r_{ji} + \zeta_i - (1 - \lambda^*_{n,ji})c_{\tau,ji}\tau_{n,ji} - H(\lambda^*_{n,ji})\zeta - c_{h,i} = 0 \tag{22}$$

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 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

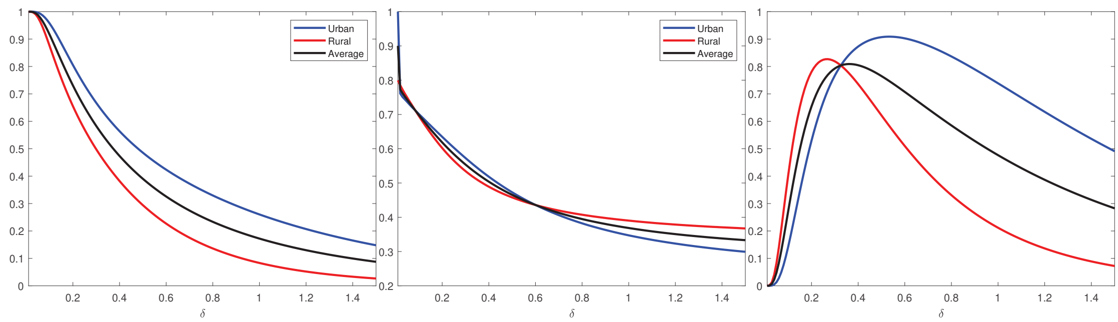
Table 9: **Understanding The shift in the labor market.**

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 $\delta = [0; 1.5]$.

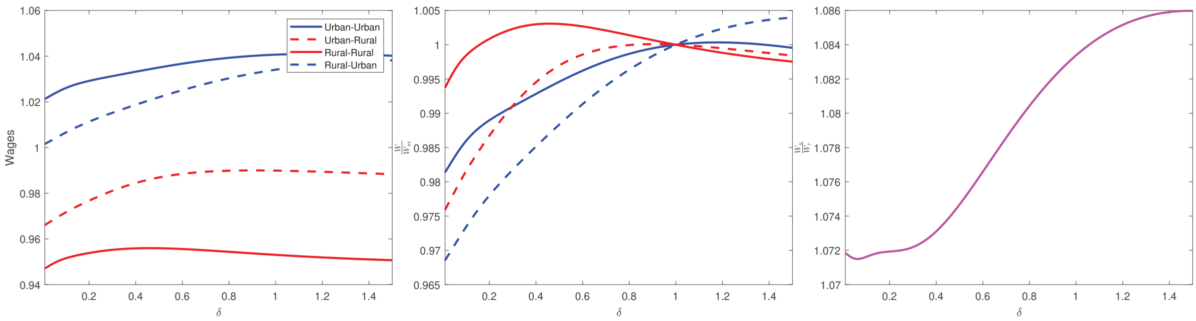
Figure 1 is divided into three panels. For $\delta = 0.712$, the economy is at its Post-COVID Benchmark. Panel a shows that the proportion of remote workers decreases as the disutility of teleworking, denoted as ζ, increases. This means that when the disutility of teleworking decreases, the relative value of WFH increases compared to WOS. At a $\zeta = 0$ level, the value of WFH (as determined by Equation 1) 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.



(a) Share of remote workers (b) Remoters in hybrid set-up (c) Share of hybrid workers

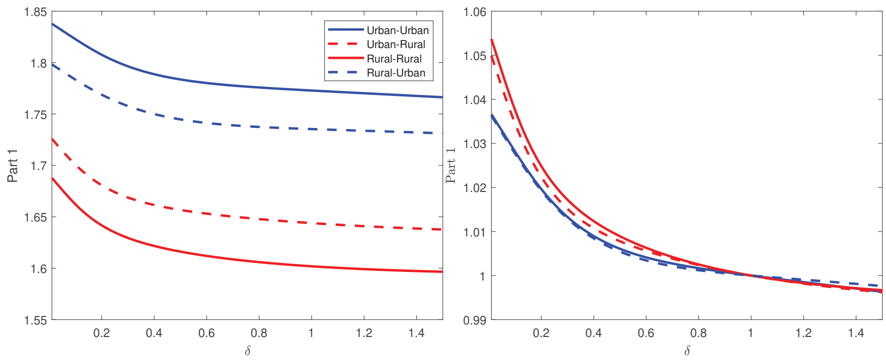
Figure 1: **Share of remote workers as a function of ζ**

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 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.

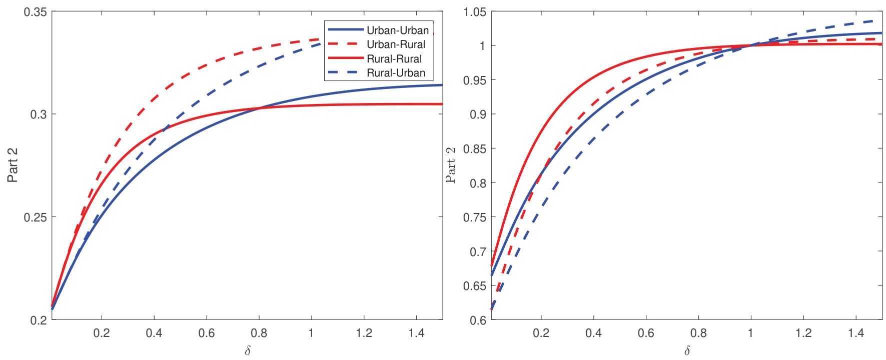


(a) In levels (b) Relative to $\delta = 1$ (c) Urban premium

Figure 2: **Wages as a function of** ζ



(a) In levels (b) Relative to $\delta = 1$



(c) In levels (d) Relative to $\delta = 1$

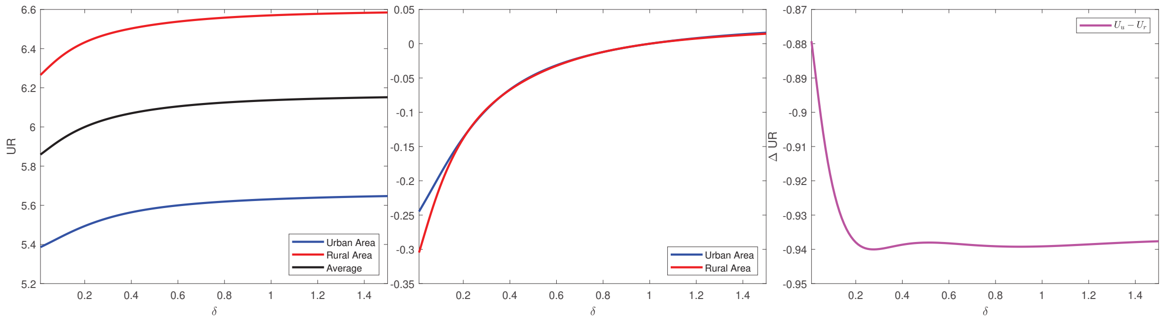
Figure 3: **Disentangling Wages**

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 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 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 2, it is shown that the wage gap between urban and rural workers decreases as δ decreases, resulting in lower inequalities.

Unemployment rate: Figure 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 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.



(a) In levels

(b) Relative to $\delta = 1$

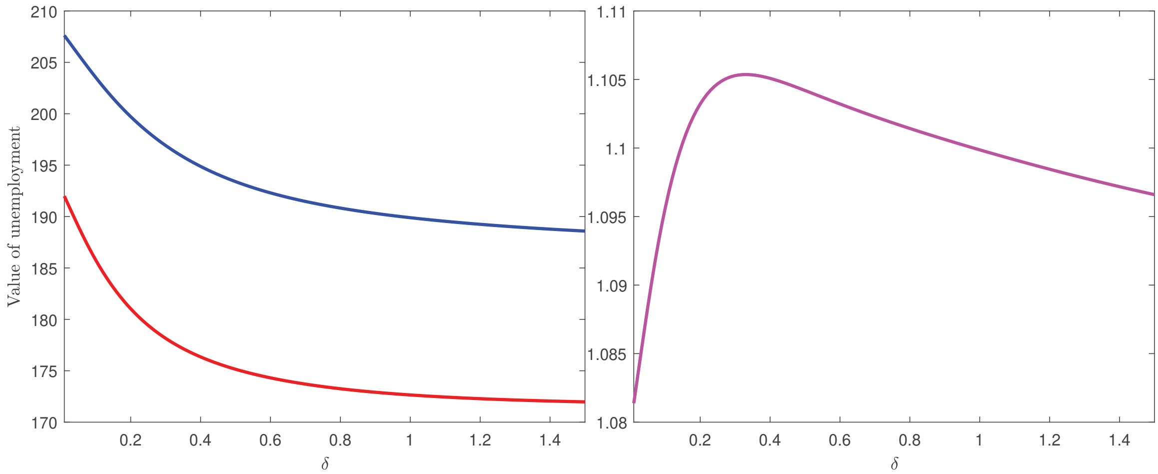
(c) $U1 - U2$

Figure 4: **Unemployment rate as a function of ζ**

4.5 The Impact of WFH on Welfare and Wealth

4.5.1 Are Unemployed Workers Better Off?

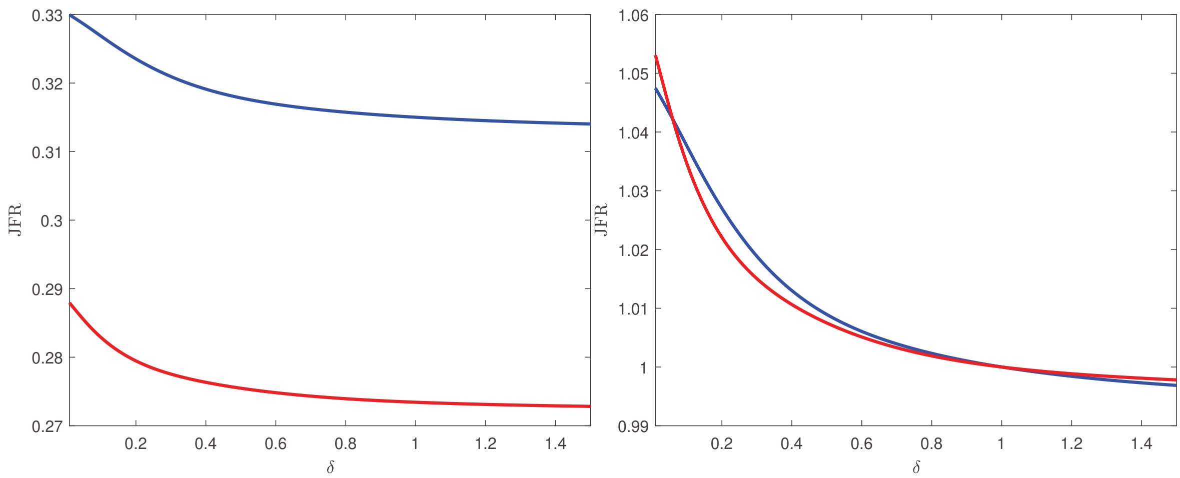
In his book Pissarides (2000), the author argues that measuring the welfare of society should not be based solely on economic growth or the welfare of those who are employed. Instead, he emphasizes the importance of considering the welfare of those who are unemployed. Hence, we evaluate the impact of WFH disutility on unemployed welfare and its inequalities. As depicted in Panel (a) of Figure 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 6. Moreover, Panel (b) of Figure 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.



(a) In levels

(b) Urban premium

Figure 5: **Measuring the Welfare of Unemployed Workers.** The blue (red) line represent the urban (rural) area.



(a) In levels

(b) Relative to $\delta = 1$

Figure 6: **Job Finding Rate.** The blue (red) line represent the urban (rural) area.

4.5.2 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 :

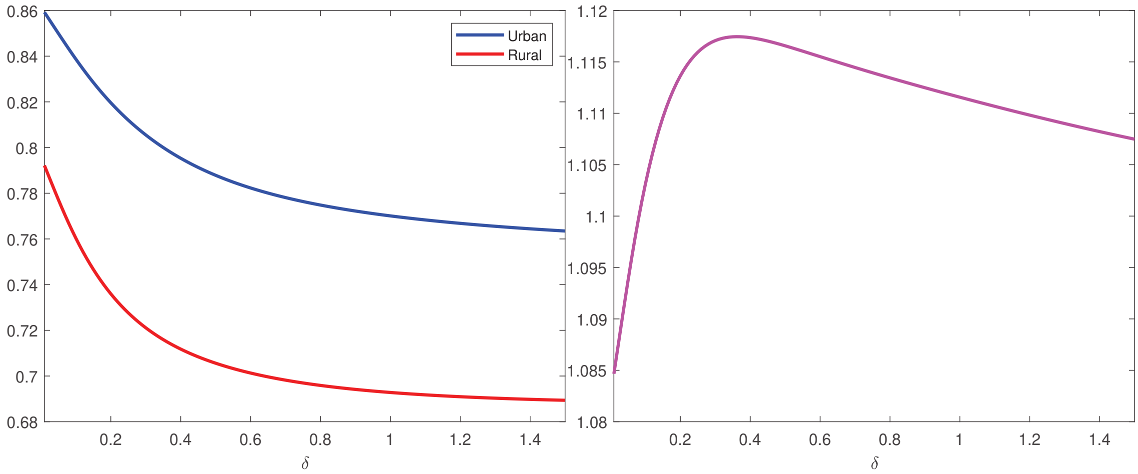
$$NP_i = \bar{y}_{ji} - \sum_J p_{ji}\bar{L}(\tau_{ji}, \lambda_{ji}) - \kappa$$

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

In Figure 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.



(a) In levels (b) Urban premium

Figure 7: **Net Production**

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 $N^c \equiv [N^o_{jj}, N^o_{ij}, N^o_{ji}, N^o_{ii}, N^h_{jj}, N^h_{ij}, N^h_{ji}, N^h_{ii} N^r_{jj}, N^r_{ij}, N^r_{ji}, N^r_{ii}]$ in order to maximize the present discounted value of output net of vacancy costs. Hence, the planner solves the following recursive problem

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

With $\mathcal{C} = \{N^c_t, V_t\}$

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

Noting, $\widetilde{J}^{p,c}_{ji} = \frac{\partial \mathcal{V}}{\partial N^c_{ji}}$ with $\widetilde{J}^{p,c}_{ji} = \frac{\int_0^{\tau max} J^{p,c}_{ji} dG(\tau)}{\mathcal{G}^c(\tau^R_{ij})}$ and $\bar{J}^p_{ji} = \sum_c^C \mathcal{G}^c(\tau^R_{ij}) \widetilde{J}^{p,c}_{t,ji}$ the first order condition leads to the following, steady state relation (See Appendix A.3.1)

$$\frac{\kappa}{\frac{\partial M_j(\gamma U_j + (1-\gamma)U_i, V_j)}{\partial V_j}} = \beta \left[(1 - \omega_{ji}) \bar{J}^p_{jj} + \omega_{ji} \bar{J}^p_{ji} \right] \tag{23}$$

$$\frac{\kappa}{\frac{\partial M_i(\gamma U_i + (1-\gamma)U_j, V_i)}{\partial V_i}} = \beta \left[(1 - \omega_{ij}) \bar{J}^p_{ii} + \omega_{ij} \bar{J}^p_{ij} \right] \tag{24}$$

Noting $\epsilon_{M|V} = \frac{\partial M}{\partial V} \frac{V}{M}$, equation 23 can be rewritten as :

$$\frac{\kappa}{\epsilon_{M_j|V_j} q_j} = \beta \left[(1 - \omega_{ji}) \bar{J}^p_{jj} + \omega_{ji} \bar{J}^p_{ji} \right] \tag{25}$$

The first order condition conditional on $N^c_{t,I}$

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

$$(1 - (1 - s_j)\beta) \bar{J}^p_{ji} = y_{ji} - \bar{L}(\tau_{ji}, \lambda_{ji}) - b - \beta \left[f_{ji} \epsilon_{M_j|JS_j} \bar{J}^p_{ji} + f_{ii} \epsilon_{M_i|JS_i} \bar{J}^p_{ii} - \mathcal{E}_{ji} \right] \tag{26}$$

$$(1 - (1 - s_i)\beta) \bar{J}^p_{ii} = y_{ii} - \bar{L}(\tau_{ii}, \lambda_{ii}) - b - \beta \left[f_{ji} \epsilon_{M_j|JS_j} \bar{J}^p_{ji} + f_{ii} \epsilon_{M_i|JS_i} \bar{J}^p_{ii} - \mathcal{E}_{ji} \right] \tag{27}$$

With,

$$\mathcal{E}_{ji} = f_{ji}(1-\omega_{ji})\left[1-\epsilon_{M_j|JS_j}\right]\left[\bar{J}^p_{jj}-\bar{J}^p_{ji}\right] + f_{ii}\omega_{ij}\left[1-\epsilon_{M_i|JS_i}\right]\left[\bar{J}^p_{ij}-\bar{J}^p_{ii}\right] \tag{28}$$

5.1 Optimality

Recall, the equilibrium in the market is defined by

$$\frac{\kappa}{(1-\eta)q_j} = \beta[(1-\omega_{ji})\bar{S}_{jj} + \omega_{ji}\bar{S}_{ji}] \tag{29}$$

$$(1-\beta(1-s_j))\bar{S}_{ji} = y_{ji} - \bar{L}(\tau_{ji},\lambda_{ji}) - b - \beta\left[f_{ji}\eta\bar{S}_{ji} + f_{ii}\eta\bar{S}_{ii}\right] \tag{30}$$

$$(1-\beta(1-s_i))\bar{S}_{ii} = y_{ii} - \bar{L}(\tau_{ii},\lambda_{ii}) - b - \beta\left[f_{ji}\eta\bar{S}_{ji} + f_{ii}\eta\bar{S}_{ii}\right] \tag{31}$$

Proposition: If $\bar{S}_{ji} = \bar{J}^p_{ji}$, $\epsilon_{M_j|V_j} = \epsilon_{M_i|V_i} = 1-\eta$, $\epsilon_{M_j|JS_j} = \epsilon_{M_i|JS_i} = \eta$ 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.

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 26 compute $\bar{J}_{\mathcal{I}}^{p}$.
6. Finally using equation 25 update the belief on θ_i and θ_j.

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 $\gamma \neq 0.5$).

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

[20] Note 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.

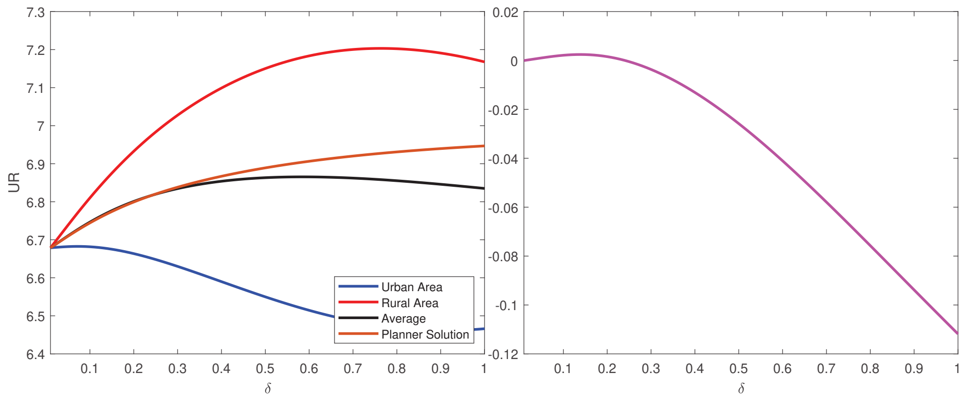
Table 10 shows that whether the economy is in the Pre or Post-COVID economy the optimal solution leads not only to a higher level of unemployment rate but also to similar levels in both areas. First, when workers take into account the externality that one unemployed worker put, by searching in both areas, 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 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 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 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.



(a) In levels

(b) $\Delta = U^m - U^p$

Figure 8: **Unemployment Rate when Search Intensity depends on WFH levels.**

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.

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A Appendix A

A.1 The intensity of WFH in WHA

A.1.1 By surplus maximisation

Recall, $S^h_{n,ji} = W^h_{n,ji} - U_i + J^h_{n,ji}$

Hence, by differentiating

$$\frac{\partial S^h_{n,ji}}{\partial \lambda_{n,ji}} = \frac{\partial (W^h_{n,ji} - U_i)}{\partial \lambda_{n,ji}} + \frac{\partial J^h_{n,ji}}{\partial \lambda_{n,ji}} = 0 \tag{32}$$

Using equation 1, 2, 5 and the free entry condition, we have

$$\frac{\partial (W^h_{n,ji} - U_i)}{\partial \lambda_{n,ji}} = \frac{\partial w^h_{n,ji}(\tau)}{\partial \lambda_{n,ji}} - \frac{\partial L^h(\tau_{n,ji}, \lambda_{n,ji})}{\partial \lambda_{n,ji}} \tag{33}$$

$$\frac{\partial J^h_{n,ji}(\tau)}{\partial \lambda_{n,ji}} = -\frac{\partial w^h_{n,ji}(\tau)}{\partial \lambda_{n,ji}} \tag{34}$$

Putting 34 and 33 in 32

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

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

Leading to

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

A.1.2 Through Nash Bargaining

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

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

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

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 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 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.

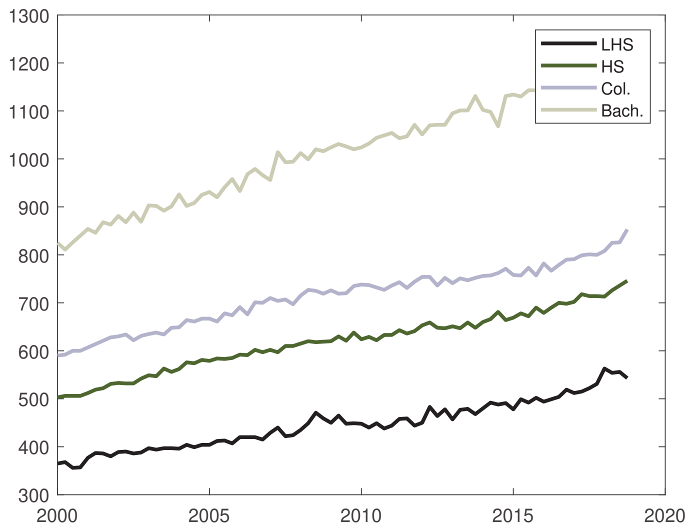

Figure 9: **Quarterly Weekly Wages**

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

Table 11: **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 $JSR_m = \frac{U_{m+1} - U_{m+1}^5}{E_m}$.

- **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)[21]. The first-order moments of worker flows used to identify the model parameters are shown in Table 12.

	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 12: **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 that high school diploma (LHS), high school diploma (HS), college diploma (Coll.) and bachelor degree or more (Bach.).

[21] See Kandoussi and Langot (2021) for the rescalling 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 10 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.

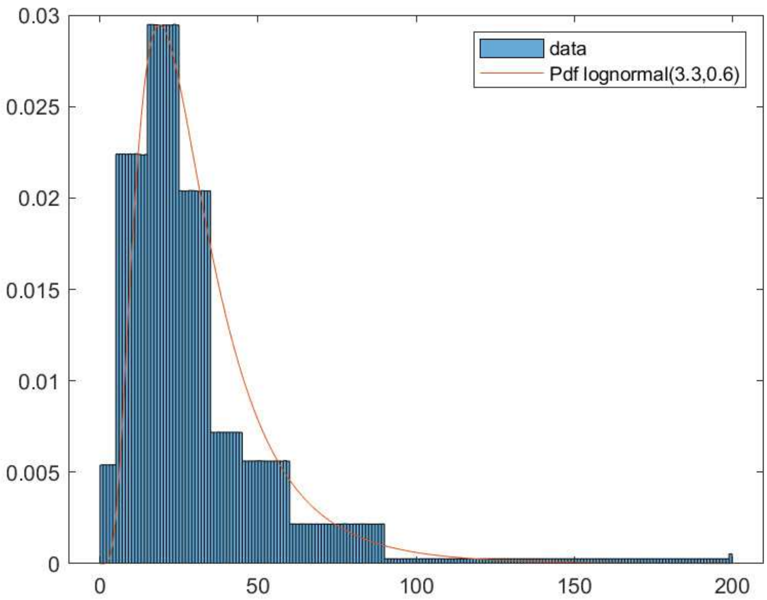

Figure 10: **Commuting time estimation in US.**

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 miles[22]) 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 meaning[23] : $c_{op} = 22 \times 14.99 \times 27/60 = 148,4\$$

[22] Assuming 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 $\bar{d} = 75 \times \tau \times \frac{2}{60} = 67.5km$

[23] This aligns with Aksoy et al. (2023)

A.3 Social Planner

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

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

$$\begin{aligned}
&\beta\left[\mathcal{G}^o(\tau^R_{t+1,jj})\tfrac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,jj}} + \mathcal{G}^h(\tau^R_{t+1,jj})\tfrac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,jj}} + \mathcal{G}^r(\tau^R_{t+1,jj})\tfrac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,jj}}\right]\tfrac{\partial M_{t,j}(\gamma U_j+(1-\gamma)U_i,V_j)}{\partial V_{t,j}}(1-\omega_{ji,t}) \\
&+\beta\left[\mathcal{G}^o(\tau^R_{t+1,ji})\tfrac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ji}} + \mathcal{G}^h(\tau^R_{t+1,ji})\tfrac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ji}} + \mathcal{G}^r(\tau^R_{t+1,ji})\tfrac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ji}}\right]\tfrac{\partial M_{t,j}(\gamma U_j+(1-\gamma)U_i,V_j)}{\partial V_{t,j}}\omega_{ji,t} \quad = \quad \kappa \\
&+(\lambda^p_{jj,t}(1-\omega_{ji,t}) + \lambda^p_{ji,t}\omega_{ji,t})\tfrac{\partial M_{t,j}(\gamma U_j+(1-\gamma)U_i,V_j)}{\partial V_{t,j}}
\end{aligned}$$

Noting, $\widetilde{J}^{p,c}_{t,ji} = \frac{\partial \mathcal{V}_t}{\partial N^c_{t,ji}}$ with $\widetilde{J}^{p,c}_{t,ji} = \frac{\int_0^{\tau_{max}} J^{p,c}_{t,ji} dG(\tau)}{\mathcal{G}^c(\tau^R_{t,ij})}$ and $\bar{J}^p_{t,ji} = \sum_c^C \mathcal{G}^c(\tau^R_{t,ij})\widetilde{J}^{p,c}_{t,ji}$, this leads to:

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

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

$$\begin{aligned}
\frac{\partial \mathcal{V}}{\partial N^o_{t,ji}} &= 0 \\
\frac{\partial \mathcal{V}}{\partial N^h_{t,ji}} &= 0 \\
\frac{\partial \mathcal{V}}{\partial N^r_{t,ji}} &= 0 \\
\frac{\partial \mathcal{V}}{\partial N^o_{t,ii}} &= 0 \\
\frac{\partial \mathcal{V}}{\partial N^h_{t,ii}} &= 0 \\
\frac{\partial \mathcal{V}}{\partial N^r_{t,ii}} &= 0
\end{aligned}$$

$$\frac{\partial \mathcal{V}_t}{\partial N^o_{t,ji}} = y_{ji} - L^o_{ji}(\tau_{t,ji}, \lambda_{t,ji}) - b + \beta \left[\begin{array}{l} \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,jj}} \frac{\partial N^o_{t+1,jj}}{\partial N^o_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,jj}} \frac{\partial N^h_{t+1,jj}}{\partial N^o_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,jj}} \frac{\partial N^r_{t+1,jj}}{\partial N^o_{t,ji}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ij}} \frac{\partial N^o_{t+1,ij}}{\partial N^o_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ij}} \frac{\partial N^h_{t+1,ij}}{\partial N^o_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ij}} \frac{\partial N^r_{t+1,ij}}{\partial N^o_{t,ji}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ji}} \frac{\partial N^o_{t+1,ji}}{\partial N^o_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ji}} \frac{\partial N^h_{t+1,ji}}{\partial N^o_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ji}} \frac{\partial N^r_{t+1,ji}}{\partial N^o_{t,ji}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ii}} \frac{\partial N^o_{t+1,ii}}{\partial N^o_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ii}} \frac{\partial N^h_{t+1,ii}}{\partial N^o_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ii}} \frac{\partial N^r_{t+1,ii}}{\partial N^o_{t,ji}} \end{array} \right]$$

$$\frac{\partial \mathcal{V}_t}{\partial N^h_{t,ji}} = y_{ji} - L^h_{ji}(\tau_{t,ji}, \lambda_{t,ji}) - b + \beta \left[\begin{array}{l} \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,jj}} \frac{\partial N^o_{t+1,jj}}{\partial N^h_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,jj}} \frac{\partial N^h_{t+1,jj}}{\partial N^h_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,jj}} \frac{\partial N^r_{t+1,jj}}{\partial N^h_{t,ji}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ij}} \frac{\partial N^o_{t+1,ij}}{\partial N^h_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ij}} \frac{\partial N^h_{t+1,ij}}{\partial N^h_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ij}} \frac{\partial N^r_{t+1,ij}}{\partial N^h_{t,ji}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ji}} \frac{\partial N^o_{t+1,ji}}{\partial N^h_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ji}} \frac{\partial N^h_{t+1,ji}}{\partial N^h_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ji}} \frac{\partial N^r_{t+1,ji}}{\partial N^h_{t,ji}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ii}} \frac{\partial N^o_{t+1,ii}}{\partial N^h_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ii}} \frac{\partial N^h_{t+1,ii}}{\partial N^h_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ii}} \frac{\partial N^r_{t+1,ii}}{\partial N^h_{t,ji}} \end{array} \right]$$

$$\frac{\partial \mathcal{V}_t}{\partial N^r_{t,ji}} = y_{ji} - L^r_{ji}(\tau_{t,ji}, \lambda_{t,ji}) - b + \beta \left[\begin{array}{l} \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,jj}} \frac{\partial N^o_{t+1,jj}}{\partial N^r_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,jj}} \frac{\partial N^h_{t+1,jj}}{\partial N^r_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,jj}} \frac{\partial N^r_{t+1,jj}}{\partial N^r_{t,ji}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ij}} \frac{\partial N^o_{t+1,ij}}{\partial N^r_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ij}} \frac{\partial N^h_{t+1,ij}}{\partial N^r_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ij}} \frac{\partial N^r_{t+1,ij}}{\partial N^r_{t,ji}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ji}} \frac{\partial N^o_{t+1,ji}}{\partial N^r_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ji}} \frac{\partial N^h_{t+1,ji}}{\partial N^r_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ji}} \frac{\partial N^r_{t+1,ji}}{\partial N^r_{t,ji}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ii}} \frac{\partial N^o_{t+1,ii}}{\partial N^r_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ii}} \frac{\partial N^h_{t+1,ii}}{\partial N^r_{t,ji}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ii}} \frac{\partial N^r_{t+1,ii}}{\partial N^r_{t,ji}} \end{array} \right]$$

$$\frac{\partial \mathcal{V}_t}{\partial N^o_{t,ii}} = y_{ii} - L^o_{ii}(\tau_{t,ii}, \lambda_{t,ii}) - b + \beta \left[\begin{array}{l} \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,jj}} \frac{\partial N^o_{t+1,jj}}{\partial N^o_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,jj}} \frac{\partial N^h_{t+1,jj}}{\partial N^o_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,jj}} \frac{\partial N^r_{t+1,jj}}{\partial N^o_{t,ii}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ij}} \frac{\partial N^o_{t+1,ij}}{\partial N^o_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ij}} \frac{\partial N^h_{t+1,ij}}{\partial N^o_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ij}} \frac{\partial N^r_{t+1,ij}}{\partial N^o_{t,ii}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ji}} \frac{\partial N^o_{t+1,ji}}{\partial N^o_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ji}} \frac{\partial N^h_{t+1,ji}}{\partial N^o_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ji}} \frac{\partial N^r_{t+1,ji}}{\partial N^o_{t,ii}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ii}} \frac{\partial N^o_{t+1,ii}}{\partial N^o_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ii}} \frac{\partial N^h_{t+1,ii}}{\partial N^o_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ii}} \frac{\partial N^r_{t+1,ii}}{\partial N^o_{t,ii}} \end{array} \right]$$

$$\frac{\partial \mathcal{V}_t}{\partial N^h_{t,ii}} = y_{ii} - L^h_{ii}(\tau_{t,ii}, \lambda_{t,ii}) - b + \beta \left[\begin{array}{l} \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,jj}} \frac{\partial N^o_{t+1,jj}}{\partial N^h_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,jj}} \frac{\partial N^h_{t+1,jj}}{\partial N^h_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,jj}} \frac{\partial N^r_{t+1,jj}}{\partial N^h_{t,ii}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ij}} \frac{\partial N^o_{t+1,ij}}{\partial N^h_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ij}} \frac{\partial N^h_{t+1,ij}}{\partial N^h_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ij}} \frac{\partial N^r_{t+1,ij}}{\partial N^h_{t,ii}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ji}} \frac{\partial N^o_{t+1,ji}}{\partial N^h_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ji}} \frac{\partial N^h_{t+1,ji}}{\partial N^h_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ji}} \frac{\partial N^r_{t+1,ji}}{\partial N^h_{t,ii}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ii}} \frac{\partial N^o_{t+1,ii}}{\partial N^h_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ii}} \frac{\partial N^h_{t+1,ii}}{\partial N^h_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ii}} \frac{\partial N^r_{t+1,ii}}{\partial N^h_{t,ii}} \end{array} \right]$$

$$\frac{\partial \mathcal{V}_t}{\partial N^r_{t,ii}} = y_{ii} - L^r_{ii}(\tau_{t,ii}, \lambda_{t,ii}) - b + \beta \left[\begin{array}{l} \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,jj}} \frac{\partial N^o_{t+1,jj}}{\partial N^r_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,jj}} \frac{\partial N^h_{t+1,jj}}{\partial N^r_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,jj}} \frac{\partial N^r_{t+1,jj}}{\partial N^r_{t,ii}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ij}} \frac{\partial N^o_{t+1,ij}}{\partial N^r_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ij}} \frac{\partial N^h_{t+1,ij}}{\partial N^r_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ij}} \frac{\partial N^r_{t+1,ij}}{\partial N^r_{t,ii}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ji}} \frac{\partial N^o_{t+1,ji}}{\partial N^r_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ji}} \frac{\partial N^h_{t+1,ji}}{\partial N^r_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ji}} \frac{\partial N^r_{t+1,ji}}{\partial N^r_{t,ii}} \\ + \frac{\partial \mathcal{V}_{t+1}}{\partial N^o_{t+1,ii}} \frac{\partial N^o_{t+1,ii}}{\partial N^r_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^h_{t+1,ii}} \frac{\partial N^h_{t+1,ii}}{\partial N^r_{t,ii}} + \frac{\partial \mathcal{V}_{t+1}}{\partial N^r_{t+1,ii}} \frac{\partial N^r_{t+1,ii}}{\partial N^r_{t,ii}} \end{array} \right]$$

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

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

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

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

Noting :

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

This leads

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

Hence,

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

A.3.3 Condition to optimality

We have

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

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

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

By dividing term by term the two equality

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

Leading to

$$\frac{f_{ji}(1-\omega_{ji})}{f_{jj}\omega_{ji}} = \frac{f_{ii}\omega_{ij}}{f_{ij}(1-\omega_{ij})}$$

$$\frac{f_j(1-\gamma)(1-\omega_{ji})}{f_j\gamma\omega_{ji}} = \frac{f_i\gamma\omega_{ij}}{f_i(1-\gamma)(1-\omega_{ij})}$$

$$\frac{(1-\gamma)(1-\omega_{ji})}{\gamma\omega_{ji}} = \frac{\gamma\omega_{ij}}{(1-\gamma)(1-\omega_{ij})}$$

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

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

Hence,

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

Leading to

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

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

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

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

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

Choice between On-site and Hybrid

$$J^{p,o}_{t,n,ji} - J^{p,h}_{t,n,ji} = \; -L^{o}_{ji}(\tau_{t,n,ji}, \lambda^{*}_{t,n,ji}) + L^{h}_{ji}(\tau_{t,n,ji}, \lambda^{*}_{t,n,ji})$$

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

$$L^{o}_{ji}(\tau_{n,ji}, \lambda^{*}_{n,ji}) - L^{h}_{ji}(\tau_{n,ji}, \lambda^{*}_{n,ji}) = 0$$

Choice between Hybrid and Remote

Similary we find :

$$L^{r}_{ji}(\tau_{n,ji}, \lambda^{*}_{n,ji}) - L^{h}_{ji}(\tau_{n,ji}, \lambda^{*}_{n,ji}) = 0$$

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 $\epsilon_{M|JS}$

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