Essays on Remote Work and Public Economics

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Dedication

To my parents, Asiye and Mehmet, and to my wife, Tamra.

Abstract

This dissertation consists of three chapters that present an empirical and structural analysis of remote work through wage differentials and examine the implications of remote work for public policy from a public finance perspective.

The first essay analyzes wage disparities between work-from-home (WFH) and onsite employees using data from the American Community Survey (ACS). I document a substantial and historically persistent wage gap favoring WFH workers. A decomposition of this differential reveals that over half can be attributed to human capital characteristics and occupation fixed effects, leaving an unexplained premium of 8–11% in log terms. I show that this premium persists across demographic groups such as education and age, and cannot be accounted for by a standard Roy model. To explore the underlying mechanisms, I develop a partial equilibrium model with discrete workplace choice that incorporates productivity losses associated with WFH. The model attributes part of the wage differential to selection into WFH, suggesting that the direction and strength of selection depend on the curvature of utility over consumption and the magnitude of productivity loss.

The second essay studies optimal income taxation in the context of remote work. Workplace choice is modeled discretely, incorporating heterogeneity in preferences and productivity losses associated with WFH. Using a Ramsey taxation framework and a parametric income tax function, the analysis highlights how remote work affects key public finance margins—specifically, the elasticity of taxable income, the degree of consumption smoothing, and the level of income inequality. I compare optimal tax schedules with and without the option to work

remotely. The results show that allowing for WFH systematically lowers the optimal marginal income tax rate—a finding that is quantitatively significant and robust across alternative calibrations. In a calibrated economy, optimal marginal tax rates are approximately 2%–3% lower for low-income groups and 4%–5% lower for high-income groups when WFH is incorporated. For an income increase of $10,000, the optimal policy with WFH reduces the tax burden by $280 to $520 across incomes ranging from $40,000 to $500,000, relative to a no-WFH benchmark.

The third essay examines optimal income taxation when tax policy can condition on workplace type. Using a Ramsey framework, I compare a uniform tax schedule with a tagging policy that assigns separate marginal tax rates for remote and on-site workers. This flexibility allows the planner to internalize productivity losses and selection effects associated with WFH. The analysis shows that the planner imposes higher tax progressivity on remote workers, discouraging WFH entirely despite its amenity value. This workplace-contingent policy achieves higher welfare than a uniform schedule, particularly when heterogeneity in WFH preferences is modeled with a log-normal distribution. In that case, the difference in optimal progressivity between WFH and No-WFH workers reaches nearly 12 percentage points, compared to about 5 points under a uniform distribution. These findings highlight the efficiency gains from conditioning tax policy on observable workplace choice.

Contents

List of Tables

List of Figures

Chapter 1

Understanding the Selection Effect of WFH: Evidence from Survey Data

Introduction

The prevalence of remote work during and after the recent pandemic has raised many economic questions. The importance of work from home (WFH) in labor market dynamics had already attracted researchers' interest before COVID-19[1]. According to the American Community Survey (ACS) data, the percentage of employees working exclusively from home increased from 2% to 8% among college graduates over the two decades preceding COVID-19 in the United States. This rate rose to approximately 35% in 2021 for the same demographic. The ACS data also provide compelling statistics on wage income for workers by workplace, whether WFH or on-site. According to ACS data, the mean wages of remote workers (non-farm, private sector) were significantly higher than those of on-site workers in 2021[2]. Historically, this wage premium has been consistent, with relative wages in log terms showing a 20% to 35% positive premium over the two decades preceding 2020, excluding any human capital controls. After

[1] See Oettinger (2011), Bloom et al. (2015), and Mas and Pallais (2017)

[2] See the Data section for details on classifications and restrictions.

accounting for a substantial number of fixed effects related to human capital and occupations, we find a 11% average wage premium for remote workers compared to individuals working on-site based on the 2021-2022 samples.

These statistics and findings are particularly intriguing when we consider the emerging literature on productivity loss associated with remote work. Emanuel and Harrington (2023) investigate the impact of remote work on productivity and worker selection. They document that remote workers completed fewer tasks per hour than their on-site counterparts, with productivity losses reaching up to 12 percent. Their study focuses on a U.S. Fortune 500 company's call centers, which employed both remote and on-site workers before and during the COVID-19 pandemic. Gibbs et al. (2023) also examine productivity changes during the COVID-19 pandemic. Their study uses data from over 10,000 IT professionals working at a large Indian IT services firm, comparing their output before and during remote work. Despite an increase in working hours, average productivity (output per hour) fell by 8% to 19%. In another study, Atkin et al. (2023) explore productivity differences between workers assigned to home-based and office-based settings through a randomized controlled trial in India's data entry sector. They found that workers assigned to WFH were 18% less productive than those in the office. The gap widened for workers who preferred WFH, with their productivity being 27% lower than their office-based counterparts.

The rising prevalence of WFH, alongside its implications for wages and productivity, has also drawn increasing policy attention. Even before the COVID-19 pandemic, policymakers were becoming attuned to the evolving nature of work. In their 2014 report, the Council of Economic Advisers highlighted growing conflicts between personal and professional responsibilities and emphasized the importance of workplace flexibility in response to shifting workforce dynamics. The report pointed to the increasing adoption of flexible work arrangements, including telecommuting and remote work. More recently, the post-pandemic shift has sparked renewed debate, with some companies now considering salary adjustments or geographic pay differentials for employees who choose to work remotely.[3]

In the first part of the paper, I document wage differentials by workplace type—remote versus on-site—using data from the American Community Survey. I begin by estimating these differentials through a standard Mincerian human capital model. The results reveal a sizable raw wage premium for remote workers of about 48 percent in log terms. Approximately half of this premium is accounted for by differences in educational attainment. Including industry and occupation fixed effects explains another quarter of the gap, while additional controls for other human capital variables contribute relatively little. A comprehensive decomposition using up to 746 fixed effects suggests that an unexplained wage premium of 8–11 percent persists. Extensions of the analysis indicate that this residual premium is concentrated among college-educated individuals and those aged 34 and older. Re-estimations using alternative samples and specifications further suggest that unobserved heterogeneity—such as time-invariant worker characteristics—does not appear to fully explain the remaining premium.

These empirical patterns are difficult to reconcile with a standard Roy model of comparative advantage (Roy, 1951), which predicts wage sorting based solely on task-specific skills. I formally show that under symmetry in productivity and technology, such a model cannot generate a wage premium for remote

[3] https://www.forbes.com/sites/jackkelly/2021/08/11/google-may-cut-the-pay-of-remote-workers/?sh=69ec16239e5d

workers. This result holds even when accounting for differences in non-wage amenities such as leisure time, suggesting that additional mechanisms—beyond comparative advantage—are needed to explain the observed premium.

To investigate this puzzle, the second part of the paper develops a partial equilibrium model that links the observed wage premium to productivity losses documented in the literature. The model posits a mechanism in which remote work may lead to productivity reductions, but where positive selection into remote work—driven by differences in individual preferences and risk aversion—generates a wage premium. I show that positive selection into WFH hinges on whether the income effect outweighs the substitution effect, with risk aversion playing a central role in shaping this balance. This framework helps explain how a productivity loss at the intensive margin can coexist with wage premiums at the extensive margin. The intuition is that, although remote workers may be less productive on average, the amenity value of WFH rises with income, making higher-skilled individuals more likely to choose remote work. This income-driven selection leads to a skill sorting effect that generates a wage premium in equilibrium, despite the underlying productivity loss.

To the best of my knowledge, this is the first paper to explain the observed wage premium for remote workers by jointly considering productivity loss and risk aversion—despite the fact that wage differentials by work location have been examined in prior literature.

The literature on compensation differentials with respect to workplace location is not new. Schroeder (2005) is one of the earliest papers to discuss the earnings of remote workers, using data from the 1997 Current Population Survey. They estimate that home-based workers earn a significant wage premium compared to on-site workers, which they attribute to the convenience and flexibility of working from home. Oettinger (2011) analyzes the impact of remote work on wages in the US over two decades (1980–2000) and links the decline in the wage penalty for home-based work to advancements in information technology. Building on Oettinger (2011) interpretation of the wage penalty for remote workers prior to the 2000s, White (2019) reports a wage premium for remote workers relative to office workers in 2014, using data from the Census and American Community Survey (ACS). White argues that this premium is the result of the declining cost of monitoring over time. Using data from the American Time Use Survey (2017–2018), Pabilonia and Vernon (2022) find that some teleworkers earn a wage premium in the US, which varies by gender, parental status, and the intensity of teleworking. Similarly, Arntz et al. (2022) document heterogeneity in the wage effects of remote work across gender and family characteristics in a cross-country European context.

Historically, some empirical studies of home-based employment have addressed questions closely related to this work by examining the determinants and wage implications of remote work. Pabilonia (2005) analyzes data from the 2001 CPS and finds that home-based workers earn a wage premium relative to their on-site counterparts, even after controlling for worker and job characteristics. Similarly, Edwards and Field-Hendrey (2002) use Census data to show that home-based work is more common among women facing higher fixed costs of market work, with important implications for earnings and occupational selection.

This study adds to the growing body of research on remote work by embedding WFH into a structural framework that connects the emerging literature on productivity effects with broader economic mechanisms. A number of recent studies examine the productivity implications of remote work—for instance, Bloom et al. (2015), Emanuel and Harrington (2023), and Gibbs et al. (2023)—while others focus on the macro-level prevalence of WFH and its relationship to worker characteristics (e.g., Dingel and Neiman, 2020; Bick et al., 2021) or the valuation of workplace flexibility (Mas and Pallais, 2017). By contrast, this paper provides a unified structural framework that links these empirical patterns to wage outcomes and selection dynamics, offering new insights into the distributional consequences of remote work.

More broadly, this paper contributes to the literature on wage differentials by examining how workplace arrangements relate to observed outcomes in earnings. Among a voluminous literature, notable studies have examined disparities by gender (Goldin, 2014), geography (Moretti, 2013), and firm affiliation (Card et al., 2018). In a similar spirit, this paper investigates how the decision to work remotely versus on-site interacts with worker characteristics and preferences to generate persistent wage differentials through selection.

The structure of the paper is as follows: In the next section, I document the data and present both the empirical methodology and the estimated results. Section 2 discusses the potential role of the Roy model, and Section 3 introduces the partial equilibrium model. Section 4 concludes the paper.

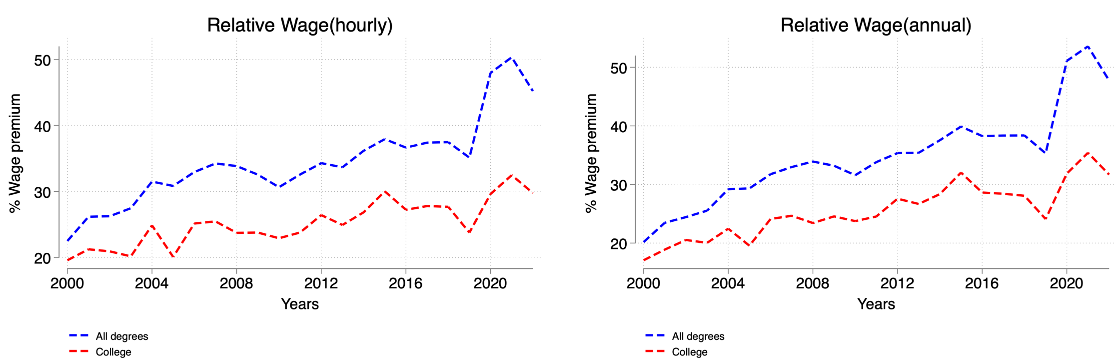
1.1 Data and Empirical Model

I use annual ACS data samples, which are available from the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2024). The samples are restricted to employed workers aged 23-65 who are salaried employees in the non-farm, non-public, private sector in the U.S. Additionally, we consider respondents who reported working the entire year (50-52 weeks) in the survey. Figure 1 illustrates relative mean real wages in log terms, conditional on workplace (home vs. on-site), defined as follows:

$$E_i(log(wage_{it})|_{wfh=1}) - E_i(log(wage_{it})|_{wfh=0}), \tag{1}$$

where $wfh = 1$ or $wfh = 0$, mean workers work from home or onsite, respectively. The sub-figures on the left and right show the wage premium based

Figure 1: Relative wage by work place: home vs. onsite



The figures show the wage premium based on work place(wfh or onsite) for hourly wage income and the total wage income respectively. Red line illustrates same statistic for college graduate workers. Sample weights are used to adjust probability of selection of respondents

on workplace (WFH or on-site) for hourly wage income and total wage income, respectively. The main reason for showing two panels is to clarify the differences in usual hours worked over the year and their potential covariation with remote work. As observed in Figure 1, there is a significant premium in hourly wages for remote workers. Specifically, the relative difference ranges between 30%

and 40% over the period 2004-2019, rising to 40% − 50% after the COVID-19 pandemic. Figure 4 (See Appendix- A.) presents the extended statistics related to the results in Figure 1, focusing on the relationship between the fraction of WFH and hourly wage statistics in log terms. Figure 4 shows that high-income workers are more likely to engage in WFH, indicating a potential selection to WFH as it will be analyzed in the following sections. With this in mind, we can identify the determinants of the observed wage premium. Naturally, working from home involves a set of covariates that help explain these differences, which we will explore further in this section.

I use the following regression model (2) to identify the role of WFH, incorporating standard human capital controls:

$$log(wage_{it}) = \beta_1 wfh_{it} + X'_{it}\beta_2 + \epsilon_{it}, \tag{2}$$

where $log(wage_{it})$ is the log of hourly relative wage of employed worker i in year t. The variable wfh is a factor that takes the value 0 for on-site workers (os) and 1 for those working from home (wfh). Various fixed effects are included in different combinations of the model, as shown in the corresponding tables. The first set of controls is primarily Mincerian. Additionally, I include location (state) fixed effects, as well as industry (3-digit Census classification) and occupation controls (3-digit Census classification). The number of fixed effects in the models may exceed 746, as noted in the last row of each table.

Table 1 presents the estimates for the empirical model defined in Equation (2), covering three different sample periods: 2021-2022, 2017-2019, and 2000-2005. Each sub-table reports the results of seven combinations (1 through 7), which sequentially introduce additional control variables related to the human capital of workers and demographic characteristics. The coefficient of the variable of interest, wfh, is shown consistently across all models and sample periods. The first column of Table 1 indicates that the expected wages of remote workers are 48% higher than those of on-site workers in real terms after COVID-19, compared to 37% in the 2017-2019 sample. After controlling for human capital, industry, and occupational fixed effects, we still observe a 11% wage premium for remote workers. This rate decreases to 8% and 6% in the 2017-2019 and 2000-2005 samples, respectively. The key takeaway from any sub-table is that education-related covariates explain a significant portion of the premium, controlling for over 20% in the 2021-2022 sample and approximately 14% in the other samples. Other Mincerian controls do not explain much of the WFH premium but still have important explanatory power on log(wage), as reflected in the R^2 statistics. The inclusion of industry and occupation fixed effects substantially reduces (almost halves) the WFH premium in all samples, as demonstrated when comparing columns (6-7) with column (5). A noteworthy point is the historical consistency of these findings, as seen in the early 2000s sample.

To complement these results, Table 5 in the Appendix- A reports estimates based on a subsample restricted to individuals who usually work exactly 40 hours per week. This allows for a direct comparison with the baseline estimates in Table 1, which include workers with any usual number of weekly hours. Restricting the sample to workers with a 40-hour workweek does not substantially change the results in the post-COVID period. However, in the earlier two periods, the wfh coefficients are approximately 3–4 percentage points higher than in the baseline

Table 1: WFH Coefficients from OLS Regressions of Wage: Model 2

Dependent variable: Log Hourly Wage							
Sample: 2021-2022	1	2	3	4	5	6	7
wfh	0.48***	0.25***	0.24***	0.24***	0.22***	0.17***	0.11***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.07	0.23	0.27	0.32	0.34	0.38	0.46
$\#Obs.(millions)$	1.37	1.37	1.37	1.37	1.37	1.37	1.37
Sample: 2017-2019							
wfh	0.37***	0.20***	0.15***	0.15***	0.14***	0.11***	0.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.01	0.22	0.28	0.33	0.35	0.40	0.48
$\#Obs.(millions)$	2.13	2.13	2.13	2.13	2.13	2.13	2.13
Sample: 2000-2005							
wfh	0.27***	0.13***	0.10***	0.10***	0.10***	0.09***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
R^2	0.01	0.21	0.25	0.31	0.33	0.38	0.45
$\#Obs.(millions)$	4.31	4.31	4.31	4.31	4.31	4.31	4.31
High School		✓	✓	✓	✓	✓	✓
Some College		✓	✓	✓	✓	✓	✓
College		✓	✓	✓	✓	✓	✓
Graduate		✓	✓	✓	✓	✓	✓
Age			✓	✓	✓	✓	✓
Age^2			✓	✓	✓	✓	✓
Race				✓	✓	✓	✓
Gender				✓	✓	✓	✓
Married				✓	✓	✓	✓
Head of Hous.				✓	✓	✓	✓
Location					✓	✓	✓
Industry						✓	✓
Occupation							✓
Year	✓	✓	✓	✓	✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓	✓
$\#Controls$		4	6	10	64	220	750

OLS estimations over pooled samples are reported in each sub-panel. The row corresponding to "Wfh" in each sub-panel indicates the estimated WFH coefficient, representing the wage premium. The numbers in brackets are robust standard errors, while the third rows in each sub-panel report the R-squared of each estimation. The row labeled "$\#Controls$" indicates the number of fixed effects included in each estimation, excluding time (Year) effects, constants, and weights. Sample weights are applied to adjust for the probability of selection of the respondent. Significance levels: *** p<0.001, ** p<0.01, * p<0.05.** Location includes both state and metropolitan status indicators. For the 2000–2005 sample, metropolitan status is excluded due to a high rate of missing observations. As a result, the number of control variables is four fewer in the last three models for this sample.

estimates. For example, in column (7), which includes all fixed effects, the estimated wfh premiums in the 2000-2005 and 2017-2019 samples - 9% and 10%, respectively - approach the post-COVID estimates under the 40-hour sample restriction. Focusing on this specific group, which comprises nearly 50% of the full sample, helps assess whether the observed wage differences are primarily driven by the main jobs of the workers.

After describing the basic results, models (3) and (4) are used to investigate how human capital factors contribute to the average premium observed in Table 1. Specifically, I introduce interaction terms such as $wfh \times education_n$, where n represents subcategories of the Education variable, which are ”Dropout, High School, Some college, College, and Graduate”. I report the term $wfh \times college$ for each estimate.

$$log(wage_{it}) = \sum_j \gamma_j wfh_{it} \times educ_{itj} + educ_{itj} + X_{it}^{'}\beta_2 + \epsilon_{it}, \tag{3}$$

Table 2 shows the estimation of model (3). The structure of Table 2 is similar to that of Table 1. In this table, I estimate the interaction of education fixed effects with wfh as specified. The coefficients in any column should be interpreted relative to the baseline of college-educated workers ($wfh \times college$). When comparing these findings with column 7 in Table 1, we see a higher premium for college graduates, approximately 33%, 50%, and 100% (0.15, 0.12, and 0.13) for the 2021-2022, 2017-2019, and 2000-2005 samples, respectively. For the 40-hour shift group prior to COVID, the premium is even higher, with coefficients of 0.15 and 0.17 in the 2017-2019 and 2000-2005 samples, respectively. These strikingly high figures suggest that the wage premium observed in Table 1 is primarily driven by covariates related to college graduate workers.

Finally, after understanding the education component, I also consider model (4) to determine whether the premium is driven by age-related covariates. The model is specified as:

$$log(wage_{it}) = \sum_{k} \zeta_k wfh_{it} \times age_{itk} + age_{itk} + X_{it}^{'}\beta_2 + \epsilon_{it}, \tag{4}$$

In this equation, the interaction term $wfh \times age_m$ is included as a new variable, where m represents subcategories of the age variable. By using the same fixed effects as in Table 1, Table 3 presents the interaction effects of WFH with each age group on the dependent variable, $log(wage)$.

Our benchmark for comparison should again be Table 1, model (7). The results suggest that the premium observed is largely driven by the covariates related to the adult age group. For the youngest group in the sample, aged 23-28, the $wfh \times Age$ interaction term is often either statistically insignificant or economically small. This suggests that the WFH wage premium is primarily explained by older, more experienced workers. Figures 5, in Appendix- A, is presented as complementary statistics to highlight the importance of WFH for different age groups. Figure 5 illustrates the WFH rate across age categories for two samples: before COVID-19 (2019) and after COVID-19 (2022). As inferred from the statistics, younger age groups have a lower fraction of WFH compared to adult groups. The stable distribution of WFH among adult age groups before COVID-19 changes significantly in 2022.

The results across the three tables underscore two critical factors explaining the wage differentials between workers who work from home (WFH) and those

Table 2: WFH Coefficients from OLS Regressions of Wage: Model 3

Dependent variable: Log Hourly Wage

	2021-2022	2017-2019	2000-2005
wfh×college	0.15***	0.12***	0.13***
	(0.00)	(0.00)	(0.01)
R^2	0.46	0.48	0.45
$\#Obs.(millions)$	1.37	2.13	4.31
Sample Restriction: 40-Hour Workweek			
wfh×college	0.15***	0.15***	0.17***
	(0.00)	(0.01)	(0.01)
R^2	0.48	0.48	0.46
$\#Obs.(millions)$	0.753	1.09	2.19
wfh×Dropout	✓	✓	✓
wfh×HighSch	✓	✓	✓
wfh×SomeCol	✓	✓	✓
wfh×Graduate	✓	✓	✓
Dropout	✓	✓	✓
High School	✓	✓	✓
Some College	✓	✓	✓
Graduate	✓	✓	✓
Age	✓	✓	✓
Age^2	✓	✓	✓
Race	✓	✓	✓
Gender	✓	✓	✓
Married	✓	✓	✓
Head of Hous.	✓	✓	✓
Location	✓	✓	✓
Industry	✓	✓	✓
Occupation	✓	✓	✓
Year	✓	✓	✓
Constant	✓	✓	✓
$\#Controls$	754	754	750

OLS estimations over pooled samples are reported in each sub-panel. The row corresponding to "$wfh \times college$" in each sub-panel indicates the estimated coefficient, representing the wage premium. The numbers in brackets are robust standard errors, while the third rows in each sub-panel report the R^2 of each estimation. The row labeled "$\#Controls$" indicates the number of fixed effects included in each estimation, excluding time (Year) effects, constants, and weights. Sample weights are applied to adjust for the probability of respondent selection. Significance levels: *** p<0.001, ** p<0.01, * p<0.05.

$**$ Location includes both state and metropolitan status indicators. For the 2000–2005 sample, metropolitan status is excluded due to a high rate of missing observations. As a result, the number of control variables is four fewer in the last three models for this sample.

who work on-site. First, industry- and occupation-related fixed effects play a significant role in explaining the WFH premium, as evidenced by the results in Table 1. The inclusion of these controls leads to a notable reduction in the premium, suggesting that much of the wage differential can be attributed to the types of jobs that are more likely to allow remote work. High-paying industries-occupations such as technology and professional services are likely driving this result, as these sectors are more conducive to remote work arrangements.

Second, skill-related factors—particularly education—are crucial in explaining the WFH premium. As shown in Table 1, the inclusion of education controls significantly reduces the overall WFH premium, highlighting the importance of educational attainment in driving wage differences. Specifically, college-educated workers experience a consistently higher premium, as demonstrated by the interaction terms in Table 2. For instance, the WFH premium for college graduates is larger than the average WFH premium from Table 1's column 7, underscoring the disproportionate benefit that highly educated workers gain from remote work. This further reinforces the idea that skill level, represented by education categories, explains a substantial portion of the WFH wage premium.

Additionally, Table 3 shows that age-related factors—particularly for mid-career workers—also contribute to the observed premium. More experienced workers tend to earn higher wages when working remotely, likely due to their accumulated skills and advanced career stages, which align with the nature of jobs that support remote work.

These findings point to the importance of selection into WFH by highly skilled individuals and those in particular industries. The wage differential is not simply a byproduct of WFH itself but rather reflects the fact that workers with

Table 3: WFH Coefficients from OLS Regressions of Wage: Model 4

Dependent variable: Log Hourly Wage

	23 – 28	29 – 33	34 – 38	39 – 43	44 – 48	49 – 53	54 – 58	59 – 65
Sample: 2021-2022								
wfh×age	0.03***	0.08***	0.11***	0.14***	0.15***	0.14***	0.15***	0.14***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46
$\#Obs.(millions)$	1.37	1.37	1.37	1.37	1.37	1.37	1.37	1.37
Sample: 2017-2019								
wfh×age	-0.01	0.04***	0.07***	0.10***	0.11***	0.11***	0.08***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48
$\#Obs.(millions)$	2.13	2.13	2.13	2.13	2.13	2.13	2.13	2.13
Sample: 2000-2005								
wfh×age	0.05**	0.08***	0.09***	0.09***	0.07***	0.04**	0.02	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
R^2	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
$\#Obs.(millions)$	4.31	4.31	4.31	4.31	4.31	4.31	4.31	4.31
wfh×$age_{[....:i]}$		✓	✓	✓	✓	✓	✓	✓
$age_{[....:i]}$	✓	✓	✓	✓	✓	✓	✓	✓
Age^2	✓	✓	✓	✓	✓	✓	✓	✓
High School	✓	✓	✓	✓	✓	✓	✓	✓
Some College	✓	✓	✓	✓	✓	✓	✓	✓
College	✓	✓	✓	✓	✓	✓	✓	✓
Graduate	✓	✓	✓	✓	✓	✓	✓	✓
Race	✓	✓	✓	✓	✓	✓	✓	✓
Gender	✓	✓	✓	✓	✓	✓	✓	✓
Married	✓	✓	✓	✓	✓	✓	✓	✓
Head of Hous.	✓	✓	✓	✓	✓	✓	✓	✓
Location	✓	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓	✓	✓
$\#Controls$	758	758	758	758	758	758	758	758

OLS estimations over pooled samples are reported in each sub-panel. The row corresponding to "$wfh \times age$" in each sub-panel indicates the estimated coefficient, representing the wage premium. The numbers in brackets are robust standard errors, while the third rows in each sub-panel report the R^2 of each estimation. The row labeled "$\#Controls$" indicates the number of fixed effects included in each estimation, excluding time (Year) effects, constants, and weights. Sample weights are applied to adjust for the probability of respondent selection. Significance levels: *** p<0.001, ** p<0.01, * p<0.05.** Location includes both state and metropolitan status indicators. For the 2000–2005 sample, metropolitan status is excluded due to a high rate of missing observations. As a result, the number of control variables is four fewer in the last three models for this sample.

higher education and experience, as well as those in certain sectors, are more likely to engage in and benefit from remote work. The significant drop in WFH premium after accounting for education, industry, and occupation fixed effects highlights how these factors jointly explain an important portion of the observed wage differentials.

1.1.1 Unobserved Heterogeneity

While the observed components of heterogeneity in human capital factors explain a significant fraction of the premium, model (7) in Table 1 shows that a substantial portion of the premium remains significant. Identifying whether unobserved heterogeneity could be a potential reason for the observed WFH premium is the next task to address. In other words, we want to determine whether any unobserved factors leading workers to choose WFH are being captured as part of the premium in the regression. Since the ACS is a repeated cross-section, we do not have data for the same individuals across years. I assume there exists an observable variable for each individual, υ_i, which captures some of the unobserved heterogeneity, α_i.

$$\upsilon_i = \alpha_i + \varepsilon_i \tag{5}$$

where $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$, and i.i.d. I use following models(6-7) to understand possible impact of unobserved heterogeneity;

$$log(wage_{it}) = \upsilon_i + X_{it}^{'}\beta_2 + \epsilon_{it}, \tag{6}$$

$$log(wage_{it}) = \upsilon_i + \sum_j \gamma_j wfh_{it}educ_{itj} + educ_{itj} + X_{it}^{'}\beta_2 + \epsilon_{it}, \qquad (7)$$

where $\upsilon_i$is defined above. This variable, υ_i, could include factors such as preferences for flexibility, self-selection into industries that support remote work, or other unmeasured attributes like job-specific skills, motivation, or personality traits that make certain workers more likely to work from home. By including this unobserved heterogeneity in the model, we aim to isolate the true effect of WFH on wages from potential bias caused by the self-selection of certain workers into WFH. The role of υ_i in this specification is primarily to capture income-related fixed effects. For this purpose, I use two proxies: the value of the house (Fe_1) and the number of vehicles owned (Fe_2). These proxies serve as stand-ins for income-related fixed effects and are intended to account for unobserved heterogeneity. The reason for using two alternatives is to consider potential endogeneity between housing and the WFH decision, as housing might be influenced by the option to work from home. While we acknowledge that these proxies do not perfectly control for unobserved heterogeneity, they are employed in an attempt to capture any relevant factors that could affect the observed wage differentials.

Table 4 presents the estimations for models (6) and (7), with a similar structure to previous tables. Columns 1 and 4 provide updated results of the 7th column of Table 2 and Table 3, respectively, for comparison with the new fixed effects. In this table, we restrict the sample to individuals with non-missing values for the ”value of house” variable, meaning that renters and those with missing entries are excluded from these estimations. This exclusion necessitates updating the benchmark estimations from Tables 2 and 3 to maintain consistency in sample selection.

The results from models 2 and 5 show that the inclusion of Fe_1 (house value) has a slight effect on the coefficient of the WFH regressor. In contrast, models 3 and 6 demonstrate that Fe_2 (number of vehicles) does not affect the relationship between WFH and log(wage) at all. These findings suggest that income-related fixed effects, as captured by these proxies, do little to mitigate the observed WFH premium. In other words, even after accounting for income-related factors through proxies like house value and vehicle ownership, the WFH premium remains robust, indicating that these fixed effects do not explain away the wage differential associated with working from home, even considering the limitations of our methodology.

Table 4: WFH Coefficients from OLS Regressions of Wage: Model 7

Dependent variable: Log Hourly Wage						
Sample: 2021-2022	1	2	3	4	5	6
wfh	0.11***	0.10***	0.11***	0.15***	0.14***	0.15***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.47	0.48	0.47	0.47	0.48	0.47
$\#Obs.(millions)$	0.998	0.998	0.998	0.998	0.998	0.998
Sample: 2017-2019						
wfh	0.08***	0.06***	0.08***	0.12***	0.10***	0.12***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.49	0.51	0.49	0.49	0.51	0.49
$\#Obs.(millions)$	1.50	1.50	1.50	1.50	1.50	1.50
Sample: 2000-2005						
wfh	0.08***	0.05***	0.08***	0.12***	0.09***	0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.46	0.48	0.46	0.46	0.48	0.46
$\#Obs.(millions)$	3.22	3.22	3.22	3.22	3.22	3.22
Fe_1		✓			✓	
Fe_2			✓			✓
wfh×Dropout				✓	✓	✓
wfh×HighSch				✓	✓	✓
wfh×SomeCol				✓	✓	✓
wfh×Graduate				✓	✓	✓
Dropout				✓	✓	✓
High School	✓	✓	✓	✓	✓	✓
Some College	✓	✓	✓	✓	✓	✓
College	✓	✓	✓			
Graduate	✓	✓	✓	✓	✓	✓
Age	✓	✓	✓	✓	✓	✓
Age^2	✓	✓	✓	✓	✓	✓
Race	✓	✓	✓	✓	✓	✓
Gender	✓	✓	✓	✓	✓	✓
Married	✓	✓	✓	✓	✓	✓
Head of Hous.	✓	✓	✓	✓	✓	✓
Location	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓
$\#Controls$	750	751	751	754	755	755

OLS estimations over pooled samples are reported in each sub-panel. The numbers in brackets are robust standard errors, while the third rows in each sub-panel report the R^2 of each estimation. Sample weights are applied to adjust for the probability of respondent selection. Significance levels: *** p<0.001, ** p<0.01, * p<0.05.
$**$ Location includes both state and metropolitan status indicators. For the 2000–2005 sample, metropolitan status is excluded due to a high rate of missing observations. As a result, the number of control variables is four fewer in the last three models for this sample.

1.2 Can the Roy Model Explain the Wage Premium?

In a simple environment, I propose to explore why a Roy model cannot explain the positive premium on the earnings of remote workers relative to on-site workers. We consider the decision-making process of workers choosing between working from home (WFH) and working on-site (OS), productivity variations, and the implications for earnings in a competitive market.

In a static framework, workers i decide whether to work from home (WFH) or on-site (OS) based on a utility function $U^i(c_k, l_k, k)$, where $k \in \{\text{wfh, os}\}$. This utility function is separable and includes an amenity function $v(l_k)$ that is strictly increasing and concave in leisure. Contract hours are supplied inelastically, but agents optimize their time use since the availability of leisure varies by type k, i.e., $l^i_k \leq l_k$. Specifically, we assume that there is additional time use for on-site work relative to WFH—such as commuting time or any other time cost required to prepare for on-site work, denoted q—such that:

$$l_{\text{wfh}} = l_{\text{os}} + q$$

This equation captures the relationship between feasible leisure based on the work location. Workers (i) optimize the following problem:

$$\max_{c_k, l_k, k} U^i(c_k, l_k, k) \quad \text{subject to} \quad c^i_{k^i} = e^i_k A_k$$

where

$$U^i(c_k, l_k, k) = c^i_{k^i} + v(l^i_{k^i})$$

Worker productivity varies by location, and each worker draws $\{e^i_k\}$. While it may seem vague to let productivity depend on the work location, our goal is to leverage the two-sector production framework while abstracting from the exact source of the variation in $\{e^i_k\}$ for each k.

In a competitive market with a single output, a representative firm produces output by hiring services provided by workers in each type of work arrangement. The aggregate output is:

$$Y_k = A_k N_k, \quad Y = \sum_k Y_k$$

In equilibrium, where workers and firms optimize, we can establish the following:

Lemma 1: Any worker i drawing $\{e^i_k\}$ will choose to WFH if and only if:

$$v(l_{\text{wfh}}) - v(l_{\text{os}}) \geq e_{\text{os}} A_{\text{os}} - e_{\text{wfh}} A_{\text{wfh}}$$

This result is straightforward given that preferences for leisure are strictly increasing.

Proposition 1: In the symmetric case, where $e_{\text{wfh}} = e_{\text{os}}$ for all i and $A_{\text{wfh}} = A_{\text{os}}$, the expected earnings of workers choosing WFH cannot be higher than those choosing on-site work.

Proof.

Given the symmetry, workers optimize their time use, even though contract hours are supplied inelastically. Since $\underbrace{v(l_{\text{wfh}}) - v(l_{\text{os}})}_{=\tau} > 0$ (because v is increasing in l, and $l_{\text{os}} < l_{\text{wfh}}$), the right-hand side of equation (6) is zero. This implies that income does not affect the decision to work from home or on-site. Furthermore:

$$E_i(A_{\text{os}} e^i_{\text{os}} | \text{os}) = A_{\text{os}} E_i(e^i) = A_{\text{wfh}} E_i(e^i) = E_i(A_{\text{wfh}} e^i_{\text{wfh}} | \text{wfh})$$

This completes the proof. $\square$

Proposition 1 shows that, in a symmetric environment, unless there is a selection mechanism leading to:

$$E_i(e^i_{\text{os}} | \text{os}) < E_i(e^i_{\text{wfh}} | \text{wfh})$$

there is no basis for remote workers to earn a positive premium relative to on-site workers. Additionally, equation (6) implies that, in the symmetric environment, all workers would prefer to work from home due to the greater leisure afforded by WFH. In the next section, we will explore a mechanism that explains how such a selection could occur without relying on unrealistic assumptions, such as $A_{\text{wfh}} > A_{\text{os}}$, or without reaching a corner solution where everyone chooses WFH.

1.3 Model

I demonstrate a partial equilibrium model with 1 measure of continuum of workers, each is indexed by heterogenity in skills and amenity value of wfh, $(\theta, \zeta) \in [\underline{\theta}, \bar{\theta}] \times [\underline{\zeta}, \bar{\zeta}]$ independently drawn from distribution of $F(\theta)$ and $G(\zeta)$. Every worker is endowed with 1 unit of leisure.

$$U(c_r, h_r, r) = u\left(c_r\right) - \psi v\left(h_r\right) + \zeta_r$$
$$u(c) = \frac{c^{1-\eta} - 1}{1-\eta}, \quad v(h) = \frac{h^{1+\rho}}{1+\rho}$$

where $r = 1, 0$ is an indicator, home or on-site respectively. $\zeta_0 = \underline{\zeta}$ and $\zeta_1 = \zeta$, st. ζ is drawn from $G(\zeta)$. That means we normalize the preferences(or benefit) of working in office by lower bound of ζ. Income process(8) of each worker is combined with price of labor; at office, $w_0 = w$ or at home, $w_1 = w(1-\kappa)$, productivity θ, and effort h_r. We assume that there exist representative firm allowing workers to choose home or on-site, and producing single consumption good with a linear technology with one factor(labor). We consider that total factor productivity of firm at home sector lower as amount of productivity loss, κ, hence it is $A(1-\kappa)$, and it is A for onsite firms

$$y_r = w(1-\kappa_r)\theta h, \tag{8}$$

where $\kappa_1 = \kappa, \kappa_0 = 0$, $\kappa \in (0,1)$, denotes productivity loss when workers work at home.

Workers optimize as presented in equation (11), by choosing consumption, hours, and workplace.

$$max_{c,h,r} U(c,h,r) \quad \text{st.} \quad c \leq y_r \tag{9}$$

By considering optimum consumption $\{c_r^*(\theta)\}_r$ and hours $\{h_r^*(\theta)\}_r$, conditional on choosing work place, r, we define indirect utilities: $\omega_1 = U(c_1^*(\theta), h_1^*(\theta), 1)$ and $\omega_0 = U(c_0^*(\theta), h_0^*(\theta), 0)$.

We drive the following expression, a threshold, in equilibrium:

$$\tilde{\zeta}(\theta) \equiv \begin{cases} \underline{\zeta}, & \text{if} \quad \omega_0(\theta) - \omega_1(\theta) < \underline{\zeta} \\ \bar{\zeta}, & \text{if} \quad \omega_0(\theta) - \omega_1(\theta) > \bar{\zeta} \\ \omega_0(\theta) - \omega_1(\theta), & \text{otherwise,} \end{cases} \tag{10}$$

Definition 1. A partial equilibrium is constituted with wages $\{w_r\}_{r=0,1}$, allocations and work places for workers $\{h_r(\theta), c_r(\theta), \mathbf{1}(\theta, \zeta)\}_{r=0,1}$ $\forall\theta \in [\underline{\theta}, \bar{\theta}]$, $\forall\zeta \in [\underline{\zeta}, \bar{\zeta}]$,
st. given $\{w_r\}_{r=0,1}$, workers solve problem in (11), and condition in (12) determines the share of optimum work place allocation.

The foundational concept behind the threshold definition and the subsequent proposition (Proposition 2) follows the logic of Scheuer (2014), who identifies a critical cost value determining entrepreneurial selection.

Proposition 2. Consider equilibrium defined in Definition(1),
$\forall\theta \in [\underline{\theta}, \bar{\theta}]$, and $\forall\zeta \in [\underline{\zeta}, \bar{\zeta}]$:

1: Any individual, i drawing ζ and θ, there exists a threshold, $\tilde{\zeta}(\theta)$ st. i works from home if and only if $\zeta \geq \tilde{\zeta}(\theta)$ in equilibrium.

2: If $\kappa = 0$

a: Equilibrium threshold , $\tilde{\zeta}(\theta)$, is constant in skills, θ

b: Share of wfh, $\tilde{G}(\tilde{\zeta}(\theta)) = 1 - G(\tilde{\zeta}(\theta))$, is also constant in skills, θ .

3: If $\eta < 1(\boldsymbol{\eta} > \mathbf{1})$, then for any $\kappa \in (0, 1)$, a: Equilibrium threshold, $\tilde{\zeta}(\theta)$, is increasing (**decreasing**) in skills, θ.

b: Share of wfh, $\tilde{G}(\tilde{\zeta}(\theta))$, is decreasing (**increasing**) in skills, θ.

Proof.

1: Existence of equilibrium is necessary and sufficient to define threshold, $\tilde{\zeta}(\theta)$

2: The proof is trivial through envelope condition:

$$\frac{\partial \tilde{\zeta}(\theta)}{\partial \theta} = \psi \left(\frac{h_0^*(\theta)}{\theta}\right)^{\rho} \frac{h_0^*(\theta)}{\theta^2} - \psi \left(\frac{h_1^*(\theta)}{\theta}\right)^{\rho} \frac{h_1^*(\theta)}{\theta^2}$$

$$= \frac{\psi}{\theta^{\rho+2}} \left({}^* h_0^{\rho+1}(\theta) - {}^* h_1^{\rho+1}(\theta)\right)$$

$$\frac{\partial \tilde{\zeta}(\theta)}{\partial \theta} = \frac{\psi}{\theta^{\rho+2}} h_0^{*\rho+1}(\theta) \left(1 - (1-\kappa)^{\frac{(1-\eta)(1+\rho)}{\eta+\rho}}\right) \tag{11}$$

Since $h_1^*(\theta) = h_0^*(\theta)(1-\kappa)^{\frac{1-\eta}{\eta+\rho}}$, when $\kappa = 0$, $\frac{\partial \tilde{\zeta}(\theta)}{\partial \theta} = 0$ in (11), and monotonicity of $G(\zeta)$ is resulted that $G(\tilde{\zeta}(\theta))$ is constant $\forall \theta$.

3: When $\kappa \in (0, 1)$, if $\eta < 1 (\boldsymbol{\eta > 1})$,

$$1 - (1-\kappa)^{\frac{(1-\eta)(1+\rho)}{\eta+\rho}} > 0 \; \mathbf{(< 0)}$$

which derives $\frac{\partial \tilde{\zeta}(\theta)}{\partial \theta} > 0$ **(< 0)** in (11) and similarly monotonicity of $G(\zeta)$ is resulted that $G(\tilde{\zeta}(\theta))$ is increasing (**decreasing**) $\forall \theta$.

□

Proposition 2 highlights a key aspect of the model: the risk aversion parameter η can explain the positive selection of workers into WFH based on their skills, provided there is some productivity loss ($\kappa \in (0,1)$). In essence, it shows that when preferences are such that the income effect outweighs the substitution effect in labor supply decisions, higher-skilled workers are more inclined to opt for WFH as their workplace.

It is important to consider the potential correlation between ζ and θ to fully explore all aspects of the selection mechanism. However, for now, we assume that ζ and θ are independently drawn in order to focus on how the mechanism described in Proposition 2 successfully explains the premium observed in the data.

To further explore the result from Proposition 2, I will make parametric assumptions about the distribution of skill and the amenity value of WFH. Specifically, I assume that θ follows a log-normal distribution, i.e.,

$$\log(\theta) \sim N(\mu, \sigma^2),$$

and that ζ is uniformly distributed over the support $\zeta \in [0, b]$.

Using the distribution functions of θ and ζ, along with equations (12) and (13), we can derive a closed-form expression for the expected conditional skill by workplace, $E(\theta \mid r)$:

$$E(\log(\theta) \mid \text{wfh}) = \int_0^\infty \log(\theta) \frac{\partial}{\partial \theta} \left[\frac{\text{Prob}\left(s < \theta, \zeta > \tilde{\zeta}(\theta)\right)}{\text{Prob}\left(\zeta > \tilde{\zeta}(\theta)\right)} \right] d\theta =$$

$$\left[\mu - \Upsilon \exp\left(\mu m + \frac{1}{2}\sigma^2 m^2\right)\left(\mu + \sigma^2 m\right)\right] \frac{1}{1 - \Upsilon \exp\left(\mu m + \frac{1}{2}\sigma^2 m^2\right)} \tag{12}$$

where the term $\left[\frac{\text{Prob}\left(s<\theta, \zeta>\tilde{\zeta}(\theta)\right)}{\text{Prob}\left(\zeta>\tilde{\zeta}(\theta)\right)}\right]$ denotes the conditional CDF of skills, which is derived using Bayes' rule (see Appendix). Here, Υ represents a component of the threshold, which is a function of the model's parameters handled using indirect utilities by workplace, and $m = \frac{(\rho+1)(1-\eta)}{\eta+\rho}$.

Similarly,

$$E(\log(\theta) \mid \text{onsite}) = \int_0^\infty \log(\theta) \frac{\partial}{\partial\theta}\left[\frac{\text{Prob}\left(s < \theta, \zeta \leq \tilde{\zeta}(\theta)\right)}{\text{Prob}\left(\zeta \leq \tilde{\zeta}(\theta)\right)}\right] d\theta = \mu + \sigma^2 m \tag{13}$$

where the term $\left[\frac{\text{Prob}\left(s<\theta, \zeta\leq\tilde{\zeta}(\theta)\right)}{\text{Prob}\left(\zeta\leq\tilde{\zeta}(\theta)\right)}\right]$ is the symmetric CDF of skills conditional on working onsite (See Appendix- B.).

Using the analytical solutions in equations (12) and (13), I use the following term to identify the effect of selection in terms of the premium in skills by workplace:

$$E(\log(\theta) \mid \text{wfh}) - E(\log(\theta) \mid \text{onsite}) \tag{14}$$

I present quantitative results in Figure 2 and Figure 3 using the model and methodology derived in equation (14). I normalize the distribution of skills, i.e., $E(\theta) = 1$, by setting $\mu = -0.5\sigma^2$, and set the dispersion parameter to $\sigma = 0.5$ or $\sigma = 0.3$. I also set $\rho = 2$, based on evidence from Keane (2011) for the inverse of the Frisch elasticity, 0.5. Additionally, I fix $\psi = 1$ and vary the remaining critical parameters in these numerical examples.

Figure 2 illustrates how the selection effect varies with the productivity loss parameter, κ, for different scales of the risk aversion parameter, η. In this figure, I set the upper bound of the CDF of WFH amenity, ζ, to 0.5. The first notable observation is that the effect is monotonically increasing in the loss parameter, and this relationship becomes significantly stronger as η increases.

When comparing the subfigures, it is important to note that the left subfigure considers a lower level of skill dispersion ($\sigma = 0.3$). This highlights a notable relationship between the degree of inequality and the impact of selection: the magnitude of the premium sharply increases when comparing the two subfigures.

Figure 2: Productivity Loss vs. Selection Effect. ($\zeta = 0.5$)

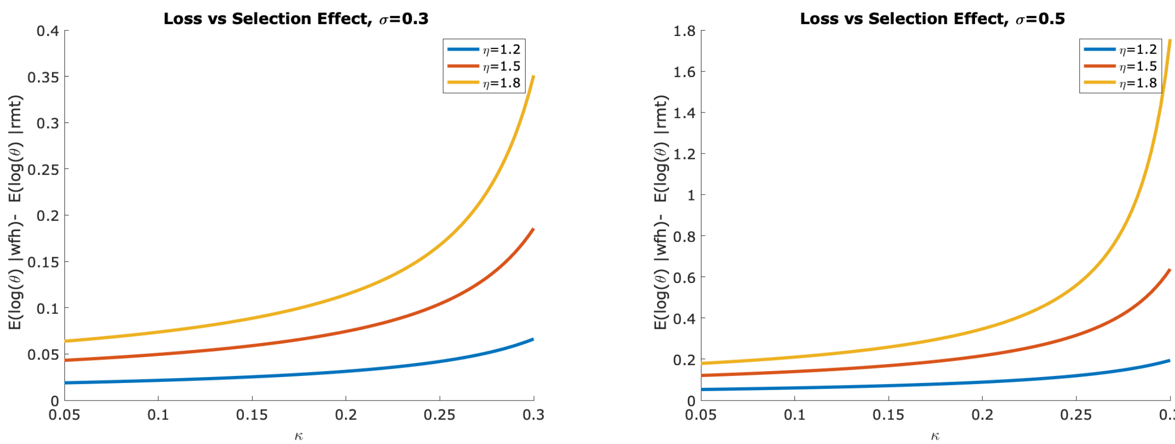
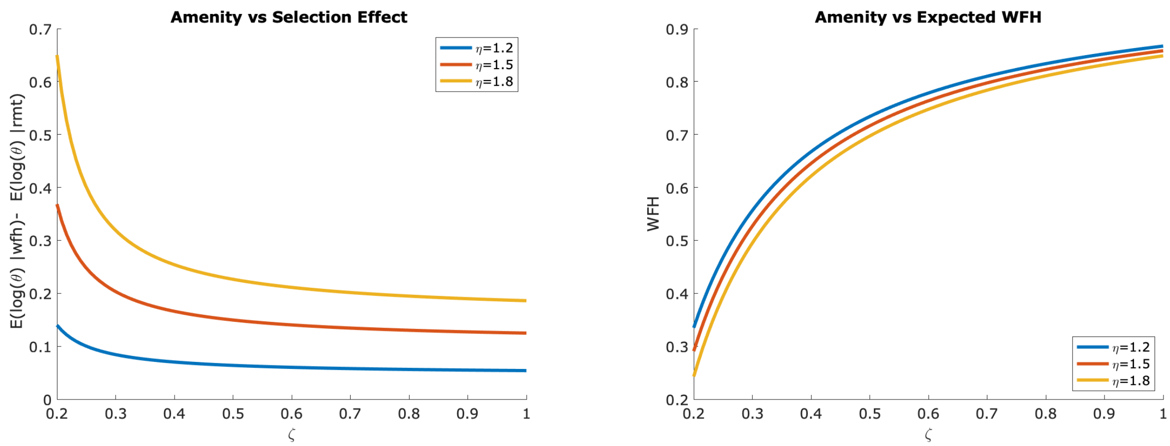


Figure 3 presents both the selection effect, similar to Figure 2, and the expected measure of WFH in the economy as it responds to changes in the scale of ζ. In this figure, I fix the productivity loss parameter at $\kappa = 0.12$ and the dispersion parameter at $\sigma = 0.5$. The figure demonstrates how the fraction of workers choosing WFH is sensitive to the scale of the amenity value of WFH, exhibiting a naturally monotonic increase. As a direct result of the selection mechanism, the premium decreases in response to an increase in ζ. Similar to Figure 2, the steepness of this relationship depends critically on the size of the risk aversion parameter, η.

Figure 3: Scale of Amenity vs. Selection Effect. (σ = 0.5)



The key takeaway from these numerical examples, as presented in the figures, is that when there is some productivity loss and the preferences exhibit an income effect that dominates the substitution effect in workers' labor supply decisions, these conditions generate a premium in favor of WFH workers. This outcome arises because higher-skilled workers are more likely to choose remote work under these circumstances.

1.4 Conclusion

This paper provides a comprehensive exploration of the observed wage premium for remote workers, offering both theoretical and empirical insights. By developing a partial equilibrium model, I demonstrate how productivity loss associated with remote work can generate positive skill selection through the income effect, particularly when risk aversion plays a central role. This mechanism, as revealed by the model, aligns with empirical findings that high-skilled workers are more likely to choose WFH despite potential productivity penalties. Using parametric assumptions and numerical examples, the results highlight that the selection effect strengthens with greater productivity loss and becomes more pronounced as risk aversion increases. These findings contribute to the literature by addressing the interplay between productivity, worker preferences, and wage outcomes, offering an alternative to traditional Roy models, which may fail to capture the observed wage premium dynamics.

Empirical evidence further supports these theoretical insights. Historical data from the ACS reveal a persistent wage premium for remote workers, even after accounting for human capital factors. This premium, averaging 11% in recent years, can be partially attributed to positive selection into remote work, as shown in this study. My findings build on previous work documenting the rise of WFH and its implications for wages and productivity, emphasizing the role of demographic and preference heterogeneity. By bridging the gap between productivity losses and wage premiums, this paper adds a novel perspective to ongoing discussions about labor market dynamics in the post-pandemic era. Future research could extend these insights by examining general equilibrium effects or exploring sector-specific variations in WFH adoption and wage outcomes.

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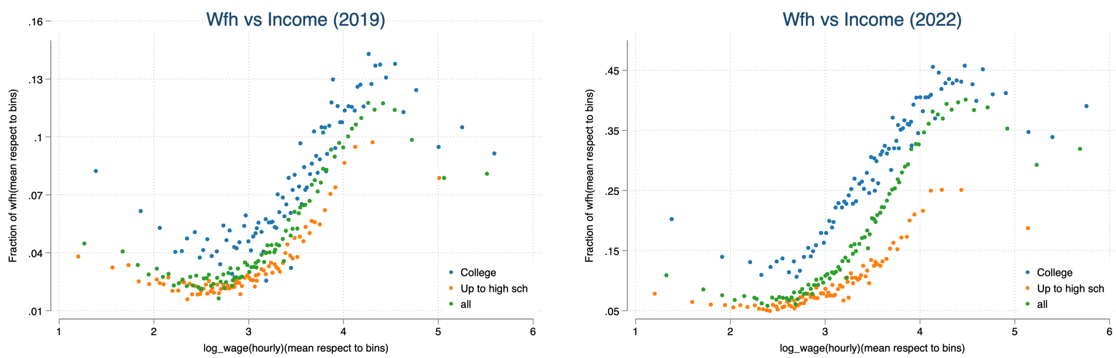
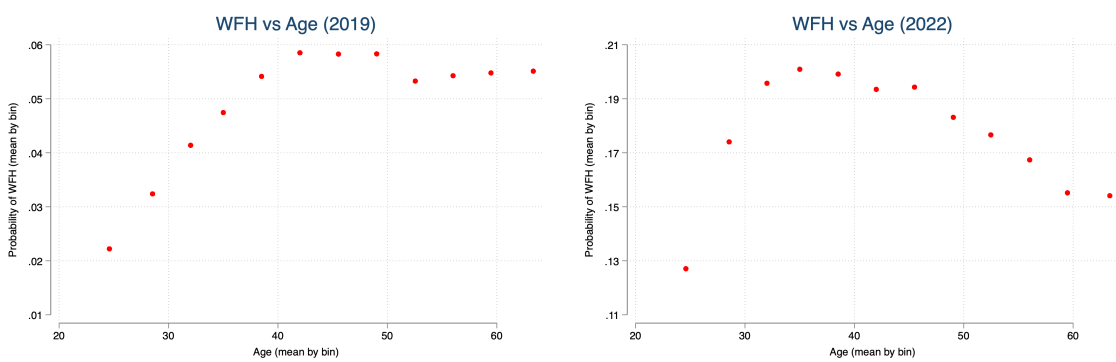
Appendix- A

Figure 4: Mean wages vs. WFH rates



The figures display the fraction of WFH relative to mean hourly wages in log terms. Mean wages are grouped into percentiles, with three demographic categories represented by education level: college (blue), high school or less (orange), and the entire sample (green).

Figure 5: Age vs. WFH rates



The figures display the share of WFH by average age. Age is divided into 12 equal percentiles within the 23–65 age range, and the mean WFH rate is plotted for each group.

Table 5: Descriptive Statistics- 1

Sample:	2021-2022			2017-2019			2000-2005		
Statistics	Wage	Log Wage	Age	Wage	Log Wage	Age	Wage	Log Wage	Age
Mean	35.20	3.25	43.39	30.01	3.11	43.34	19.14	2.72	41.16
SD	44.82	0.73	12.04	36.10	0.71	11.97	20.01	0.63	10.52
Median	24.04	3.18	43	21.57	3.07	43	14.63	2.68	41
#Obs.	1,371,817			2,131,049			4,313,054		

Table 6: Descriptive Statistics- 2.

Variable	2021-2022 (%)	2017-2019 (%)	2000-2005 (%)
College+	12.71	10.89	6.98
College	26.28	24.14	18.44
High Sch.	32.96	34.31	41.68
Dropout-	5.17	5.69	8.01
Female	43.58	44.01	42.51
White	76.28	79.48	83.57
Married	56.71	57.26	63.82
Head of HH	52.48	53.30	59.37
Not Metro	8.45	8.65	
Met. Central	12.52	12.98	
Met. Not Central	31.29	31.49	
#Obs.	1,371,817	2,131,049	4,313,054

Variables for state, industry, and occupation are included in the regressions as fixed effects but are not reported in the table due to the large number of categories. Industry codes follow the 1950 Census classification; occupation codes use the 2018-onward Census occupational classification system. State refers to the household's location, coded using the Federal Information Processing Standards (FIPS). All classifications and variables are sourced from IPUMS.

Table 7: WFH Coefficients from OLS Regressions of Wage: Model 2

Sample Restriction: 40-Hour Workweek
Dependent variable: Log Hourly Wage

Sample: 2021-2022	1	2	3	4	5	6	7
wfh	0.47***	0.25***	0.24***	0.24***	0.22***	0.18***	0.12***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.08	0.24	0.29	0.34	0.36	0.40	0.48
$\#Obs.(millions)$	0.753	0.753	0.753	0.753	0.753	0.753	0.753
Sample: 2017-2019							
wfh	0.38***	0.23***	0.18***	0.17***	0.17***	0.14***	0.10***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.01	0.21	0.27	0.33	0.35	0.39	0.48
$\#Obs.(millions)$	1.09	1.09	1.09	1.09	1.09	1.09	1.09
Sample: 2000-2005							
wfh	0.30***	0.17***	0.14***	0.13***	0.13***	0.13***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.01	0.20	0.24	0.31	0.32	0.37	0.46
$\#Obs.(millions)$	2.19	2.19	2.19	2.19	2.19	2.19	2.19
High School		✓	✓	✓	✓	✓	✓
Some College		✓	✓	✓	✓	✓	✓
College		✓	✓	✓	✓	✓	✓
Graduate		✓	✓	✓	✓	✓	✓
Age			✓	✓	✓	✓	✓
Age^2			✓	✓	✓	✓	✓
Race				✓	✓	✓	✓
Gender				✓	✓	✓	✓
Married				✓	✓	✓	✓
Head of Hous.				✓	✓	✓	✓
Location					✓	✓	✓
Industry						✓	✓
Occupation							✓
Year	✓	✓	✓	✓	✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓	✓
$\#Controls$		4	6	10	64	220	750

OLS estimations over pooled samples are reported in each sub-panel. The row corresponding to ”Wfh” in each sub-panel indicates the estimated WFH coefficient, representing the wage premium. The numbers in brackets are robust standard errors, while the third rows in each sub-panel report the R-squared of each estimation. The row labeled ”$\#Controls$” indicates the number of fixed effects included in each estimation, excluding time (Year) effects, constants, and weights. Sample weights are applied to adjust for the probability of selection of the respondent. Significance levels: *** p<0.001, ** p<0.01, * p<0.05.

$**$ Location includes both state and metropolitan status indicators. For the 2000–2005 sample, metropolitan status is excluded due to a high rate of missing observations. As a result, the number of control variables is four fewer in the last three models for this sample.

Appendix- B

First, it is important to note that due to the additive nature of the threshold we define, the random component, θ, can be multiplicatively decomposed using indirect utilities. Thus, I redefine it as:

$$\tilde{\zeta}(\theta) = \Upsilon \theta^m,$$

where $m = \frac{(\rho+1)(1-\eta)}{\eta+\rho}$. The probability expression, measure of total WFH workers, is denoted by:

$$\text{Prob}\left(\zeta > \tilde{\zeta}(\theta)\right) = \int_0^{\infty} (1 - \Upsilon\theta^m) \frac{1}{\theta\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln\theta - \mu)^2}{2\sigma^2}\right) d\theta \qquad (15)$$

Substitute $\ln\theta$: let $u = \ln\theta$. Then, $du = \frac{1}{\theta}d\theta$, and $d\theta = \theta du = e^u du$. Re-write the integral in terms of u:

$$\int_{-\infty}^{\infty} (1 - \Upsilon e^{mu}) \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(u-\mu)^2}{2\sigma^2}\right) du. \qquad (16)$$

Using the MGF of a normal distribution $N(\mu, \sigma^2)$ evaluated at m and solving integration in 16:

$$\text{Prob}\left(\zeta > \tilde{\zeta}(\theta)\right) = 1 - \Upsilon \exp\left(\mu m + \frac{1}{2}\sigma^2(1-\eta)^2\right) \qquad (17)$$

We need to express the equation deriving skill distribution for remote workers to add in Bayes' rule is:

$$\text{Prob}\left(s < \theta, \zeta > \tilde{\zeta}(\theta)\right) = \int_0^\theta \left(1 - \Upsilon s^m\right) \frac{1}{s\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln s - \mu)^2}{2\sigma^2}\right) ds \quad (18)$$

Using the change of variables again, $u = \ln s$, and re-write the integral in terms of u:

$$\int_{-\infty}^{\ln\theta} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(u-\mu)^2}{2\sigma^2}\right) du - \Upsilon \int_{-\infty}^{\ln\theta} e^{mu} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(u-\mu)^2}{2\sigma^2}\right) du$$

When we valuate the first term above, it is the cumulative distribution function (CDF) of the normal distribution evaluated at $\ln\theta$:

$$\Phi\left(\frac{\ln\theta - \mu}{\sigma}\right)$$

Similarly, the second term in (18) involves the moment-generating function (MGF) of the normal distribution. The expression is:

$$\Upsilon \int_{-\infty}^{\ln\theta} e^{mu} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(u-\mu)^2}{2\sigma^2}\right) du = \Upsilon \int_{-\infty}^{\ln\theta} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(mu - \frac{(u-\mu)^2}{2\sigma^2}\right) du$$

Expanding and rearranging the exponent term:

$$\Upsilon \exp\left(\mu m + \frac{1}{2}\sigma^2 m^2\right) \int_{-\infty}^{\ln\theta} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{\left(u - (\mu + \sigma^2 m)\right)^2}{2\sigma^2}\right) du$$

The remaining integral above is the cumulative distribution function (CDF) of a normal distribution evaluated at $\ln\theta$:

$$\Phi\left(\frac{\ln\theta - (\mu + \sigma^2 m)}{\sigma}\right)$$

Combine the results:

$$\text{Prob}\left(s < \theta, \zeta > \tilde{\zeta}(\theta)\right) =$$

$$\Phi\left(\frac{\ln\theta - \mu}{\sigma}\right) - \Upsilon \exp\left(\mu m + \frac{1}{2}\sigma^2 m^2\right) \Phi\left(\frac{\ln\theta - (\mu + \sigma^2 m)}{\sigma}\right) \tag{19}$$

Finally:

$$\frac{\partial}{\partial\theta}\text{Prob}\left(s < \theta, \zeta > \tilde{\zeta}(\theta)\right)$$

$$= \frac{1}{\theta}\left[\frac{1}{\sigma}\phi\left(\frac{\ln\theta - \mu}{\sigma}\right) - \Upsilon \exp\left(\mu m + \frac{1}{2}\sigma^2 m^2\right)\frac{1}{\sigma}\phi\left(\frac{\ln\theta - \mu - \sigma^2 m}{\sigma}\right)\right]$$

where ϕ is pdf of standard normal distribution.

Since $\text{Prob}\left(\zeta > \tilde{\zeta}(\theta)\right)$ is constant in θ,

$$\frac{\partial}{\partial\theta}\left[\frac{\text{Prob}\left(s < \theta, \zeta > \tilde{\zeta}(\theta)\right)}{\text{Prob}\left(\zeta > \tilde{\zeta}(\theta)\right)}\right] = \left[\frac{\frac{\partial}{\partial\theta}\text{Prob}\left(s < \theta, \zeta > \tilde{\zeta}(\theta)\right)}{\text{Prob}\left(\zeta > \tilde{\zeta}(\theta)\right)}\right]$$

Hence, using the expression we solved for $\frac{\partial}{\partial\theta}\text{Prob}\left(s < \theta, \zeta > \tilde{\zeta}(\theta)\right)$, and $\text{Prob}\left(\zeta > \tilde{\zeta}(\theta)\right)$ above and solving appropriate algebra:

$$E(log(\theta)|wfh) = \int_0^\infty log(\theta)\frac{\partial}{\partial\theta}\left[\frac{\text{Prob}\left(s < \theta, \zeta > \tilde{\zeta}(\theta)\right)}{\text{Prob}\left(\zeta > \tilde{\zeta}(\theta)\right)}\right] d\theta =$$

$$\int_0^\infty ln(\theta)\left[\frac{1}{\theta}\left[\frac{1}{\sigma}\phi\left(\frac{\ln\theta - \mu}{\sigma}\right) - \Upsilon \exp\left(\mu m + \frac{1}{2}\sigma^2 m^2\right)\frac{1}{\sigma}\phi\left(\frac{\ln\theta - \mu - \sigma^2 m}{\sigma}\right)\right]\right] \times$$

$$\frac{1}{1-\Upsilon \exp\left(\mu m + \frac{1}{2}\sigma^2 m^2\right)} d\theta$$

$$= \left[\mu - \Upsilon \exp\left(\mu m + \frac{1}{2}\sigma^2 m^2\right)\left(\mu + \sigma^2 m\right)\right] \frac{1}{1-\Upsilon \exp\left(\mu m + \frac{1}{2}\sigma^2 m^2\right)} \tag{20}$$

Conditional probabilities for onsite workers are solved with similar steps. Since

$$\text{Prob}\left(\zeta \leq \tilde{\zeta}(\theta)\right) = \int_0^\infty (\Upsilon \theta^m) \frac{1}{\theta\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln\theta - \mu)^2}{2\sigma^2}\right) d\theta$$

and when we substitute $\ln\theta$: $u = \ln\theta$, similarly, we get the same expression of second component in equation 17. Hence solution follows same steps and:

$$\text{Prob}\left(\zeta \leq \tilde{\zeta}(\theta)\right) = \Upsilon \exp\left(\mu(m) + \frac{1}{2}\sigma^2(m)^2\right)$$

Similarly, using the same steps for the relevant parts(since they are identical for additive components) from previous result derived for WFH workers,

$$\text{Prob}\left(s < \theta, \zeta \leq \tilde{\zeta}(\theta)\right) =$$

$$\Upsilon \exp\left(\mu(m) + \frac{1}{2}\sigma^2(m)^2\right) \Phi\left(\frac{\ln\theta - (\mu + \sigma^2(m))}{\sigma}\right)$$

Hence:

$$\frac{\text{Prob}\left(s < \theta, \zeta \leq \tilde{\zeta}(\theta)\right)}{\text{Prob}\left(\zeta \leq \tilde{\zeta}(\theta)\right)} = \Phi\left(\frac{\ln\theta - (\mu + \sigma^2(m))}{\sigma}\right) \tag{21}$$

and

$$E(log(\theta)|onsite) = \int_0^\infty log(\theta) \frac{\partial}{\partial \theta} \left[\frac{\text{Prob}\left(s < \theta, \zeta \leq \tilde{\zeta}(\theta)\right)}{\text{Prob}\left(\zeta \leq \tilde{\zeta}(\theta)\right)} \right] d\theta =$$

$$\int_0^\infty log(\theta) \left[\frac{1}{\theta\sigma} \phi \left(\frac{\ln\theta - (\mu + \sigma^2(m))}{\sigma} \right) \right] d\theta$$

$$= \mu + \sigma^2 m \tag{22}$$

Chapter 2

Remote Work: Implications for Optimal Income Taxation

Introduction

The widespread adoption of remote work during and after the recent pandemic has sparked numerous economic questions. A notable policy concern emerged regarding the taxation of remote workers. Some states[4] updated their policies to tax households if they work for an employer located within the state, regardless of where they reside. In this paper, I analyze how WFH affects optimal income taxation. I argue that this question is relevant for policy implications regarding aggregate tax revenue and the elasticity of taxable income, as it requires consideration of the fraction of labor supplied from home, the structure of WFH, and the productivity loss associated with remote work.

According to data from the American Community Survey (ACS), the proportion of college graduates working exclusively from home in the U.S. increased

[4]Arkansas, Connecticut, Delaware, Massachusetts, Nebraska, New York, and Pennsylvania (OCT-2021)

from 2% to 8% over the two decades leading up to the pandemic. This figure surged to around 35% in 2021 for the same group. ACS data also highlight significant differences in wage income based on workplace type—whether remote or onsite. In 2021, remote workers (in non-farm, private sectors) earned substantially higher average wages than their onsite counterparts. Historically, this wage premium has persisted, with relative wages showing a 20% to 35% premium in log terms over the two decades before 2020, without controlling for human capital factors. Akil (2024) shows that after adjusting for numerous fixed effects related to human capital and occupation, the data from 2021–2022 reveal an average wage premium of 12% for remote workers compared to those working onsite. Moreover, he shows that this observed premium could result from positive selection into WFH, meaning that high-productivity workers are more likely to work from home.

The statistics and findings become even more compelling when viewed in the context of the growing body of research on the productivity loss associated with remote work. Emanuel and Harrington (2023) demonstrate that remote employees at a U.S. Fortune 500 call center completed fewer tasks up to 12% per hour than their onsite counterparts, both before and during the COVID-19 pandemic. Similarly, Gibbs et al. (2023) analyze data from over 10,000 IT professionals at a leading Indian firm, finding that despite working longer hours, remote productivity declined by 8% to 19%. In a randomized controlled trial within India's data entry sector, Atkin et al. (2023) further document a productivity gap of 18% between WFH and onsite workers, which widened to 27% among those with a preference for remote work.

This paper studies optimal income taxation in the context of remote work. The choice of workplace is discretely modeled in a simple setting that incorporates heterogeneity in the amenity value of WFH and productivity losses associated with WFH. The core of the model is a static general equilibrium with endogenous workplace choice, which workers with heterogeneous skills make decisions for labor supply, and consumption of a single good. A representative firm allows workers to choose their workplace without friction, with productivity varying based on the chosen setting. In this context, the paper studies taxation of labor income using a Ramsey approach and a parametric income tax function.

The paper first examines how the model captures the positive selection of higher-skilled workers into WFH, consistent with observed data. Second, it explores the interaction between the model's mechanism and income taxation, using Heathcote et al. (2017)'s tax system (hereafter HSV) and considers the potential role of public policy in this context. Analytical motivations are also derived, focusing on the elasticity of taxable income, consumption smoothing, and inequality—each linking WFH to income taxation. I show that WFH increases the elasticity of taxable income, reduces shock transmission, and lowers inequality. Finally, optimal income taxation is solved within a

Ramsey framework, with and without WFH, applying the HSV tax system. The environment is structured to align with a No-WFH equilibrium in every dimension of the model.

The main result indicates that incorporating WFH reduces optimal tax progressivity and, consequently, the marginal income tax rate. This reduction is quantitatively significant and robust to alternative specifications, including changes in key parameters, preferences, and government policies. Optimal marginal tax rates are approximately 2% to 3% lower for low-income groups and around 4% to 5% lower for high-income groups when WFH is considered in the Ramsey framework. In a further extension, the paper studies differential tax policy by workplace—allowing the planner to condition taxes on workers' remote or on-site status. This leads to substantially higher progressivity for remote workers, and as a result of the optimal policy, almost no one chooses WFH in equilibrium.

These outcomes highlight the role of workplace choice in shaping redistribution and efficiency under optimal tax policy. The intuition behind the results is as follows. While the data confirm the presence of WFH, modeling income tax without accounting for WFH overlooks the economic impact on workplace choice. Workplace choice involves a trade-off between efficiency losses, driven by WFH productivity, and the amenity value it provides. When preferences reflect stronger income effects than substitution effects in labor supply decisions, wealthier individuals are more likely to choose WFH, leading to differences in income distribution across workplaces. When WFH amenity is not taxed but income is, changes in tax progressivity influence both the proportion of individuals choosing WFH and the skill distribution across workplaces. Thus, WFH impacts optimal income taxes through well-known mechanisms in public finance: First, WFH increases income responsiveness to marginal tax rates (i.e., higher elasticity of taxable income). Second, it reduces inequality, as WFH tends to attract wealthier workers while being associated with lower productivity. Third, it smooths the transmission of income shocks to consumption. Together, these factors imply a reduction in optimal tax progressivity.

To the best of my knowledge, this is the first paper to address the problem of optimal income taxation in the context of remote work. I demonstrate that modeling workplace choice, while accounting for the amenity value and productivity of WFH, has significant implications for income taxation.

This research contributes to several streams of literature. First, it relates to Ramsey (1927)-style studies that explore optimal income taxation in heterogeneous-agent models. A recent study that addresses optimal tax schedules in a static environment is Heathcote and Tsujiyama (2021), which compares optimal policies with the Mirrleesian approach (Mirrlees, 1971). The literature on optimal income taxation is voluminous, extending beyond the Ramsey-style framework. Most papers focus on dynamic economies and fiscal policies aimed at redistribution, including notable studies such as Werning (2007), Stantcheva (2017)), and HSV (2017), and many others.[5]

This paper also contributes to the literature on tagging by examining income taxation based on workplace, accounting for changes in the distribution of skills across remote and onsite workers. The idea of tagging was pioneered by Akerlof (1978), who proposed that incorporating immutable characteristics into tax policies can enhance redistribution. This concept has been applied across various contexts. Recent studies explore tagging through age-based taxation (Weinzierl, 2011; HSV, 2020), gender-based taxation (Alesina et al., 2011; Guner et al., 2012), asset-based taxation (Karabarbounis, 2016), and entrepreneurial-based taxation (Scheuer, 2014).

Finally, my work contributes to the growing literature on WFH by incorporating remote work into a general equilibrium model, deriving structural results, and exploring its policy implications. Research on WFH, both before and after the COVID-19 pandemic, has predominantly focused on empirical patterns and measurements related to; wages and the prevalence of remote work (Oettinger, 2011; Dingel and Neiman, 2020; Bick et al., 2021), productivity of remote workers (Bloom et al., 2015; Emanuel and Harrington, 2023; Gibbs et al., 2023; Atkin et al., 2023), and the value of flexibility (Mas and Pallais, 2017).

The structure of the paper is as follows. Section 1 introduces the model and discusses the role of WFH in competitive equilibrium. Section 2 presents

[5] Diamond (1975, 1980), Lucas and Stokey (1983), Jones et al. (1993), Kaplow (2024).

the model with taxation and outlines the analytical motivations. Section 3 describes the optimal income taxation framework, while Section 4 introduces the calibration strategy and presents the quantitative results. Finally, Section 5 extends the benchmark model by introducing differential taxation based on workplace choice, and Section 6 concludes

2.1 Model

2.1.1 Workplace Choice with Preference Heterogeneity

I consider a static environment with measure one of heterogeneous individuals indexed by $(\theta, \chi) \in [\underline{\theta}, \bar{\theta}] \times [\underline{\chi}, \bar{\chi}]$ indicates skills and amenity value of remote work, respectively. Each dimension of heterogeneity is independently drawn from $F(\theta)$ and $Z(\chi)$, which are cumulative distribution functions of θ and χ respectively.

Workers can choose workplace, home or onsite. Any agent choosing home, supply effective labor $(1-\kappa)h(\theta, \chi)$ while she is able to supply as $h(\theta, \chi)$ onsite. Preferences over consumption, labor and workplace benefit are:

$$U(c, h, r) = u\,(c) - \psi v\,(h) + \chi_r$$

where $r = 1, 0$, and indicator, denotes home or office, respectively. Workplace heterogeneity is based on benefit at office, normalized over, $\chi_0 = 0$ and $\chi_1 = \chi$, st. χ is drawn from $Z(\chi)$.

$$u(c) = \frac{c^{1-\eta} - 1}{1 - \eta}, \quad v(h) = \frac{(h/\theta)^{1+\sigma}}{1 + \sigma}$$

Utility over consumption, $u(c)$, has CRRA form with risk aversion parameter η and $v(h)$ is the function of effective hours supplied controlled with leisure weight, ψ in the preferences. Parameter σ on $v(h)$ directs the elasticity of labor supply, inverse of which; $\frac{1}{\sigma}$, indicates Frisch elasticity.

Pre-tax income of each worker is by:

$$y_r(\theta, \chi) = w(1 - \kappa_r)h(\theta, \chi) \tag{1}$$

where $w(1 - \kappa_r)$ is the wage such that $\kappa_1 = \kappa, \kappa_0 = 0$, $\kappa \in (0, 1)$ captures the productivity loss for WFH. $h(\theta, \chi)$ denotes the effective labor supply for each index (θ, χ).

Workers are endowed with a unit of time and there exists a single consumption good in the environment, produced by representative firm with linear technology:

$$Y = \sum_r A_r N_r. \tag{2}$$

where $A_1 = A(1 - \kappa)$, $A_0 = A$.

The parameter χ in preferences characterizes the amenity value of WFH, such as commuting cost, having a large house, enjoying remote work, whether you are offered-available for wfh or not etc.

Definition 1. A competitive equilibrium without government is constituted with wages $\{w_r\}_r$, allocation and work place for workers $\{h_r(\theta,\chi), c_r(\theta,\chi), \mathbf{1}(\theta,\chi)\}_{r=0,1}$ $\forall\theta \in \mathbf{\Theta}$, $\forall\chi \in \boldsymbol{\chi}$, and quantities for firm $\{N_r, Y_r\}_{r=0,1}$ st. individuals and firm solve the problems described below and markets clear:

equilibrium in the labor market;

$$N_1 = \int_\Theta \int_\chi \mathbf{1}_{\chi \geq \tilde{\chi}(\theta)} h_1(\theta,\chi) dZ(\chi) dF(\theta) \tag{3}$$

$$N_0 = \int_\Theta \int_\chi \mathbf{1}_{\chi < \tilde{\chi}(\theta)} h_0(\theta,\chi) dZ(\chi) dF(\theta), \tag{4}$$

where the effective labor hours supplied at each workplace and skill level are expressed as products of the measure of workers at each location—home and office—determined by the indicator functions $\mathbf{1}_{\chi<\tilde{\chi}(\theta)} = Z(\tilde{\chi}(\theta))$ and $\mathbf{1}_{\chi\geq\tilde{\chi}(\theta)} = 1 - Z(\tilde{\chi}(\theta))$, respectively, and the conditional labor supplies $h_0(\theta,\chi)$ and $h_1(\theta,\chi)$. The threshold $\tilde{\chi}(\theta)$ represents the equilibrium cutoff determining workplace choice, defined explicitly later.

By using same notation, equilibrium in the good market represented by:

$$Y = \int_\Theta \int_\chi \left[\mathbf{1}_{\chi\geq\tilde{\chi}(\theta)} c_1(\theta,\chi) + \mathbf{1}_{\chi<\tilde{\chi}(\theta)} c_0(\theta,\chi)\right] dZ(\chi) dF(\theta). \tag{5}$$

Firm's problem. The representative firm chooses optimum amount of hours by considering following problem:

$$max_{N_r} \sum_r A_r N_r - \sum_r w_r N_r, \tag{6}$$

Individuals' problem. Given $\{w_r\}_r$, we can write workers' problem in two steps; first, as conditional on choosing home or office, $r = 1$ or $r = 0$. An agent with pair of (θ, χ), st. $\theta \in \Theta \equiv [\underline{\theta}, \bar{\theta}]$ and $\chi \in \boldsymbol{\chi} \equiv [\underline{\chi}, \bar{\chi}]$:

$$max_{c_r, h_r} U(c_r, h_r, r) \quad \text{st.} \quad c_r \leq y_r, \quad c_r \geq 0. \tag{7}$$

Then, $c_r^*(\theta), h_r^*(\theta)$ are the solution for agents' problem by following second step as following:

$$max\{U(c_r^*(\theta, \chi), h_r^*(\theta, \chi), r)\}_{r=0,1}. \tag{8}$$

Equilibrium threshold. This specification of individuals' decision problem allows us to define indirect utilities as: $\omega_1 = U(c_1^*(\theta, \chi), h_1^*(\theta, \chi), 1)$ and $\omega_0 = U(c_0^*(\theta, \chi), h_0^*(\theta, \chi), 0)$. The following expression $\tilde{\chi}(\theta)$, by dropping χ dimension, can be handled with indirect utilities, which features a threshold property in the equilibrium:

$$\tilde{\chi}(\theta) \equiv \begin{cases} \underline{\chi}, & \text{if} \quad \omega_0(\theta) - \omega_1(\theta) < \underline{\chi} \\ \bar{\chi}, & \text{if} \quad \omega_0(\theta) - \omega_1(\theta) > \bar{\chi} \\ \omega_0(\theta) - \omega_1(\theta), & \text{otherwise,} \end{cases} \tag{9}$$

The underlying idea of threshold definition and the following proposition follows the logic of Scheuer (2014), who derives a critical cost value governing entrepreneurial choice.

Proposition 1. Consider the equilibrium defined in Definition(1),

$\forall\theta \in \Theta$ and $\forall\chi \in \boldsymbol{\chi}$:

1: For any individual, i drawing χ and θ, there exists a threshold, $\tilde{\chi}(\theta)$ st. i works from home if and only if $\chi \geq \tilde{\chi}(\theta)$ in equilibrium.

2: If $\kappa = 0$, equilibrium threshold , $\tilde{\chi}(\theta)$ and share of wfh, $\tilde{Z}(\tilde{\chi}(\theta)) = 1 - Z(\tilde{\chi}(\theta))$ are both constant in skills, θ.

3: If $\eta < 1$($\boldsymbol{\eta > 1}$), then for any $\kappa \in (0, 1)$, equilibrium threshold, $\tilde{\chi}(\theta)$, is increasing (**decreasing**) in skills and share of wfh, $\tilde{Z}(\tilde{\chi}(\theta))$, is decreasing (**increasing**) in skills, θ.

Proof. See Appendix A. □

Proposition 1 summarizes an important feature of the model that the risk aversion parameter η could be enough to illustrate a positive selection of workers to WFH through their skills when there exists any productivity loss, $\kappa \in (0, 1)$. In other words, it tells us that having preferences with income effect dominating substitution effect on labor supply decision is a mechanism, which delivers the result that workers with higher skills are more likely to choose WFH as workplace. That feature of the environment is important from economics perspective having the independence assumption of $Z(\chi)$ and $F(\theta)$.

Appendix B documents the empirical patterns of wage statistics and the fraction of WFH across different income groups, using data from the American Community Survey for the U.S. The key takeaway from these empirical results is the evidence of selection into WFH. I argue that part of the observed wage premium may result from the interaction between preferences (with stronger income effects) and productivity losses (Akil, 2024). Consequently, the remainder of the paper focuses on the case where $\eta > 1$.

Figure 6: Optimum Threshold. $\kappa = 0.12$, $\eta = 1.5$

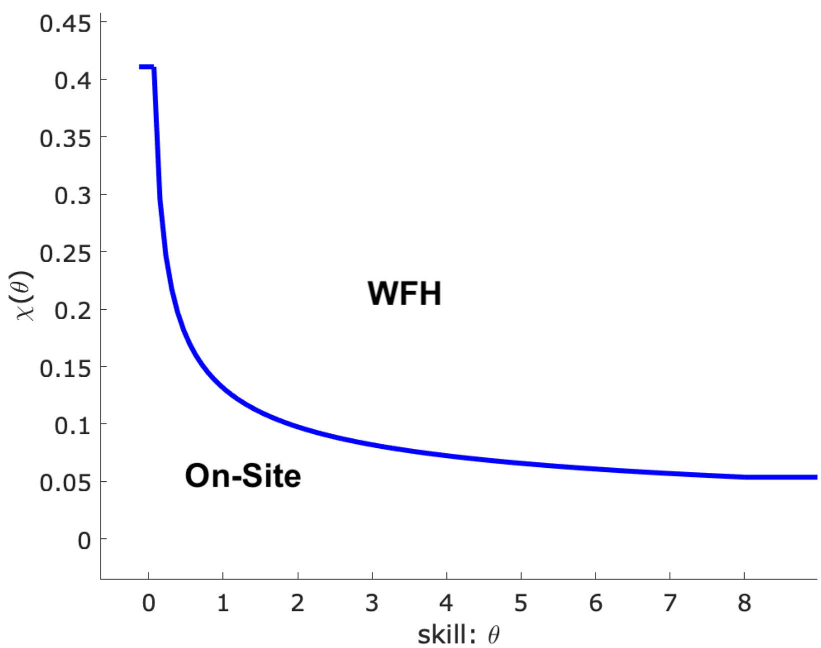
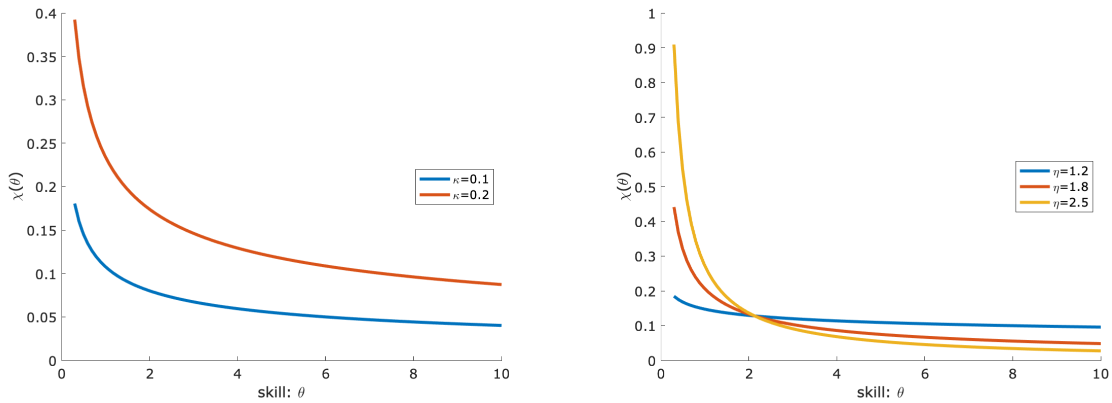


Figure 1 illustrates a numerical example of optimum threshold defined in equation (9). By choice of the parameters, it also illustrates Proposition 1(3). I also consider using mild level productivity loss, $\kappa = 0.12$, from Emanuel and

Figure 7: Optimum Threshold



Harrington's(2023) documentation. In the figure, area above the line simply representing increasing fraction of workers choosing WFH over varying skill level by x axis. Naturally area under the curve, measure of office workers, is decreasing as productivity level increases as pointed out in the Proposition 1. Figure 2 replicates Figure 1, focusing on the margin defined within the bounds of the threshold, using alternative parameters: $\kappa = 0.1$ or 0.2 (left) and $\eta = 1.2$, 1.8, or 2.5 (right). A higher productivity loss, κ, shifts the threshold upward and disproportionately decreases the fraction of WFH. As risk aversion, η, increases, the threshold becomes much steeper, leading to greater selection—i.e., a higher share of skilled agents among the workers choosing WFH.

2.2 Equilibrium With Government

We now introduce the government in the problem. The government taxes workers' income to finance some exogenous expenditure G. The tax system follows the parametric form introduced by HSV (2017), with parameters λ and τ, as follows:

$$T(y) = y - \lambda y^{1-\tau}$$

Using the definition of y_r from equation (1), we obtain the following budget constraint for each individual, conditional on their workplace:

$$c_r \leq y_r - T(y_r). \tag{10}$$

We replace the constraint in individuals' problem (7) with (10) and update the remaining equations characterizing Definition 1. Based on these updates, we label the revised equations as $(2', 3', 4', 6', 7', 8', 9')$. We now use the following good market equilibrium:

$$\int_{\Theta}\int_{\chi} \left[\mathbf{1}_{\chi \geq \tilde{\chi}(\theta)} c_1(\theta,\chi) + \mathbf{1}_{\chi < \tilde{\chi}(\theta)} c_0(\theta,\chi)\right] dZ(\chi) dF(\theta) + G = Y \tag{11}$$

and finally introducing government budget in equation (12)

$$G = \int_{\Theta}\int_{\chi} \Big\{ \mathbf{1}_{\chi \geq \tilde{\chi}(\theta)} \left[Ah_1(\theta,\chi)(1-\kappa) - \lambda \left(Ah_1(\theta,\chi)(1-\kappa)\right)^{1-\tau}\right] +$$

$$\mathbf{1}_{\chi<\tilde{\chi}(\theta)}\left[Ah_0(\theta,\chi)-\lambda\left(Ah_0(\theta,\chi)\right)^{1-\tau}\right]\Big\}dZ(\chi)dF(\theta) \tag{12}$$

Definition 2 A competitive equilibrium is defined as; given government policy $\{T(y);\lambda,\tau\}$, wages $\{w_r\}_r$, allocation and work place for workers $\{h_r(\theta,\chi), c_r(\theta,\chi), \mathbf{1}(\theta,\chi)\}_{r=0,1}$ $\forall\theta\in\Theta$, $\forall\chi\in\boldsymbol{\chi}$, and quantities for firm $\{N_r,Y_r\}_{r=0,1}$ st individuals solve problem in (7′), (8′) and firm solves problem in (6′) and we characterize equilibrium such that :

- (9′) determines equilibrium threshold, $\tilde{\chi}(\theta)$
- (2′), (3′), (4′), (11)and (12) hold.

Proposition 2. Consider the equilibrium defined in Definition 2, and let $h^*(\theta)$ be the effective labor supply for $\theta\in\Theta$:

If $\eta>1$ and $\kappa\in(0,1)$, then for any θ st. $\frac{\partial h^*(\theta)}{\partial\tau}<0$:

The selection effect, $\left|\frac{\partial\tilde{\chi}(\theta)}{\partial\theta}\right|$, is also decreasing in tax progressivity, τ.

Proof. See Appendix A. □

Proposition 2 highlights a key feature of the model under taxation. It states that the slope of the relationship between skill and the WFH threshold becomes flatter as tax progressivity increases. In other words, the skill composition across workplaces becomes more equal when taxes are more progressive—higher progressivity reduces skill inequality between on-site and remote workers.

This mechanism introduces a potential policy trade-off: more progressive taxation may improve the equity of skill distribution across workplace types but could also influence the allocation of WFH in the economy, potentially affecting aggregate efficiency. To explore this trade-off, we need to ask whether tax progressivity, τ, also shifts the WFH threshold, $\tilde{\chi}(\theta)$—and in which direction. This determines whether the fraction of workers choosing WFH at any given skill level θ increases or decreases with τ.

When $\eta > 1$, $\tilde{\chi}(\theta)$ tends to decrease in most moderate cases (e.g., for low or moderate values of θ, or when η is not too large). However, this is not universally true. The threshold $\tilde{\chi}(\theta)$ may become non-decreasing for sufficiently high θ or high η. A useful caveat is that the function is almost surely decreasing for low-skilled workers—specifically, when $y(\theta) < 1$—and more generally for low to moderate skill levels (including those with $y(\theta) \geq 1$), holding for nearly all θ whenever $1 < \eta \leq 1.5$.

Taken together, these results offer two key insights. First, under the stated assumptions on preferences—particularly when $\eta > 1$—tax progressivity can alter the fraction of workers selecting WFH at a given skill level by shifting the WFH threshold, $\tilde{\chi}(\theta)$. Although the direction of this shift may not be uniform across all skill levels or parameter configurations, it is generally downward, implying a higher WFH share across most of the skill distribution as τ increases.

Second, Proposition 2 shows that tax progressivity mitigates the steepness of the relationship between skill and WFH established earlier in Proposition 1. While Proposition 1 demonstrated that WFH participation is increasing in skill due to a decreasing threshold, Proposition 2 clarifies that this selection effect weakens as τ increases. Importantly, the threshold $\tilde{\chi}(\theta)$ tends to decrease with higher tax progressivity, leading to a flatter selection gradient. This underscores a key policy trade-off between greater equity in workplace composition and the skill-based sorting that may support productivity.

Figure 8: Optimum Threshold with tax schedule. $\kappa = 0.12$, $\eta = 1.5$

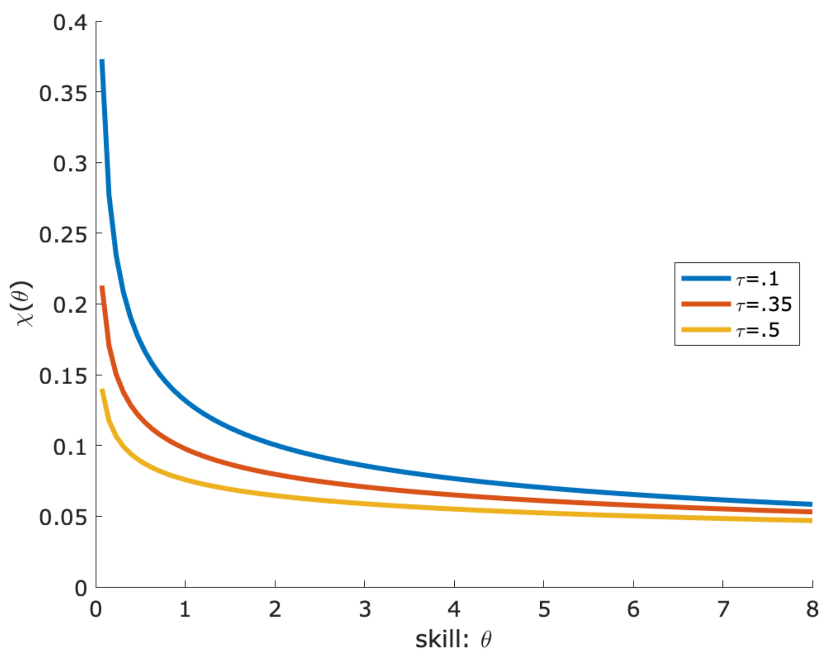


Figure 3 shows a numerical example of optimum threshold with tax schedule in partial equilibrium, as varying tax progressivity. It shows that higher progressivity, i.e. higher marginal taxes on richer, leads lower threshold(more WFH) with non-parallel downward shift. That means tax and transfer system would re-allocate optimum WFH amenity consumed by different productivity levels.

We have summarized the main features of the model with WFH, with and without tax policy, and discussed key factors in Propositions 1 and 2 so far. However, we have not yet addressed the theoretical motivation for considering WFH in an income taxation problem. One critical aspect of this environment is the elasticity of taxable income (ETI). ETI plays a central role in the theory and policy of income taxation, particularly in public finance literature, as it measures how taxpayers respond to changes in tax rates. Understanding ETI is essential because it reflects various behavioral responses—such as changes in labor supply, tax avoidance, and tax evasion—that directly influence optimal tax design and the efficiency of tax systems. The elasticity of taxable income is crucial for understanding the trade-offs in income tax policy, as discussed in Feldstein (1995), Saez (2001), Gruber and Saez (2002), Diamond and Saez (2011), and Saez et al. (2012), among others. This body of literature has significantly shaped how ETI is used in both theoretical models and empirical policy discussions.

Let's consider an alternative definition (**Definition 3.**$_{No-WFH}$, See Appendix C.), a similar competitive equilibrium, which all workers work onsite. We should note that since we normalize amenity value of onsite workers as zero and $\kappa_0 = 0$ considering the equilibrium with exogenously given workplace(onsite) should also give No -WFH equilibrium in our initial setting. This feature will help comparison of two environments.

Proposition 3. Consider the equilibrium defined in Definition 2 and Definition 3 (No-WFH).

If $\eta > 1$, $\kappa \in (0,1)$, and $\frac{d\tilde{\chi}(\theta)}{d\tau} < 0$, then $\forall \theta \in \Theta$:

The elasticity of taxable income (ETI) is higher in the WFH environment compared to the No-WFH environment—that is, compared to an equilibrium in which all workers are required to work on-site:

$$|ETI^*_{wfh}| > |ETI^*_{no-wfh}|$$

$$\frac{dlog(y(\theta))}{dlog(\tau)} = \underbrace{\frac{dlog y_0(\theta)}{d\tau}\tau}_{\text{no-wfh}} + \frac{dlog}{d\tau}\left(\overbrace{Z(\tilde{\chi}(\theta))}^{office} + \overbrace{(1 - Z(\tilde{\chi}(\theta)))}^{home}(1-\kappa)^{\frac{(1+\sigma)}{\tau+\eta(1-\tau)+\sigma}}\right)\tau \tag{13}$$

where,

$$\frac{dlog y_0(\theta)}{d\tau}\tau < 0$$

$$\frac{dlog}{d\tau}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{\tau+\eta(1-\tau)+\sigma}}\right) < 0$$

and using the definition of $\frac{dlog(y)}{dlog(\tau)}$ for tax elasticity.

Proof. See Appendix A. ∎

Proposition 3 shows that the elasticity of taxable income (ETI) is higher in the WFH environment compared to the No-WFH environment. It highlights that workers' taxable income is more responsive to tax rate changes when WFH options are available than when all workers are required to work onsite. The proposition decomposes the ETI into two components: The No-WFH part, which captures the response of taxable income for onsite workers, as $y_0(\theta)$ is the main component of the income for both WFH or onsite workers. An additional WFH term, which accounts for the availability of WFH and its impact on the overall responsiveness of taxable income to tax rate changes. The main result is that the absolute value of ETI is greater in the WFH environment, indicating that tax changes have a larger effect on taxable income when workers have the option to work from home. With mathematical terms, in equation (13), $Z(\tilde{\chi}(\theta))$ and $1 - Z(\tilde{\chi}(\theta))$ denote the fraction of onsite and WFH workers, respectively, for any skill level θ. As discussed earlier, the arguments of each term decrease with the progressivity parameter, τ, under the assumption that $\frac{d\tilde{\chi}(\theta)}{d\tau} < 0$. Since the term multiplying $1 - Z(\tilde{\chi}(\theta))$ carries a lower weight and is dominated, the second component on the right-hand side (RHS) of (15) contributes a larger negative magnitude.

Income inequality, measured through metrics like variance, plays a central role in income taxation theory and redistribution policy. Greater inequality strengthens the case for redistribution by increasing the marginal utility of transferring income to the poor. However, redistribution comes with potential efficiency losses, as higher taxes can distort labor supply and other economic behaviors. The optimal tax literature, from Mirrlees (1971) to recent work by Saez and Stantcheva (2016), emphasizes the need to balance equity and efficiency. Theoretical models show that while high inequality justifies more progressive taxation, policymakers must consider behavioral responses, such as reduced labor supply or tax avoidance, which constrain how much redistribution can be achieved. Foundational contributions include Mirrlees (1971), Atkinson (1970), Piketty and Saez (2003), Diamond and Saez (2011), and Saez and Stantcheva (2016), among others.

Proposition 4. Consider the equilibrium defined in Definition 2 and Definition 3 (No-WFH).

If $\eta > 1$ and $\kappa \in (0, 1)$, and using the variance of income as a measure of inequality, then:

Income inequality in the WFH environment is lower than in the No-WFH environment:

$$\mathrm{Var}(y_{\text{wfh}}) < \mathrm{Var}(y_{\text{no-wfh}}),$$

where the reduction in inequality implies a diminished need for redistribution and provides support for lower tax progressivity in the WFH setting.

Proof. See Appendix A.

□

The result follows naturally from the selection mechanism within the model. WFH involves some productivity loss, but since a higher fraction of richer workers choose the WFH option, the efficiency losses are carried disproportionately by richer agents. This shifts the income distribution and reduces overall inequality in the WFH setting.

Proposition 5. Consider the equilibrium defined in Definition 2 and Definition 3 (No-WFH) within a partial equilibrium setting—that is, treating λ as exogenous.

If $\eta > 1$, $\kappa \in (0, 1)$ then $\forall \theta \in \Theta$:

The elasticity of consumption with respect to marginal income changes is lower in the WFH environment compared to the No-WFH environment:

$$\begin{aligned} \frac{dlog(c(\theta))}{dlog\theta} &= \underbrace{(1-\tau)\frac{dy_0(\theta)}{dlog\theta}}_{\text{no- wfh}} + \frac{dlog}{d\theta}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)(1-\tau)}{\tau+\eta(1-\tau)+\sigma}}\right)\theta \\ &< (1-\tau)\frac{dy_0(\theta)}{dlog\theta} \end{aligned} \tag{14}$$

Proof. See Appendix A.

□

This reduced sensitivity of consumption to income changes weakens the demand for public insurance, thereby supporting lower tax progressivity. While the model is static, this proposition adopts a comparative statics approach to examine how consumption responds to marginal changes in income, allowing for a useful analogy to the role of income shocks in dynamic public finance contexts. It is worth noting that equation (14) illustrates this relationship through a shock to skill, θ, but a similar mechanism could be represented by a shock to the market wage, w, as an alternative source of income variation.

In public finance, one of the key roles of progressive taxation and welfare systems is to provide public insurance against income shocks by helping individuals smooth their consumption and maintain well-being. Higher consumption elasticity with respect to income implies greater difficulty in stabilizing consumption, which increases the need for public insurance through progressive taxes or transfers. The relationship between private consumption smoothing and public insurance aligns with Aiyagari (1994), who emphasizes the role of precautionary savings and public insurance under uncertainty; Chetty and Finkelstein (2013), who argue that private adjustments reduce the need for public intervention; and Blundell et al. (2008), who demonstrate the importance of consumption smoothing in shaping optimal taxation policies, and introduces the concept of pass-through of income shocks to consumption. The idea behind Proposition 5 follows similar logic to that demonstrated by Malkov (2022) in the context of the taxation of singles and couples.

In equation (14), the term $1 - \tau$ reflects how much of an income shock is transmitted to consumption in the No-WFH environment, indicating that a 1% shock in skill, θ, leads to a $(1 - \tau)\frac{dy_0(\theta)}{dlog\theta}$% change in household consumption. However, Proposition 5 shows that this pass-through is lower in the WFH environment, as the second term on the RHS is negative and reduces the total elasticity. The WFH environment provides workers with more tools for private consumption smoothing, reducing the sensitivity of consumption to income shocks. Consequently, the need for public insurance through progressive taxation decreases, supporting the case for lower tax progressivity in the WFH setting. The basic idea is that, since there are no frictions in workplace choice, individuals can always raise extra insurance by switching workplaces, as WFH comes with a productivity loss. This theoretical insight aligns with the idea that when individuals can better manage risk privately, the role of government intervention and redistribution becomes less critical.

2.3 Optimum Income Tax Problem

2.3.1 Ramsey Problem

The Ramsey problem aims to characterize how including remote work affects optimal income tax policy. In the planner problem, I first consider a single tax system, comparing the optimum policies with and without remote work. In the absence of remote work, the heterogeneity in workplace choice is dropped, and all workers are assumed to work onsite as described in the previous sections.

2.3.2 Planner Problem Without WFH

In the planner's problem without WFH, the objective is to maximize social welfare by choosing the optimal tax schedule $\tau^*, \lambda(\tau^*)$ as following:

$$\tau^* \equiv argmax_\tau \int_\Theta U(c(\theta,\tau,\lambda(\tau)), h(\theta,\tau,\lambda(\tau)), 0)\, dF(\theta)$$

such that $\lambda(\tau^*)$ satisfies (18)-good market clearing, in equilibrium

$$\int_\Theta (c(\theta,\tau,\lambda(\tau)) - Ah(\theta,\tau,\lambda(\tau)))\, dF(\theta) + G = 0 \tag{15}$$

where $\{(c(\theta,\tau,\lambda(\tau)), h(\theta,\tau,\lambda(\tau,g))\}_{\theta\in\Theta}$ are optimum allocations characterized in

Definition($2._{No-WFH}$). Here, G represents public good provision, which must satisfy the government budget.

In addition to that problem, I also consider planner problem with government expenditures in utility such that optimum fraction of government expenditure out of output in the economy is endogenously determined. Following objective function solves optimum policy as:

$$\tau^*, g^* \equiv argmax_{\tau,g} \int_\Theta U(c(\theta,\tau,g,\lambda(\tau,g)), h(\theta,\tau,g,\lambda(\tau)), 0)\, dF(\theta)$$

such that $\lambda(\tau^*, g^*)$ similarly satisfies (19)-good market clearing, in equilibrium

$$\int_\Theta (c(\theta,\tau,g,\lambda(\tau,g)) - Ah(\theta,\tau,g,\lambda(\tau,g)))\, dF(\theta) + G = 0 \tag{16}$$

where $\{(c(\theta,\tau,g,\lambda(\tau,g)), h(\theta,\tau,g,\lambda(\tau,g))\}_{\theta\in\Theta}$, and $G = gY$, are optimum allocations characterized in Definition($3._{No-WFH}$), as using the following the preferences:

$$U(c,h,r) = u\,(c) - \psi v\,(h) + \chi_r + \omega logG$$

2.3.3 Planner Problem With WFH

When WFH is introduced, the planner incorporates workplace heterogeneity. Workers can choose between working onsite or remotely, with corresponding utility functions for each choice. The planner maximizes:

$$\tau^* \equiv argmax_\tau \int_\Theta \int_\chi \Big\{ \mathbf{1}_{\chi<\tilde{\chi}(\theta,\tau,\lambda(\tau))} U\,(c_0(\theta,\chi,\tau,\lambda(\tau)), h_0(\theta,\chi,\tau,\lambda(\tau)), 0) \quad +$$

$$\mathbf{1}_{\chi\geq\tilde{\chi}(\theta,\tau,\lambda(\tau))} U(c_1(\theta,\chi,\tau,\lambda(\tau)), h_1(\theta,\chi,\tau,\lambda(\tau)), 1)\Big\} dZ(\chi) dF(\theta) \quad +$$

$$\int_\Theta \int_{\tilde{\chi}(\theta,\tau,\lambda(\tau))}^{\bar{\chi}} \chi\, dZ(\chi) dF(\theta)$$

such that $\lambda(\tau^*)$ satisfies following good market clearing, in equilibrium

$$G + \int_\Theta \int_\chi \mathbf{1}_{\chi < \tilde{\chi}(\theta,\tau,\lambda(\tau))} \left[c_0(\theta,\chi,\tau,\lambda(\tau)) - Ah_0(\theta,\chi,\tau,\lambda(\tau))\right] dZ(\chi)dF(\theta) \quad +$$

$$\int_\Theta \int_\chi \mathbf{1}_{\chi \geq \tilde{\chi}(\theta,\tau,\lambda(\tau))} \left[c_1(\theta,\chi,\tau,\lambda(\tau)) - A(1-\kappa)h_1(\theta,\chi,\tau,\lambda(\tau))\right] dZ(\chi)dF(\theta) = 0$$

where $\{\{(c_r(\theta,\chi,\tau,\lambda(\tau)), \quad h_r(\theta,\chi,\tau,\lambda(\tau))\}_{\theta\in\Theta}\}_{r=0,1}$ and $\{(\tilde{\chi}(\theta,\tau,\lambda(\tau))\}_{\theta\in\Theta}$ are optimum allocations characterized in Definition 2.

Similarly, I solve following planner problem for the endogenously determined government expenditure:

$$\tau^*, g^* \equiv argmax_{\tau,g} \int_\Theta \int_\chi \Big\{ \mathbf{1}_{\chi < \tilde{\chi}(\theta,g,\tau,\lambda(\tau,g))} U\left(c_0(\theta,\chi,g,\tau,\lambda(\tau,g)), h_0(\theta,\chi,g,\tau,\lambda(\tau,g)), 0\right)$$

$$+ \quad \mathbf{1}_{\chi \geq \tilde{\chi}(\theta,g,\tau,\lambda(\tau,g))} U(c_1(\theta,\chi,g,\tau,\lambda(\tau,g)), h_1(\theta,\chi,g,\tau,\lambda(\tau,g)), 1)\Big\} dZ(\chi)dF(\theta)$$

$$+ \quad \int_\Theta \int_{\tilde{\chi}(\theta,g,\tau,\lambda(\tau,g))}^{\bar{\chi}} \chi \, dZ(\chi)dF(\theta)$$

such that $\lambda(\tau^*, g^*)$ satisfies following good market clearing, in equilibrium:

$$G+\int_\Theta \int_\chi \mathbf{1}_{\chi < \tilde{\chi}(\theta,g,\tau,\lambda(\tau,g))} \left[c_0(\theta,\chi,g,\tau,\lambda(\tau,g)) - Ah_0(\theta,\chi,g,\tau,\lambda(\tau,g))\right] dZ(\chi)dF(\theta) \quad +$$

$$\int_\Theta \int_\chi \mathbf{1}_{\chi \geq \tilde{\chi}(\theta,g,\tau,\lambda(\tau,g))} \left[c_1(\theta,\chi,g,\tau,\lambda(\tau,g)) - A(1-\kappa)h_1(\theta,\chi,g,\tau,\lambda(\tau,g))\right] dZ(\chi)dF(\theta)$$

$$= 0$$

where $\{\{(c_r(\theta,\chi,g,\tau,\lambda(\tau,g)),h_r(\theta,\chi,g,\tau,\lambda(\tau,g))\}_{\theta\in\Theta}\}_{r=0,1},\{(\tilde{\chi}(\theta,\tau,g,\lambda(\tau,g))\}_{\theta\in\Theta}$, and $G = gY$, are optimum allocations characterized in Definition 2. as using the following the preferences:

$$U(c,h,r) = u\,(c) - \psi v\,(h) + \chi_r + \omega logG$$

2.4 Calibration

I calibrate the model using U.S. data. I assume skills, θ, is log-normal distributed, with moments $\mu = -0.5\rho^2$ and ρ^2, where:

$$log(\theta) \sim N(-0.5\rho^2, \rho^2)$$

st. normalizing

$$E(\theta) = 1.$$

Then I assume WFH amenity is uniformly distributed with support $[0, \zeta]$, where $\zeta > 0$, i.e.

$$Z(\chi) \equiv \mathcal{U}_{0,\zeta}$$

Empirical evidence supports the uniform assumption for $Z(\chi)$, CDF of amenity for WFH. Figure 7 (See Appendix C.), illustrates a CDF crafted from data(blue line) by using definition threshold as comparing with uniform CDF(orange line). While $Z(\chi(\theta))$ is denoting fraction of office workers at skill level θ, and with the uniform assumption on Z, we should consider $\frac{\chi(\theta)}{\zeta}$ to identify distribution function. I first create a grid for θ by using log of hourly wage as a proxy, and taking $\zeta = 1$, I create a CDF using fraction of office workers at every grid. Figure 7 illustrates the case for $\zeta = 1$, which shows a close pattern for uniform distribution as it can be inferred by comparing continuous CDF in the plot.

I use log consumption in model to consider it's variance and calibrate ρ:

$$log(c_r) = log\left(\lambda^{\frac{1+\sigma}{P}}\left(\frac{(1-\tau)^{\frac{(1-\tau)}{P}}(A(1-\kappa_r))^{\frac{(1+\sigma)(1-\tau)}{P}}}{\psi^{\frac{(1-\tau)}{P}}}\right)\right) + \frac{M}{1-\eta}log(\theta)$$

where , $M = \frac{(\sigma+1)(1-\tau)(1-\eta)}{\tau+\eta(1-\tau)+\sigma}$ and then when take the variance of this expression conditional on workplace, i.e. onsite, we get:

$$Var(log(c)|onsite) = \left(\frac{M}{1-\eta}\right)^2 Var(log(\theta|onsite)) \tag{17}$$

Equation (17) is the key one to determine ρ, but we need to show how to deal with conditional variance.

Lemma 1. $Var(log(\theta)) = Var(log(\theta)|onsite)$

Proof. See Appendix A.

□

Using the result in lemma 1., we can plug $Var(log(\theta|onsite)) = \rho^2$ and M to (17):

$$Var(log(c)|onsite) = \left(\frac{(\sigma+1)(1-\tau)}{\tau+\eta(1-\tau)+\sigma}\right)^2 \rho^2 \tag{18}$$

I set $Var(\log(c) \mid \text{onsite})_{\text{data}} = 0.234$, using the result from Heathcote and Tsujiyama (2021) for $Var(\log(c))$. We should note that using rent expenditures from ACS data as a proxy for conditional expenditures also gives a parallel result. I set $\tau^{\text{data}} = 0.181$ from HSV (2017), and $\sigma = 2$, as microeconomic evidence from Keane (2011) for the inverse of Frisch elasticity. I set the risk aversion parameter, $\eta = 1.24$, based on evidence for a static environment provided in Chetty (2006). Considering sensitivity analysis, the set of risk aversion parameters, η, is as follows: $\eta \in \{1.1, 1.24, 1.5, 2\}$, used for calibration. I solved for ρ using the relevant parameter values in equation (18) and for each η specified. The corresponding values of ρ for each η are presented in Table 1 and Table 2. We can derive the following expression to handle both conditional distributions and to calibrate measure of WFH in the economy:

$$\pi_{onsite} = \text{Prob}\left(\chi \leq \tilde{\chi}(\theta)\right) = \int_0^\infty \left(\frac{\tilde{\chi}(\theta)}{\zeta}\right) f(\theta)d\theta = \frac{\upsilon}{\zeta}\exp\left(\mu M + \frac{1}{2}\rho^2 M^2\right) \tag{19}$$

where π_{onsite} is equilibrium measure of office workers in the model. I set $\pi_{onsite}^{data} = 0.79$ using the statistics from 2021 for WFH in ACS data and $\kappa = 0.12$ using the evidence from Emanuel et al. (2023). We should note that υ in (19)

Table 8: Parameters: baseline calibration

η	ρ	ζ
1.24	0.629	0.148

Table 9: Parameters: sensitivity calibrations

η	ρ	ζ	ω	ρ^*	ζ^*	ω^*
1.1	0.607	0.139	0.238	0.4	0.138	0.232
1.24	0.629	0.148	0.250	0.4	0.145	0.240
1.5	0.671	0.170	0.275	0.4	0.159	0.252
2	0.752	0.228	0.349	0.4	0.185	0.280

also a function term of tax schedule as it is part of indirect utility with tax schedule, i.e. $\tilde{\chi}(\theta) = \upsilon\theta^M$. Hence, I solve λ^{data} and ζ as solving 2 system of equations, which are (19) and good market equilibrium, given τ^{data}. For the good market clearing equation I set government expenditure, G, to be 19% of total output relying on the common statistics used in the literature. Table 1 reports the calibrated value of ζ, which is 0.148.

For the cases, when we consider preferences with government expenditure(endogenous G case), I set ω as such government expenditure in the data to be optimum while using grid for g, where $g = 0.19 = G/Y$. The set of values for ω and other parameters considered for sensitivity analysis is shown in Table 2. The last three columns of Table 2 report the calibrated parameters when $\rho = 0.4$ is fixed, bypassing Equation (18) for calibration. Fixing the dispersion parameter, ρ, to a lower value than the main calibration is an important sensitivity case to consider. Simplifying the environment by including only a single component of

Table 10: Calibrated Policies and Results

	η	τ	λ	Y	C	G/Y	wfh
WFH	1.24	0.319	0.787	0.855	0.681	0.204	0.339
No- WFH	1.24	0.367	0.794	0.872	0.698	0.2	

inequality can lead to ρ being over-calibrated. Although this is neither a primary focus of the paper nor does it affect its main hypothesis, we will see in the next section that this situation results in optimal policies being naturally high as a mathematical outcome.

2.4.1 Quantitative Results

I compute the policy parameters using the calibration methodology outlined in the previous section. Given the simplified environment of our analysis, I consider alternative specifications as described in the model section and reserve their discussion for the sensitivity analysis section. To emphasize the primary effect of incorporating WFH, I focus on comparing WFH and No-WFH scenarios across various cases rather than introducing additional complexities to the model.

Table 3 presents the optimal policy schedules for the calibrated models, focusing on the *Exogenous G* case, where government expenditure is exogenously determined. This serves as the benchmark calibration. In the HSV (2017) framework, τ represents the degree of tax progressivity, which is the key parameter influencing the level of marginal taxes. Given τ, the parameter λ balances the government budget, allowing both parameters together to shape the tax and transfer system.[6] Comparing the progressivity parameters between WFH and No-WFH environments, we find that the results align with the motivations described in the propositions, with lower progressivity observed in the WFH setting. For the benchmark estimation, I find a progressivity value of 0.319 for WFH, approximately 5 percentage points lower than in the No-WFH[7] case (0.367). The difference in two models validates the quantitative importance of the main argument of the paper. In the table, Y, C, and G/Y denote output, consumption, and the share of government expenditure in output, respectively. The variable wfh in the last column denotes the fraction of individuals working from home under the optimal policy, which is 0.339—a higher value than in the calibrated data. As discussed in Proposition 2, this is an expected result, since the fraction of WFH increases with higher tax progressivity (recall, $\tau^{data} = 0.181$). Moreover, we observe a 1.95% implied efficiency loss with WFH when comparing output (Y) results across the models. This results in a 2% increase in fiscal pressure, as indicated by the government expenditure share (G/Y).

Figure 4 visualizes the optimal marginal taxes (left) and average taxes (right) using the parameters from Table 3, with income levels presented in U.S. dollar terms. The income level of $70,000 corresponds to the average income level in this calibration. In the HSV framework, a notable characteristic of their non-linear tax structure is the monotonicity of marginal taxes, as the progressive

[6] Specifically: Marginal tax function: $T'(y) = 1 - (1-\tau)\lambda y^{-\tau}$, Average tax function: $T(y)/y = 1 - \lambda y^{-\tau}$.

[7] See the Sensitivity section for a discussion on the comparability of this result with the literature.

Figure 9: Optimum Policy: Marginal Tax(left), Average Tax(right)

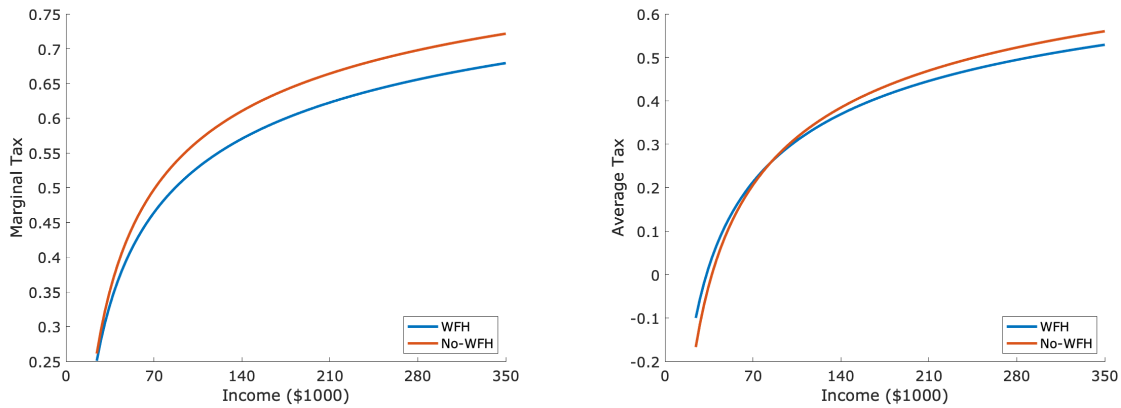


Table 11: Marginal Taxes with $ Income

Income	$40,000	$80,000	$250,000	$500,000
M. Tax_{wfh}	0.359	0.486	0.643	0.714
M.Tax_{no-wfh}	0.383	0.521	0.685	0.756
Difference				
Add. inc. $10,000	−$259.1	−$357.1	−$421.0	−$420.0

tax function they design results in increasing marginal taxes when $\tau > 0$. The differences in optimal marginal taxes between the two models are clearly observable in the plot. An important takeaway is that the inclusion of WFH in the income taxation model leads to a more dramatic reduction in marginal taxes for higher-income individuals. Average taxes also show notable changes. As a result of the decreased progressivity, optimal transfers are also reduced, as observed in the plot (right). Additionally, the average taxes owed by lower-income groups are higher under the WFH model.

Table 4 presents the marginal taxes for selected income levels,

$\{\$40, \$80, \$250, \$500\} \times 1000$, and the differences in tax owed for each model in dollar terms for an additional $10,000 in income. The table shows that the difference in optimum marginal tax rates between the two models varies from 2.4% to 4.2% across these income levels. The results indicate that, under the WFH model compared to the No-WFH model, we would propose a lower tax amount of $\{\$259, \$357, \$421, \$420\}$ for this income group on their additional earnings, respectively. These figures highlight the most significant implication of WFH for optimal income taxation from a tax accounting perspective.

To summarize, the quantitative analysis shows that incorporating WFH decreases tax progressivity by approximately 5 percentage points, resulting in a 2.5% to 4.5% reduction in marginal taxes across the income levels analyzed ($\$40,000 - \$500,000$). For an additional $10,000 in income, the WFH model implies a $250 to $420 reduction in taxes owed compared to the No-WFH scenario. This reduction aligns with the expected impact of WFH, where lower productivity and positive selection lead to modest reductions in income inequality, though with less public insurance due to decreased transfers to lower-income agents. These findings reinforce the analytical insights that WFH environments naturally support a lower degree of public insurance.

Table 12: Sensitivity Analysis: η

	η	τ	λ	Y	C	G/Y	wfh
WFH	1.1	0.272	0.799	0.871	0.697	0.2	0.296
No- WFH		0.321	0.803	0.884	0.71	0.197	
WFH	1.24	0.319	0.787	0.855	0.681	0.204	0.339
No- WFH		0.367	0.794	0.872	0.698	0.2	
WFH	1.5	0.4	0.766	0.83	0.656	0.21	0.411
No- WFH		0.442	0.778	0.854	0.68	0.204	
WFH	2	0.533	0.728	0.796	0.622	0.219	0.54
No- WFH		0.565	0.748	0.828	0.654	0.21	

2.4.2 Sensitivity Analysis

In this section, I explore alternative specifications of the benchmark calibration to evaluate the robustness of the findings discussed in the quantitative results. I begin by examining different values for the risk aversion parameter, (η). Optimal policies are computed using $\eta \in \{1.1, 1.24, 1.5, 2\}$, while recalibrating the benchmark specification accordingly. As outlined in the calibration section, the skill dispersion parameter, (ρ), is determined by satisfying equation (18). Table 1 presents the corresponding values of (ρ) for each value of (η).

Table 6 presents the optimal policies for the first sensitivity analysis, illustrating how variations in risk aversion (η) affect the optimal progressivity (τ) in both WFH and No-WFH environments. For $\eta = 1.1$, it is noteworthy that the No-WFH value (0.321) is comparable to HSV (2020), which reports a progressivity parameter of 0.317 under log preferences and an exogenous skill distribution. The reductions in progressivity for each model are $\{5, 4.7, 4.2, 3.1\}$ percentage

Table 13: Sensitivity Analysis: $\rho = 0.4$

	η	τ	λ	Y	C	G/Y	wfh
WFH	1.1	0.1	0.819	0.954	0.78	0.182	0.134
No- WFH		0.153	0.819	0.952	0.778	0.183	
WFH	1.24	0.118	0.816	0.952	0.776	0.185	0.153
No- WFH		0.174	0.817	0.952	0.776	0.185	
WFH	1.5	0.146	0.813	0.953	0.775	0.187	0.18
No- WFH		0.207	0.814	0.955	0.777	0.186	
WFH	2	0.191	0.809	0.96	0.777	0.191	0.218
No- WFH		0.263	0.81	0.963	0.78	0.19	

points for the set of (η) values, respectively. As observed, the values of (τ) are significantly higher, particularly for higher levels of risk aversion. This outcome is primarily due to having a single component for skill dispersion, which leads to a relatively high calibration for (ρ) as a mathematical consequence. Therefore, Table 5 reflects the combined effects of increased risk aversion and skill dispersion, with (ρ) ranging between 0.6 and 0.75. As a trivial outcome, higher risk aversion (η) reflects the need for greater redistribution when individuals are more risk-averse. Similarly, higher skill dispersion (ρ) leads to increased tax progressivity as a result of increased inequality.

Table 7 presents the optimal policies in a manner similar to Table 6, but here I fix the skill dispersion at $\rho = 0.4$, thereby bypassing the calibration step (equation 18) for (ρ). This approach allows us to assess the role of a simplified income process, as 0.4 represents a considerably lower value for (ρ) compared to previous specifications. The reductions in progressivity for each model are

Table 14: Marginal Taxes with \$ Income. $\eta = 1.24$, $\rho = 0.4$

Income	\$40,000	\$80,000	\$250,000	\$500,000
M. Tax_{wfh}	0.231	0.291	0.381	0.429
M.Tax_{no-wfh}	0.256	0.341	0.459	0.521
Difference				
Add. inc. \$10,000	−\$293.6	−\$509.6	−\$789.8	−\$915.3

$\{5.3, 5.6, 6.1, 7.2\}$ percentage points for the corresponding set of (η) values. Unlike the results in Table 5, the values of (τ) here are not excessively high due to the lower skill dispersion, though they continue to increase with higher risk aversion.

Using the optimal tax parameters for $\eta = 1.24$ from Table 7, I replicate Table 4 from the benchmark calibration to provide a complementary analysis of marginal taxes in dollar terms, focusing on the effects of lower skill dispersion. The results are presented in Table 8. The table shows that the difference in optimal marginal tax rates between the two models now varies from 2.5% to 9.2% across income levels ranging from $\$40,000$ to $\$500,000$. These figures highlight a greater difference in marginal taxes for wealthier agents compared to the benchmark results. For example, the difference in tax owed between the models for an additional \$10,000 in income is \$915.3 at the \$500,000 income level, more than twice the previous amount of \$420.0.

Table 9 shows the calibrated policies under different configurations for government expenditures in the model. The last four columns combine these results with those from Table 6, which presents the optimal policies when there

Table 15: Sensitivity Analysis with G

				G=0		Endogenous G	
	η	τ	λ	τ	λ	τ	λ
WFH	1.1	0.272	0.799	0.386	0.961	0.279	0.806
No- WFH		0.321	0.803	0.418	0.969	0.325	0.808
WFH	1.24	0.319	0.787	0.425	0.945	0.326	0.798
No- WFH		0.367	0.794	0.454	0.956	0.37	0.801
WFH	1.5	0.4	0.766	0.491	0.916	0.409	0.779
No- WFH		0.442	0.778	0.518	0.932	0.446	0.786
WFH	2	0.533	0.728	0.602	0.863	0.542	0.74
No- WFH		0.565	0.748	0.619	0.887	0.567	0.752

is no government expenditure ($G = 0$) and when government expenditure is included in utility, i.e., *Endogenous G*, respectively. The sensitivity of the progressivity parameter to government expenditure is a well-known feature discussed in HSV (2017), which demonstrates that optimal progressivity is higher when $G = 0$ compared to when $G > 0$. The table presents results consistent with this feature, showing that optimal progressivity is higher in the $G = 0$ case compared to our benchmark. However, the main finding is preserved in this configuration, with progressivity remaining higher in the No-WFH model compared to the WFH model by approximately 2%–3%. Endogenous public good provision results in similar optimal tax rates compared to exogenous provision; thus, the difference in progressivity between the WFH and No-WFH models remains largely unchanged.

Finally, Table 10 replicates Table 9 with a calibration of $\rho = 0.4$ across all levels of risk aversion. For both the $G = 0$ and Endogenous G cases, the

Table 16: Sensitivity Analysis with G, ρ = 0.4

	η	τ	λ	G=0 τ	G=0 λ	Endogenous G τ	Endogenous G λ
WFH	1.1	0.1	0.819	0.242	0.984	0.093	0.812
No- WFH		0.153	0.819	0.275	0.986	0.147	0.812
WFH	1.24	0.118	0.816	0.26	0.98	0.112	0.811
No- WFH		0.174	0.817	0.295	0.982	0.168	0.812
WFH	1.5	0.146	0.813	0.286	0.973	0.144	0.81
No- WFH		0.207	0.814	0.325	0.975	0.205	0.811
WFH	2	0.191	0.809	0.328	0.963	0.191	0.809
No- WFH		0.263	0.81	0.372	0.965	0.263	0.81

comments and reasoning applied to the results in Table 8 remain applicable. The main difference is that the reductions in progressivity for each model are larger in percentage points across the set of (η), consistent with previous discussions on alternative skill dispersion (ρ = 0.4, Table 7). This indicates that the quantitative findings summarized thus far are robust to alternative specifications of preferences regarding government expenditure.

To summarize, the robustness check validates the findings from the quantitative results in the previous section, confirming that the WFH environment features lower tax progressivity. The results show that the model is robust to changes in preferences, skill dispersion, and alternative configurations of public policy, consistently supporting the main argument of the paper.

Chapter 3

Differential Tax System By Workplace

This section shows how modeling WFH in optimum income taxaton could be more important from the taggin motivation. The optimal income taxation with tagging explores how observable characteristics enhance redistribution while minimizing efficiency losses. As Akerlof (1978) pioneered the concept, literature has many examination of tagging with some characteristics like age, marital status, job type etc. The model in this section introduces workplace- WFH or not, as an observable characteristics in the tagging context. I am aware of that workplace might not necessarily be an unimmutable characteristics. But I claim that the observed statistics about WFH related to selection effect, which is strong and consistent over years, should be first important reason to consider WFH for tagging feature. Because it reveals an important feature for planner as we can have more information about skill distribution due to workplace. In other words workplace information reveals whether the skill distribution of certain group agents first order stochastically dominates the other one or not. Second reasons should be the observed quantitative impacts of WFH on tax progressivity, which is documented in the previous section.

Differential tax system based on workplace choice allows the tax function $T_r(y)$ to be defined as following:

$$T_r(y) = y - \lambda_r y^{1-\tau_r}$$

where tax schedules $\{\lambda_r, \tau_r\}_r$ vary by r, WFH or onsite, in HSV system. The planner's objective is to maximize welfare by choosing the the parameters $\{\lambda_r, \tau_r\}_r$, with the following problem:

$$\mathcal{T}^* = \tau_1^*, \tau_0^*, \lambda_1^* \equiv argmax_{\mathcal{T}} \int_\Theta \int_\chi \Big\{ \mathbf{1}_{\chi < \tilde{\chi}(\theta,\mathcal{T})} U(c_0(\theta,\chi,\mathcal{T}), h_0(\theta,\chi,\mathcal{T}), 0)$$

$$+ \quad \mathbf{1}_{\chi \geq \tilde{\chi}(\theta,\mathcal{T})} U(c_1(\theta,\chi,\mathcal{T}), h_1(\theta,\chi,\mathcal{T}), 1) \Big\} dZ(\chi) dF(\theta)$$

$$+ \int_\Theta \int_{\tilde{\chi}(\theta,\mathcal{T})}^{\bar{\chi}} \chi \, dZ(\chi) dF(\theta)$$

such that $\lambda_0(\mathcal{T}^*)$ satisfies following good market clearing, in equilibrium:

$$G + \int_\Theta \int_\chi \mathbf{1}_{\chi < \tilde{\chi}(\theta,\mathcal{T})} \left[c_0(\theta,\chi,\mathcal{T})) - A h_0(\theta,\chi,\mathcal{T}))\right] dZ(\chi) dF(\theta) \quad +$$

$$\int_\Theta \int_\chi \mathbf{1}_{\chi \geq \tilde{\chi}(\theta,\mathcal{T})} \left[c_1(\theta,\chi,\mathcal{T}) - A(1-\kappa) h_1(\theta,\chi,\mathcal{T})\right] dZ(\chi) dF(\theta) = 0$$

where $\mathcal{T} = (\tau_1, \tau_0, \lambda_1)$' denotes vector of policies,$\{\{(c_r(\theta,\chi,\mathcal{T}),\ h_r(\theta,\chi,\mathcal{T})\}_{\theta\in\Theta}\}_{r=0,1}$

and $\{(\tilde{\chi}(\theta, \mathcal{T})\}_{\theta\in\Theta}$ are optimum allocations characterized in Definition 2. as considering updated tax schedules defined with $T_r(y)$ in place of $T(y)$ in the individuals' problem.

3.0.3 Quantitative Results

We should first note that under the assumption of a uniform distribution for χ, the planner's problem with tagging cannot be solved using the first-order condition, as the problem is no longer concave. Therefore, in this section, I assume that the amenity value of WFH, χ, follows a log-normal distribution:

$$\log(\chi) \sim \mathcal{N}(\mu_\chi, \sigma_\chi).$$

Naturally, this update requires some adjustments to the benchmark calibration, which are discussed in Chapter 2 for the uniform policy case. I now replace Equation (19) with the following:

$$\begin{aligned}
\pi_{onsite} &= \text{Prob}\left(\chi \leq \tilde{\chi}(\theta)\right) \\
&= \int_0^\infty \Phi\left(\frac{M \ln\theta + \ln\upsilon - \mu_\chi}{\sigma_\chi}\right) \frac{1}{\theta\rho\sqrt{2\pi}} \exp\left(-\frac{(\ln\theta - \mu)^2}{2\rho^2}\right) d\theta \\
&= \Phi\left(\frac{M\mu + \ln\upsilon - \mu_\chi}{\sqrt{\sigma_\chi^2 + M^2\rho^2}}\right) \qquad (20)
\end{aligned}$$

where $\Phi(\cdot)$ denotes the standard normal CDF, and as mentioned in Section 2.4,

Table 17: Calibrated Policies - with Tagging

$\tau_{o.site}$	$\lambda_{o.site}$	τ_{wfh}	λ_{wfh}	Y	C	G/Y	wfh	welfare
0.367	0.795	0.409	0.711	0.872	0.698	0.20	0.0000	-0.7064

we define $\tilde{\chi}(\theta) = \upsilon\theta^M$. Similar to the benchmark calibration, our objective is to identify the parameters λ^{data}, μ_χ, and σ_χ. To do so, we require one additional equation for calibration. I use the observed fraction of office workers at the median skill level in the data, 0.832 (from 2021), and match it to the corresponding value in the model using $Z(\chi)$:

$$Z(\tilde{\chi}(\theta_{med.})) = \Phi\left(\frac{\ln(\upsilon\theta^M_{med.}) - \mu_\chi}{\sigma_\chi}\right), \tag{21}$$

where $\theta_{\text{med.}}$ denotes the median skill level in the model. Similarly, I use a system of three equations, equations (20) and (21), matched to their corresponding values in the data, along with the feasibility condition of the planner's problem under the uniform tax policy (Section 3.3), to calibrate λ^{data}, μ_χ and σ_χ. An important final note is that Lemma 1 does not necessarily hold when $Z(\chi)$ follows a log-normal distribution. Therefore, I now assume that $\text{Var}(\log(\theta)) \approx \text{Var}(\log(\theta) \mid \text{onsite})$, and I maintain the same parameterization for all other parameters calibrated in Section 2.4.

Considering the adjustments in the parameters, I solve the planner's problem with tagging to obtain the optimal tax schedules, $\{\lambda_r, \tau_r\}_r$. Table 10 presents the resulting optimal policies.

Table 18: Calibrated Policies - Uniform Tax policy

	τ	λ	Y	C	G/Y	wfh	welfare
WFH	0.240	0.802	0.878	0.705	0.197	0.315	-0.7408
No- WFH	0.367	0.795	0.872	0.698	0.20		-0.7064

The findings are quite interesting. I find optimal progressivity values of 0.409 for remote workers (τ_{wfh}) and 0.367 for on-site workers ($\tau_{o.site}$). This indicates that the planner chooses to levy higher tax progressivity on labor income for those who work from home compared to those who work on-site. This result clearly suggests that the planner internalizes the efficiency loss associated with remote work—particularly the loss triggered by selection—and responds by discouraging remote work through the tax system. As a result, almost no one chooses to work from home, as shown by the outcome in the table (wfh = 0.0000). The existence of a positive amenity value of WFH in utility, modeled as an additive term, is not sufficient to compensate for the efficiency loss resulting from the lower productivity of WFH. Consequently, WFH is almost entirely discarded under the optimal policies in this economy.

We can quickly address the intuition behind this inference by comparing the results with those under the optimal tax policy with a uniform schedule. Table 11 presents the resulting policies for the uniform schedule, incorporating the adjustments in parameterization introduced in this section. Naturally, the results in the No-WFH environment are identical to the previous findings in Section 2.4, as the adjustments made in this section are irrelevant for that case.

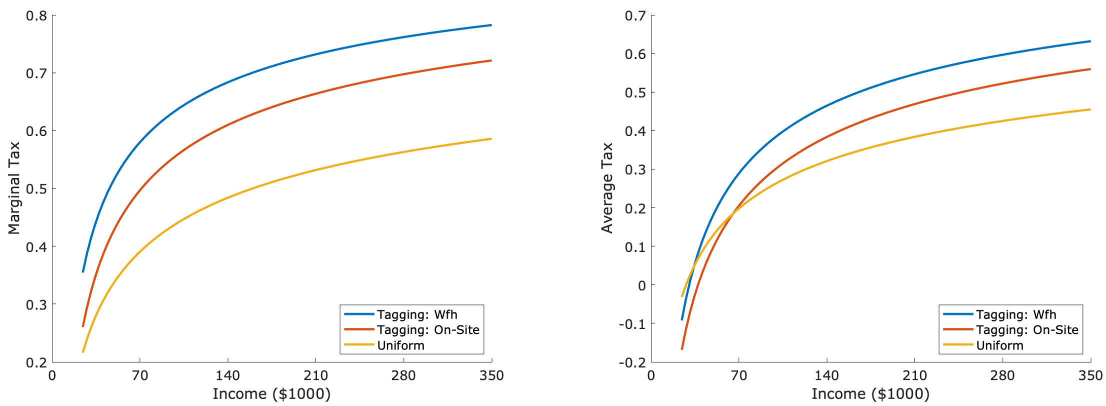
However, this also serves as a useful confirmation that the calibrated policies and welfare outcomes in the No-WFH environment are nearly identical to those under tagging, since almost no one chooses WFH in equilibrium. On the other hand, the policies are quite different compared to the WFH environment. For instance, under the uniform policy, the optimal progressivity is 0.240. This implies that when workplace choice is allowed but tax policy cannot differentiate by workplace, approximately 31.5% of workers choose WFH and face lower marginal tax rates compared to the No-WFH environment. As a result, the economy achieves lower overall welfare, as reported in Table 11.

This highlights that when tax policy cannot be differentiated by workplace, the planner must strike a balance between the efficiency loss due to lower productivity in WFH and the contribution of the amenity value of WFH to overall welfare. In contrast, under the tagging policy, the planner retains the ability to directly incorporate workplace choice and its associated amenity value into the optimization problem, leading to more efficient outcomes. Since the planner can now differentiate tax policy by workplace, she imposes higher marginal taxes on workers who choose to work remotely. This discourages workers from selecting WFH, resulting in an equilibrium where almost no one works from home—an outcome that is, in fact, the most beneficial from the perspective of the planner's objective. A clear indicator of this is the higher welfare achieved under the tagging policy (-0.7064) compared to the uniform policy (-0.7408).

This confirms that the planner's ability to differentiate tax policy by workplace leads to a more efficient allocation and greater overall welfare.

To further illustrate these results, Figure 5 visualizes the optimal marginal tax rates (left) and average tax rates (right) using the parameter values from Tables 10 and 11, with income levels presented in U.S. dollar terms. Nearly an income of $70,000 corresponds to the average income level in this calibration. The differences in optimal marginal taxes between the tagging and uniform

Figure 10: Optimum Policy with Tagging: Marginal Tax(left), Average Tax(right)



systems are clearly visible. A key takeaway is that the tagging policy results in a steeper increase in marginal tax rates for higher-income individuals compared to the uniform policy. In terms of average taxes, the plots show that the tagging policy provides larger transfers to low-income workers while imposing a higher average tax burden on richer individuals—an expected outcome due to the higher degree of progressivity under tagging.

3.1 Conclusion

The policy implications of incorporating remote work into optimal income taxation are thoroughly analyzed in this paper. Drawing on evidence from U.S. data on selection into WFH and the growing literature on WFH productivity, this paper concludes that tax policy could significantly influence the allocation of skills across workplaces and the proportion of WFH in the economy.

Building on a standard Ramsey framework with endogenous workplace choice, the analysis demonstrates that the presence of WFH reshapes fundamental public finance trade-offs. In particular, remote work affects key margins such as the elasticity of taxable income, the degree of consumption smoothing, and the level of income inequality. Analytically, the model shows that WFH tends to raise taxable income elasticity and improve insurance, while reducing inequality across workers. All of these forces contribute to a lower optimal degree of tax progressivity when WFH is allowed.

The quantitative results confirm these theoretical insights. When comparing the optimal policies under a uniform tax system, I find that allowing WFH leads to a meaningful reduction in marginal tax rates: about 2–3 percentage points for low-income groups and around 5 percentage points for high-income groups. In dollar terms, this implies that an additional income of $10,000 results in a reduction in the tax burden of roughly $280–$520 when WFH is accounted for. These findings remain robust across alternative parameterizations, showing consistent support for the hypothesis that WFH reduces the optimal level of tax progressivity.

The sensitivity analysis reveals that the policy findings—particularly the reduction in optimal tax progressivity with WFH—are robust to changes in parameter values and preference configurations. Notably, the difference in progressivity between the WFH and No-WFH environments becomes significantly more pronounced when the amenity value of WFH is modeled as log-normally distributed rather than uniform. While the uniform case results in a progressivity gap of about 5 percentage points, the log-normal specification leads to a difference of nearly 12 percentage points.

To explore the implications of observability and heterogeneity in workplace choice, the paper extends the analysis to consider a differential tax policy by workplace. In this setting, the planner is allowed to condition tax schedules on whether a worker is remote or on-site. This flexibility enables the design of tax instruments that internalize the efficiency losses associated with lower productivity and selection into WFH. The resulting policy—effectively a form of tagging—imposes higher marginal taxes on remote workers, which in turn discourages WFH altogether, despite the presence of a positive amenity value. This outcome improves welfare relative to a uniform tax system, underscoring the value of observable workplace information in tax policy design.

Overall, these findings highlight the importance of incorporating workplace flexibility and observability into the design of modern tax policy. As remote work becomes a persistent feature of the labor market, understanding how it interacts with redistribution, efficiency, and worker heterogeneity is essential for crafting equitable and effective fiscal systems. Future work could further enrich the analysis by incorporating more detailed income processes, dynamic considerations, or employer-side heterogeneity to refine the policy implications.

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Appendix- A

Proposition 1. Consider the equilibrium defined in Definition(1),

$\forall\theta \in \Theta$ and $\forall\chi \in \boldsymbol{\chi}$:

1: For any individual, i drawing χ and θ, there exists a threshold, $\tilde{\chi}(\theta)$ st. i works from home if and only if $\chi \geq \tilde{\chi}(\theta)$ in equilibrium.

2: If $\kappa = 0$, equilibrium threshold , $\tilde{\chi}(\theta)$ and share of wfh, $\tilde{Z}(\tilde{\chi}(\theta)) = 1 - Z(\tilde{\chi}(\theta))$ are both constant in skills, θ.

3: If $\eta < 1$($\boldsymbol{\eta} > \mathbf{1}$), then for any $\kappa \in (0, 1)$, equilibrium threshold, $\tilde{\chi}(\theta)$, is increasing (**decreasing**) in skills and share of wfh, $\tilde{Z}(\tilde{\chi}(\theta))$, is decreasing (**increasing**) in skills, θ.

Proof. 1: Existence of equilibrium is necessary and sufficient to define threshold, $\tilde{\chi}(\theta)$

2: The proof is trivial through envelope condition:

$$\frac{\partial\tilde{\chi}(\theta)}{\partial\theta} = \psi\left(\frac{h_0^*(\theta)}{\theta}\right)^{\sigma}\frac{h_0^*(\theta)}{\theta^2} - \psi\left(\frac{h_1^*(\theta)}{\theta}\right)^{\sigma}\frac{h_1^*(\theta)}{\theta^2}$$

$$= \frac{\psi}{\theta^{\sigma+2}}\left({}^*h_0^{\sigma+1}(\theta) -{}^* h_1^{\sigma+1}(\theta)\right)$$

$$\frac{\partial\tilde{\chi}(\theta)}{\partial\theta} = \frac{\psi}{\theta^{\sigma+2}}h_0^{*\sigma+1}(\theta)\left(1 - (1-\kappa)^{\frac{(1-\eta)(1+\sigma)}{\eta+\sigma}}\right) \tag{22}$$

Since $h_1^*(\theta) = h_0^*(\theta)(1-\kappa)^{\frac{1-\eta}{\eta+\sigma}}$, when $\kappa = 0$, $\frac{\partial\tilde{\chi}(\theta)}{\partial\theta} = 0$ in (11), and monotonicity of $Z(\chi)$ is resulted that $Z(\tilde{\chi}(\theta))$ is constant $\forall\theta$.

3: When $\kappa \in (0,1)$, if $\eta < 1(\boldsymbol{\eta > 1})$,

$$1 - (1-\kappa)^{\frac{(1-\eta)(1+\sigma)}{\eta+\sigma}} > 0 \ \mathbf{(< 0)}$$

which derives $\frac{\partial \tilde{\chi}(\theta)}{\partial \theta} > 0$ **(< 0)** in (11) and similarly monotonicity of $Z(\chi)$ is resulted that $Z(\tilde{\chi}(\theta))$ is increasing (**decreasing**) $\forall \theta$.

$\square$

Proposition 2. Consider the equilibrium defined in Definition 2, and let $h^*(\theta)$ be the effective labor supply for $\theta \in \Theta$:

If $\eta > 1$ and $\kappa \in (0,1)$, then for any θ st. $\frac{\partial h^*(\theta)}{\partial \tau} < 0$:

The selection effect, $\left|\frac{\partial \tilde{\chi}(\theta)}{\partial \theta}\right|$, is also decreasing in tax progressivity, τ.

Proof. Consider the equation in (22), $\frac{d\tilde{\chi}(\theta)}{d\theta}$, that is analyzed in **Proposition 1.**, which is updated with tax schedules in the following:

$$\frac{\partial \tilde{\chi}(\theta)}{\partial \theta} = \frac{\psi}{\theta^{\sigma+2}} h_0^{*\sigma+1}(\theta)\left(1-(1-\kappa)^m\right)$$

where, $m = \frac{(\sigma+1)(1-\tau)(1-\eta)}{\tau+\eta(1-\tau)+\sigma}$ and then:

$$\frac{\partial^2 \tilde{\chi}(\theta)}{\partial \theta \partial \tau} = \frac{\psi}{\theta^{\sigma+2}}(\sigma+1) h_0^{*\sigma}(\theta) \frac{\partial h_0^*(\theta)}{\partial \tau}\left(1-(1-\kappa)^m\right) - \frac{\psi}{\theta^{\sigma+2}} h_0^{*\sigma+1}(\theta) \frac{\partial (1-\kappa)^m}{\partial \tau} \tag{23}$$

$$\frac{\partial (1-\kappa)^m}{\partial \tau} = -log(1-\kappa)\frac{\partial m}{\partial \tau} < 0$$

$$\frac{\partial m}{\partial \tau} = \frac{-(\sigma+1)^2(1-\eta)}{P^2} > 0$$

where $P = \tau + \eta(1-\tau) + \sigma$. Since $\frac{\partial m}{\partial \tau} > 0$, $m < 0$ and $\kappa \in (0,1)$ the term, $(1-\kappa)^m > 1$, is strictly decreasing in τ. Since $\frac{\partial h_0^*(\theta)}{\partial \tau} < 0$, combined result in (23) is positive, hence $\frac{\partial^2 \tilde{\chi}(\theta)}{\partial \theta \partial \tau} > 0$. Since $\frac{\partial \tilde{\chi}(\theta)}{\partial \theta} < 0$ the cross derivation decreases in magnitude.

$\square$

Proposition 3. Consider the equilibrium defined in Definition 2 and Definition 3 (No-WFH).

If $\eta > 1$, $\kappa \in (0,1)$, and $\frac{d\tilde{\chi}(\theta)}{d\tau} < 0$, then:

The elasticity of taxable income (ETI) is higher in the WFH environment compared to the No-WFH environment—that is, compared to an equilibrium in which all workers are required to work on-site:

$$|ETI^*_{wfh}| > |ETI^*_{no-wfh}|$$

$$\frac{dlog(y(\theta))}{dlog(\tau)} = \underbrace{\frac{dlog y_0(\theta)}{d\tau}\tau}_{\text{no-wfh}} + \frac{dlog}{d\tau}\left(\overbrace{Z(\tilde{\chi}(\theta))}^{office} + \overbrace{(1 - Z(\tilde{\chi}(\theta)))}^{home}(1-\kappa)^{\frac{(1+\sigma)}{\tau+\eta(1-\tau)+\sigma}}\right)\tau \tag{24}$$

where,

$$\frac{dlog y_0(\theta)}{d\tau}\tau < 0$$

$$\frac{dlog}{d\tau}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{\tau+\eta(1-\tau)+\sigma}}\right) < 0$$

and using the definition of $\frac{dlog(y)}{dlog(\tau)}$ for tax elasticity.

Proof. We can write income level for any skill, $y(\theta)$, with weighted terms by workplace, i.e.

$$y(\theta) = y_0(\theta)\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{P}}\right)$$

where $y_0(\theta)$ is equilibrium income level for skill θ, at office, which is common term in both WFH and No-WFH environments. Hence, the term $\frac{dlogy_0(\theta)}{d\tau}\tau < 0$, both denotes income elasticity in No-WFH environment, and can be decomposed in WFH environment. Consider taking logs and differentials as following:

$$logy(\theta) = logy_0(\theta) + log\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{P}}\right)$$

$$\frac{dlogy(\theta)}{d\tau} = \frac{dlogy_0(\theta)}{d\tau} + \frac{dlog}{d\tau}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{P}}\right)$$

$$\frac{dlog}{d\tau}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{P}}\right) =$$
$$\frac{1}{Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{P}}}\frac{d}{d\tau}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{P}}\right)$$

$$\frac{d}{d\tau}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{P}}\right) =$$

$$\frac{dZ(\tilde{\chi}(\theta))}{d\tau} + \frac{d(1 - Z(\tilde{\chi}(\theta))}{d\tau}(1-\kappa)^{\frac{(1+\sigma)}{P}} + (1 - Z(\tilde{\chi}(\theta))\frac{d(1-\kappa)^{\frac{(1+\sigma)}{P}}}{d\tau} =$$

Since $\frac{dZ(\tilde{\chi}(\theta))}{d\tau} = -\frac{d1-Z(\tilde{\chi}(\theta))}{d\tau}$

$$= \frac{dZ(\tilde{\chi}(\theta))}{d\tau}\left(1 - (1-\kappa)^{\frac{(1+\sigma)}{P}}\right) + (1 - Z(\tilde{\chi}(\theta))\frac{d(1-\kappa)^{\frac{(1+\sigma)}{P}}}{d\tau}$$

Note that $\left(1 - (1-\kappa)^{\frac{(1+\sigma)}{P}}\right) > 0$ and $\frac{dZ(\tilde{\chi}(\theta))}{d\tau} < 0$ as $\frac{d\tilde{\chi}(\theta)}{d\tau} < 0$, which is shown before. Therefore first term above is negative. The last object in the second term:

$$\frac{d(1-\kappa)^{\frac{(1+\sigma)}{P}}}{d\tau} = -log(1-\kappa)\frac{(1+\sigma)}{P^2}(1-\eta) < 0$$

Hence:

$$\frac{dZ(\tilde{\chi}(\theta))}{d\tau} + \frac{d(1 - Z(\tilde{\chi}(\theta))}{d\tau}(1-\kappa)^{\frac{(1+\sigma)}{P}} + (1 - Z(\tilde{\chi}(\theta))\frac{d(1-\kappa)^{\frac{(1+\sigma)}{P}}}{d\tau} < 0$$

and:

$$\frac{dlog}{d\tau}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{P}}\right) < 0$$

,

□

Proposition 4. Consider the equilibrium defined in Definition 2 and Definition

3 (No-WFH).

If $\eta > 1$ and $\kappa \in (0, 1)$, and using the variance of income as a measure of inequality, then:

Income inequality in the WFH environment is lower than in the No-WFH environment:

$$\mathrm{Var}(y_{\text{wfh}}) < \mathrm{Var}(y_{\text{no-wfh}}),$$

where the reduction in inequality implies a diminished need for redistribution and provides support for lower tax progressivity in the WFH setting.

Proof. Similar to Proposition 3, we write income level for any θ as following:

$$y(\theta) = y_0(\theta)\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{\tau+\eta(1-\tau)+\sigma}}\right) < y_0(\theta)$$

Note that while $\eta > 1$ and $\tau \in (0, 1)$, $\frac{(1+\sigma)}{\tau+\eta(1-\tau)+\sigma} \in (0, 1)$, and for any $\kappa \in (0, 1)$

$$(1-\kappa)^{\frac{(1+\sigma)}{\tau+\eta(1-\tau)+\sigma}} \in (0, 1)$$

and finally:

$$\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)}{\tau+\eta(1-\tau)+\sigma}}\right) \in (0, 1)$$

as $Z(\tilde{\chi}(\theta)) \in (0, 1)$ indicating measure of office workers for any θ. That implies $Var(y(\theta)) < Var(y_0(\theta))$, which means inequality implied in the model is always lower with WFH model compared to No-WFH model.

□

Proposition 5. Consider the equilibrium defined in Definition 2 and Definition 3 (No-WFH) within a partial equilibrium setting—that is, treating λ as exogenous.

If $\eta > 1$, $\kappa \in (0, 1)$ then $\forall \theta \in \Theta$:
The elasticity of consumption with respect to marginal income changes is lower in the WFH environment compared to the No-WFH environment:

$$\frac{dlog(c(\theta))}{dlog\theta} = \underbrace{(1-\tau)\frac{dy_0(\theta)}{dlog\theta}}_{\text{no- wfh}} + \frac{dlog}{d\theta}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)(1-\tau)}{\tau+\eta(1-\tau)+\sigma}}\right)\theta \tag{25}$$

$$< (1-\tau)\frac{dy_0(\theta)}{dlog\theta}$$

Proof.

$$logc(\theta) = (1-\tau)logy_0(\theta) + log\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)(1-\tau)}{P}}\right) + const.$$

Note that, $y_0(\theta)$ indicating both equilibrium income of office workers and also main component of home workers' as there is no other heterogeneity affecting equilibrium income, i.e. $y_1(\theta) = y_0(\theta)(1-\kappa)^{\frac{(1+\sigma)}{P}}$. For instance, as considering any shock to income, either systemic or idiosyncratic,

$$dlog(y_1(\theta)) = dlog(y_0(\theta)),$$

since the remaining component is constant,

Hence, $dlog(y_0(\theta))$, indicating any shock to income, either systemic wage or idiosyncratic productivity shocks. Then:

$$dlogc(\theta) = (1-\tau)dlogy_0(\theta)+dlog\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)(1-\tau)}{\tau+\eta(1-\tau)+\sigma}}\right)$$

$$\frac{dlog(c(\theta))}{dlog\theta} = (1-\tau)\frac{dy_0(\theta)}{dlog\theta} + \frac{dlog}{dlog(\theta)}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)(1-\tau)}{\tau+\eta(1-\tau)+\sigma}}\right)$$

Since

$$\frac{dlog}{dlog(\theta)}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)(1-\tau)}{\tau+\eta(1-\tau)+\sigma}}\right) =$$

$$\frac{dlog}{d\theta}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)(1-\tau)}{\tau+\eta(1-\tau)+\sigma}}\right)\theta$$

Note that, the term $\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)(1-\tau)}{\tau+\eta(1-\tau)+\sigma}}\right) > 0$,
and $\frac{\partial(1-Z(\tilde{\chi}(\theta))}{\partial\theta} > 0$, and $\frac{\partial(1-Z(\tilde{\chi}(\theta))}{\partial y_0(\theta)} = -\frac{\partial Z(\tilde{\chi}(\theta)}{\partial y_0(\theta)}$. Since, $(1-\kappa)^{\frac{(1+\sigma)(1-\tau)}{\tau+\eta(1-\tau)+\sigma}} < 1$, when $\eta > 1$.

Then, $\frac{\partial}{\partial\theta}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)(1-\tau)}{\tau+\eta(1-\tau)+\sigma}}\right) < 0$, hence:

$$\frac{dlog}{d\theta}\left(Z(\tilde{\chi}(\theta)) + (1 - Z(\tilde{\chi}(\theta)))(1-\kappa)^{\frac{(1+\sigma)(1-\tau)}{\tau+\eta(1-\tau)+\sigma}}\right) < 0$$

$\square$

Lemma 1. $Var(log(\theta)) = Var(log(\theta)|onsite)$

Proof.

$$E(log(\theta)|onsite) = \int_0^\infty ln(\theta)\frac{\partial}{\partial\theta}\left[\frac{\text{Prob}\,(s<\theta,\chi\leq\chi(\theta))}{\text{Prob}\,(\chi\leq\chi(\theta))}\right]d\theta \qquad (26)$$

$$= \int_0^\infty ln(\theta)\left[\frac{1}{\theta\rho}\phi\left(\frac{\ln\theta-(\mu+\rho^2(M))}{\rho}\right)\right]d\theta$$

where, using $u = ln(\theta)$ and $d_u = d_\theta\frac{1}{\theta}$, and $\phi(.)$ is standard normal PDF:

$$= \int_{-\infty}^\infty u\left[\frac{1}{\rho}\phi\left(\frac{u-(\mu+\rho^2(M))}{\rho}\right)\right]du = \mu+\rho^2 M$$

where expression $\frac{\text{Prob}(s<\theta,\chi\leq\tilde{\chi}(\theta))}{\text{Prob}(\chi\leq\tilde{\chi}(\theta))}$ represents conditional CDF derived by Bayes rule, and

$$\text{Prob}\,(\chi\leq\tilde{\chi}(\theta)) = \int_0^\infty\left(\frac{\tilde{\chi}(\theta)}{\zeta}\right)f(\theta)d\theta = \frac{\upsilon}{\zeta}\exp\left(\mu M+\frac{1}{2}\rho^2M^2\right)$$

where, we re-define $\tilde{\chi}(\theta) = \upsilon\theta^m$, υ denotes components of threshold except skill, θ, using indirect utilities since it is feasible to decompose. Solving a similar algebra:

$$\text{Prob}\,(s<\theta,\chi\leq\tilde{\chi}(\theta)) = \int_0^\theta\left(\frac{\tilde{\chi}(s)}{\zeta}\right)f(s)ds = \frac{\upsilon}{\zeta}\exp\left(\mu M+\frac{1}{2}\rho^2M^2\right)\Phi\left(\frac{\ln\theta-(\mu+\rho^2M)}{\rho}\right)$$

where, $\Phi\left(\frac{\ln\theta-(\mu+\rho^2 M)}{\rho}\right)$ CDF of normal distribution evaluated at $ln\theta$. Finally, we already know the key equation (19), and using as following:

$$E(log(\theta)^2|onsite) = \int_0^{\infty} ln(\theta)^2 \frac{\partial}{\partial\theta}\left[\frac{\text{Prob}\,(s<\theta,\chi \le \chi(\theta))}{\text{Prob}\,(\chi \le \chi(\theta))}\right] d\theta = \rho^2 + \left(\mu+\rho^2 M\right)^2 \tag{27}$$

Using and (24) and (25)

$$Var(log(\theta)|onsite)) = \rho^2 + \left(\mu+\rho^2 M\right)^2 - \left(\mu+\rho^2 M\right)^2 = \rho^2$$

□

Appendix- B

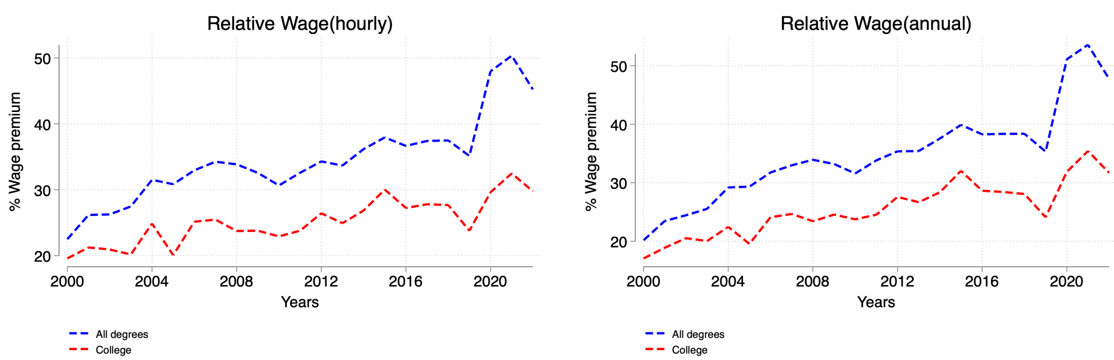
Empirical Patterns About WFH

Figure 5 presents the relative mean real wages in log terms, conditioned on the work environment (home vs. onsite), defined as follows:

$$E_i(log(wage_{it})|_{wfh=1}) - E_i(log(wage_{it})|_{wfh=0}), \tag{28}$$

where $wfh = 1$ or $wfh = 0$, mean workers work from home or onsite, respectively.

Figure 11: Relative wage by work place: home vs. onsite

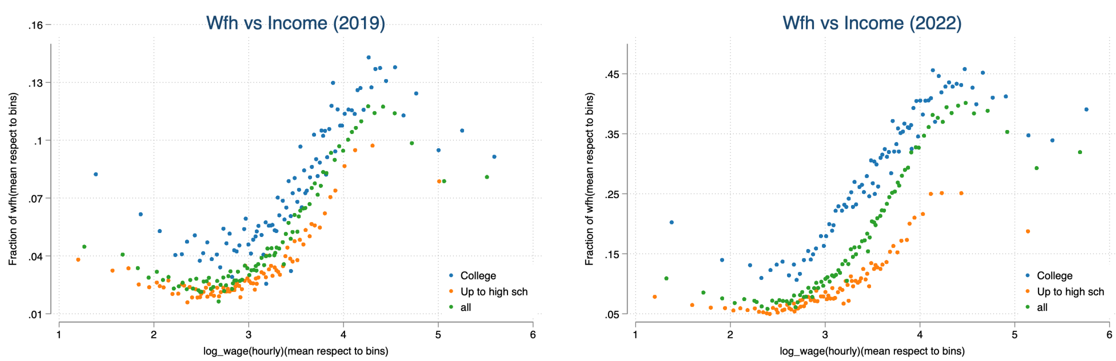


(a) The figures show the wage premium based on work place(wfh or onsite) for hourly wage income and the total wage income respectively. Red line illustrates same statistic for college graduate workers. Sample weights are used to adjust probability of selection of respondents

The figures illustrate the wage premium associated with workplace type (WFH or onsite) for hourly wage income and total wage income, respectively. Displaying both clarifies the differences in usual hours worked throughout the year and how these may correlate with remote work. As shown in Figure 5, there is a notable wage premium for remote workers, especially in terms of hourly wages. Specifically, the relative wage difference ranges from 30% to 40% during the period 2004–2019, increasing to 40%–50% after the COVID-19 pandemic.

Before presenting the components of wage differentials, I introduce Figure 6 to provide another perspective on the statistic by combining the fraction of WFH across productivity levels. Figure 6 illustrates the fraction of WFH relative

Figure 12: Mean wages vs. WFH rates



to the mean hourly wages in log terms for two sample years, 2019 and 2022. Mean wages are grouped into percentiles, with three demographic categories represented by education levels: college, high school, and dropout, as well as the entire sample. The corresponding fraction of WFH is calculated for each bin of wages. It is not hard to predict that the rate of WFH would be higher for the college-educated or higher-income groups even without plotting the data. However, the presence of a monotone-like shape over productivity patterns is interesting in the plot. This pattern is largely preserved after COVID-19, with the rate of WFH reaching up to 45% for the higher-income college-educated group, while ranging between 5% and 15% for lower-income groups based on demographics—a tripling of the rate compared to 2019.

Akil (2024) models that the observed premium in Figure 5 could be a result of positive selection into WFH. Specifically, relying on the growing literature on productivity loss associated with WFH, he shows that preferences in which the income effect dominates the substitution effect in labor supply decisions are sufficient to generate the observed premium. In other words, the selection effect for WFH is observable in survey data. I apply the same identification procedure of the differentials in wage statistics from that paper using ACS data. The following regression model is used:

$$log(wage_{it}) = \beta_1 wfh_{it} + X_{it}^{'}\beta_2 + \epsilon_{it}, \tag{29}$$

where $log(wage_{it})$ is the log of hourly relative wage of employed worker i in year t. The variable wfh serves as a binary indicator, taking the value 0 for onsite workers (os) and 1 for those working from home (wfh). The empirical model incorporates several fixed effects in various combinations, detailed in the corresponding tables. The first set of controls follows the Mincerian framework. Additionally, the model includes fixed effects for location (state), industry (based on 3-digit Census classification), and occupation (also classified at the 3-digit Census level). As noted in the tables, the total number of fixed effects across models can exceed 746.

Table 11 displays the results for the empirical model specified in equation (27). It organizes the estimates by three different sample periods—2021-2022, 2017-2019, and 2000-2005. Each sub-table presents results for multiple models (numbered 1 to 7), each using different combinations of control variables, capturing both human capital and demographic factors.

In the first column of Table 11, the data show that, in real terms, remote workers earned 48% higher wages than their onsite counterparts in the 2021-2022 period, up from 37% in the 2017-2019 sample. After accounting for human capital, industry, and occupational fixed effects, the wage premium for remote workers narrows to 11%. This premium declines further to 8% for the 2017-2019 sample and 6% for the 2000-2005 sample. A central insight from these results is that education-related covariates account for a significant share of the wage premium, explaining over 20% in the 2021-2022 sample and around 14% in the earlier periods. While other Mincerian controls have less influence on the WFH premium, they still play a crucial role in explaining variation in log wages, as reflected in the R^2 statistics. Including fixed effects for industry and occupation notably reduces the WFH premium—nearly halving it—across all samples, as seen by comparing models 6 and 7 with model 5. An important takeaway is the historical consistency of these trends, evidenced by similar patterns in the 2000-2005 data.

Table 19: WFH Coefficients from OLS Regressions of Wage (27):

Dependent variable: Log Hourly Wage							
Sample: 2021-2022	1	2	3	4	5	6	7
wfh	0.48***	0.25***	0.24***	0.24***	0.22***	0.17***	0.11***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.07	0.23	0.27	0.32	0.34	0.38	0.46
$\#Obs.(millions)$	1.37	1.37	1.37	1.37	1.37	1.37	1.37
Sample: 2017-2019							
wfh	0.37***	0.20***	0.15***	0.15***	0.14***	0.11***	0.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.01	0.22	0.28	0.33	0.35	0.40	0.48
$\#Obs.(millions)$	2.13	2.13	2.13	2.13	2.13	2.13	2.13
Sample: 2000-2005							
wfh	0.27***	0.13***	0.10***	0.10***	0.10***	0.09***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
R^2	0.01	0.21	0.25	0.31	0.33	0.38	0.45
$\#Obs.(millions)$	4.31	4.31	4.31	4.31	4.31	4.31	4.31
High School		✓	✓	✓	✓	✓	✓
Some College		✓	✓	✓	✓	✓	✓
College		✓	✓	✓	✓	✓	✓
Graduate		✓	✓	✓	✓	✓	✓
Age			✓	✓	✓	✓	✓
Age^2			✓	✓	✓	✓	✓
Race				✓	✓	✓	✓
Gender				✓	✓	✓	✓
Married				✓	✓	✓	✓
Head of Hous.				✓	✓	✓	✓
Location					✓	✓	✓
Industry						✓	✓
Occupation							✓
Year	✓	✓	✓	✓	✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓	✓
$\#Controls$		4	6	10	64	220	750

(a) OLS estimations over pooled samples are reported in each sub-table. The row corresponding to "Wfh" in each sub-panel indicates the estimated WFH coefficient, representing the wage premium. The numbers in brackets are robust standard errors. The row labeled "$\#Controls$" indicates the number of fixed effects included in each estimation, excluding time (Year) effects, constants, and weights. Sample weights are applied to adjust for the probability of selection of the respondent. Significance levels: *** p<0.001, ** p<0.01, * p<0.05.
$**$ Location includes both state and metropolitan status indicators. For the 2000–2005 sample, metropolitan status is excluded due to a high rate of missing observations. As a result, the number of control variables is four fewer in the last three models for this sample.

The takeaway from these empirical results is that there is selection into WFH. I propose that part of the observed premium could arise from the interaction between preferences and productivity loss. The mechanism leading to this effect is demonstrated in the model section.

Appendix- C

No-WFH Equilibrium

The representative firm chooses optimum amount of hours by considering following problem:

$$max_N AN - wN, \tag{30}$$

Individuals optimize as following:

$$max_{c,h} U(c,h,0) \quad \text{st.} \quad c \leq y_0 - T(y_0), \quad c \geq 0. \tag{31}$$

equilibrium in the labor and good markets holds in 28, 29 respectively:

$$\int_\Theta h((\theta) dF(\theta) = N \tag{32}$$

$$\int_\Theta c(\theta) dF(\theta) + G = AN = Y \tag{33}$$

government budget holds with:

$$G = \left(Ah(\theta) - \lambda (Ah(\theta))^{1-\tau} \right) \} dF(\theta) \tag{34}$$

Definition 2.(No-WFH) A competitive equilibrium is constituted with wage w, government policy $\{\lambda, \tau\}$, allocation for workers $\{h(\theta), c(\theta)\}$ $\forall \theta \in \Theta$, and quantities for firm $\{N, Y\}$ st individuals solve the problem in (29) and firm solve the problem in (28) , and (30) and (31) determine labor market and good market equilibrium respectively, (32) balances the government budget.

Distribution of Amenity

Figure 13: Distribution of Amenity: crafted CDF(blue) vs uniform CDF(orange)