Work from Home, Work for Less?

How workplace flexibility affects mothers' careers

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Abstract

The rise of work-from-home (WfH) has become a durable feature of 21st-century labor markets, raising a key question for gender equality: Is WfH a stepping stone or a stumbling block for women's careers? While WfH could help women reconcile professional and family responsibilities, it may also slow career advancement through productivity losses and lead to stronger specialization in domestic work. To study the short- and long-run macroeconomic implications of an expansion in WfH opportunities, I develop a quantitative general-equilibrium, overlapping-generations model calibrated to pre-COVID U.S. data. Couples jointly choose their time allocation between market and domestic work, WfH adoption, and occupation. The model predicts that expanding WfH opportunities strengthens mothers' careers in the long-run: women's earnings growth between ages 25 and 40 increases by 7.2 percentage points, and the gender earnings gap narrows by 7.4 percent. Women benefit both from their own and their spouses' WfH adoption as well as through re-sorting into higher-paying occupations. However, some women experience career losses when working in occupations where WfH entails high productivity penalties. At the aggregate level, welfare rises by 11.1 percent and output by 0.5 percent. Important for the current policy debate, I find short-run losses in women's earnings from WfH adoption, as occupational choices are fixed and the expansion of WfH is large and unexpected.

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1 Introduction

Spurred by the COVID-19 pandemic, remote work expanded rapidly and has become a durable feature of the U.S. labor market (Barrero et al. 2023). Because women tend to demand greater job flexibility than men to balance work and family life, the rise of work-from-home (WfH) raised the question of whether women's careers would benefit disproportionately from this expansion of workplace flexibility.[1] However, little is known about its long-run impact on women's earnings trajectories. If WfH allows women or their spouses to save commuting time and better manage household responsibilities, it may yield particularly high career returns for mothers and possibly encourage switching toward higher-paying occupations where WfH opportunities expanded more strongly. Yet, WfH could also reduce productivity and hinder learning and promotions over time, potentially reinforcing women's specialization in domestic work and consequently, harming their careers. This raises the central question of my paper: Is WfH a stepping stone or a stumbling block for women's careers? At a time when firms and policymakers increasingly signal intentions to scale back remote work, understanding the potential long-term labor market implications of WfH is critical for informing debates on workplace policy and labor market inequality.[2]

To address this question, this paper studies how a sudden and large expansion in WfH opportunities reshapes mothers' careers and reduces gender disparities, both in the short and long run, against the backdrop of persistent gender gaps in earnings, labor supply, and wage growth in the United States.[3] I build a quantitative, general-equilibrium, overlapping-generations model in which couples jointly decide each spouse's time allocation between market and domestic work, occupation choice, and WfH adoption. The main finding is that expanding WfH opportunities improves mothers' long-run career outcomes: by age 40, their average earnings growth is 7.2 percentage points higher relative to the old, low-WfH economy. However, the underlying heterogeneous career gains or losses from WfH adoption depend critically on occupation-specific trade-offs associated with WfH.

In the model, married individuals differ in their initial education and accumulate human capital at a pace that depends on their occupation, workplace, and work hours. The framework's novelty lies in introducing a trade-off in job flexibility through remote work. Workers have idiosyncratic preferences for WfH, and the saved commuting time can be reallocated to other activities, helping them better balance career demands and childcare responsibilities. Yet this advantage may entail an occupation-specific wage penalty, driven by both instantaneous productivity losses and slower human-capital accumulation from reduced learning and promotion opportunities. This tension is particularly critical early in women's careers, when steep learning curves meet heightened childcare demands. Moreover, access to WfH opportunities increases with human capital, capturing that

[1] See e.g. Albanesi and Kim (2021), Alon et al. (2022), Alon et al. (2020a), Alon et al. (2020b) and Goldin (2022).
[2] See e.g. Bindley (2025), Hoff and Dorman (2025) and Iacurci (2025).
[3] Henceforth, I will use remote work or work-from-home interchangeably.

remote work is technically more feasible in jobs higher up the human capital ladder. Thus, the upfront investment of work hours needed to build human capital creates a dynamic trade-off between workplace flexibility and time allocation. I distinguish between higher-skill *abstract* and lower-skill *routine* occupations following the task-based framework of Acemoglu and Autor (2011). Similar to Adda et al. (2017), this occupation classification captures women's occupational trade-off between lifetime earnings and job flexibility. In my setting, occupations additionally differ in both the productivity effects and the availability of WfH opportunities, making them central to evaluating this trade-off for women's careers.

I calibrate the model to U.S. data from the 2010s, prior to the particular context of the pandemic recession. The Survey of Income and Program Participation (SIPP) provides detailed information on workers' remote work behavior, wages, and occupations, while the American Time Use Survey (ATUS) captures gender differences in time allocation between market and domestic work. The model is calibrated to match the overall level and life-cycle patterns of married couples' market and domestic work, occupational wage profiles, the distribution of remote workers across occupations, and female occupation shares. In a simulated event study, the model also reproduces the surge in WfH adoption following the pandemic-induced shock. The simulated economy further replicates several patterns not directly targeted in the calibration. These include work hours by occupation and workplace, gender-specific WfH take-up by occupation, and the empirical relationship between own and spousal WfH adoption and market hours observed in the SIPP. Moreover, the model's implied human capital depreciation rates from work interruptions and returns to work experience by occupation are comparable to previous estimates in the literature. To calibrate instantaneous productivity effects of remote work, I draw on recent empirical evidence: average productivity losses following WfH adoption are 3.5% in routine jobs and 11.5% in abstract jobs.[4] Exploiting the panel structure of the SIPP, I further discipline workers' selection into WfH and estimate its effect on wage growth. WfH participation slows human capital accumulation by 2.3% in abstract occupations but raises it by 7% in routine jobs. These contrasting effects may reflect differences in task characteristics—abstract jobs involve stronger coordination needs and lower worker substitutability than in routine jobs, making physical proximity more valuable for productivity and learning.

To assess the short- and long-term impact of remote work on women's careers, I simulate a permanent and unexpected shock that expands WfH availability to its estimated full potential—37% of all jobs (Dingel and Neiman 2020). Accounting for general-equilibrium effects that operate through changes in occupation-specific labor supply and the resulting relative wage adjustments, I analyze how this expansion affects the transition path and the new steady-state equilibrium with a high prevalence WfH opportunities. The analysis focuses on changes in occupational allocation,

[4] I compile empirical estimates of WfH productivity effects from Bloom et al. (2015), Atkin et al. (2023), Bloom et al. (2024), Emanuel and Harrington (2024), Gibbs et al. (2021), and Gibbs et al. (2024).

market hours, domestic time, earnings growth, and wages for both men and women, allowing for heterogeneity by education, occupation and age.

In doing so, this paper contributes to the literature by developing a structural framework that embeds workplace flexibility into the analysis of gender inequality, linking gender gaps in domestic responsibilities and occupational sorting to remote work opportunities. By endogenizing occupational choice, couples' joint time allocation between market and domestic work, and potential WfH productivity penalties, the model enables a unified assessment of how remote work reshapes intra-household decisions, career dynamics, and gender disparities over time. It further extends existing quantitative frameworks by capturing not only short-term but also long-term effects of WfH. These arise through occupational re-sorting and dynamic productivity impacts on human capital accumulation.

Three main insights emerge from my analysis. First, in the long run, expanding WfH opportunities raises women's career outcomes: average earnings growth between ages 25 and 40 increases by 7.2 percentage points. However, the effects are heterogeneous and depend on both spouses' occupations, creating career winners and losers. Women in abstract occupations experience career losses from their own WfH take-up due to the static and dynamic productivity penalties associated with WfH in these jobs. By contrast, women in routine occupations benefit because the saved commuting time and lower productivity penalties result in positive net career gains. Women also benefit indirectly when their male spouses—who are disproportionately employed in abstract occupations—adopt WfH. Spousal WfH in abstract occupations increases men's contributions to domestic work and reduces household income, both of which encourage women to raise their market hours and accumulate more human capital. The largest gains accrue to a small group (4.6%) of highly educated women who switch into abstract occupations in response to the WfH expansion. This group experiences particularly strong earnings growth, as occupational switching exposes them to higher wages and faster human capital accumulation.

Second, in the long run, women's career gains translate into narrower aggregate gender gaps in labor outcomes. Gaps in hourly wages (-2.9%), market hours (-6.6%), and labor earnings (-7.4%) all decline, while men increase their domestic work (+6.3%) and the share of female breadwinners rises (the gap narrows by 14.7 percentage points). The reduction in gender gaps is mainly driven by women's stronger re-sorting into abstract occupations relative to men. This pattern reflects women's higher demand for workplace flexibility, which expands more strongly in abstract jobs. Since switching to abstract work is only profitable for highly educated workers, women in routine occupations are particularly likely to switch: they are initially overrepresented among highly educated routine workers—those near the occupational switching threshold—because of their comparative advantage in home production. As WfH opportunities expand more in abstract jobs, this group has a higher probability of transitioning into abstract work. Moreover, women are less affected by productivity losses from their own WfH adoption, as they more often use WfH in

routine jobs than men where net career gains prevail. At the same time, they benefit more from their spouses' WfH adoption: since men are concentrated in abstract jobs, spousal WfH generates stronger negative cross-income effects, which incentivize women to increase market hours and accumulate human capital.

Third, expanding WfH opportunities raises both welfare and output. Average ex-ante welfare increases by 11.1% in consumption-equivalent terms, as couples value workplace flexibility and more of them benefit from a broader set of workplace choices after the expansion of WfH. Aggregate output rises by 0.47%, driven by higher market hours and greater human capital accumulation among workers in routine jobs and workers switching into abstract occupations. These gains more than offset the efficiency losses from WfH adoption in abstract jobs.

These findings shed light on the long-run effects of remote work on women's careers and thereby carry important insights for economic policy. If productivity penalties from working from home were to vanish in the long run, output would rise less and women would still experience career gains, but smaller ones. The muted response in women's careers primarily stems from women in routine jobs whose spouses take up WfH in abstract occupations. With productivity penalties, women react strongly to the negative cross-income effects of male WfH adoption; without them, this channel weakens. Nevertheless, women's market hours and earnings growth still rise. This pattern reflects men's continued increase in domestic work after adopting WfH: despite higher own productivity, these men are already high-hour, high–human-capital workers for whom additional market hours yield limited returns. The resulting intra-household substitution in home production incentivizes women to maintain higher levels of market hours.

Finally, these long-run effects mask important short-run dynamics. I find that in the short run women's earnings decline. Along the start of the transition path, when WfH opportunities expand unexpectedly and substantially, supplied labor efficiency units in routine jobs increase (due to productivity gains and saved commuting time), while they decline in abstract jobs (due to stronger productivity penalties). This temporarily raises abstract wages and lowers routine wages, reducing women's aggregate earnings since they are more concentrated in routine jobs. Over time, as new cohorts anticipate WfH and more women shift into abstract occupations, the supply of abstract labor rises, routine wages recover, and aggregate female earnings grow.

This paper is structured as follows. Section 2 situates my work within the existing literature. Section 3 presents the empirical facts that guide the specification and estimation of the model. Section 4 introduces the model, while Section 5 details the estimation strategy. Section 6 discusses the key features of the baseline economy. Section 7 presents the main counterfactual analysis of the WfH opportunity shock. Section 8 decomposes the contribution of the model's main mechanisms, and Section 9 analyzes the transition dynamics. Finally, Section 10 concludes.

2 Related Literature

In the following, I discuss the three main strands of literature to which I relate and contribute with my paper.

2.1 Job Flexibility and Gender Inequality

Despite substantial convergence over recent decades, gender disparities in earnings, labor force participation, work hours, and career progression remain persistent in the United States (Blau and Kahn 2017; Blau et al. 2024). Explanations for these gaps—centered on gender differences in human capital accumulation or discrimination—have increasingly been supplemented by insights from household economics. This line of research emphasizes the role of intra-household dynamics, showing that women, and especially mothers, devote considerably more time to childcare and household tasks than men (Cortés and Pan 2023; Bertrand et al. 2010). These patterns heighten the value of job flexibility for working mothers to reconcile domestic work with career aspirations.

Job flexibility is inherently multidimensional, encompassing both temporal flexibility—the ability to adjust when one works—and workplace flexibility—the ability to choose where one works. Much of the prior literature has concentrated on temporal flexibility, including flexible schedules, the ability to interrupt work, part-time work, or the avoidance of long hours (Cortés and Pan 2019; Cubas et al. 2022; Erosa et al. 2022; Goldin and Katz 2011; Goldin 2014). A key insight from this body of work is that women's higher demand for temporal flexibility drives occupational sorting into more accommodating jobs, which typically offer lower wages and slower wage growth. This sorting mechanism contributes to the persistence of gender pay gaps, as it effectively locks women into flatter career trajectories.

While much of the existing literature has focused on when people work, comparatively less attention has been given to where they work—that is, to workplace flexibility and the rise of remote work. My paper bridges this gap by embedding the gender inequality narrative, centered on unequal domestic responsibilities and occupational sorting, into a structural framework that explicitly introduces a trade-off through workplace flexibility decisions.

2.2 Workplace Flexibility and the COVID-19 Pandemic

Motivated by the COVID-19 pandemic–induced surge in remote work, a growing body of research has exploited this large-scale shock as a natural experiment to understand the impact of remote work on female labor market outcomes and gender disparities. The pandemic-induced recession

provided a particular context, as widespread school closures, lockdowns, and sector-specific disruptions intensified the conflict between family responsibilities and career demands.

Overall, women—especially mothers—were disproportionately affected by the pandemic, experiencing sharper employment and hours losses than men. However, the availability of WfH arrangements helped shield some women from job loss (Couch et al. 2022). Beyond the immediate pandemic context, researchers began to ask to what extent the post-pandemic "new normal" of permanently higher remote work opportunities might benefit women, and particularly mothers.

Theoretical and empirical studies have offered contrasting perspectives. Some conjecture that if primarily women take up WfH, this could have adverse consequences for their careers by reinforcing existing gender norms (Albanesi and Kim 2021). Others adopt a more optimistic view, suggesting that increased job flexibility—especially the option to work from home—has the potential to substantially benefit women by facilitating a more equal division of domestic labor within households (Alon et al. 2022 and Alon et al. 2020a). At the same time, these studies acknowledge that WfH may in some cases lead to further specialization of women into domestic tasks and potential productivity losses.

A key insight emerging from this literature is the importance of considering both spouses' workplace flexibility. Several studies document that fathers who worked from home during the pandemic increased their participation in household work (Alon et al. 2020b; Adams-Prassl et al. 2020; Arntz et al. 2020; Buckman et al. 2025; Gaudecker et al. 2023; Yahmed and Malavasi 2024). Yet, when both partners have the option to work remotely, mothers often end up shouldering a greater share of domestic responsibilities than their male partners (Collins et al. 2021).

Finally, it has been noted that the benefits of remote work were largely confined to highly educated women in occupations suitable for telework, highlighting the unequal access to such arrangements across the skill distribution. While WfH may enhance career continuity for these women, it may also come at the cost of slower advancement or lower earnings growth (Goldin 2022).

I contribute to this growing literature by developing a novel structural framework that integrates these adjustment margins within a unified model. The framework endogenizes occupational sorting by accounting for individuals' heterogeneous educational backgrounds—which shape access to remote work opportunities—and models couples' joint allocation of time between market and domestic work. It further incorporates potential productivity penalties associated with WfH and explicitly accounts for both own and *spousal* workplace flexibility options. This approach allows for a comprehensive assessment of how expanding remote work opportunities reshape intra-household decisions, career dynamics, and gender disparities in the labor market.

2.3 The Long-run Economic Consequences of Workplace Flexibility

A growing body of quantitative and structural research examines the long-run implications of an economy-wide shift toward remote work. Much of this literature focuses on the spatial dimension of WfH adoption. Davis and Ghent (2024), Richard (2024), and Van Nieuwerburgh (2023) study how increased remote work opportunities reshape housing demand and migration patterns, as workers gain flexibility in their residential location choices. Monte et al. (2025) explore how remote work alters the relationship between city structure and agglomeration effects.

Another strand of research emphasizes the interaction of WfH with spatial misallocation of labor arising from housing regulation and tax progressivity (Zavarzin 2025). These models highlight how policy distortions may amplify or dampen the gains from remote work by constraining household mobility or altering labor supply incentives. Ji et al. (2024) show that reduced commuting time through work-from-home increase work hours and welfare. Finally, Bagga et al. (2025) investigate how remote work affects labor market dynamics more directly, focusing on vacancies, matching efficiency, and unemployment outcomes.

My contribution builds on this literature by studying the long-term and transitional effects of an expansion in remote work opportunities on married couples' labor market outcomes. I extend the existing frameworks by incorporating dynamic productivity effects of WfH through human capital accumulation and accounting for occupation re-sorting that adjusts only gradually in the short run.

3 Empirical Motivation

This section provides empirical evidence that underpins the specification of my model and informs its calibration and estimation.

3.1 Data Sources, Sample Construction and Occupation Classification

I draw on two primary data sources: the Survey of Income and Program Participation (SIPP) and the American Time Use Survey (ATUS).

For the SIPP, I focus on the 2013–2016 period, a monthly panel dataset that provides detailed information on individuals' income, work hours and employment. Crucially, this panel includes the "Commuting and Work Schedule" module, which offers rich data on commuting behavior and work-from-home arrangements. I define a remote worker as someone who is employed for pay and works at least one full day per week exclusively from home. Table 35 reports summary

statistics for WfH workers in the SIPP sample of married individuals.[5] This dataset is among the few U.S. sources to provide comprehensive pre-pandemic measures of remote work. As discussed in greater detail later, the panel structure of the SIPP is particularly valuable to exploit wage growth by workplace setting and self-selection into the workplace.

For the American Time Use Survey (ATUS), I use cross-sectional data spanning the years 2012 to 2019, opting for a slightly broader time window to ensure sufficient statistical power. The ATUS provides detailed time diary information on individuals' daily activities, which I use to construct measures of domestic work (childcare and non-market work) and market work hours, following the methodology of Aguiar et al. (2013b).

In both the SIPP and ATUS samples, I restrict the analysis to married individuals aged 24 to 65 who are not enrolled in school. After applying these restrictions, the SIPP sample includes 24,412 unique individuals, or 698,885 person-month observations, while the ATUS sample consists of 16,639 unique married individuals. Life-cycle profiles are estimated as a polynomial in age, controlling for cohort effects. Nominal values are expressed in 2010 U.S. dollars. The corresponding statistical weights are applied in both datasets.

I classify workers into two occupation types: abstract and routine occupations. This classification follows the task-based framework of Acemoglu and Autor (2011). They use information from the Occupational Information Network by the U.S. Department of Labor (O*NET) on work activities and work context to construct composite task measures.[6] Table 1 provides examples of typical routine and abstract occupations by prevalence of work-from-home.

Table 1: Census Occupation Examples

WfH Prevalence	**Abstract Occupations**
Low	Physicians, Surgeons, Industrial Production Managers
High	Natural Science Managers, Computer Systems Analysts
WfH Prevalence	**Routine Occupations**
Low	Cooks, Dental Assistants, Dishwashers
High	Technical Writers, Photographers, Legal Support Workers

Note: The table lists example occupations from the 2010 Census, classified as abstract or routine jobs with high and low WfH prevalence.

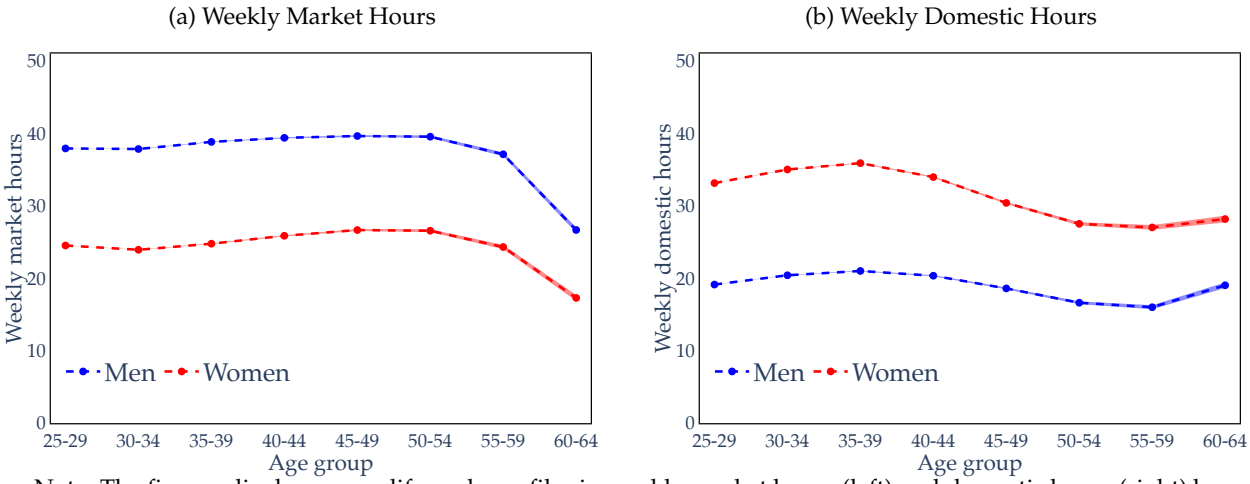
[5] In Table 35, I compare married teleworkers from the 2013–2016 SIPP to those in the 2022–2025 CPS. The two samples are similar in terms of the share of college-educated individuals, the share of women, age, and weekly work hours. The 2013–2016 SIPP contains relatively more self-employed, part-time, and fully remote workers.

[6] The composite task measures are (i) non-routine cognitive analytic, (ii) non-routine interpersonal, (iii) routine cognitive, (iv) routine manual, (v) non-routine manual physical, (vi) non-routine manual interpersonal, and (vii) offshorability. Following Adda et al. (2017), I aggregate tasks (i) and (ii) into abstract occupations, and tasks (iii) and (iv) into routine occupations. I exclude all manual occupations from the analysis, leaving me with occupations that represent 66% of U.S. employment in the considered years. Shares of total employment are calculated using national U.S. employment figures from the Bureau of Labor Statistics (2010), measured at the census occupation level.

3.2 Life-cycle Profiles in Work Hours

I estimate life-cycle profiles of weekly domestic and market work for married men and women using the ATUS data described earlier. Hours include the extensive margin. Figure 1 presents the resulting profiles. On average, married women supply fewer market hours (24.20 v.s. 37.09) and more domestic hours (31.36 v.s. 18.85) than married men. This gender gap is particularly pronounced during early adulthood (age 25-39), when childcare demands are typically highest: women substantially increase domestic work and reduce market hours more than their male counterparts. This is consistent with prior literature showing that gender disparities in labor market outcomes are closely tied to the presence of children and female specialization in non-market hours (Cortés and Pan 2023).

Figure 1: Life-cycle in Weekly Work Hours



Note: The figures displays mean life-cycle profiles in weekly market hours (left) and domestic hours (right) by gender. Profiles are estimated with a polynomial in age controlling for cohorts effects. Hours include the extensive margin. Lines are plotted with 95% confidence intervals. Domestic hours include non-market work and childcare time. I follow the estimation approach in Aguiar et al. 2013a.

3.3 Occupational Sorting and Life-cycle Wage Profiles

Using the SIPP, I estimate the share of abstract workers among married men and women, as well as life-cycle profiles of hourly wages by occupation group. I find that the share in abstract jobs is 41.4% among men and 29.8% among women. Thus, married women are 12 percentage points less prevalent in abstract occupations than married men. The resulting wage profiles are shown in Figure 2. Average wage trajectories differ markedly across occupation groups: while wages in routine occupations are relatively flat and low over the life cycle, abstract occupations exhibit higher and more steeply rising wage profiles. These differences may reflect both self-selection based on worker skills and the greater potential for wage growth in abstract occupations due to

better technologies than in routine occupations. These findings are in line with previous literature on gender differences in occupational sorting, suggesting that married women are less likely to enter occupations with higher wage growth, instead favoring non-pecuniary benefits such as temporal job flexibility offered more by lower-paying occupations (see, e.g., Adda et al. 2017). This dynamic tends to lock them into occupations with lower and flatter wage trajectories, thereby amplifying gender disparities in labor market outcomes. Consistent with Adda et al. (2017), I find that transition rates between routine and abstract occupations are generally low. Figure 3 illustrates the monthly transition rates across occupational groups by age. On average, the monthly transition rate from routine to abstract occupations is 1.30%, while the transition rate from abstract to routine occupations is 0.95%, with little variation across age groups.

Figure 2: Hourly Wages of Onsite Workers

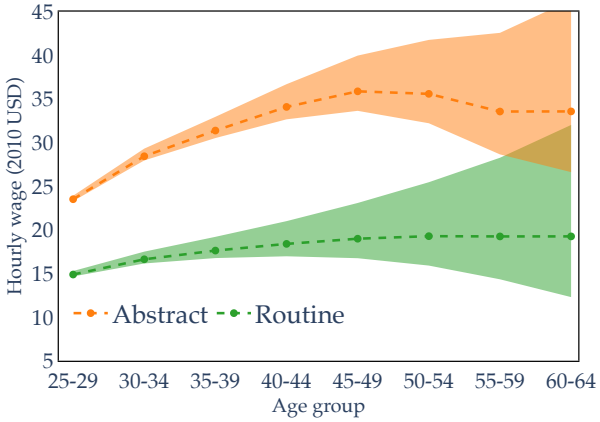
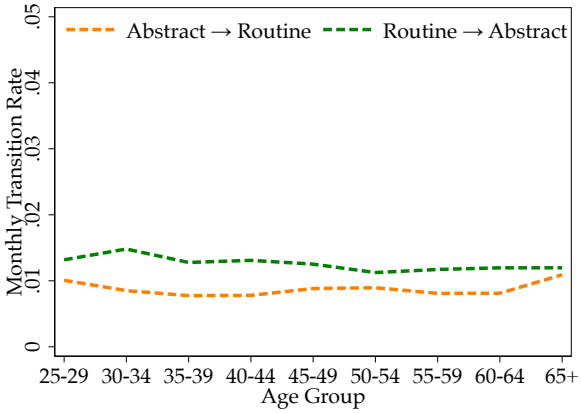


Figure 3: Occupation Transition Rates



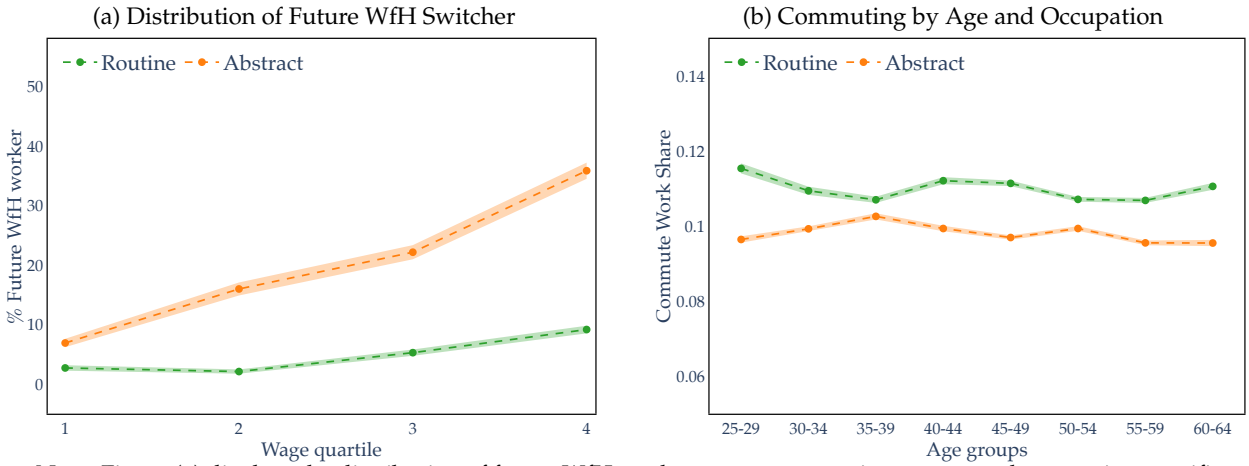
Note: The figures display life-cycle profiles in hourly 2010 USD wage rates (left) of workers working onsite in either abstract or routine occupations and monthly transition rates between occupations by age groups (right). Occupation groups are based on task-based approach from Acemoglu and Autor (2011) and constitute 66% of US employment.

3.4 Work-from-Home Adoption across Occupations

I exploit the panel structure of the SIPP to identify workers who transition to working from home (WfH) in the future. Conditional on observing at least one year of employment and wage history prior to the switch, I calculate their mean pre-switch wages and situate them within the wage quartile distribution of their occupation based on this value, controlling for age. Figure 4a shows the resulting distribution. Accordingly, the combined area under the two lines integrates to one. Two main observations emerge. First, the share of future WfH workers is higher in abstract occupations than in routine ones (81% v.s. 19%). This likely reflects the greater technological suitability of abstract occupations for remote work—e.g., computer systems analysts (abstract) versus dental assistants (routine). Second, the share of future WfH switchers increases with a worker's relative wage position within their occupation. To the extent that wages proxy human capital, this pattern suggests that even within occupation groups, workers with higher skills are

more likely to transition to WfH. This can be interpreted as implying that investing in human capital—whether by working longer hours or acquiring additional qualifications such as a data science degree—may improve access to remote-work opportunities over the course of one's career.

Figure 4: WfH Adoption and Commuting Time across Occupations



Note: Figure (a) displays the distribution of future WfH workers across occupation groups and occupation-specific wage quartiles. Data points sum up to one. Sample consists of workers with available work history for at least 1 year prior to switching to WfH or staying onsite. Figure (b) represents the mean weekly commuting time as a share of usual work hours. Values are plotted separately for abstract and routine workers with 95% confidence intervals. Values are displayed with 95% confidence intervals.

3.5 Work-from-Home and Potential Commuting Time Savings

I quantify the potential commuting time savings for married individuals using the SIPP. Specifically, it reports one-way travel time to work in minutes. Using this information, along with data on usual weekly working hours, number of days worked per week, and the number of days worked exclusively from home, I calculate the total potential weekly commuting time saved, expressed as share of weekly market work hours.[7] Proportionality is motivated by the positive co-movement between weekly commuting time and weekly work hours, as well as between weekly workdays and weekly work hours (see Figure 20 in the Appendix A), conditional on age, census occupation, and gender.[8] Accordingly, individuals who work more hours also tend to work more days per week and, mechanically, spend more total time commuting. Figure 4b displays the estimated commuting time share by occupation and age group. The share of commuting time relative to weekly market hours remains remarkably stable across age groups and

[7]Weekly market work hours exclude commuting time.
[8]Appendix A Figure 20 further present these relationships separately by gender.

is similar across occupation types—averaging 11% in abstract occupations and 10% in routine ones.[9]

3.6 Work-from-Home and Short-run Productivity

To quantify the short-term productivity effects of switching to work-from-home (WfH) in routine and abstract occupations, I review a growing body of empirical literature that aims to causally estimate these effects. Table 36 in Appendix A summarizes the relevant studies, categorizing them by occupation type—routine (e.g., call center or data-entry work) and abstract (e.g., engineers or high-skilled professionals). Beyond occupation type, the studies differ in several key dimensions. In terms of study design, some adopt randomized controlled trials (e.g., Bloom et al. 2015, Atkin et al. 2023, and Bloom et al. 2024), while others rely on event-study approaches (e.g., Emanuel and Harrington 2024, Gibbs et al. 2021, and Gibbs et al. 2024), often leveraging the exogenous shift to WfH caused by the Covid-19 pandemic or using pre-pandemic data for comparison.[10]

The definition of productivity also varies across studies, partly reflecting the nature of the work. In routine jobs, productivity is typically measured using direct performance metrics such as hourly call volumes or error rates in data-entry tasks. In contrast, for abstract jobs, productivity indicators include lines of code written, performance evaluations, number of deliverables (e.g., reports or code segments) completed per month, or the volume and quality of submitted ideas.

To synthesize findings across studies, I compute average productivity effects by occupation type. To account for differences in work-from-home intensity, I assign half the weight to studies examining fully remote work—typically associated with more negative productivity effects—relative to studies focusing on hybrid arrangements. This approach yields an average productivity effect of -3.5% for routine occupations and -11.5% for abstract occupations. The lower productivity impact in routine work may reflect the limited scope for performance losses in more standardized tasks. In contrast, abstract jobs, which often rely on collaboration and innovation, appear more sensitive to changes in work environment, with hybrid WfH arrangements generating short-run average productivity losses.

[9] a 40-hour workweek, this corresponds to approximately 48 minutes of potential commuting time saved — close to the 55 minutes of daily time savings from working from home estimated by Aksoy et al. (2023) for the U.S.

[10] Note that I have excluded several empirical studies from my calculation that rely on self-assessed productivity measures. The challenge with self-reported productivity measures lies in the potential for disparities in workers' and managers' interpretations of what productivity entails. These differences may stem from individual perceptions of productivity or a tendency to conflate productivity with personal preferences for remote work.

3.7 Work-from-Home and Wage Growth

To date, there is limited evidence on the long-run productivity effects of working from home (WfH), underscoring the need for further research in this area. Existing studies, if anything, point to negative long-term consequences. For instance, Bloom et al. (2015) show in their WfH RCT that the promotion rate conditional on performance declined by about 50% over a two-year horizon. Likewise, Emanuel et al. (2023) exploit WfH variation during the COVID-19 pandemic to study the role of coworker proximity in long-run human capital development. They find that proximity increases long-run pay as workers accumulate more human capital, with particularly strong effects for younger employees who depend on feedback and mentorship from senior colleagues. To approximate potential long-run effects—particularly the concern that WfH may hinder learning or reduce promotion prospects over time—I use wage growth as a proxy. Specifically, I exploit annual wage growth differences by workplace setting using SIPP panel data, and extrapolate these differences to the five-year horizon of my model. This approach relies on the parametric structure of the wage and human capital process in my model as identifying restrictions and leverages variation in wage growth among workplace switchers. The wage process is specified as follows:

$$w = \phi_o(1 + \delta_o(p))H. \tag{1}$$

The coefficient ϕ_o captures the occupation-specific return to human capital H. The parameter $\delta_o(p)$ represents the workplace-specific productivity adjustment, where $\delta_o(\text{onsite}) = 0$ and $\delta_o(\text{WfH}) < 0$, as estimated in the previous section. Human capital evolves over time according to the following accumulation process:

$$H' = L_o(1 + \Delta_o(p))(Hh)^{\alpha_o}. \tag{2}$$

The parameter L_o captures the occupation-specific learning ability and can be interpreted as the occupation-specific intercept of wage growth, conditional on current human capital, workplace setting (WfH or onsite), and hours worked. Analogous to the wage process, $\Delta_o(p)$ denotes the WfH adjustment factor for dynamic productivity effects, with $\Delta_o(\text{onsite}) = 0$ and $\Delta_o(\text{WfH})$ potentially reflecting slower ($\Delta_o(\text{WfH}) < 0$) or faster ($\Delta_o(\text{WfH}) > 0$) human capital accumulation when working remotely. Current human capital and work hours are denoted H and h respectively. The parameter α_o captures the elasticity of wage growth with respect to work hours and human capital. Focusing on occupation stayers but workplace switchers, dividing by current human capital H and replacing human capital with observable hourly wages, the human capital accumulation process can be

rewritten in log-linear form as follows:

$$\begin{aligned}\log\left(\frac{w'}{w}\frac{(1+\delta_o(p))}{(1+\delta_o(p'))}\right) &= \log(L_o) + \log(1+\Delta_o(p)) + \alpha_o\log(h) + (\alpha_o-1)\log\left(\frac{w}{\phi_o(1+\delta_o(p))}\right)\\ \Leftrightarrow \quad \log\left(\frac{w'}{w}\right) &= \log(L_o) + (1-\alpha_o)\log(\phi_o) + \alpha_o\log(h) + (\alpha_o-1)\log(w)\\ &\quad + \log(1+\Delta_o(p)) + (-\alpha_o)\log(1+\delta_o(p)) + \log(1+\delta_o(p'))\,,\end{aligned}$$

where w' is next period's hourly wage and p' is next period's workplace. The empirical regression counterpart, with observation of worker i of occupation-group o (abstract or routine) and year t is then:

$$\log\left(\frac{w_{iot+1}}{w_{iot}}\right) = \beta_0^o + \beta_1^o\log(h_{iot}) + \beta_2^o\log(w_{iot}) + \beta_3^o\text{WfH}_{iot} + \beta_4^o\text{WfH}_{iot+1} + \Omega_{iot} + \epsilon_{iot}. \qquad (3)$$

The variable WfH_{iot} is an indicator for working from home, while Ωiot includes additional controls: age, gender (female dummy), parental status, marital status, number of weeks worked per year, individual fixed effects, census occupation fixed effects, and cohort fixed effects.[11] The mapping from the estimated regression coefficient to the one-year learning ability effect is:

$$\begin{aligned}\hat{\beta}_3^o &= \log(1+\Delta_o(p)) + (-\alpha_o)\log(1+\delta_o(p))\\ \Leftrightarrow \quad \Delta_o(p) &= \exp\left(\hat{\beta}_3^o + \alpha_o\log(1+\delta_o(p))\right) - 1,\end{aligned}$$

which can then be translated into a five-year effect using the following transformation:

$$1 + \Delta_o^{5y}(\text{WfH}) = (1+\Delta_o(\text{WfH}))^{1+\hat{\beta}_1^o+\hat{\beta}_1^{o\,2}(1+\hat{\beta}_1^o)}\,.$$

Table 2: Estimated 5-year Dynamic Productivity Effect of WfH

	Δ_o(WfH)			
	(1)	(2)	(3)	(4)
Abstract	.0202	-.0357	-.0228	-.0226
Routine	.1304	.0512	.0689	.0696
Individual fixed effects		✓	✓	✓
Census occ. fixed effect			✓	✓
Cohort fixed effect				✓

Note: The table reports the estimated long-run productivity effect over a 5-year (model period) horizon, based on regression 3.

[11] I aggregate the data from a monthly to a yearly frequency to estimate the regression. Since I control for weekly work hours, as in the model, I also account for the number of weeks worked per year to ensure consistency in the comparison.

The resulting estimates for Δ_o^{5y} are presented in Table 2.[12][13][14] I first report results without fixed effects, and then progressively add individual, census occupation, and cohort group fixed effects. Individual fixed effects account for self-selection based on unobserved time-invariant characteristics such as ability. Occupation fixed effects address the concern that occupations with greater WfH opportunities may also exhibit systematically different wage growth trajectories, irrespective of whether an individual actually works from home, thereby potentially confounding the estimated impact of WfH on learning. Finally, cohort fixed effects capture the possibility that differences in cohort-specific wage growth correlate with variation in WfH take-up.

Upon introducing individual fixed effects, the dynamic productivity effect of abstract occupations turns negative, amounting to a -3.6% five-year penalty, while the corresponding effect in routine occupations is reduced by half to +5.1%. This pattern suggests that self-selection on unobserved individual characteristics may play an important quantitative role. After further adding occupation and cohort fixed effects, the estimates shift slightly to –2.3% in abstract occupations and +7.0% in routine occupations. Overall, the results indicate that working from home reduces learning ability over time in abstract jobs, whereas it exerts a modestly positive effect in routine jobs. Consistent with the static penalty discussed in the previous section, abstract jobs exhibit larger costs of WfH relative to routine jobs. This could be attributed to the nature of tasks in abstract occupations, where greater reliance on coordination and lower substitutability between workers might make proximity more valuable.

3.8 Life-cycle Dynamics in Work-from-Home Take-up

I estimate the life-cycle profile of work-from-home (WfH) take-up among all workers and among married women specifically, using data from the SIPP. Figure 5 presents the resulting profiles alongside the average number of children under age 18 in the household, calculated using data from the American Community Survey. Details on both data sources and sample construction are provided in Appendix A. Overall, WfH take-up increases sharply during the phase of the life cycle characterized by intense childcare responsibilities, as proxied by the average number of children in the household. In contrast, take-up is relatively low at both the beginning and end of the working life.[15] These patterns align with previous literature in several ways. Emanuel et al. (2023) show that junior and senior workers were more likely to return to the office after the pandemic-induced rise in WfH, due to their greater need for receiving (juniors) or providing (seniors) mentorship.

[12] Table 37 in Appendix A reports the full regression output of Equation (3).

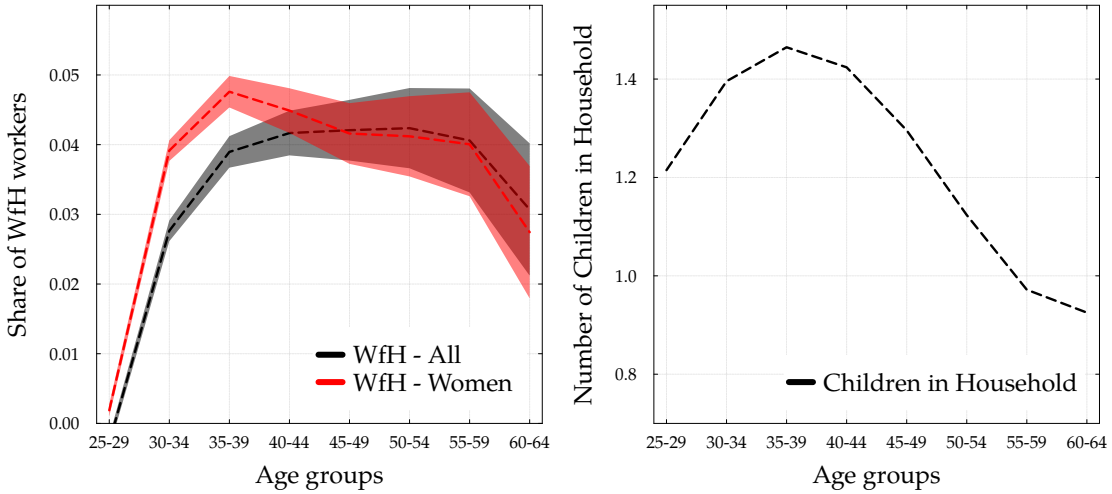
[13] Consistent with the static productivity estimates, non-married workers are included in the baseline regression sample. To assess the plausibility of these estimates, I provide additional census-occupation-level examples in Table 38 in Appendix A.

[14] In Table 39 I further present estimates for Δ_o^{5y} assuming no static productivity penalty of WfH.

[15] Assuming equal age-group sizes, I find an average work-from-home take-up rate of 3.3% among married individuals. Barrero et al. (2023) report estimates for full days worked from home as a share of all paid workdays for individuals aged 20–64 between 3.4% and 6.8% over the same period.

Moreover, the increase in WfH during peak childcare years is particularly pronounced for women. This is consistent with findings from Arntz et al. (2022), who show that the presence of children significantly increases the likelihood of WfH take-up among women, but not among men.

Figure 5: Work-from-Home Take-up over the Life-cycle and the Presence of Children



Note: The left figure displays shares of work-from-home workers over the life-cycle among all working married individuals and among women only. The right figures shows the number of children under the age of 18 years in the household over the life-cycle (right). Figures are plotted with 95% confidence intervals.

4 Model

I develop a general equilibrium, overlapping-generations model to evaluate the impact of work-from-home (WfH) on married women's career paths and gender inequality in labor outcomes. My main career measure is earnings growth achieved by age 40, complemented by an analysis of life-cycle profiles of earnings, wages, and hours. The model captures two key trade-offs associated with WfH, reflecting two different dimensions of job flexibility. First, WfH eliminates commuting time, potentially helping to balance career demands with domestic work. However, this advantage entails both short- and long-term productivity penalties—a tension that is especially pronounced for working mothers, as the steepest learning curve on the job often overlaps with the most demanding period of home production due to childrearing. Moreover, access to WfH jobs increases with a worker's human capital, which itself requires an upfront investment of work time at the expense of other activities. This creates a more nuanced, dynamic trade-off between workplace flexibility and time allocation. Second, both spouses make an occupational choice at the start of their careers, selecting between two task-based occupation types: *abstract* and *routine* occupations. As in Adda et al. 2017, this classification effectively captures the trade-offs faced by working mothers early in their careers: abstract occupations tend to offer higher wages than routine ones but also impose larger wage penalties for career interruptions and generally provide fewer job amenities.[16] In addition, I find that abstract and routine occupations differ in the availability of WfH jobs and the productivity effects associated with WfH take-up. While WfH is more prevalent in abstract occupations, it entails both static productivity penalties—reducing the efficiency units of labor supplied in a given period—and dynamic productivity penalties—slowing down human capital accumulation. By contrast, routine occupations exhibit a smaller static penalty and no dynamic productivity penalty.

The main ingredients of the model are as follows. At every point in time, $J + J_R$ generations co-exist.[17] A life-stage j is discrete and lasts for 5 years. In the first $j \in J$ life-stages, individuals can supply market work and face periods of heightened home production importance due to childcare early and mid-career. In the last J_R periods they are jointly retired. A cohort j consists of a unit mass of couples, each denoted by i that maximize in a unitary setup under full commitment. Spouses differ in their gender $g \in \{f, m\}$ (female or male).[18] Couples choose consumption, how to allocate their individual time between market work, home production and leisure and whether to

[16] Adda et al. 2017 also include *manual* occupations as a third category. I exclude this group in my analysis, though the framework could, in principle, be extended to incorporate it.

[17] I will abstract from time indices as I will focus on stationary environments in the main analysis. Transition dynamics will be study in a separate section.

[18] In this paper, I focus on heterosexual couples, as my primary interest lies in gender inequality stemming from their relationship dynamics. Nevertheless, several of the underlying mechanisms may also generalize to differences between primary and secondary earners within couples more broadly.

work form home.[19] Individuals have to wait for a stochastic WfH opportunity to be able to choose it. In the first life-stage, couples decide jointly on the type of occupation o_{ig} they each want to pursue throughout their career: abstract or routine.[20][21] They retire deterministically and couples stay married throughout their life-cycle. I first present the building blocks of the model, followed by the definition of the stationary equilibrium.

Ex-ante Heterogeneity Ex ante heterogeneity arises from spouses' initial human capital pairs (H_{if1}, H_{im1}), the educational attainment of individuals in the first period. I model those pairs as discrete mass points from a joint distribution to account for assortative matching.

Children The number of children in the household is deterministic, identical for all couples and follows the life-cycle profile of the average number of children in a household observed in the data. It is recorded through the number of children state variable n_j and captures the importance of home production over the life-cycle.

Occupation and Labor Supply Each occupation ($o_{ig} = \{\text{routine}, \text{abstract}\}$) is characterized by several key features. First, occupations differ in how they remunerate human capital H_{igj}, leading to differences in wage *levels*. Second, they vary in the rate at which human capital accumulates over time. This results in different wage *growth* over time across occupation groups. Thus, human capital is an auxiliary variable that reflects the career progression of an individual over time. Third, occupations differ in the stochastic arrival rate of WfH opportunities and in how WfH affects both the *static* (wage process) and *dynamic* (human capital accumulation) returns to human capital. Further details on these mechanisms will be provided below. Finally, occupations differ in their utility amenity value $A(o_{ig})$, capturing residual occupation-specific characteristics that influence workers' sorting decisions.[22] In any occupation, individuals can choose their labor market hours h_{igj} from a continuous and bounded hours choice set. They can also choose not to work which I record as the lowest hours grid point $h_{igj} = 0$.

WfH Job Opportunities and Workplace Workers make workplace decisions p_{igj} that depend on whether they have the job opportunity to work from home. Every period, they receive a stochastic WfH opportunity at a rate $\rho(o_{ig}, H_{igj}) \in [0, 1]$. The arrival rate depends on the type of occupation and the worker's human capital level, reflecting that the prevalence of opportunities vary with

[19] During retirement, periods $j \in J_R$, individuals do not supply market work and thus, do not make a workplace decision.

[20] In the model, occupational decisions are made based on educational attainment observed at ages 25–29. The key assumption is that individuals do not adjust their educational path in anticipation of changes in future WfH opportunities. Instead, they internalize the implications of WfH only upon entering the labor market and forming a couple. This is because WfH is primarily a form of job flexibility, and the demand for such flexibility typically arises after couple formation—when relative differences in education and human capital become important drivers of that demand.

[21] Occupation are assumed to be a one-time initial choice as occupation groups are defined coarsely and thus transition rates across groups are low. Adda et al. 2017 estimate annual transition rates between 0.7% (from abstract to routine) and 1.5% (from routine to abstract). In my sample, I find slightly larger annual transition rates of 9% (from abstract to routine) and 14% (from routine to abstract).

[22] For instance, abstract occupations typically offer lower temporal job flexibility, which is reflected in a relatively lower amenity value compared to routine occupations.

occupational type and, conditional on the occupation, rise with higher levels of human capital. A WfH job opportunity broadens the individual workplace choice set for a period, enabling them to choose between two distinct work settings: *onsite* or *WfH*. This dynamic is recorded in the individual state variable $Flex_{gj} \in \{I,\ F\}$, I stands for *inflexible* (only onsite work) and F stands for *flexible* (can vary between onsite and WfH work). Given that both spouses are subject to this state variable, the couple can encounter four possible flexibility states. Flexibility states are not absorbing and WfH can only be chosen if a positive amount of market hours are provided.

The workplace influences several key aspects of careers. First, it affects the dynamic and static returns to human capital, reflecting the productivity effects of WfH. Second, it affects the time cost of market work, accounting for the additional commuting time associated with onsite work.

Preferences Preferences are separable across time and states of the world. Individual period utility takes the form:

$$u(c_{igj},\ l_{igj},\ Q_{ij},\ n_j,\ o_{ig}) = \frac{c_{igj}^{1-\eta}}{1-\eta} + \lambda(n_j)\frac{Q_{ij}^{1-\kappa}}{1-\kappa} - \psi\frac{\Big(q_{igj} + h_{igj}(1+\chi_p)\Big)^{1+\gamma}}{1+\gamma} + A_{o_{igj}}, \quad (4)$$
$$\text{with } (\eta, \gamma, \psi, \kappa) \in \mathbb{R}_+^4.$$

An individual in couple i, gender g at age j derives utility from own consumption c_{igt}, the jointly produced home good Q_{it} of the couple that is public within the household and the additive occupation-specific amenity $A(o_{igt})$. Further, labor dis-utility is generated from market work h_{igt} and domestic work q_{igt}. The effective market work time that enters the labor dis-utility is $h_{igj}(1+\chi_p)$, where χ_p is the proportional commuting time cost.[23] Thus, $\chi_{onsite} > 0$ and $\chi_{WfH} = 0$. This specification reflects that workers incur an additional commuting time cost when opting to work onsite. The importance of the home-produced good Q_{it} is captured by the parameter $\lambda(n_j)$, which depends on the number of children n_j, with $\lambda'(n_j) > 0$. Finally, the additive occupation-specific amenity $A(o_{gt})$, captures other occupation-specific features that affect occupational choices.[24]

Public Home Good Home production is a public good within the household and captures the well-being of a couple's children and goods and services produced within the household, such as household chores and childcare. The specification follows Foerster (2024) and takes the form:

$$Q_{ij} = (a_f q_{ifj}^{\sigma} + (1-a_f) q_{imj}^{\sigma})^{\frac{1}{\sigma}}, \quad (5)$$

[23] The proportionality between commuting time and market hours is motivated as discussed in Section 3. Empirically, workers who work longer hours also tend to work more days per week and, consequently, spend more time commuting, conditional on working onsite. I find differences in the share of market work spent commuting by occupation group and age to be small.

[24] The occupation-specific amenity is important for the calibration to jointly match observed occupational sorting and wage profile differences between abstract and routine occupation groups. This captures other occupation-specific amenities that differ by occupation group and affect occupation decisions. For a similar approach see for example Alon et al. 2025.

where male and female home production time q_{igj} enters a CES production form. The parameter a_f captures the female comparative advantage in home production and σ captures the degree of substitutability between male and female home production time.[25]

Joint Budget Constraint The joint budget constraint of the household is given by

$$e(n_j)(c_{ifj} + c_{imj}) = y_{ij}(1 - \tau). \tag{6}$$

Total consumption expenses are equal to the sum of spouse's consumption c_{igj} weighted by an expenditure scale that depends on the number of children $e(n_j)$, with $e'(n_j) > 0$. Further, I denote by $y_{ij} = y_{ifj} + y_{imj}$ the total gross labor income, the sum of the husband's and wife's labor incomes. Labor income is taxed through a flat income tax rate $\tau \in (0, 1)$. During retirement, both spouses receive a fraction of their last earnings.

Individual Time Constraint The individual time constraint of each spouse is defined as:

$$T = l_{igj} + q_{igj} + (1 + \chi_p)h_{igj}, \tag{7}$$

where the time endowment T is allocated between leisure l_{igj}, home production time q_{igj} and market work time h_{igj}. If the individual works onsite an additional commuting time cost $\chi_{onsite} > 0$ scales up market work time.

Human Capital and Efficiency Units of Labor Individuals accumulate human capital while working through learning-by-doing.[26] The human capital process is defined as:

$$H_{igj+1} = L(o_{ig})(1 + \Delta_{o_{ig}}(p_{igj}))(h_{igj}H_{igj})^{\alpha_{o_{ig}}}. \tag{8}$$

Human capital accumulates as a function of market hours and the current human capital level. Based on the mapping introduced in the empirical section, the learning ability $L(o_{ig})$, can be understood as the intercept wage growth, conditional on current work hours and human capital. Meanwhile, $\alpha_{o_{ig}}$ regulates the wage-growth elasticity relative to provided labor units $h_{igt}H_{igt}$, with $\alpha_{o_{ig}} \in (0, 1)$ capturing decreasing returns to scale. Parameter $\Delta_{o_{ig}}(p_{igj})$ alters human capital

[25] As noted by Fernandez et al. (2004), the comparative advantage in home production can be interpreted as stemming either from gender productivity differences in domestic tasks or from gender-specific attitudes toward housework shaped by prevailing social norms. Following the approach in Foerster (2024), this paper treats this comparative advantage as exogenous. As a potential extension, it would be valuable to endogenize this advantage and explore its interaction with work-from-home (WfH) arrangements. In particular, increased male participation in housework facilitated by WfH could influence the accumulation of domestic human capital—or shift normative attitudes toward domestic labor—potentially accelerating convergence in the gender gap in home production.

[26] The functional form follows the standard learning-by-doing form discussed by Blandin 2018. I augment it by a role for the occupation type and workplace.

accumulation, with $\Delta_{o_{ig}}(onsite) = 0$ and $\Delta_{o_{ig}}(\text{WfH}) \geq 0$ or $\Delta_{o_{ig}}(\text{WfH}) \leq 0$, capturing the *dynamic* productivity effects of WfH. [27]

The efficiency units of labor supplied by a worker every period are:

$$h_{igj}(1 + \delta_{o_{ig}}(p_{igj}))H_{igt}, \tag{9}$$

with a discount rate $\delta_{o_{ig}}(p_{igj})$ ($\delta_{o_{ig}}(onsite) = 0$ and $\delta_{o_{ig}}(\text{WfH}) < 0$), captures the *static* productivity effects of WfH. Total individual gross labor income is then:

$$y_{igj} = w_{o_{ig}}(1 + \delta_{o_{ig}}(p_{igj}))h_{igj}H_{igt}, \tag{10}$$

where $w_{o_{ig}}$ is the occupation-specific equilibrium wage rate.

Married Household Planning Problem Couples behave according to a unitary household model and maximize their joint, equally-weighted individual utilities. At the start of each period, a couple i takes as given the variables from their state space Ω_{ij}:

$$\Omega_{ij} = \{H_{ifj}, H_{imj}, Flex_{ifj}, Flex_{imj}, o_{if}, o_{im}\}.$$

The state space consists of both spouses' current human capital H_{igj} and also comprises their respective occupation choice o_{ig} picked at the beginning of their careers. The state space includes the workplace flexibility states for both spouses $Flex_{igj}$ that record their workplace options in the current state and realizes at the beginning of the period. Define $\iota_{ij} = \{c_{ifj}, c_{imj}, p_{ifj}, p_{imj}, h_{ifj}, h_{imj}, q_{ifj}, q_{imj}\}$ the vector of choice variables over which the household maximizes in period j. The Bellman equation for a couple i in period j is given by:

$$\begin{aligned} V_t(\Omega_{it}) = \max_{\iota_j} \quad & u_f(c_{ifj}, l_{ifj}, Q_{ij}, n_j, o_{if}) + u_m(c_{imj}, l_{imj}, Q_{ij}, n_j, o_{im}) + \\ & \beta \mathbb{E}_{Flex_{ifj+1}, Flex_{imj+1}} \Big[V_{j+1}(\Omega_{ij+1}) \Big], \\ \text{s.t. } & (4),\ (5),\ (6),\ (7),\ (8),\ \text{and } (10) \end{aligned} \tag{11}$$

where $\beta \in (0, 1)$ is a discount factor and $\mathbb{E}$ is the expectation operator over the WfH opportunities of both spouses. The couple maximizes the discounted flow of expected utilities over their joint life-cycle subject to their joint budget constraint, individual time constraints, preferences, home production technology, the definition of labor income and the human capital process.

[27] Note that the human capital process does not include an explicit additive depreciation rate when not working. This specification facilitates mapping the process into an empirically estimable regression for identifying the dynamic productivity effects. However, it also implies that not working for five years results in a complete depreciation of the human capital stock. Consequently, the model does not perform very well at the participation margin, as the incentives for non-participation are excessively penalized. Instead, the participation margin in the model can instead be approximated by low values of market hours—such as working on average only 10 hours per week over a five-year period.

Initial Occupation Choice At time $j = 0$, prior to starting their career, husband and wife jointly decide on the type of occupation o_{ig} they each want to work for periods $j \in J$ by comparing the expected, discounted utility flows for an abstract versus routine occupation:

$$\{o_{if}^*, o_{im}^*\} = \underset{o_{if}, o_{im}}{\arg\max} \quad \mathbb{E}_{Flex_{if1}, Flex_{im1}} \Big\{ V_1 \Big(H_{if1}, H_{im1}, Flex_{if1}, Flex_{im1}, o_{if}, o_{im} \Big) \Big\}. \tag{12}$$

The occupation choices depends on their initial human capital pairs (educational attainment). Individuals make their occupation choice while forming expectations about their flexibility state in the first period. Once they made their occupation choice the flexibility state realizes.

Retirement After period J, couples deterministically transition into retirement for the final two life-cycle periods, facing a simplified version of their previous maximization problem. The detailed formulation is provided in Appendix B.

Final Good Production There is a representative firm that produces the numéraire consumption good Y^C with a CES technology:

$$Y^C = \Theta(\omega_A E_A^{\epsilon} + (1 - \omega_A) E_R^{\epsilon})^{\frac{1}{\epsilon}}, \tag{13}$$

where E_A and E_R are the supplied aggregated efficiency units of abstract and routine labor, respectively. Total factor productivity is captured by Θ, the elasticity of substitution between both factors is $\frac{1}{1-\epsilon}$ and the relative importance of abstract efficiency units for the production technology is denoted by ω_A. Accordingly, the firm does not discriminate based on workers' workplace arrangements but instead considers the efficiency units of labor supplied, treating each unit equally regardless of whether it comes from onsite or WfH workers. I therefore follow the specifications in Braun et al. (2022) and Kaplan et al. (2020). Profits are maximized under perfect competition:

$$\Pi^Y = Y^C - w_A E_A - w_R E_R, \tag{14}$$

with price of consumption normalized to one and taking equilibrium wage rates, w_A and w_R, as given. First-order conditions with respect to E_R and E_A then pin down equilibrium wages, workers are remunerated competitively according to their marginal product.

Gender Differences Gender differences arise from differences in the comparative advantage of home production and differences in the initial human capital endowment.

Discrete Choices Couples make two distinct discrete decisions: (i) the initial occupation choices of both spouses, and (ii) the workplace location(s), conditional on receiving a work-from-home offer that allows for workplace flexibility. To handle the discontinuities inherent in discrete choice models, I introduce choice-specific, independently and identically distributed random taste shocks for both decisions. These shocks serve both computational and conceptual purposes: they smooth decision rules near non-differentiable points, generate more realistic distributions of types across

choices, and help stabilize the calibration by preventing large parameter updates in response to small changes in the model (see, e.g., Iskhakov et al. 2017). Appendix B provides analytical details, and Section 5.2 outlines the identification strategy.

Stationary Equilibrium The stationary equilibrium of this economy with consumption numéraire is defined by prices $\{w_A, w_R\}$ and policy functions $\{h_g(\Omega_j),\, a_g(\Omega_j),\, q_g(\Omega_j),\, o_g(\Omega_j),\, p_g(\Omega_j)\}$ for $g \in \{f, m\}$ such that for given prices households maximize their constrained, discounted lifetime utility and the representative firm maximizes profits under perfect competition, equating wage rates to workers marginal product. The two labor markets clear and the consumption goods market clears by Walras' law. In the stationary equilibrium, the distribution over $\Omega = [\Omega_1, ..., \Omega_{J+J_R}]$ is constant over time. Let $\Phi(\Omega)$ be the stationary distribution over Ω then labor markets clear as follows:

$$
\begin{aligned}
E_A &= \sum_{j=1}^{J} \int_{\Omega_j} \left[\sum_{g \in f,m} I\{o_g(\Omega_j) = \text{abstract}\} H_g(\Omega_j) h_g(\Omega_j) (1 - \delta_{\text{abstract}})^{I\{p_g(\Omega_j) = wfh\}} \right] d\Phi(\Omega) \\
E_R &= \sum_{j=1}^{J} \int_{\Omega_j} \left[\sum_{g \in f,m} I\{o_g(\Omega_j) = \text{routine}\} H_g(\Omega_j) h_g(\Omega_j) (1 - \delta_{\text{routine}})^{I\{p_g(\Omega_j) = wfh\}} \right] d\Phi(\Omega),
\end{aligned}
\tag{15}
$$

where $I\{.\}$ denotes an indicator function.

5 Model Calibration

The model estimation involves two steps. In the first step, standard parameters are drawn from the literature, estimated directly from the data, or normalized without loss of generality. In the second step, the remaining structural parameters are calibrated by matching the simulated model moments with the empirical data moments.

5.1 Exogenous Parameters

Table 3 summarizes the exogenously set parameters.

Life-Cycle Time To limit the computational complexity of the solution routine, each model period represents 5 years. Both spouses share an identical life-cycle: beginning at ages 25-29 ($j = 1$) and retiring after 60-64 (end of $j = 8$), followed by two periods in retirement, after which they die deterministically (end of $j = 10$).

Parameters from Other Studies I draw a set of parameters directly from previous studies. The annual discount rate is set at 0.98, and the coefficient of relative risk aversion at 1.5, as per Attanasio et al. (2008). Erosa et al. (2022) develop a framework with married couples who experience labor dis-utility from both market and domestic labor, akin to mine. They calibrate the Frisch elasticity of

Table 3: Exogenous Parameters

Parameters	Notation	Value	Reference
I. Life-cycle Timeline			
Years in each period	j	5	
Time periods in work life stage	J	8	
Time periods in retirement stage	J_R	2	
Initial age	$j = 1$	25	
Retirement age	$j = 9$	65	
II. Parameters from Other Studies			
Annual discount rate	β	0.98	Attanasio et al. 2008
Relative risk aversion	η	1.5	Attanasio et al. (2008)
Intertemporal Elasticity of Labor	γ	3	Erosa et al. (2022)
Elasticity between abstract and routine in CES	ϵ	0.66	Acemoglu and Autor (2011)
Proportional labor income tax rate	τ	0.061	OECD (2016)
Net pension replacement rates	w_R	0.47	OECD (2013)
Child-dependent expenditure weights	$(e(0), e(1), e(2))$	$(1, 1.23, 1.46)$	Voena (2015)
Static productivity effect of WfH in abstract (routine)	δ_o	-11.5% (-3.5%)	See Section 3
III. Own Estimated External Parameters			
Dynamic productivity effect of WfH in abstract (routine)	Δ_o	-2.3% $(+7.0\%)$	See Section 3
Commuting time cost	χ	0.10	See Section 3
Mean work hours for pension income men	h_{mR}	39	ACS (2013-2016)
Mean work hours for pension income women	h_{fR}	26	ACS (2013-2016)
Number of children by age group	n_j	See Figure 7f	ACS (2013-2016)
Initial Spousal Human Capital Distribution	(H_{f1}, H_{m1})	See Figure 6b	PSID (2001-2019)
IV. Normalization and Preset Parameters			
Weekly hours time endowment	T	80	Normalized
Initial Human Capital for *No College*	$H_{no_college}$	1.0	Normalized

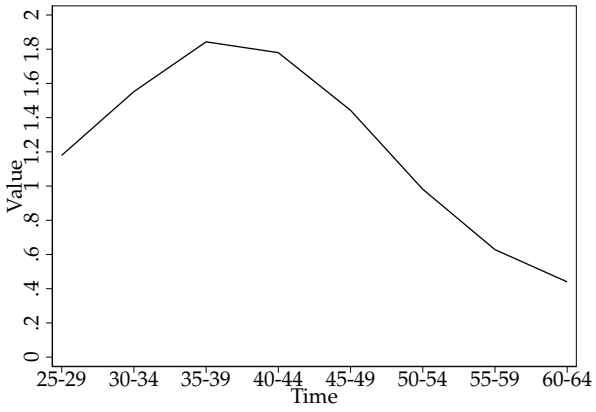
Note: ACS stands for American Community Survey and PSID stands for Panel Study of Income Dynamics. Mean work hours for pension income include the extensive margin.

labor supply to $\frac{1}{3}$, setting $\gamma = 3$. Acemoglu and Autor (2011) estimate the elasticity of substitution between high-skill and low-skill labor in a CES Production technology and find an elasticity of 2.9, implying $\epsilon = 0.66$. I calibrate the tax rate to 6.1% which is the average U.S. labor income tax rate of a married couple with two children earning an average US total gross labor income of $50,964 per year (OECD 2016). The US net pension replacement rate upon retirement is 47% and is based on the pension report OECD (2013). Child-dependent expenditure weights are chosen following Voena (2015). Values between $n_j = \{0, 1, 2\}$ are linearly interpolated. The static returns to human capital for WfH in the wage process of each occupation group is estimated compiling empirical studies on the short-term productivity effects of remote work, as described in detail in Section 3. On average, returns to human capital decrease by 11.5% in abstract occupations and by 3.5% in routine occupations in the short run.

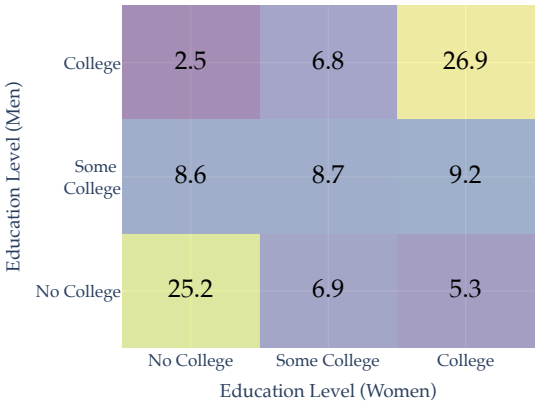
Own Estimated External Parameters I estimate a set of parameters directly from several data sources. To estimate the dynamic, 5-year productivity effect of WfH I exploit workplace differences in wage-growth in the SIPP panel data as described in Section 3. I find that over a five year horizon, human capital accumulation is 2.3% lower in abstract and 7.0% higher in routine occupations when working from home compared to onsite work. Similarly, I use SIPP panel data to estimate commuting time costs as a share of usual work hours, as described in Section 3. I find negligible variation across occupations and age groups and therefore set the value to the average of 10%. The work hours, used to compute retirement pension income for both men and women, are set to the average respective work hours observed in the American Community Survey (ACS). The average life-cycle profile in the number of own children per household is estimated from the American Community Survey (ACS), controlling for both cohort and time effects. This estimation is depicted in Figure 7f. For detailed information regarding the ACS samples and the estimation process, please refer to Appendix A. The initial joint distribution of spousal educational attainments is estimated using the Panel Study of Income Dynamics (PSID). The levels are categorized as no college, some college, or at least a college degree, and mapped on the human capital grid by exploiting wage differences of young workers observed in the data. Estimation details are provided in Appendix C. Figure 6b depicts the initial human capital distribution of couples. Most mass concentrates on the diagonal, indicating assortative matching in educational attainment, with more mass above than below, suggesting women typically pursue higher degrees than their male spouses.

Normalized Parameters I standardize both spouses' weekly time endowment to 80 hours, which can be allocated among leisure, home production, or labor market activities. As implied by the estimation procedure for the initial human capital endowments, initial human capital from having no college is set to one.

Figure 6: External Parametrization in Fertilty and Education



(a) Life-cycle Fertility Estimate



(b) Distribution of Initial Spousal Education

Note: Figure (a) plots the estimated life-cycle of age-specific fertility using the American Community Survey (2013-2016). The average number of own children in the household is used by age, controlling for cohort and time effects, assuming that time effects average out to zero and are orthogonal to the time trend. PSID (2000-2020), married couples between the age 25-30. Figure (b) depicts the joint discrete education distribution along three education attainments: "at most high-school degree", "more than high-school but no college degree" and "at least college degree".

5.2 Indirect Inference

In total, I calibrate 19 parameters internally using the method of simulated moments to match 67 data targets. This involves solving the model via backward induction and simulating a panel of $N = 10^5$ couples to compute the equilibrium wage rates under the stationary state distribution.

Table 4 presents the full set of data moments used for identification. I target moments that capture the key life-cycle trends and levels observed in the data. In addition, I include higher-order and dynamic moments that leverage the panel dimension of the SIPP, such as the future share of WfH workers along the occupation-specific wage distribution. To identify the workplace taste shock, I replicate the pandemic-induced surge in WfH take-up in a separate simulation exercise, which I explain in more detail below. The resulting parameter estimates are shown in Table 5, and the model fit is displayed in Figure 7 and Table 6. Overall, the model fits the data well, both in terms of first moments and dynamic patterns. I now turn to a more detailed explanation of the parameter identification via indirect inference.

Preference Parameters To identify the preference parameters governing labor dis-utility and home production, I rely on first-moment statistics that replicate key life-cycle trends in market and domestic hours by gender. Non-working individuals are assigned zero hours, and average market hours incorporate both the intensive and extensive margins. In particular, the average levels of domestic and market work inform the parameters ψ and κ. The co-movement between domestic hours and the fertility profile over the life cycle informs the home production weight, which I model

Table 4: Data Targets

Target	Data Source
Life-cycles in domestic hours by gender	ATUS (2013-2016)
Life-cycles in market hours by gender	ATUS (2013-2016)
Life-cycle in share of WfH workers	SIPP (2013-2016)
Share in abstract occupation by gender	SIPP (2013-2016)
Life-cycle wage profiles of onsite workers by occupation	SIPP (2013-2016)
Distribution of future WfH switcher by occupation and wage quartile	SIPP (2013-2016)
WFH Take-up in Response to the COVID-19 Pandemic Shock	Barrero et al. (2023)

Note: The abbreviations are for the American Time Use Survey (ATUS) and the Survey of Income and Program Participation (SIPP). All life-cycle profiles are estimated using a polynomial in age groups while controlling for cohort effects.

Table 5: Parameters Estimated Through Indirect Inference

Description	Notation	Value
I. Preferences		
Labor dis-utility weight	ψ	0.25
Weight home good (scale)	b	0.05
Weight home good (# of children)	b_n	6.99
Home good curvature	κ	1.98
II. Home Production		
Degree of substitution home production	σ	0.71
Female rel. productivity in home production	a_f	0.53
III. Occupation Amenity & Taste shocks		
Relative amenity utility of routine occupation	$A(routine)$	0.03
Scale of occupation taste shock	σ_p	0.05
Scale of workplace taste shock	σ_o	0.02
IV. Final Good CES		
Total Factor Productivity	Θ	30.58
Relative weight of abstract labor	ω_A	0.67
V. Human Capital Process		
Labor unit elasticity abstract	$\alpha_{abstract}$	0.19
Labor unit elasticity routine	$\alpha_{routine}$	0.05
Learning Ability in abstract	$L_{abstract}$	0.77
Learning Ability in routine	$L_{routine}$	1.27
V. Arrival Rate of WfH Job Opportunities		
Intercept in abstract	ρ_1	-0.39
Return to Human capital in abstract	ρ_2	0.48
Decreasing returns to Human capital in abstract	ρ_3	-0.10
Routine Scale	$\rho_{routine}$	0.40

Note: 19 internal parameters and 67 targets (life-cycle targets in share of WfH workers, in market and domestic hours by gender and wages in occupation and workplace as well as share in abstract occupation by gender and share of future remote worker by wage quintile and occupation). Amenity value in abstract occupation group is normalized to zero.

as a function of the number of children: $\lambda(n) = b(1 + b_n n)$ similar to Foerster (2024). As indicated, by $b_n > 0$, the importance of home production increases with the presence and number of children in the household. Furthermore, substitution in male and female home production ($1/(1-\sigma) \approx 3.45$) inputs, together with a female comparative advantage in domestic tasks ($\alpha_f = 0.53 > 0.5$) , helps to reproduce observed gender differences in time allocations over the life cycle and the occupational distribution across abstract and routine jobs.

Occupation-specific Amenity The occupation-specific amenity utility is informed by the share of workers in the abstract occupations by gender as well as the level differences in wages by occupation. I normalize the amenity value for abstract occupations to zero. Consequently, $A(routine)$ represents the relative amenity utility derived from working in a routine occupation compared to a abstract one. This parameter aligns observed patterns of occupational sorting and wage profile differences between abstract and routine occupation groups. In particular, $A(\text{routine}) > 0$ captures that workers sort into occupations not solely based on monetary compensation, but also due to non-pecuniary amenities more prevalent with routine work.[28]

Table 6: Model Fit - Part 2/2

Target Description	Model	Data
WfH Opportunities	37.0%	37.0%
Factor Increase in WfH Take-up (Covid-19 Shock)	+8.80	+8.54

Note: Changes are expressed in multiples, i.e. WfH Take-up increase by 8.54 fold in response to the Pandemic Shock.

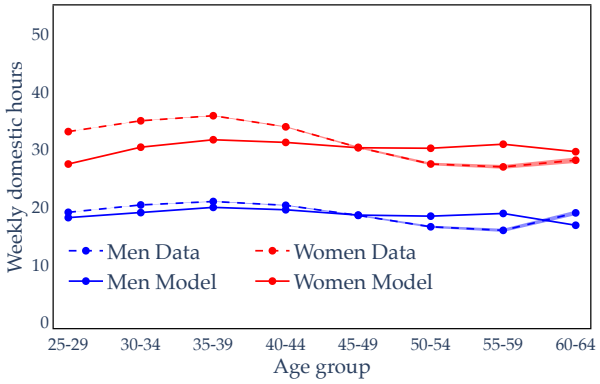
Discrete Workplace Choice Taste Shocks To identify the workplace taste shocks, I conduct an additional counterfactual simulation designed to replicate the increase in WfH take-up observed in response to the Covid-19 pandemic shock. Specifically, I simulate an unanticipated expansion in WfH opportunities up to their full estimated potential—37% of jobs on average—based on Dingel and Neiman (2020). Simultaneously, I incorporate pandemic-specific conditions, following Kaplan et al. (2020), by modeling a sharp increase in the relative dis-utility of onsite market work due to the health risk. This increase is captured by the function $\nu(D) = \exp(v_1 D^{v_2})$, with parameters $v_1 = 8.0$ and $v_2 = 0.6$, where D denotes the excess death rate in the population (normalized to zero prior to the pandemic).

Formally, if an individual works onsite, this modifies the labor dis-utility term in equation 4 to

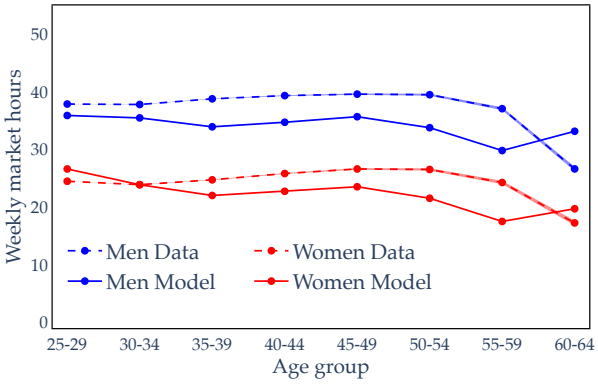
$$-\psi \frac{(q + \nu(D)h(1 + \chi_p))^{1+\gamma}}{1+\gamma}.$$

[28]The higher additive amenity value of routine occupations could reflect, as in Adda et al. (2017), the "child-raising value" associated with these jobs, or more generally, the greater temporal flexibility often found in lower-paying occupations, as emphasized by Goldin (2014).

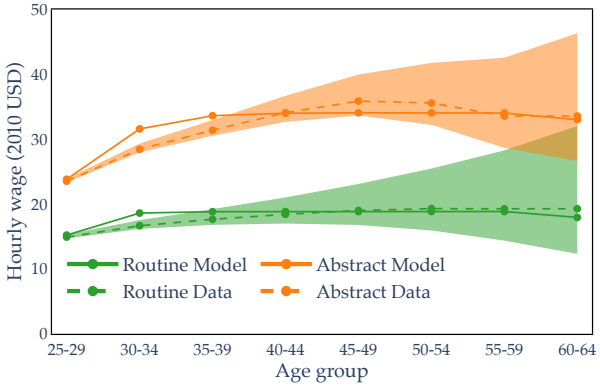
Figure 7: Model Fit - Part 1/2



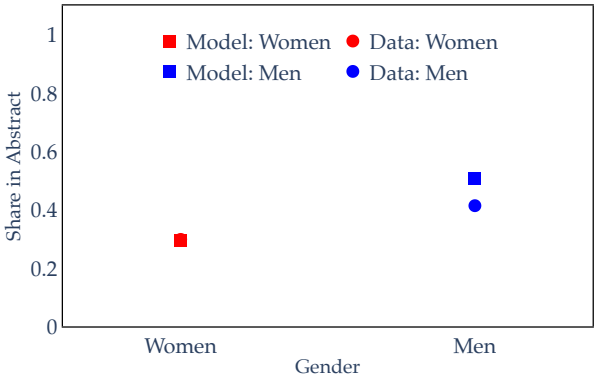
(a) Domestic Hours



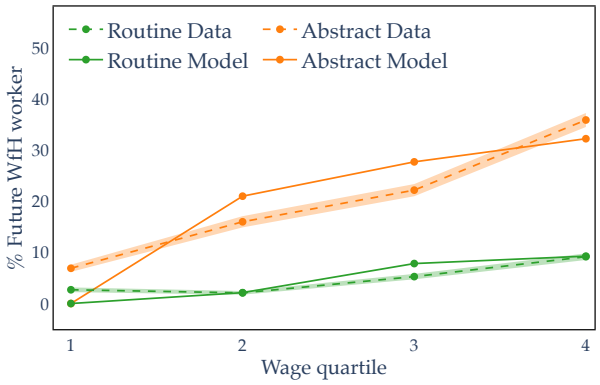
(b) Market Hours



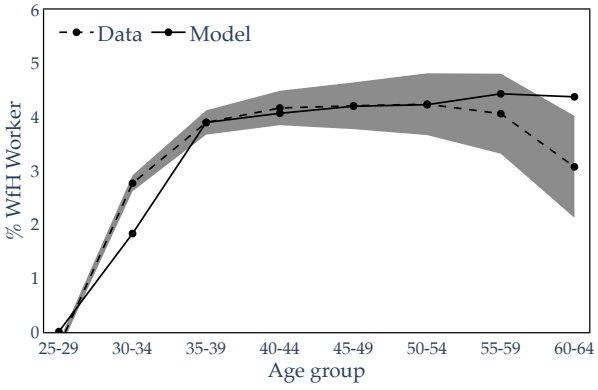
(c) Hourly Wage



(d) Share of Abstract Workers



(e) Future WfH Switcher Share



(f) Share of WfH Worker

According to Karlinsky and Kobak (2021), the United States experienced an estimated excess death rate of 22% during the pandemic. This corresponds to a $\exp(v_1 \cdot 0.22^{v_2}) = 25.16$-fold increase in the dis-utility of onsite work relative to remote work. As shown in Figure 1 of Barrero et al. (2023), WfH

take-up rose from 7.2% to 61.5% in the immediate aftermath of the shock—an 8.54-fold increase. This observed increase serves as the empirical target used in the indirect inference procedure.[29] Table 6 reports the model fit, showing that the 37% expansion in opportunities is matched exactly. The increase in WfH take-up in the model is modestly higher and deviates from the empirical value by 0.26 percentage points.

Final Good Technology The parameters of the final goods production technology—namely total factor productivity (Θ) and the relative productivity weights of abstract and routine efficiency units (ω_A)—are informed by the overall wage level and the average abstract wage premium, both of which are targeted via the life-cycle wage profiles by occupation group. The average wage level across occupations and life stages is 25.01 (in 2010 US dollars), and the average abstract wage premium is $+77\%$.

Human Capital Process To identify the parameters of the human capital process I target the life-cycle profiles of wages across occupations and wages, as well as the life-cycle profile of market hours. The steepness of wage profiles informs the speed of human capital accumulation over time, paired with the evolution of market hours over time informs the elasticity of human capital accumulation in the supplied labor efficiency units. As established in Section 3, α_o can be interpreted as the elasticity of wage growth with respect to market hours, while L_o captures the intercept of wage growth for onsite workers. As shown in Table 5, abstract occupations exhibit a higher elasticity (0.19 in abstract v.s. 0.05 in routine), reflecting the greater returns to market hours in high-paying, high-skill jobs. In contrast, intercept wage growth is higher in routine occupations (0.77 in abstract v.s. 1.27 in routine), indicating that these occupations penalize low human capital and low market hours less severely. Put differently, abstract occupations offer greater wage growth potential, but only conditional on working long hours and being a high human capital worker.

Arrival Rate of WfH Opportunities To model how the arrival rate WfH opportunities varies across workers' human capital levels—and how this relationship differs by occupation—I leverage a workplace-mover design using SIPP panel data from 2013 to 2016. My analysis centers on the distribution of future WfH movers across occupations and occupation-specific wage distributions. Assuming that high-human capital workers generally earn higher wages prior to transitioning, I identify the positive gradient of WfH opportunity as the increasing share in future WfH movers along the wage distribution. I assume the arrival rate $\rho(H, o)$ of WfH opportunities follows a quadratic function of human capital H, differing by occupation type $o \in \{\text{routine}, \text{abstract}\}$:

$$\rho(H, o) = \begin{cases} \min\left\{\max\left\{\rho_{\text{routine}}(\rho_1 + \rho_2 H + \rho_3 H^2),\, 0\right\},\, 1\right\}, & \text{if } o = \text{routine}, \\ \min\left\{\max\left\{\rho_1 + \rho_2 H + \rho_3 H^2,\, 0\right\},\, 1\right\}, & \text{if } o = \text{abstract}. \end{cases} \tag{16}$$

[29] In this experiment, I do not re-solve for general equilibrium wage adjustments, assuming that wages remained rigid in the short-term context of the pandemic.

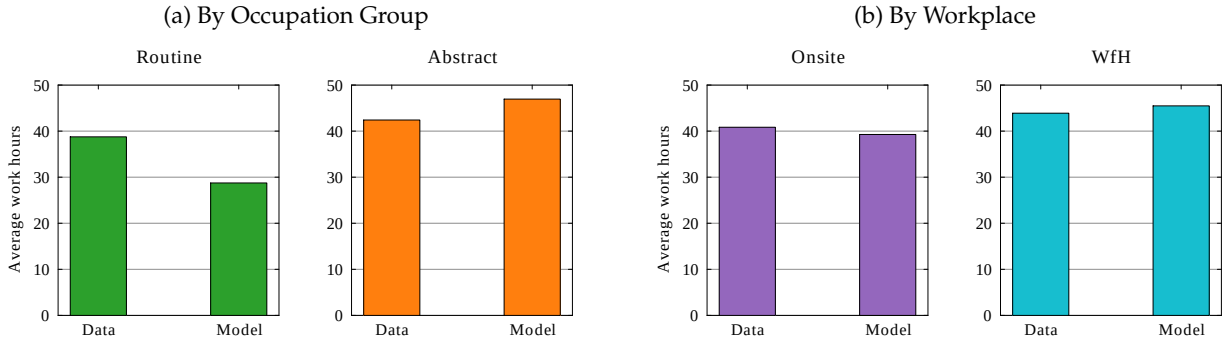
Thus, $\rho_{\text{routine}} = 0.40$ indicates that routine occupations receive only 40% as many WfH opportunities as abstract occupations for any given human capital level. A positive coefficient $\rho_2 > 0$ confirms that WfH opportunities increase with human capital. A negative coefficient $\rho_3 < 0$ implies diminishing returns to human capital. When $\rho_1 = -0.39$, the quadratic model—together with the non-negativity constraint—implies that workers with human capital below approximately 1.04 receive no WfH opportunities proxying the technical infeasibility of WfH for a share of jobs.

5.3 Non-Targeted Moments

This subsection evaluates the identification of the model's parameters by comparing selected non-targeted moments with their empirical counterparts.

Average Market Hours Recall that average work hours by gender over the life cycle were targeted in the calibration. The model performs well in matching non-targeted differences in market hours across occupation groups: it captures that individuals in abstract occupations work more hours than those in routine occupations (Figure 8a). It slightly overestimates hours in abstract jobs and underestimates them in routine ones. Moreover, the model successfully replicates that workers supply more market hours when working remotely than onsite, closely matching the magnitudes observed in the data (Figure 8a).

Figure 8: Non-targeted Average Weekly Work hours (Intensive Margin)



Note: The figures display the average weekly market hours of the model and the data by occupation (left) and workplace (right). Data moments are from the SIPP (2013-2016).

Work-from-Home Take-up In the model estimation, I also targeted average WfH take-up rates over the life cycle. Table 7 reports the model's performance on non-targeted WfH take-up rates. As in the data, the model reproduces higher average WfH take-up among men than among women, largely driven by occupational sorting and differences in human capital accumulation. For women, the model closely matches the observed WfH take-up rates in both routine and abstract occupations.

Implied Atrophy Rates and Returns to Experience I compare the implied atrophy rates from job interruptions and the wage returns to full-time market work to Adda et al. (2017), who also distinguish between routine and abstract occupations. Table 8 summarizes the comparison of these

Table 7: Non-targeted Moments in WfH Take-Up

Moment (in %)	Model	Data
Female WfH take-up	2.92	3.57
Male WfH take-up	3.84	4.44
Female take-up in routine	1.70	1.67
Female take-up in abstract	5.85	5.22

Note: The table displays non-targeted moments of work-from-home take-up. Data moments are from the SIPP (2013-2016).

Table 8: Non-targeted Moments in Atrophy Rates and Returns to Experience

Moment (in %)	Model	Data
Atrophy rate in routine	-5.98	-3.01
Atrophy rate in abstract	-13.4	-12.5
Returns to experience in routine	0.4	0.6
Returns to experience in abstract	1.2	4.4

Note: The table displays non-targeted moments of implied atrophy rates and returns to full-time experience.

non-targeted moments. Specifically, I examine the implied human capital atrophy rate following a job interruption—defined as working fewer than 10 hours on average over five years—after having accumulated ten years of full-time experience. The model qualitatively replicates that atrophy rates are higher in abstract than in routine occupations. Quantitatively, the values are close for abstract occupations, while I slightly overestimate the atrophy rate for routine jobs. I also analyze the implied wage returns to five additional years of full-time experience, conditional on having accumulated ten years of prior experience. Again, I match the qualitative pattern that returns to experience are higher in abstract than in routine occupations. Quantitatively, the model matches the observed returns well for routine jobs but underestimates them for abstract ones.

Response in Market Hours to Own or Spousal WfH Take-up by Occupation Group In the calibrated economy presented below, I find that (i) WfH take-up affects market hours differently across occupations, and (ii) within a given occupation, own and spousal WfH take-up have distinct effects on market hours.

The SIPP data allow me to merge spouses living in the same household. I obtain a sample of 22,471 heterosexual, married couples, corresponding to 575,427 monthly observations. For each spouse, I observe market hours, WfH take-up, occupation, and a relevant set of covariates.

I estimate the following regression in the SIPP data and replicate the same specification in the model, where I abstract from month and year fixed effects (given the assumption of stationarity) and omitting covariates not included in the model. For individual i in couple c, occupation group o, and time t, I estimate:

$$\begin{aligned} h_{icot}^{own} = \beta_0 + \beta_1 WfH_{icot}^{x} + \beta_2 abstract_{icot} + \beta_3 WfH_{icot}^{x} abstract_{icot} \\ + \beta_4 w_{icot} + \beta_5 w_{icot}^{spouse} + X_{icot}'\lambda + \theta_m + \theta_y + \theta_c + \epsilon_{icot}, \end{aligned} \tag{17}$$

where I regress average weekly market hours h_{icot}^{own} on either the individual's own WfH dummy ($x = own$) or the spouse's WfH dummy ($x = spouse$). I control for own and spousal wages to proxy

for both spouses' human capital levels, as well as for month, year, and couple fixed effects. I further control for a set of covariates such as age of both spouses and parental status in $X'_{icot}\lambda$.

Table 9 summarizes the estimates of the effect of own or spousal WfH take-up on market hours in routine jobs ($\hat{\beta}_1$) and abstract jobs ($\hat{\beta}_3$) , both in the SIPP data and in the model.

Table 9: The Effect of Own or Spousal WfH-take-up on Market Hours (SIPP 2013–2016)

	Routine		Abstract	
	Model	Data	Model	Data
WfH^{own}	+5.78***	+15.27***	−6.23***	−13.84***
	(0.053)	(0.158)	(0.065)	(0.178)
WfH^{sp}	−2.34***	−7.09***	+5.63***	+6.58***
	(0.041)	(0.148)	(0.049)	(0.175)

Note: The table displays estimates for $\hat{\beta}_1$ and $\hat{\beta}_3$ from the SIPP data and the simulated baseline economy according to equation 17. Standard errors in parentheses. $^{***}p < 0.01$.

The data successfully replicate the following patterns: Own WfH take-up increases market hours in routine occupations but decreases them in abstract occupations. The opposite holds for spousal WfH take-up: when the spouse works from home in a routine occupation, own market hours decline, whereas they rise when the spouse works from home in an abstract occupation.

6 The Baseline Economy

This section outlines the main features of the calibrated baseline economy, emphasizing the career effects of WfH, the determinants of its adoption, and the role of occupational sorting in shaping its implications for gender disparities.

6.1 What are the Career Effects of WfH?

While WfH reduces commuting time, it entails static productivity penalties and, in abstract jobs, even dynamic ones. This raises the question: to what extent can WfH be leveraged for career advancement? By career, I primarily refer to human capital and earnings growth over the life-cycle, but I will also look at market hours and wages. There are two channels through which WfH could advance careers: a direct and an indirect channel. In the direct channel, I examine how an individual's *own* WfH take-up affects their career outcomes. In the indirect channel, I assess how a *spouse's* WfH take-up influences the individual's career outcomes.

Career Gains from own WfH Take-up in Routine Jobs (Direct Channel) In the direct channel, career gains arise only if commuting time savings can be reallocated to offset productivity penalties.

I assumed that wages are linear in provided efficiency units of labor. This allows for a straightforward comparison with the static productivity penalty δ_o: commuting time savings of 10% can more than compensate for the routine-occupation penalty of 3.5%, provided at least that share of the saved time is devoted to additional market work. By contrast, the abstract-task penalty of 11.5% exceeds the commuting-time savings, requiring abstract workers to increase their market hours by at least an additional 1.5 percentage points beyond the saved commuting time to keep hourly wage constant. *Hence, routine workers experience an immediate income gain if they reallocate more than* 3.5% *of their saved commuting time to work, while abstract workers do not.*

However, WfH also entails dynamic productivity effects that influence human capital accumulation and thus long-term earnings. Specifically, while routine jobs benefit from a learning premium of 7% in human capital accumulation, abstract occupations face a dynamic penalty. Using the human capital accumulation process in Eq. (8), a simple calculation yields the increase in work hours necessary to offset dynamic productivity losses in abstract jobs. Assuming that a worker engages in WfH for one period (five years), given current human capital H in occupation $o = \{\text{abstract}\}$ and counterfactual onsite work hours h, at least $\tilde{h}$ hours under WfH would be required to compensate for productivity losses induced by Δ_o:

$$\begin{aligned} & \frac{L_o(1+\Delta_o)(\tilde{h}H)^{\alpha_o}}{L_o(hH)^{\alpha_o}} \geq 1, \quad o = \{\text{abstract}\} \\ \Leftrightarrow \quad & \frac{\tilde{h}}{h} \geq \left(\frac{1}{1+\Delta_o}\right)^{1/\alpha_o} \approx 1.128 \end{aligned} \tag{18}$$

Since the additional work hours required in abstract occupations exceed the commuting time saved ($12.8\% > 10\%$)*, the dynamic productivity penalty through increased labor supply can only be partially offset in abstract jobs.*

Table 10: The Career Effects of WfH Take-up

Individual's occupation	Log-wage rate	Participation margin	Market hours	Log-earnings	Human capital growth (in ppt.) for $t+1$
Routine	-0.04***	0.07***	5.14***	0.39***	9.28***
	(.000)	(.002)	(.055)	(.004)	(.030)
Abstract	-0.12***	0.00***	0.72***	-0.11***	-1.71***
	(.000)	(.000)	(.025)	(.001)	(.020)

Note: Depicts estimation results of coefficient $\hat{\beta}_1$ from regression: $Y_{igo} = \beta_0 + \beta_1 Wf H_{igo} + \delta_1 H_{igo} + \delta_2 H_{i-go} + \epsilon_{igo}$. Estimated separately for each occupation group with standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Market hours are expressed as weekly market hours.

Table 10 illustrates how the career effects of WfH unfold in the simulated economy. To assess its impact on key outcomes–wage rates, work hours, earnings, and in particular human capital

growth–I regress each outcome variable on a WfH dummy, controlling both spouses' human capital.[30] Coefficients are reported separately by occupation.

Consistent with the static WfH penalty, log wages decrease with WfH take-up in both occupations. In routine jobs, market hours rise significantly by 5.14 hours per week, and earnings increase substantially by 39%. This large increase is driven primarily by the response at the participation margin (defined as working fewer than 10 hours in one period over 5 years) to WfH take-up, which increases by 7 percentage points. As expected, take-up generates short-term earnings gains. These income gains propagate over time through increased market hours: human capital growth increases by 9.28 percentage points in the following period relative to individual that doe not work from home. In abstract jobs, market hours hardly change, and log earnings decline by 11%. As opposed to routine work, WfH take-up has negative long-term effects on human capital growth.

Career Gains when Spouse Teleworks in Abstract Occupation (Indirect Channel) In the indirect channel, I examine to what extent WfH take-up of the spouse can enhance a worker's own career prospects. Especially in abstract jobs where WfH offers limited direct career benefits, a worker who teleworks may instead devote more effort to domestic production. This is especially relevant as WfH opportunities are more common among high-human-capital individuals, who already tend to work long hours and therefore face limited marginal dynamic returns from additional paid work at reduced wages. Given substitutability of household inputs in the home production technology and the negative cross-income effect through penalties of WfH, an individual might therefore increase market hours if their spouse takes up WfH in compensate for the occurred household income losses.

Table 11: The Career Effects of Spousal WfH Take-up

Spouse's Occupation	Domestic hours (spouse)	Domestic hours (own)	Market hours (own)	Labor Participation (own)	Human capital growth in ppt. (own)
Routine	-2.95***	2.01***	-2.42***	0.00	-1.33***
	(.050)	(.036)	(.046)	(.000)	(.055)
Abstract	2.05***	-2.88***	2.56***	0.05***	2.09***
	(.018)	(.026)	(.026)	(.001)	(.025)

Note: Depicts estimation results of coefficient $\hat{\beta}_1$ from regression: $Y_{igo} = \beta_0 + \beta_1 Wf H_{i-go} + \delta_1 H_{i-go} + \delta_2 H_{igo} + \epsilon_{igo}$. Estimated separately for each occupation group with standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To investigate this aspect, I analyze the effect of spousal WfH take-up on an individual's own career in the simulated baseline economy. Since the direct career effects of WfH differ by occupation, I

[30] I control for both spouses' human capital, since WfH take-up is positively correlated with human capital through the greater availability of WfH opportunities, which could otherwise bias the results toward a spurious positive relationship between WfH take-up and labor outcomes.

examine outcomes separately by each spouse's occupational choice reported in Table 11. When the spouse in an abstract occupation takes up WfH, the non-WfH individual increases their market hours by about 2.56 per week, resulting in an average 2.09 percentage point rise in human capital growth. Because abstract WfH reduces both instantaneous and long-term earnings, the non-WfH spouse works more to compensate for the income loss. Meanwhile, the WfH spouse raises their domestic hours by 2.05 per week, while the non-WfH individual reduces theirs—indicating a reshuffling of household production in response to spousal WfH. By contrast, when the spouse in a routine occupation takes up WfH, the non-WfH individual cuts back on market hours by 2.42 weekly hours, and their human capital growth is negative with -1.33 percentage points. The freed time is shifted into domestic work, while the WfH spouse reduces their own domestic contribution by -2.95 hours. In routine occupations, WfH can generate immediate earnings gains if the worker reinvests saved commuting time into additional paid work. In this case, the WfH spouse's positive income effect induces the non-WfH individual to specialize more in domestic work, thereby foregoing career returns. *Thus, indirect incentives to advance one's career through increased market hours and human capital growth arise when the spouse takes up remote work in an abstract occupation. The mechanism is twofold: earnings losses from abstract WfH need to be compensated, and the spouse's greater contribution to domestic production allows the individual to reallocate time toward market work.*

6.2 What are the Determinants of Work-from-Home Uptake?

The WfH Trade-off has Bite: Not Everyone Accepts or Rejects the Opportunity Over the J periods of the life cycle, workers receive WfH opportunities at an intensity that depends on their occupation and human capital level. Figure 9 shows both the share of WfH opportunities and the actual share of workers who take up WfH, by occupation. As workers accumulate human capital over time, the likelihood of receiving a WfH opportunity rises due to the positive gradient of the arrival rate in human capital. Despite this, the take-up rate remains below the offer rate, suggesting a meaningful trade-off in the WfH decision. Both opportunities and take-up are generally higher in abstract occupations. The average probability of receiving a WfH opportunity over the life-cycle is 12.4% in abstract occupations and 3.8% in routine occupations. This is driven by two factors: technology–WfH is more feasible in occupations with abstract tasks–and selection–higher-human capital individuals are more likely to sort into abstract occupations, further increasing their chances of receiving a WfH opportunity.

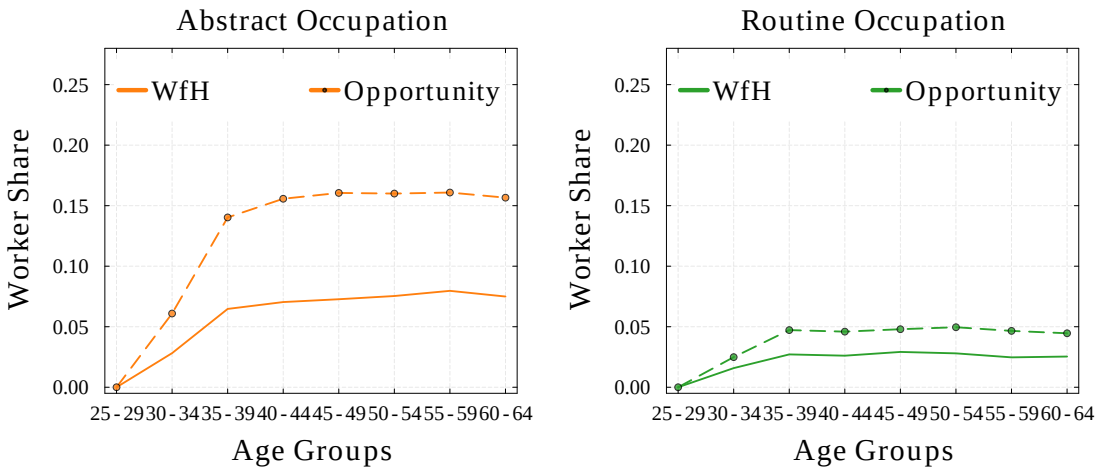


Figure 9: WFH Opportunities and Take-up

Note: Displays the share of WfH opportunities and actual WfH take up for abstract (left) and routine (right) workers in the stationary baseline economy.

WfH Uptake is Driven by Preferences or Earnings Gains WfH take-up is driven by two factors: potential earnings gains from working remotely or preferences reflected in a high taste shock for WfH. Potential earnings gains arise only in routine occupations. As discussed earlier, a worker in a routine job can offset the static wage penalty of remote work if they reinvest enough of the commuting time saved into additional market hours and reap dynamic productivity gains. In contrast, in abstract occupations, compensating for the higher wage penalties would require investing more time than what is saved from commuting. Consequently, conditional on receiving an opportunity to work remotely, take-up rates are higher in routine jobs for both men and women. As shown in the first two columns of Table 12, 53% of routine workers accept the opportunity, compared to only 47% in abstract occupations.

Table 12: Take-up Rates by Occupation and Preference Shock

$\sigma_p = 0.021$		$\tilde{\sigma}_p = 0.002$	
Routine	Abstract	Routine	Abstract
0.53	0.47	0.72	0.24

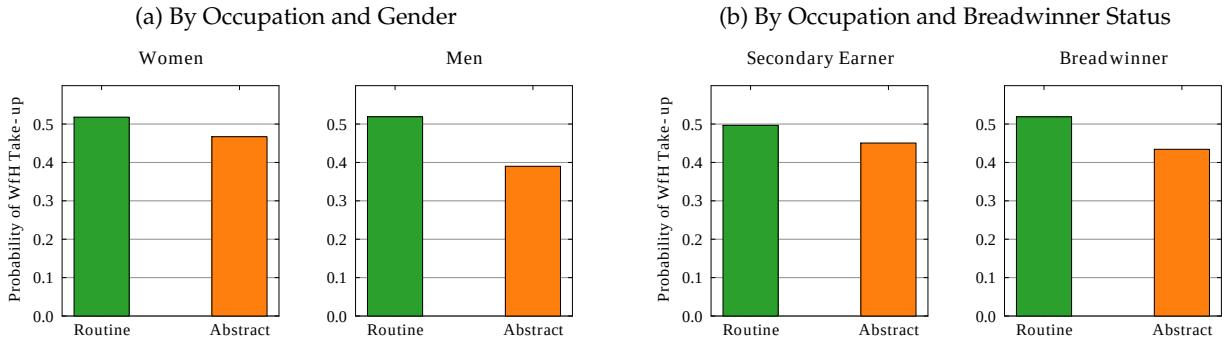
Note: The table displays the WfH take-up rate, conditional on receiving an opportunity, by occupation group for to scenarios: under the baseline taske shock (first two columns) and under a lower taste shock (last two columns).

The preference motive arises because, upon receiving an opportunity, workers draw choice-specific taste shocks for each workplace. A sufficiently high taste shock for remote work may lead a worker to choose WfH despite potential static and dynamic penalties it entails. Table 12 illustrates the quantitative role of preference shocks in WfH take-up by occupation. To this end, I compare the baseline simulation with a preference shock of $\sigma_p = 0.021$ to a counterfactual simulation where the

dispersion of shocks around zero—and equivalently the additive weight of the shock in the utility function—is reduced by 10-fold, with $\tilde{\sigma}_p = 0.002$. As expected, preference shocks are the main driver of WfH take-up in abstract occupations, where the static and dynamic penalties of remote work are too large to justify adoption based on income motives alone. When the preference shock is reduced, the take-up rate falls from 47% to 24%. By contrast, in routine occupations WfH take-up is largely explained by the prospect of instantaneous earnings gains rather than by preference shocks. In fact, take-up rises to 72%, since workers who previously experienced an unfavorable shock place less weight on preferences and more on the pecuniary gains from WfH adoption.

Women and Secondary Earner are More Likely to Take up WfH in Abstract Jobs With the discrete taste-shock in my model, I can compute the choice probabilities of WfH take-up conditional on receiving an opportunity. The computation follows the approach in Iskhakov et al. (2017) and is described in detail in Appendix B. Figure 10 displays the average choice probabilities by occupation and gender (Figure 10 Panel (a)) and by occupation and breadwinner status (Figure 10 Panel (b)), where I proxy breadwinner status by whether current human capital exceeds that of the spouse. Consistent with my earlier results, WfH take-up is higher in routine (green) than in abstract

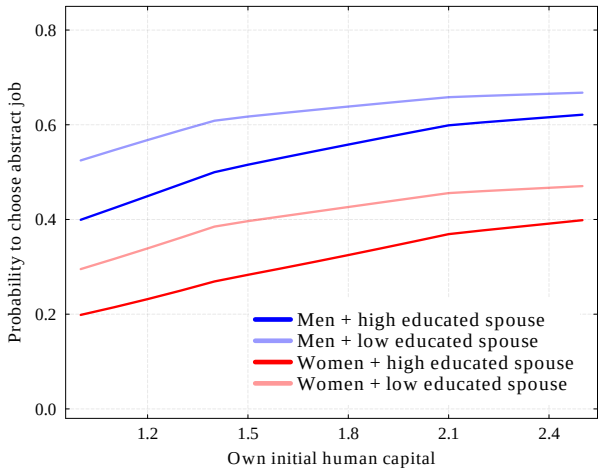
Figure 10: Average WfH Choice Probabilities



Note: The figures display the average remote work probabilities by gender and occupation (a) as well as by occupation and breadwinner status (b).

(orange) occupations, reflecting the absence of productivity penalties in routine jobs. Notable gender differences emerge as well: while men and women exhibit similar average take-up probabilities in routine occupations (52%), women are more likely to choose WfH in abstract occupations than men (47% vs. 39%). The only difference between groups is that women possess a comparative advantage in home production, which effectively insures them against the productivity penalties associated with WfH. Recall that WfH take-up in abstract occupations is primarily preference-driven rather than motivated by pecuniary gains, given the sizable productivity losses. Women's comparative advantage in home production thus makes them relatively more willing to accept these penalties. Differences by breadwinner status follow a similar logic. Given the potential static and dynamic productivity gains from WfH in routine jobs and the specialization motive within households, breadwinners are slightly more likely to take up WfH in routine occupations than secondary earners

Figure 11: Choice Probabilities for Abstract Job



Note: The figure reports the initial probability to choose an abstract job by gender and own initial human capital (education) given the spouse has a low or high initial education.

(52% vs. 50%). Conversely, in abstract occupations, secondary earners are more likely to take up WfH than breadwinners (45% vs. 43%). This reflects the fact that secondary earners can rely on the income of the primary earner, making the productivity penalties from WfH less consequential for total household income.

6.3 What is the Effect of WfH on Gender Disparities in the Baseline Economy?

Gender Differences in Occupation Choices Affect the Prevalence of WfH Career Gains Career effects of WfH vary across occupation groups. To assess the role of WfH in shaping gender disparities, it is therefore important to examine the occupational composition by gender. In the first period of the model, couples jointly choose their occupations—routine or abstract—based on their initial educational endowments. Given occupation-specific taste shocks in this period, I compute and report the choice probabilities of selecting an abstract occupation by gender, own human capital, and spousal human capital, as illustrated in Figure 11.

Let me highlight three key observations. First, ignoring gender for the moment, higher-educated individuals are more likely to sort into abstract occupations. This pattern arises because workers trade off amenities against income potential. Individuals with high human capital exhibit stronger wage growth potential in abstract occupations—conditional on supplying high market hours—due to higher human capital growth elasticities. By contrast, routine occupations impose smaller penalties for reduced market hours through higher intercept wage growth (greater baseline learning ability) and offer higher additive amenity values. Second, individuals are more likely to choose an abstract occupation when they are more educated than their spouse. This reflects a specialization motive within the joint household framework: resources are pooled, and home production is a

public good with high substitutability. The more-educated partner typically specializes in market work and becomes the primary earner. Because market hours generate dynamic returns through learning by doing, this further amplifies the incentive to specialize. Meanwhile, the less-educated partner tends to allocate more time to home production and select into routine occupations, where lower work hours are less costly and amenities are higher. Finally, men generally sort more often into abstract occupations than women, even though women are, on average, more highly educated. This pattern highlights the role of home production in the household and women's comparative advantage in it, which can outweigh the education premium associated with abstract occupations in the couple's occupational trade-off. Figure 12 displays the resulting distribution of the simulated economy, showing the share of workers choosing abstract occupations for women (panel a) and men (panel b), conditional on their own and their spouse's initial education. As expected, higher-educated individuals are more likely to select into abstract occupations, particularly when they are more educated than their spouse. Further, men are more likely to sort into abstract occupations than female counterparts.

Figure 12: Share of Abstract Workers by Gender and Initial Education



(a) Women (b) Men

Note: Displays the share of abstract workers (in %) among women (a) and men (b) by spousal educational background in the baseline stationary economy.

In response to those occupational compositional effects the following WfH pattern emerges. Table 13 displays the share of WfH by gender and occupation. Male remote workers are more prevalent in abstract and female remote workers are more prevalent in routine.

Thus, women are more likely to benefit from WfH take-up for their careers through both the direct and indirect channels discussed earlier. They are more exposed to the career gains of the indirect WfH channel, as spousal WfH take-up is more prevalent among men in abstract occupations, and they are also more likely to adopt WfH themselves in routine occupations (gains through direct WfH channel), where career gains are present.

Table 13: Take-up Rates by Occupation and Gender

Routine		**Abstract**	
Men	Women	Men	Women
0.009	0.012	0.029	0.017

Note: The table displays share of teleworkers among men and women by occupation.

Table 14: Effect of WfH Take-up on Gender Disparities in Labor Outcomes

	log(wage)		log(market work)		Human capital growth $t+1$	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	3.15***	3.18***	3.22***	3.25***	5.13***	5.09***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.017)	(0.017)
Female dummy	-0.14***	-0.14***	-0.69***	-0.68***	-1.86***	-1.74***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.025)	(0.025)
Telework dummy	0.11***		0.46***		-4.70***	
	(0.002)		(0.006)		(0.091)	
Telework (spouse)		-0.12***		-0.50***		-4.49***
		(0.002)		(0.007)		(0.104)
Female × Telework	**0.03*****		**0.28*****		**3.46*****	
	(0.003)		(0.009)		(0.138)	
Female × Telework (spouse)		**0.03*****		**0.03*****		**1.40*****
		(0.003)		(0.009)		(0.138)

Note: Depicts the regression output from regressing log-wages, log-market work or human capital growth between t and $t+1$ on a female dummy, own or spousal WfH take-up and the interaction between a female dummy and WfH take-up.

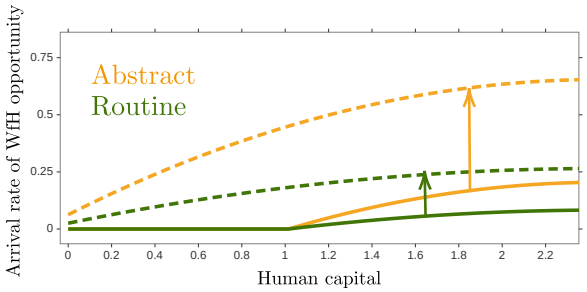
WfH has a Gender Equalizing Effect Table 14 summarizes aggregate gender disparities in the effects of WfH take-up. I regress log wages, log market hours, and human capital growth between t and $t+1$ on WfH, distinguishing between own and spousal take-up and interacting these variables with a female dummy. Abstracting from WfH, across all specifications, the female dummy is negatively associated with outcomes: women supply fewer market hours, earn lower wages, and exhibit slower human capital growth than men. The coefficient on the telework dummy (male take-up) is positive. This reflects that men are more likely to take up WfH in abstract occupations, and irrespective of WfH, men in abstract occupations tend to work more hours and earn higher wages. Moreover, men with higher human capital are more likely to receive a WfH opportunity. However, the dynamic productivity penalty on human capital growth translates into a negative coefficient for human capital growth. By contrast, WfH take-up by female spouses (Telework (spouse)) has a negative effect. Women are more likely to adopt WfH in routine occupations, which, via a positive cross-income effect, incentivizes men to work fewer hours and earn less—also translating into reduced human capital growth. Importantly, the interaction terms—female with

own WfH take-up and female with spousal take-up—are positive. This suggests that WfH take-up has an equalizing effect on gender disparities through both own and spousal channels, consistent with the compositional effects described above.

7 The Long-Run Effects of an Economy-wide WfH Opportunity Shock

In the following, I use my structural model to evaluate the long-run impact of a (WfH) opportunity shock on mothers' careers and gender disparities in labor supply and outcomes. Specifically, I increase the intercept ρ_1 in the arrival rate of WfH opportunities by 0.45, raising the average WfH availability from 7% to 37% in the new steady state—consistent with the estimated share of jobs that can be done remotely from Dingel and Neiman (2020). Figure 13 displays the change in the arrival rate by occupation. In routine occupations (green lines), the arrival rate is scaled by $\rho_{\text{routine}} = 0.40$, such that the opportunity shock affects routine jobs only 40% as strongly as abstract occupations (orange lines).

Figure 13: Change in the Arrival Rate of WfH Opportunities through Expansion



Preferences, technologies, and ex-ante heterogeneity remain unchanged. As such, the analysis mirrors the interpretation in Monte et al. (2025).[31]

I proceed by comparing the stationary baseline equilibrium to the counterfactual stationary economy after the positive WfH opportunity shock.

7.1 The Long-run Effects on Economics Aggregates

WfH Expansion Increases Welfare and Output. Table 15 displays the aggregate comparison between the two steady-states. In response to the expansion of WfH opportunities, aggregate

[31] As argued by the authors, while the steady rise in remote work since the 1980s can be attributed to gradual improvements in communication technologies, changing preferences, and compositional shifts in the labor force, the sharp post-pandemic increase is unlikely to be driven by these factors alone. Notably, relative wages between remote and on-site workers remained stable between 2018 and 2022, controlling individual characteristics and compositional changes. Instead, outside of the model it could be argued like Monte et al. (2025): coordination frictions among economic agents in cities can give rise to multiple stationary equilibria. In such a setting, a temporary shock to WfH can trigger a transition to a new, high-remote-work equilibrium with lasting structural changes.

output increases by 0.47%. At the same time, ex-ante welfare rises. In consumption equivalence variation (CEV), couples in the old steady-state would require on average a 11.14% increase in lifetime consumption to be indifferent between the old steady-state and an expansion in WfH opportunities in terms of average ex-ante welfare.

Table 15: Aggregate Effects Through Shift

Output (in %)	+0.47
CEV in old steady-state (in %)	+11.14

Note: The table reports aggregate changes between the baseline steady-state in the economy after the WfH opportunity shock.

Output Gains are Driven by an Increase in Market Hours and Human Capital of Occupation Switcher. To understand the sources of aggregate output gains, it is instructive to examine Table 16. The table displays the change in occupation-specific labor outcomes between the two steady-states. In response to a WfH expansion, supplied efficiency units of labor decline in routine occupations by 2.3% but increase in abstract occupations by 1.25%. Since efficiency units of abstract work carry a higher weight in the final goods' production ($\omega_A = 0.67$), the gains in abstract labor more than offset the losses in routine labor, resulting in a modest overall increase in output.

Table 16: Aggregate Occupation Effects

	Routine	**Abstract**
Δ Labor Efficiency units (in %)	-2.33	+1.25
Δ WfH worker shares (in ppt.)	+9.48	+20.88
Δ Occupation shares (in ppt.)	-2.28	+2.28
Δ Wages per efficiency unit (in %)	+0.97	-0.26

Note: The table reports aggregate changes by occupation in response to the WfH opportunity shock, comparing the new stationary equilibrium to the baseline. Δ denotes the change between equillibria. By construction, the three components in the decomposition sum to one.

At first glance, the occupation-specific patterns in labor efficiency units may appear counterintuitive. As shown in Table 16, WfH take-up increases substantially more in abstract jobs—by 20.9 percentage points—than in routine jobs, where it rises by only 9.5 percentage points. Moreover, abstract occupations experience larger productivity penalties from WfH than routine ones. To better understand why the stronger efficiency losses from WfH in abstract occupations are not reflected in the aggregates, let's decompose the supplied efficiency units of labor using the following formula for a worker in couple i, of gender g, age j and occupation o:

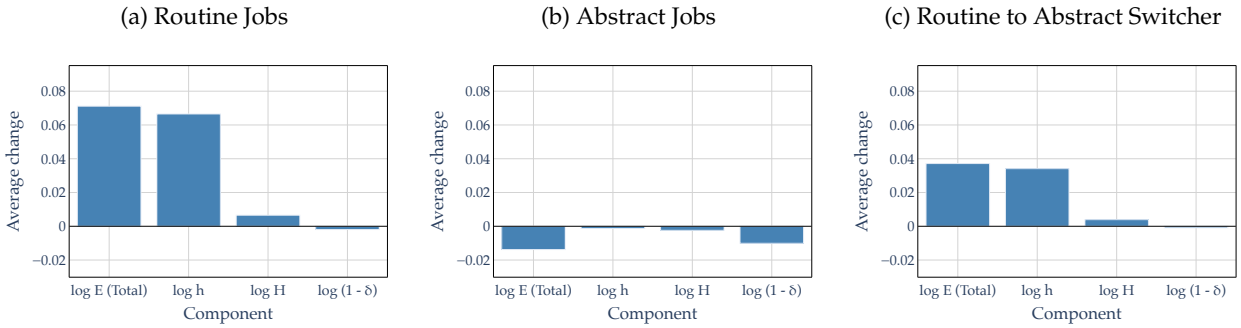
$$\log(E_{igjo}) = \log(h_{igjo}) + \log(H_{igjo}) + \log(1 - \delta_o(p_{igjo})).$$

Accordingly, the average of aggregate changes can be decomposed as:

$$\frac{1}{J \times N \times 2} \sum_{igjo} \Delta \log(E_{igjo}) = \frac{1}{J \times N \times 2} \sum_{igjo} \Delta \log(h_{igjo}) + \Delta \log(H_{igjo}) + \Delta \log(1 - \delta_o(p_{igjo})),$$

where Δ denotes the difference between the new and old steady-state values at the couple i, gender g, age j, and occupation o level. Figure 14 shows that indeed, among occupation stayers, the average change in supplied labor efficiency units is actually positive in routine jobs (panel (a)) but negative in abstract jobs (panel (b)). This decline in abstract occupations reflects the sizable static and dynamic productivity penalties associated with WfH in these jobs. At the same time, however, there is net re-sorting of workers toward abstract occupations—by 2.28 percentage points, as reported in Table 16. We can thus, further decompose the average change in labor efficiency units for this group, as shown in Figure 14, panel (c).[32] For workers switching into abstract occupations, labor efficiency units rise, driven primarily by higher market hours and human capital accumulation in these occupations. Given that those workers are exposed to a higher wage rate and a better technology to accumulate human capital the responses are large. Hence, it is the switchers into abstract jobs who drive the increase in abstract labor efficiency units and thus, the aggregate output gains.[33]

Figure 14: Decomposition of Changes in Aggregate Labor Efficiency Units Among Occupation *Stayers* (by Occupation) and Occupation *Switchers* (into Abstract Occupations)



Note: The figure displays the decomposition of average log-changes in labor efficiency units between the old and new steady-state. Changes are displayed by occupation group, among occupation stayers and separately for switchers into abstract jobs. Changes cannot be disaggregated by occupation group among occupation switchers. Total changes in efficiency units consists of changes in market hours, human capital (which includes the effect of the dynamic WfH productivity effect) and the exposure to the static WfH penalty.

The Net Shift Toward Abstract Occupations is Concentrated among High Educated Women. The larger increase in WfH opportunities in abstract occupations induces a net reallocation of workers toward these jobs—despite their higher WfH productivity penalties—raising their employment share by 2.3 percentage points, while routine occupations experience a corresponding decline (Table 16). Consequently, the abstract wage premium per efficiency unit of labor, measured

[32] As further elaborated in Table 17, aggregate flows from abstract to routine occupations are negligible at around 0.1% for both men and women.

[33] Section A.5 in the appendix presents early qualitative evidence on the occupation re-sorting channel.

as $\frac{w_A}{w_R}$, decreases by 1.2%. The relative expansion in the aggregate supply of abstract efficiency units of labor makes routine labor relatively scarcer, thereby increasing the relative wage of routine workers.

Table 17 disaggregates occupation switches between steady-states by gender as share of the male or female population. The majority of switches occur among women, particularly those moving from routine to abstract jobs between steady states (4.6%). Women who switch into abstract occupations tend to have higher initial human capital compared to routine stayers (1.27 vs. 1.23), as well as relatively higher human capital relative to their male spouse compared to routine stayers (1.06 vs. 1.03).

Table 17: Occupation Switches between Steady-States

	Transition	Share	Average initial human capital	
		(in %)	(in levels)	(rel. to spouse)
Men	R $\rightarrow$ A	0.1	1.34	1.03
	A $\rightarrow$ R	0.0	0.82	0.83
	R $\rightarrow$ R	48.4	1.20	0.98
	A $\rightarrow$ A	50.8	1.24	1.03
Women	R $\rightarrow$ A	4.6	1.27	1.06
	A $\rightarrow$ R	0.1	1.34	1.04
	R $\rightarrow$ R	66.1	1.23	1.03
	A $\rightarrow$ A	28.4	1.27	1.09

Note: Describe the distribution of occupation transitions between steady-states, as well as the average level of initial human capital in levels and relative to the spouse. "A" stands for abstract job and "R" stands for a routine job.

7.2 The Long-run Effects on Women's Careers

In the following section, I discuss the long-term effects of a WfH expansion on women's career outcomes by comparing aggregate changes between the old and new steady states.

In the Aggregate, Women Experience Career Gains from the WfH Expansion. Table 18 reports the aggregate percentage changes in average female labor outcomes between the two steady states—hourly wages, market hours, labor earnings (their product), and earnings growth. On average, female hourly wages rise by 1.72%, market hours by 6.59%, leading to an overall increase in labor earnings of 5.31%. Those changes translate into persistent career gains: I report the change in earnings growth between age 25-40, which is higher by 7.22 percentage points in the new steady state. Figure 15 illustrates female earnings growth relative to $j = 1$ in both steady states. In the old steady state (solid line), earnings growth declines during the child-intensive years early in the life cycle and barely recovers thereafter. In the new steady state (dashed line), women's earnings similarly dip between ages 35–44 but recover better afterwards. Overall, earnings growth is higher,

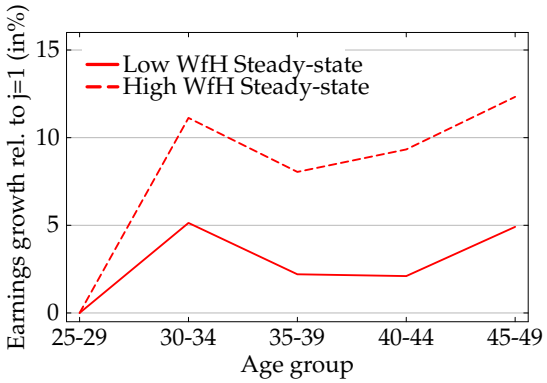
particularly at the onset of their careers (ages 30–34).[34] Thus, to answer whether WfH serves as a stepping stone or a stumbling block for women's careers: in the aggregate, women—and mothers in particular—experience overall career gains from the expansion of WfH opportunities.

Table 18: Steady-state Comparison of Female Labor Outcomes (Aggregate Effects)

Δ (in %)			Δ (in ppt.)
Hourly wages	Market hours	Labor earnings	Earnings growth between age 25-40
+1.72	+6.59	+5.31	+7.22

Note: The table reports the average percentage change in women's aggregate labor outcomes—hourly wages, market hours, and labor earnings (the product of the two)—between the old and new steady states.

Figure 15: Female Earnings Growth relative to $j = 1$ (Steady-state Comparison)



Note: The Figure reports the average earnings growth for women relative to the first life-stage in the old and new steady-state.

Table 19 provides further insight into the driving forces and underlying heterogeneities in women's labor market responses. It reports the percentage change in average women's outcomes between the old and new steady states. To disentangle the decision margins at play in response to the WfH expansion, the table presents results by subgroups. I first separate, among occupation stayers, women by whether they, or their male spouses, *ever* take up WfH during their life cycle in the new steady state. This accounts for the persistent effects of WfH adoption, which are not captured if one considers only periods of actual WfH use. Restricting to those periods would be misleading, since the dynamic productivity effects of WfH unfold over time. Second, I examine women who switch occupations in response to the expansion of WfH. I do not explicitly distinguish occupational switches by male spouses, as their incidence is negligible (see Table 17). Among occupation switchers, I include individuals who simultaneously ever take up WfH—either themselves or their spouse.[35]

To isolate the effect of increased WfH opportunities on women's labor outcomes, I compare women in the new steady-state to their "identical twin" in the old steady-state, defined as women (and their spouses) with identical initial human capital endowments.[36]

I focus on the sample of couples whose twins (as just defined) never adopted WfH in the old steady state. This restriction isolates the impact of the expansion by abstracting from couples who had

[34] I report the equivalent Table 18 for male individuals in Appendix D in Table 42.

[35] Table 43 in Appendix D explicitly distinguishes between the effects of own and spousal WfH take-up among occupation switchers and shows the resulting changes in women's labor market outcomes.

[36] In computing identical twins I also hold constant the underlying randomness. Every shock draw can be represented as a uniform draw mapped to the cumulative probability matrix. These draws are held constant across steady states, while the cumulative probabilities themselves adjust with the increased arrival rate of WfH opportunities.

already worked from home prior to the shift. For comparison, Table 44 in the Appendix D reports results including couples who already worked from home in the old steady state. The qualitative and quantitative magnitudes are very similar.

Table 19: Steady-state Comparison of Female Labor Outcomes by Subgroups

Subgroup			Δ (in %)			Δ (in ppt.)	
Occ. stayer		Occ. switcher	Hourly wages	Market hours	Labor earnings	Earnings growth between age 25-40	Share (in %)
Own WfH	Spousal WfH						
			+0.73	+0.31	+0.62	+0.04	4.7
✓			-2.52	+1.76	-1.98	+0.69	12.2
	✓		+1.59	+5.46	+5.35	+4.56	18.4
✓	✓		-0.36	+4.79	+0.83	+2.99	19.0
		✓	+69.79	+97.23	+231.58	+43.26	2.9
Aggregate Effect (Table 18)			+1.72	+6.59	+5.31	+7.22	100

Note: The table shows the average percentage change in women's labor outcomes—hourly wages, market hours, labor earnings (the product of the two) as well as earnings growth between age 25 and 40—between the old and new steady states. To isolate the role of increased WfH opportunities, I compare the same couples across environments that differ only in the availability of WfH. Specifically, steady-state outcomes are compared between female *twins*, defined as women (and their spouses) with identical initial human capital endowments and identical realizations of exogenous shocks. I look at changes by subgroups depending on women's own WfH take-up and their spouses, as well on wether they switched their occupation group.

Career Gains for *Stayers* are Driven by Incentives to Secure Future WfH Opportunities and General Equilibrium Effects. Among the most restrictive group of female occupation *stayers* in Table 19—those for whom neither them or their spouse ever takes up WfH throughout the life cycle or switches occupation in the new steady state—I find an modest increase across all margins: hourly wages increase by $+0.73\%$, market hours 0.31%, an overall increase in labor earnings of 0.11% and an increase of 0.04 percentage points in earnings growth by the age of 40.

The increase in wages stems from general equilibrium effects. In this subgroup, I find that the majority of women (84%) is employed in routine jobs, where the wage rate per efficiency units rises by 0.97% due to the relative increase in scarcity of routine work (see Table 16).

The increase in market hours is primarily driven by the incentive to accumulate additional human capital, thereby improving the likelihood of gaining a WfH opportunity in the future. Table 20 reports the average increase in market hours between the two steady states, differentiated by spouses' occupation and life stage. I distinguish four phases of the life cycle: early career ($j = 1, 2$), child-intensive periods ($j = 3, 4$), mid-career ($j = 5, 6$), and late career ($j = 7, 8$). Women raise their hours more strongly when their spouses work in abstract occupations, as the higher household income provides a financial buffer if they themselves adopt WfH and face penalties—particularly dynamic ones. The rise in hours is most pronounced during child-intensive periods, when home production carries a higher utility weight, and at the end of the career, when the materialization of dynamic WfH penalties is no longer relevant.

Table 20: Change in Female Market Hours by Spousal Occupation and Life-Stage (Occupation Stayers and Onsite Workers)

	Δ Female Market hours (in %)	
Life stage	Spouse in Routine	Spouse in Abstract
Early career	0.0	+5.8
Child intense	0.0	+9.3
Mid career	0.0	+8.2
End career	0.0	+3.8

Note: The table shows the increase in market hours between the two steady-states of women that do not ever take-up WfH or switch their occupation in response to the WfH expansion. Changes are displayer by life-stage and spousal occupation.

Female Career Effects of Own WfH Take-up Depend Crucially on the Occupation. Among the second group in Table 19—women who ever take up WfH in the new steady state—average hourly wages decline by 2.52%. A modest rise in market hours of 1.76% is insufficient to offset this decline, resulting in an overall earnings loss of 1.98%. Nevertheless, earnings growth by age 40 increases slightly by 0.69 percentage points. Given that the productivity effects of WfH differ by occupation, Table 21 decomposes these effects by occupation. The wage drop associated with WfH originates entirely from abstract occupations, where wages fall by 4.08%, while wages in routine occupations rise by 1.89%. This pattern reflects the stronger productivity penalties of WfH in abstract work. In routine jobs, the combination of short-term earnings gains and the dynamic productivity premium from WfH lead women to expand market hours by 5.38% and reduce domestic hours by 2.18%, generating lifetime earnings gains of 7.04% and a rise in earnings growth by age 40 of 4.18 percentage points. In contrast, women in abstract occupations shift toward home production: market hours increase only slightly (0.67%), while domestic hours rise markedly (6.98%). Consequently, their labor earnings fall by 3.49%, and earnings growth by age 40 declines by 0.17 percentage points. Thus, even though women benefit overall from the WfH expansion in terms of career outcomes, the gains from own WfH take-up depend critically on occupation. Women in routine jobs experience clear benefits, whereas those in abstract occupations do not.

Table 21: Change in Labor Outcomes - Own WfH Take-up

	Δ in %				Δ in ppt.	
Own Occupation	Hourly wages	Market hours	Labor earnings	Domestic hours	Earnings growth between 25-40	Share
Routine	+1.89	+5.38	+7.04	-2.18	+4.18	0.39
Abstract	-4.08	+0.67	-3.49	+6.98	-0.17	0.61

Note: The table shows the change in hourly wages, market hours, labor earnings, domestic hours and earnings growth between old and new steady-state, after expansion of WfH opportunities. The sample consists of female occupation stayer who ever take-up WfH along their life-cycle in response to the WfH expansion in the new steady-state. Changes are split by women's occupation group.

Spousal WfH Take-up Benefits Women's Careers if the Spouse Works in Abstract Jobs. In group three of Table 19, where only male spouses take up WfH, women experience average career gains across all margins: hourly wages rise by 1.59%, market hours increase by 5.46%, labor earnings grow by 5.35%, and earnings growth by age 40 increases by 4.56 percentage points relative to the old steady state.

As shown earlier, the indirect WfH channel through which spousal WfH affects women's careers depends critically on the spouse's occupation. Table 22 decomposes these changes by spousal occupation. The results indicate that career gains are driven primarily by spousal WfH take-up in abstract occupations. In this case, incentives for the non-WfH spouse to increase market hours and accumulate human capital are particularly strong, due to negative cross-income effects arising from the spouse's WfH take-up. Specifically, hourly wages increase by 2.00%, market hours rise by 22.00% (largely driven by women at the participation margin, proxied by those working less than 10 hours on average over five years), labor earnings increase by 24.09%, and earnings growth by age 40 rises by 8.69 percentage points. In contrast, when spouses take up remote work in routine jobs, female labor is crowded out: market hours decline by 2.70%, translating into persistent negative career effects. For these women, earnings growth by age 40 falls by 3.25 percentage points. Given that men predominantly take up WfH in abstract occupations (75%), the positive effects of the indirect WfH channel dominate at the aggregate level. Thus, while own WfH take-up in routine jobs benefits women's careers, spousal WfH take-up in routine jobs crowds out their market work and reinforces their specialization in domestic tasks, thereby slowing their career progression.

Table 22: Change in Labor Outcomes - Spousal WfH Take-up

	Δ in %				Δ in ppt.	
Spousal Occupation	Hourly wages	Market hours	Labor earnings	Domestic hours	Earnings growth between 25-40	Share
Routine	+0.55	-2.70	-2.03	+2.93	-3.25	0.25
Abstract	+2.00	+22.00	+24.09	-2.30	+8.69	0.75

Note: The table shows the change in hourly wages, market hours, labor earnings and domestic hours between old and new steady-state, after expansion of WfH opportunities. The sample consists of women who's spouses ever take-up WfH along their life-cycle in response to the WfH expansion in the new steady-state. Change are split by the male spouse occupation group.

If Both Spouses Ever Take Up WfH, the Positive Career Effects for Women Prevail. In group four of Table 19, where both spouses ever take up WfH in the new steady state, women experience net career gains. The positive effects from own WfH take-up in routine jobs and spousal WfH take-up in abstract on women's careers prevail. On average, earnings growth by the age of 40 increases by 2.99 percentage points.

Female Occupation Switchers Into Abstract Benefit the Most from The WfH Expansion. The largest career gains in the new steady state accrue to women who switch occupations across steady states (last subgroup in Table 19). The majority of female occupation switcher move into abstract

occupations (see Table 17). Given the sizable extensive margin effects—switching into a more productive technology for human capital accumulation and earning a higher wage per efficiency unit—changes are substantial: hourly wages rise by 69.79%, market hours double, and labor earnings surge by 231.58% (more than tripling). Those women increase their earnings growth by the age of 40 by 43.26 percentage points. These effects are further amplified by positive cross-income effects within the household, which encourage their male spouse to specialize more in domestic work, despite the relative decrease in the abstract wage premium induced by general equilibrium effects. Although this group is small—only about 4.6% of the female population—it consists of high educated women, both in absolute terms and relative to their spouses, who were close to the occupational decision threshold in the old steady state. Their response are an important driver of the observed aggregate female labor outcome changes.[37]

As explained previously, in the old steady state women were less likely than men with comparable human capital to enter abstract occupations because of their comparative advantage in home production. Consequently, a larger share of high educated women than men remained in routine work. The relatively stronger expansion of WfH opportunities in abstract work now incentivizes these women—especially the highly educated in routine occupations—to switch. They benefit disproportionately because (i) highly educated workers have a higher probability of receiving WfH opportunities, given the positive gradient of the arrival rate with human capital, and (ii) they are better positioned to reap the benefits of steep wage profiles in abstract occupations, which feature low intercept wage growth but strong elasticities in supplied efficiency units. Incentives are particularly strong when women are more educated than their spouses, as specialization motives further encourage the switch. Conditional on household human capital, women are also more likely than men to accept a WfH opportunity due to their comparative advantage in home production, which provides implicit insurance against the productivity penalties of WfH in market work. Table 43 in the Appendix D disentangles the contributions of own and spousal WfH take-up for female occupation switchers. The large responses mirror, but amplify, the qualitative findings for occupation stayers describe previously.

7.3 The Long-run Gender Gap Effects

This section examines how women's career adjustments in response to the WfH expansion translate into aggregate gender disparities.

As Women's Careers Rise, the Gender Gaps Falls. Table 23 reports the gender gaps in the old steady state and their percentage changes following the WfH expansion. The gap is defined as the ratio of average male to average female labor outcomes. Across all margins, gender disparities decline: the hourly wage gap falls by 2.85%, the market hours gap by 6.64%, and consequently the

[37] Recall that male occupational re-sorting is virtually absent; women drive the occupational reallocation into abstract work.

labor earnings gap by 7.40%. By contrast, in domestic work—where men initially supplied 38% fewer hours than women—the gap widens by 6.33% as men increase their relative domestic labor supply. The gap in abstract occupations narrows by 9.25%, reflecting women's stronger re-sorting into abstract jobs, and the breadwinner gap (defined as the share earning more than their spouse) decreases by 14.74%.

Female relative gains in market hours and wages translate into tangible career improvements over the life cycle: the gap in earnings growth by age 40 shrinks by 16.64 percentage points. Figure 17 illustrates the evolution of earnings growth for men and women in the old and new steady states. Both men and women experience higher earnings growth over their careers after the WfH expansion, but the increase is stronger for women—particularly after child-intensive periods, when they catch up from earlier slowdowns. In the old steady state, by contrast, women's earnings growth would stagnate at low levels.

Within-couple dynamics adjust accordingly. Table 16 shows the average within-couple difference in male–female time allocation. In the baseline, men supplied 11.87 more weekly market hours but 11.55 fewer domestic hours than their wives. Following the WfH expansion, both gaps narrow by about one hour per week.

Table 23: Steady-state Comparison of Gender Gaps

	Hourly wages	Market hours	Labor earnings	Domestic hours	Abstract Jobs	Primary earner	Earnings growth 25-40
X_m/X_f baseline	1.15	1.53	1.64	0.62	1.57	2.56	1.15
Δ (in %)	-2.85	-6.64	-7.40	+6.33	-9.25	-14.74	-16.64

Note: The table shows gender gaps in hourly wages, market hours, labor earnings, domestic hours, share in abstract jobs and breadwinner status. If further shows gender gaps in the earnings growth by age 40. It displays the level gap defined as X_m/X_f (X_m and X_f are the male and female respective outcome variables of interst) for the old steady-state (baseline economy) as well as its percentage change in the new steady-state, after the WfH expansion. A spouse is a breadwinner if their labor earnings are higher than their spouse's.

Table 24: Steady-state Comparison of Gender Gaps by Subgroups

Subgroup			**Δ (in %)**			**Δ (in ppt.)**	
Ever take-up WfH		Occ. switcher	Hourly	Market	Labor	Earnings growth	Share (in %)
own	spousal	own	wages	hours	earnings	between age 25-40	
			-0.33	-0.29	-0.41	+1.64	4.7
✓			-0.78	-0.48	-0.55	-2.12	22.2
✓	✓		-1.27	-3.01	-2.54	-8.33	94.5
✓	✓	✓	-2.85	-6.64	-7.40	-16.64	100

Note: The table shows the change in gender gaps (defined as X_m/X_f) between the old and new steady state in hourly wages and market hours across different subgroups.

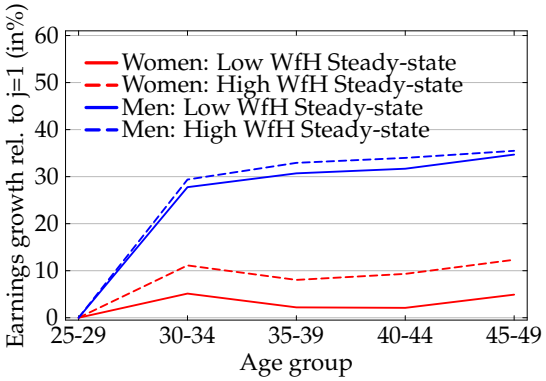
Occupation Switches and Spousal Workplace Flexibility Fuel the Decline in Gender Disparities. To disentangle the role of different decision margins, I compute gender gaps in hourly wages and

Figure 16: Steady-state Comparison of Within-couple Specialization

	Average weekly within-couple difference in ...	
Steady-state	Market hours	Domestic hours
Old	11.87	-11.55
New	10.24	-10.04

Note: The table shows average within-couple differences in time allocation (market and domestic hours) in the baseline as well in the new steady-state. To compute within-couple differences I take the difference $X_{ijm} - X_{ijf}$ of outcome variable X for couple i at age j and average across couples and age groups.

Figure 17: Female and Male Cumulative Earnings Growth (Steady-state Comparison)



Note: The Figure reports the average cumulative earnings growth for women and men in the old and new steady-state.

market hours for several subgroups, as displayed in Table 24. Specifically, I distinguish individuals by (i) whether they or their spouse ever take up WfH over the life cycle in the new steady state, and (ii) whether they or their spouse switch occupations. By progressively adding subgroups, I trace the margins that drive the aggregate changes in gender wage gaps. Among workplace and occupation stayers, the hourly wage gap decreases slightly (-0.33%) due to mostly general equilibrium effects: the abstract wage premium decreases, and men in this group work more in abstract jobs (Table 25) than women (34% for men v.s. 16% for women). At the same time, the market hours gap narrows because women have stronger incentives to accumulate human capital in pursuit of WfH opportunities.

Table 25: Workers across Occupation Groups in New Steady-state (Occupation Stayers and Onsite Workers)

	Share in Routine	Share in Abstract
women	0.84	0.16
men	0.66	0.34

Note: The table shows the distribution across occupation groups of workers that do not ever take-up WfH or switch their occupation in response to the WfH expansion.

Including own WfH take-up reduces all gaps: the hourly wage gap falls by 0.78% and the market hours gap by 0.48%. This is because women predominantly take up WfH in routine jobs, while men do so in abstract jobs. Table 26 shows the share of WfH workers across occupation among the group of men and women of this sample. Both groups suffer wage losses from WfH penalties, but these penalties are smaller—both statically and dynamically—in routine jobs, enabling routine workers to achieve short-term earnings gains.

Adding spousal WfH take-up, which covers a large share of the population since many couples have both partners working from home at some point, further reduces the gaps, particularly in

Table 26: WfH Workers across Occupation Groups in New Steady-state
(Occupation Stayers and Own WfH Take-up)

	WfH in routine	WfH in Abstract
women	7.2	9.0
men	5.7	13.6

Note: The table shows the distribution across occupation groups of workers that take-up WfH at some point in their life or switch their occupation in response to the WfH expansion.

market hours. This is driven by women's higher exposure to spousal WfH in abstract jobs: the negative cross-income effects raise women's market work and human capital accumulation. This translates into persistent career gains for women: the gap in earnings by age 40 decrease by 8.33 percentage points.

The largest single margin comes from own occupational switching, which is predominantly women re-sorting into abstract jobs. Although only a small share of the population switches occupations, this group has a disproportionate impact on reducing gender gaps in labor outcomes.

While Gender Gaps Close in Routine Occupations, They Expand in Abstract Work. The aggregate changes in gender gaps conceal important heterogeneities. Table 27 reports changes in gender gaps in hourly wages and market hours between the two steady states by occupation group. The results show that gender gaps decline in routine jobs but widen in abstract occupations. These patterns are driven both by compositional changes from occupation switches between steady states and by differential WfH take-up by gender *conditional* on occupation choice. Women are more likely to adopt WfH in abstract jobs, while men do so more often in routine jobs. As a result, women in abstract occupations and men in routine occupations are disproportionately exposed to WfH penalties, producing a reduction of gender gaps in routine jobs but a widening in abstract jobs (Table 28). In addition, although women exhibit greater re-sorting into abstract jobs and achieve substantial career gains reflected in the aggregates, a (smaller) share of men also switches into abstract. These men experience even stronger wage and hours responses than women (Table 29). Since women retain a comparative advantage in home production, they specialize more into market work, while men who switch into abstract tend to reinforce their role as primary earners.

Table 27: Change in Gender Gaps *within* Occupation Groups

	Gender Gaps	
	Routine	**Abstract**
Δ Hourly wage gap (in %)	-0.43	+0.24
Δ Market hours gap (in %)	-7.52	+0.39
Δ Earnings gap (in %)	-7.45	+0.72
Δ Gap in earnings growth by age 40 (in %)	-13.86	+14.61

Note: The table reports the changes in gender gaps between old and new steady-state, conditional on the occupation groups. Gender gaps are generally defined as X_m/X_f where X stands for the outcome variable of interest. "Δ" stands for a change relative to the baseline.

Table 28: WfH Take-up in the New Steady-state by Gender *Conditional* on the Occupation Group

	Share in WfH *conditional* on occupation	
	Routine	**Abstract**
Women	9.8	23.3
Men	10.5	22.5

Note: The table displays the share of WfH workers by gender, conditing on the occupation group.

Table 29: Labor Response of Occupation Switchers into Abstract by Gender

	Change in % between steady states	
	Market hours	**Hourly wages**
Women	+205.5	+69.3
Men	+725.9	+84.1

Note: The table displays the change in market hours and hourly wages between the two steady-states in response to a switch to abstract occupations for men and women.

8 Decomposition of the Main Channels

So far, I have examined the long-run effects of a WfH opportunity shock on mothers' careers and gender disparities, accounting for the fact that WfH is accompanied by negative productivity effects, occupational re-sorting, general equilibrium effects on relative wages, and that WfH opportunities can be increased up to their full potential. In this long-run counterfactual experiment, I have shown that the opportunity shock improves overall female labor market outcomes and reduces gender inequality. These effects are driven by women's re-sorting into abstract occupations and women's careers benefiting through both their own and their spouses' WfH take-up. To understand how individual model components contribute to these general results, I will decompose the key mechanisms through a series of counterfactual exercises. Specifically, I compare the baseline steady state to a counterfactual steady state that features the same WfH expansion as before but switches off single model ingredients.

Table 30 summarizes the decomposition exercises. Specifically, I separately shut down (or weaken) four distinct ingredients of the model to isolate their individual contributions. First, I turn off the WfH productivity penalties, static and dynamic. Further, I isolate general equilibrium (GE) effects by fixing occupation-specific wage rates at their baseline values, prior to the WfH shock, thereby removing wage adjustments due to changes in the aggregate supply of occupation-specific labor

Table 30: Overview of the Decomposition Exercises

Decomposition	**Description**
(1) No WfH Penalties	Removes the static and dynamic productivity penalties from working from home.
(2) Fixed Wages	Holds occupation-specific wage rates (per efficiency unit of labor) at baseline levels to eliminate general equilibrium wage adjustments.
(3) Fixed Occupation Choice	Prevents re-sorting by fixing occupation choices to the baseline.
(4) Opportunities below potential	This leaves work-from-home opportunities below the full potential of 37% because the intercept shifter in the arrival rate increases by only half as much. Accounting for the endogenous response in human capital, this results in a 15–percentage-point reduction in work-from-home opportunities in the new steady state.

Note: This table gives an overview of the five counterfactual decomposition exercises. Through that I quantify the effect of the main model ingredients on the long-term economic changes generated by a WfH opportunity shock.

efficiency units. I fix occupational re-sorting, meaning that for a given initial couple type defined by their education pairs, I maintain their occupation choices constant across the two steady-states, both before and after the WfH expansion. Finally, motivated by the recent political and corporate pushback in the U.S., I also consider a counterfactual in which WfH opportunities expand but remain below their full potential level in the new steady state. Formally, I increase the intercept shifter in the arrival rate ρ_1 by only half as much as in the main counterfactual.

Table 31 displays the decomposition results. Displaying the change in gender gaps from the WfH opportunity shock under different decomposition counterfactuals.

Table 31: Steady-State Comparison of Female Labor Outcomes - A Decomposition

	Δ female outcomes (in %)				Δ in ppt.
	Hourly wages	Market hours	Labor Earnings	Abstract workers	Earnings growth between 25-40
Main counterfactual	+1.72	+6.59	+5.31	+12.27	+7.22
(1) No WfH penalties	+4.62	+5.89	+8.53	+13.17	+6.72
(2) No GE	+1.55	+5.43	+5.08	+14.47	+5.26
(3) No occupation changes	-1.66	+3.26	+0.21	0.00	+3.63
(4) Opportunities below potential	+0.8	+3.0	+2.3	+5.6	+1.67

Note: The table reports aggregate changes in female outcomes between the old steady state and a counterfactual scenario with increased WfH opportunities. It presents changes in hourly wages, market hours, labor earnings, the share of abstract work, and cumulative earnings growth by age 40. Results are shown for the main counterfactual as well as for the decomposition exercises summarized in Table 30.

Eliminating WfH Productivity Penalties: Higher Wages, Weaker Hour Responses. When all WfH productivity penalties—both static in routine and abstract jobs and the dynamic one in abstract—are removed, a mixed picture emerges. Women experience larger wage, earnings, and re-sorting gains into abstract jobs, but smaller increases in market hours and mid-career earnings growth (ages 25–40) compared to the main counterfactual. Hourly wages rise strongly due to both the direct removal of the productivity penalty and faster human capital accumulation through WfH learning. These wage gains translate into higher average labor earnings. The stronger re-sorting into abstract occupations reflects the removal of the large WfH penalty previously deterring women from these jobs. However, market hours increase less than in the main counterfactual. This muted response stems mainly from routine-working women whose spouses take up WfH in abstract occupations. Table 32 compares this case to the main counterfactual. The table displays the estimated coefficient of spousal WfH take-up on market hours and domestic hours of both spouses. With penalties, women strongly reacted to the negative cross-income effect of male WfH take-up in abstract jobs (+3.07 weekly hours). Without penalties, female market hours rise but the effects are mitigated (+0.59 weekly hours) and lowering the drop in domestic hours (-1.01 weekly hours). This persistence reflects men's continued increase in domestic work after WfH take-up—despite higher own productivity. These men are already high-hour, high-human-capital workers for whom additional market hours yield limited returns. The resulting household substitution in home production encourages women to maintain higher market work.

I further find that removing WfH productivity penalties also leads to output gains of +0.16% after the WfH expansion, but these are in fact smaller than the gains with penalties (+0.47%). Without penalties, the re-sorting into abstract occupations is stronger than in the main counterfactual following the WfH expansion. This results in a relatively larger decline in routine efficiency units. Given the limited substitutability between abstract and routine efficiency units in production, the crowding out of routine work translates into smaller overall output gains than in the main counterfactual.

General-Equilibrium Effects Boost Women's Career Gains as Most Are Employed in Routine Jobs. Shutting off general-equilibrium feedback effects modestly dampen women's career improvements. Female labor outcomes still rise across all margins in response to the expansion in WfH opportunities, but to a smaller extent—except for the share of women in abstract occupations, which continues to increase. Recall that under general-equilibrium adjustments, the wage rate in abstract jobs declines while the wage rate in routine jobs rises. Thus, even more women switch into abstract jobs (+14.47%) when the counteracting adjustment in abstract wages is turned off. However, the aggregate dampening effect on a decline in the routine wage rate dominates, as the majority of women remain employed in routine occupations.

Occupation Re-sorting Drives the Largest Gains in Women's Careers. Allowing workers to change their occupation in the long run in response to the WfH opportunity shock is the most

Table 32: The Career Effects of Spousal WfH Take-up in Abstract
(New Steady-state v.s. Counterfactual with no WfH Productivity Penalties)

	Market hours		Domestic hours	
	(own)	(spouse)	(own)	(spouse)
Main counterfactual	3.07***	0.96***	-3.03***	2.10***
	(.018)	(.014)	(.015)	(.011)
No productivity penalties of WfH	0.59***	1.66***	-1.01***	1.30***
	(.0173)	(.013)	(.015)	(.010)

Note: Depicts estimation results of coefficient $\hat{\beta}_1$ from regression: $Y_{igo} = \beta_0 + \beta_1 Wf H_{i-go} + \delta_1 H_{i-go} + \delta_2 H_{igo} + \epsilon_{igo}$. Estimated separately for women working in routine with male spouses in abstract with standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

important driver—among the model mechanisms studied—of improvements in female labor market outcomes (see last row in Table 31). Introducing the WfH opportunity shock while disabling occupational re-sorting reduces hourly wages further (by –1.66%) and leads to a smaller increase in overall market hours (+3.26).[38] Gains in earnings growth between ages 25 and 40 relative to the old steady state are also smaller, increasing by only half as much (+3.63%) when sorting is shut off. Although only a small share of women were able to re-sort in the main counterfactual, the quantitative effect on aggregates is sizable, reflecting the extensive-margin shift that grants access to higher wage rates and more effective human capital accumulation technologies associated with abstract work. Because occupational re-sorting generates both static (instantaneous wage-level) and dynamic (faster wage-growth) gains, it plays a central role in explaining the overall expansion of women's career prospects.[39]

Equity and Efficiency Losses When WfH Opportunities Remain Below Potential

If work-from-home (WfH) opportunities remain below the estimated potential of 37% of jobs (Dingel and Neiman 2020), the resulting equity and efficiency gains are substantially reduced. Women's career improvements decline disproportionately relative to the main counterfactual with full WfH potential because they are more exposed to the reduction in opportunities. Recall that in routine occupations the expansion of WfH is only 40% as strong as in abstract occupations. Since women are overrepresented in routine jobs, they benefit considerably less from the career gains associated with WfH.

[38] By construction, the change in the share of abstract work is zero when occupational re-sorting is disabled, as workers are prevented from switching occupations in response to the shock.

[39] Table 46 in Appendix D further displays the changes in output and gender gaps in labor outcomes under the difference decomposition exercises.

As shown in Table 31, the increase in female labor outcomes is markedly smaller than in the main counterfactual. In particular, career gains are more than four times lower (1.67 vs. 7.22).

Table 33: Steady-State Comparison of Output and Welfare: The Role of WfH Opportunities

	Output	Welfare
Main counterfactual	+0.47	+11.14
(4) Opportunities below potential	+0.22	+5.79

Note: The table reports aggregate changes in output and welfare (in CEV) between the old steady state and a counterfactual scenario with increased WfH opportunities. Results are shown for the main counterfactual as well as for the decomposition exercise with WfH opportunities below potential, summarized in Table 30.

From a policy perspective, the impact on output and welfare is particularly informative. Table 33 compares the steady-state outcomes under full WfH potential with those under curtailed opportunities. Both output and welfare gains are roughly half as large as in the main counterfactual, highlighting substantial efficiency and well-being losses when WfH expansion is limited.

The welfare channel is straightforward: when valued flexibility is restricted, welfare falls. The output losses operate through two mechanisms. First, routine workers experience weaker career gains, reducing aggregate routine efficiency units. Second, relatively fewer workers sort into abstract occupations when WfH expansion is limited, dampening the increase in abstract efficiency units. Taken together, these mechanisms suggest that resisting the expansion of WfH would be costly—not only from an equity perspective but also in terms of aggregate efficiency.

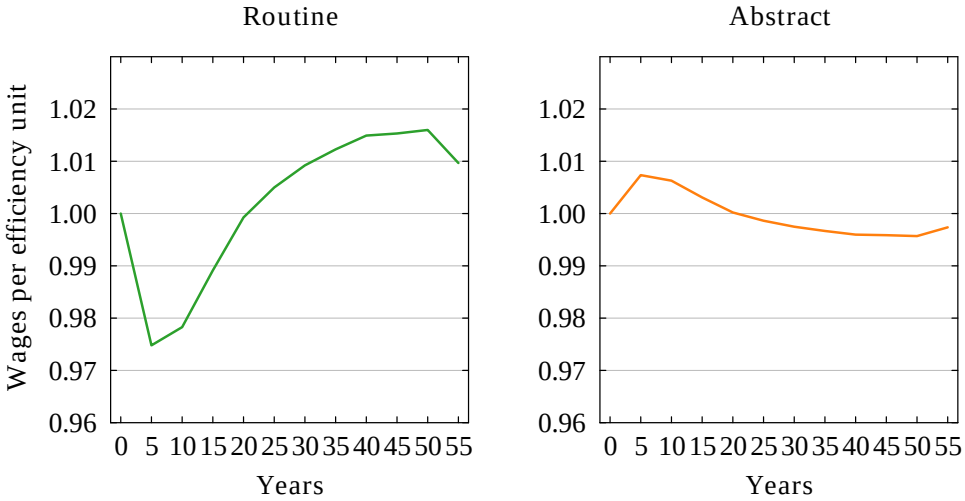
9 The Transition Effects of a WfH Opportunity Shock

So far, I have analyzed the long-term effects of a work-from-home (WfH) expansion on the economy by comparing steady states before and after the shift. To assess the short- to medium-run dynamics, I now compute the transition path between these two steady states. This step is particularly important because, in the short run, the shift is unexpected, and workers remain "stuck" in the occupations they chose prior to the realization of the WfH opportunity shock.

Formally, this requires solving for the price path of routine and abstract wage rates per efficiency unit of labor during the transition. Since the shock is unanticipated for the first $J-1$ cohorts that experience it, I solve their optimal life-cycle problem under the expectation of no WfH expansion up to the period when the shift occurs, and subsequently under the expectation of the new WfH regime.[40] The remaining cohorts, who are born during the transition, fully internalize the WfH shift from birth.

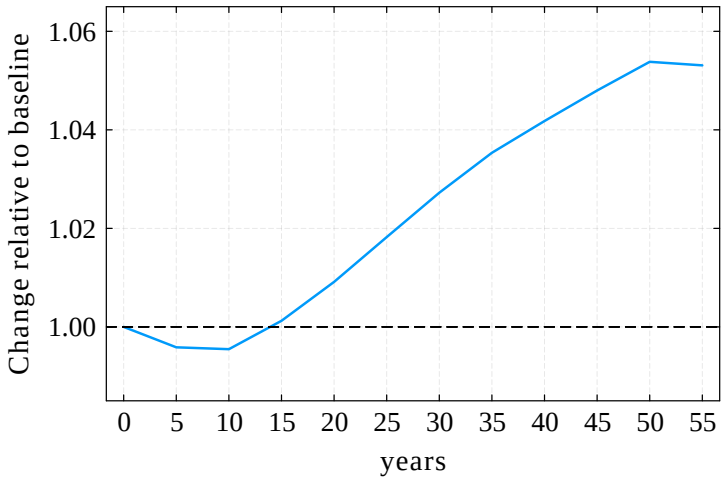
[40] This entails solving their Bellman equations recursively twice—once for the pre-shift steady state and once for the actual realization of the WfH expansion.

Figure 18: Transition Path in Wages per Efficiency Unit of Labor by Occupation Group



Note: Transition path in wage rates per efficiency units of labor by occupation group between the old and the new steady-state that arises from an expansion in WfH opportunities.

Figure 19: Female Labor Earnings along the Transition Path relative to Old Steady-State



Note: Female average earnings over the transition path between the old and the new steady-state that arises from an expansion in WfH opportunities.

Upon the emergence of the large and unexpected increase in WfH opportunities, supplied efficiency units in routine tasks rise, while those in abstract tasks fall. This pattern reflects short-term gains in routine work, where saved commuting time outweighs static WfH productivity penalties, whereas in abstract work, the larger productivity penalty dominates. Consequently, the relative scarcity of abstract efficiency units raises abstract wages and lowers routine wages (Figure 18). Since women are predominantly employed in routine jobs, aggregate earnings initially decline at the onset of the transition (Figure 19). Over time, however, as new cohorts enter the labor market anticipating higher WfH opportunities—while older cohorts, previously "locked" into their career paths, gradually exit—the share of abstract workers increases, particularly among women. This gradual reallocation raises the relative supply of abstract labor, thus, lifts routine wages, and boosts aggregate earnings. Continued female re-sorting into abstract work further amplifies these earnings gains along the transition path.

10 Conclusion

This paper provides new insights into how the expansion of WfH opportunities reshapes mothers' careers. I develop a rich structural framework to analyze how increased WfH availability affects intra-household decisions on WfH adoption, occupational sorting, time allocation, and human capital accumulation, in the context of persistent gender disparities in U.S. labor market outcomes.

The analysis shows that WfH generally improves women's labor market outcomes—raising hourly wages, market hours, and earnings growth—thereby narrowing gender gaps. However, these effects vary across households, depending on both partners' occupations and WfH adoption. Trade-offs differ by occupation: abstract jobs offer greater WfH potential but carry higher productivity penalties, while routine jobs offer fewer WfH opportunities but lower penalties. Own and spousal WfH adoption also have distinct impacts—own WfH in routine jobs can boost career prospects, whereas a spouse's WfH may reinforce domestic specialization. The reverse is observed in abstract occupations, where WfH can entail substantial productivity losses.

A critical dimension of the WfH expansion lies in its long-run effects on human capital accumulation and occupational re-sorting. WfH penalties not only affect current earnings but can slow future human capital accumulation. While current cohorts are constrained by their existing occupations, future cohorts can adjust their sorting, reshaping career trajectories. Quantitatively, a key driver of aggregate gains for women is the increased sorting into abstract occupations with higher WfH potential, granting access to higher wage paths and more productive human capital accumulation.

Transition dynamics matter: in the short run, women experience temporary earnings losses. Initially, efficiency in routine work rises due to productivity gains and saved commuting time, while abstract work suffers from productivity penalties. This reduces aggregate female earnings, given women's

concentration in routine jobs. Over time, as cohorts anticipate WfH and more women shift to abstract occupations, abstract labor supply rises, routine wages recover, and aggregate female earnings increase.

Given that firms and policymakers in the U.S. are increasingly signaling intentions to scale back remote work, understanding the long-term labor market consequences of WfH is crucial for designing effective workplace policies and addressing labor market inequality. I find that, despite the presence of WfH-related productivity penalties, an expansion in remote work opportunities generates aggregate output and welfare gains. Output increases because workers in routine occupations can offset productivity losses through saved commuting time, while those switching from routine to abstract tasks raise abstract efficiency units. Welfare gains arise as workers value workplace flexibility and benefit from a broader set of workplace choices. Hence, an excessive policy or corporate pushback against WfH may be counterproductive to both welfare and output growth. Beyond the model, policies could aim to enhance WfH productivity through investments in digital infrastructure, coordination technologies, and managerial practices adapted to remote environments. However, I find that fully eliminating WfH productivity penalties paradoxically reduces both aggregate output and women's career gains. The absence of penalties induces stronger re-sorting into abstract occupations, crowding out routine work. Because abstract and routine efficiency units are imperfect substitutes in production, the larger decline in routine work leads to smaller overall output gains than in the baseline case with moderate penalties. Moreover, the removal of WfH penalties in abstract occupations dampens women's incentives to expand market hours in response to spousal WfH take-up. When productivity penalties from WfH across occupations disappear, the positive labor supply response of women—previously driven by negative cross-income effects—is muted. This mechanism helps explain why some degree of heterogeneity in WfH productivity may actually sustain both aggregate efficiency and gender-specific career gains.

Finally, this framework opens interesting avenues for future research, such as exploring WfH's impact on fertility decisions and bargaining power within households.

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A Empirical Facts

A.1 Description of Data Sources and General Definitions

Data Sources and Sample Restrictions I rely on four primary U.S. data sources for the model estimation: the Survey of Income and Program Participation (SIPP), the American Time Use Survey (ATUS), the American Community Survey (ACS), and the Panel Study of Income Dynamics (PSID). In general, I limit each dataset's sample to married men and women aged 24 to 65, who are not enrolled in school, during the years 2013 to 2016. Across all data sources, I apply the provided statistical weights. Resulting sample sizes are summarized in Table 34.

Table 34: Data Sources and Sample Sizes

Data Source	Years	Sample Size
Survey of Income and Program Participation (SIPP)	2013-2016	698,885
American Time Use Survey (ATUS)	2013-2016	16,639
American Community Survey (ACS)	2013-2016	3,348,082
Panel Study of Income Dynamics (PSID)	2001-2019	1,637

The shared time span across datasets is limited to the pre-pandemic availability of SIPP data (2013–2016 panel), which provides detailed information on workers' occupations, wages, work hours, commuting times, and remote work behavior. Notably, it is one of the few U.S. datasets offering comprehensive remote work data from before the COVID-19 pandemic. The panel structure of the SIPP dataset is valuable for analyzing self-selection into workplace locations based on unobserved human capital, enabling credible estimation of the dynamic productivity effects associated with transitioning to remote work. After applying the aforementioned sample restrictions, my SIPP dataset consists of 698,885 month-year-individual observations and 24,412 unique individuals.

The 2012–2019 ATUS provides cross-sectional data with detailed information on daily activities, which I use to construct measures of home production hours, following the framework outlined by Aguiar et al. 2013b, and market work hours. Based on the sample restrictions, the ATUS dataset includes 16,639 individual observations. The 2013–2016 ACS offers large cross-sectional data (N = 3,348,082), which I use to construct representative life-cycle profiles of the number of children in households and average work hours by gender. I use the latter to calculate pension benefits.

For the PSID, I extend the sample years to 2001–2019 to ensure a sufficiently large dataset. The PSID is a longitudinal panel survey particularly suited for estimating joint initial educational attainment of couples due to its rich spousal data. This leaves me with a final sample of 1,637 unique couples.

Table 35: Descriptive Statistics of WfH Workers in the SIPP Sample

Variable	SIPP (2013-2016)	CPS (2022-2025)
Share college educated	0.76	0.76
Share self-employed	0.22	0.13
Share female	0.43	0.49
Average number of WFH days	3.85	–
Share fully remote	0.61	0.44
Average age	47.33	45.08
Average weekly hours	41.27	41.06
Share part-time workers	0.171	0.09

Note: Baseline statistics for WfH workers among married individuals, age 24-65, not enrolled in school of the SIPP panel 2013-2016 and the Consumer Panel survey (CPS) from 2022-2025. Uses statistical weights provided by the SIPP and CPS.

General Definitions In the following, I introduce the definitions used throughout the construction of data moments. I define *remote workers* (or WfH workers) as individuals who work for pay and spend at least one workday per week exclusively working from home. Table 35 compares married teleworkers from the 2013–2016 SIPP to those in the 2022–2025 CPS. The two samples are similar in terms of the share of college-educated individuals, the share of women, age, and weekly work hours. The 2013–2016 SIPP contains relatively more self-employed, part-time, and fully remote workers.

I categorize occupations into two main groups which I label as *abstract* and *routine* occupations. This classification relies on the task-based approach from Acemoglu and Autor (2011). In this approach, the authors use task descriptions from O*NET work activities and work context files to create composite task measures: i) non-routine cognitive analytic, ii) non-routine interpersonal, iii) routine cognitive, iii) routine manual, iv) non-routine manual physical, v) non-routine manual interpersonal and (vi) offshorability. Similar to Adda et al. (2017) I aggregate those into either routine ((iii) and (iii)) or abstract ((i) and (ii)) occupations, but exclude manual occupation altogether. I aggregate the occupation category on census 2010 occupation code level to use the data in my SIPP dataset.

A.2 Static Productivity Effect of Work-from-Home

Table 36: Empirical WfH Productivity Studies

Authors	Occupation Group	Productivity Effect
Bloom et al. (2015)	routine	4%
A RCT with 503 Ctrip call center employees assigned to WfH (4 of 5 days) or in the office for 9 months found a 13% performance increase for remote workers. This was due to a 9% increase in work time and a 4% improvement in calls per minute.		
Emanuel and Harrington (2024)	routine	-4%
A study of a Fortune 500 call center examined 344 remote and 1,592 on-site workers during the Covid-19 shift to remote work. It found a 4% decrease in productivity, measured by hourly call volume, for those who transitioned to fully remote work, six months after offices closed.		
Atkin et al. (2023)	routine	-18%
A RCT in the Indian data-entry sector assigned 235 participants to work either inoffice or fully remotely for eight weeks. The study found that remote workers had 18% lower productivity, measured by input per minute, error rates, and working time.		
Bloom et al. (2024)	abstract	0%
A 6-month RCT involving 1,612 engineering, marketing, and finance employees at a Chinese tech company from 2021 to 2022 found that hybrid working (2 days/week) had no effect on performance. Measured through performance reviews, promotion outcomes and lines of code written.		
Gibbs et al. (2021)	abstract	[-19%, -8%]
Studied over 10,000 highly skilled professionals over 17 months at an Indian IT company after a sudden shift to fully remote work during the Covid-19 pandemic. The study found a 8–19% decrease in productivity, measured by e.g. number of code segments, code reviews, or reports delivered per month input, which was attributed to remote work rather than pandemic-related factors		
Gibbs et al. (2024)	abstract	-22%
An event study on the impact of hybrid work on innovation activities among over 48,000 highly educated IT professionals in India around the pandemic-induced shift to work-from-home. Measured the quantity and quality of submitted ideas, which were incentivized by the company. The study found a 22% decrease in the quantity of ideas submitted per employee per month following the shift from onsite to hybrid work. There were no statistically significant effects on the quality of ideas, as measured by acceptance rates, client sharing, and client ratings.		

A.3 Wage-growth Effect of Work-from-Home

Table 37 displays the regression output from Equation (3). To further assess the plausibility of the dynamic productivity effects, Table 38 reports estimated 5-year dynamic productivity effects of WfH at the census-occupation level. The magnitude of these effects varies across occupations. For example, among abstract jobs, chief executives as well as marketing and sales managers exhibit large negative effects (-23% and -25%), while accountants and auditors even show positive effects (+10%). Similarly, within routine jobs, electricians and clinical laboratory technologists and technicians experience modest positive effects (around 1%), whereas medical assistants, for instance, are subject to much larger negative effects (-17%).

Table 37: Regression output Equ. (3)

	Wage Growth in $t+1$
WfH_{iot}	0.067
	(0.064)
$\log(h_{iot})$	-0.004
	(0.039)
$\log(w_{iot})$	-1.240***
	(0.024)
WfH_{iot+1}	-0.019
	(0.067)
$WfH_{iot}\times$ Abstract	-0.073
	(0.068)
$\log(h_{iot})\times$ Abstract	0.124**
	(0.056)
$\log(w_{iot})\times$ Abstract	0.004
	(0.030)
$WfH_{iot+1}\times$ Abstract	0.036
	(0.071)

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Omitted constant and controls which include individual fixed effects, census occupation fixed effects, cohort fixed effects, as well as the number of weeks worked per year. Dummies indicate whether the respondent is a parent, married, or a woman.

Table 38: Census occupation examples of dynamic WfH productivity effect

Census Occupation	Δ_o^{5y}(WfH)
Abstract	
• Accountants and auditors	+.10
• Software developers, applications and systems software	+.06
• Chief executives	-.23
• Marketing and sales managers	-.25
Routine	
• Electricians	+.01
• Clinical laboratory technologists and technicians	+.008
• Medical assistants	-.17
• Miscellaneous agricultural workers	-.26

Note: The table displays census occupational examples for Δ_o^{5y}(WfH).

Table 39: Estimated 5-year dynamic productivity effect of WfH (assuming no static productivity effect of wfH)

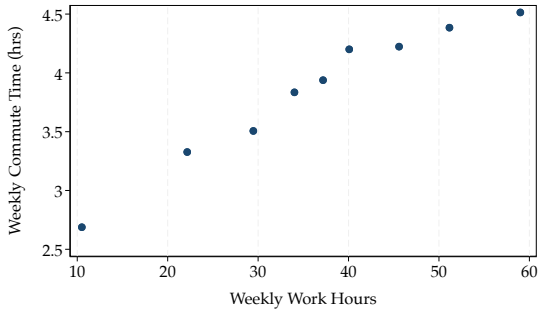
	Δ_o(WfH)			
	(1)	(2)	(3)	(4)
Abstract	.0483	-.0149	-.0064	-.0063
Routine	.1354	.0514	.0687	.0695
Individual fixed effects	No	Yes	Yes	Yes
Census occ. fixed effect	No	No	Yes	Yes
Cohort fixed effect	No	No	No	Yes

Note: The table reports productivity discount for 5-year (model period) horizon.

A.4 Commuting Time and Work Time

Figure 20: Commuting Time and Work Time, by Gender and Overall

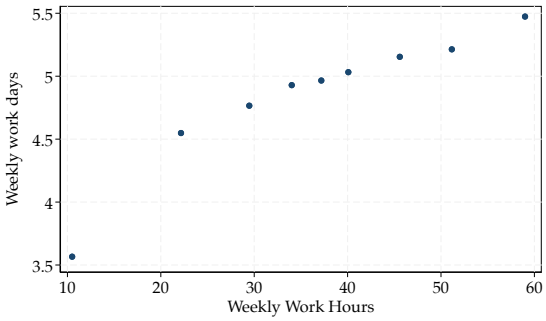
(a) Weekly Commuting Time by Work Hours



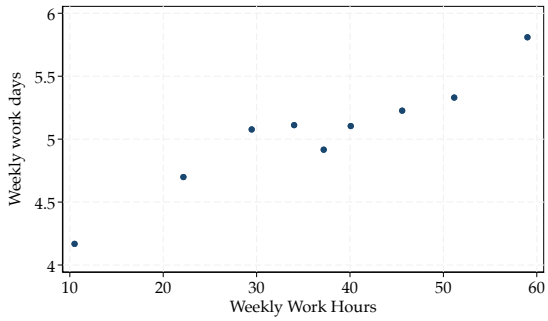
(b) Weekly Workdays by Work Hours



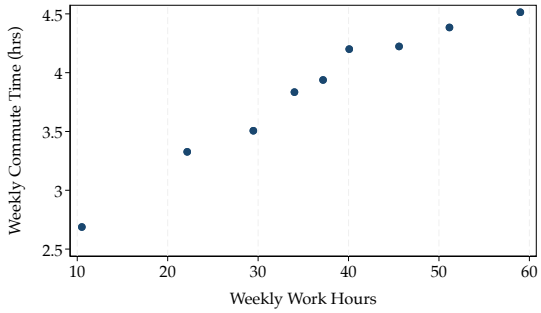
(c) Workdays, Women



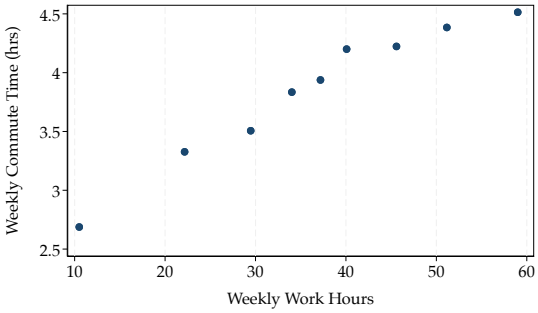
(d) Workdays, Men



(e) Commuting, Women



(f) Commuting, Men



Note: Figures show mean weekly commuting time and number of weekly workdays by weekly work hours, controlling for census occupation, gender, and age. Top row: overall sample; middle row: by gender (workdays); bottom row: by gender (commuting). Source: SIPP, 2013–2016.

A.5 Suggestive Early Empirical Evidence - The Aftermath of the Pandemic Recession

Although data from the post-pandemic period in the United States are still limited due to its recency—and although the pandemic introduced many confounding forces beyond the expansion of WfH—it is nevertheless informative to look for early empirical patterns that relate to the key

predictions of my model. Two such patterns are: (i) a relative increase of workers in abstract occupations, where WfH adoption rose more strongly than in routine occupations; and (ii) a disproportionately large increase in abstract work among women. These correlations should be interpreted cautiously, as pandemic-specific disruptions may bias the results and prevent a clean identification of the mechanisms captured by my model. This, in turn, highlights the value of a structural model for projecting long-run effects outside the particular context of COVID-19.

To speak to these predictions, I use the American Community Survey (2000–2023), focusing on married individuals aged 25–65 who are not enrolled in school, and estimate the following specification:

$$\text{abstract}_{it} = \beta_0 + \beta_1\, t^{2000} + \beta_2\, \text{post}_t + \beta_3\, t^{2000} \times \text{post}_t + \varepsilon_{it}, \tag{19}$$

where abstract_{it} is an indicator for whether worker i is in an abstract occupation, t^{2000} is a linear time trend benchmarked to 2000, and post_t flags the post-pandemic period (2022–2023). The main coefficient of interest is β_3, capturing whether the trend in abstract work accelerates after the pandemic. A positive value indicates that the share of abstract workers is rising faster than prior to the pandemic-induced WfH expansion.

This specification addresses two key concerns. First, women—who are overrepresented in contact-intensive service jobs—were disproportionately affected by pandemic-related job losses. This could mechanically raise the relative share of abstract workers even without genuine occupational switches. To gauge the sensitivity of the results, I therefore estimate the specification both with and without the pandemic years. Second, the share of abstract work—especially among women—has been increasing for decades. To avoid confounding the post-pandemic acceleration with this long-run trend, I include a linear time trend and assess to what extent the post-pandemic has accelerated the upward trend.

Table 40: Acceleration in Abstract Work After the Pandemic

	All years			**Excl. pandemic years**		
	Full	Women	Men	Full	Women	Men
t^{2000}	0.003473***	0.004859***	0.002351***	0.002802***	0.004189***	0.001689***
	(0.000023)	(0.000034)	(0.000032)	(0.000029)	(0.000043)	(0.000040)
post	−0.003974	−0.041483	0.029988	−0.008259	−0.045768	0.025769
	(0.021326)	(0.031237)	(0.029171)	(0.021390)	(0.031335)	(0.029255)
$t \times$ **post**	0.000937	0.002563*	−0.000548	0.001608*	0.003233**	0.000113
	(0.000948)	(0.001388)	(0.001296)	(0.000951)	(0.001393)	(0.001300)
Constant	0.5216***	0.5015***	0.5378***	0.5259***	0.5058***	0.5420***
	(0.000286)	(0.000423)	(0.000388)	(0.000308)	(0.000455)	(0.000417)
Observations	12,429,642	5,738,957	6,690,685	10,803,313	4,980,666	5,822,647
R^2	0.0029	0.0053	0.0015	0.0024	0.0045	0.0013

Note: Weighted regressions using ACS 2000–2023. Pandemic years defined as 2019–2021. Standard errors in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Table 40 reports the results of specification (19) for the full sample and separately by gender, both with and without the pandemic years. Consistent with long-run occupational patterns, the share of abstract work exhibits a positive underlying trend: in the full sample, the linear trend coefficient is $\beta_1 = 0.003473$, implying that the share of abstract workers increased by roughly 0.35 percentage points per year over the pre-pandemic period. This trend is substantially stronger for women ($\beta_1 = 0.004859$) than for men ($\beta_1 = 0.002351$), while men start from a higher initial level of abstract work, as reflected in the constants (0.5378 for men vs. 0.5015 for women).

The key coefficient of interest, β_3, captures the post-pandemic acceleration in the trend. In the full sample, the estimated acceleration is modest and not statistically significant. For men the effect is not statistical significant as well and even negative. Meanwhile, for women the trend accelerates significantly ($\beta_3 = 0.002563$).

The pattern becomes more pronounced when excluding the pandemic years (2019–2021), where the estimates likely suffer less from pandemic-specific composition effects. In this sample, the acceleration is higher and significant: $\beta_3 = 0.001608$ for the full sample, with women again showing a somewhat stronger response (0.003233) than men (0.000113). Quantitatively, this implies an additional 0.3 percentage-point annual increase in the share of abstract work after the expansion of WfH for women.

Taken together, these results qualitatively align with the predictions of my model: the rise in WfH is associated with a small but noticeable acceleration in abstract occupational upgrading—especially among women. However, these correlations should be interpreted cautiously given the confounding effects and compositional shifts induced by the pandemic.

B Details on Model Specifications

B.1 Retirement Problem

After period J, couples deterministically enter the final two retirement periods. In retirement, children have left the household, and couples derive income from net retirement benefits. Gross retirement income at age j is defined as:

$$y_{ij}^R = w_R \left(w(onsite, o_{if}, H_{ifJ+1})\, h_{fR} + w(onsite, o_{im}, H_{imJ+1})\, h_{mR} \right) \tag{20}$$

Each spouse's income equals their hypothetical onsite wage ($w(onsite, o_{ig}, H_{igJ+1})$), evaluated after human capital has been realized at the beginning of period $J+1$, and scaled by the replacement rate w_R and average working hours h_{gR}. Their retirement budget constraint simplifies to:

$$c_{ifj} + c_{imj} = y_{ij}^R, \tag{21}$$

The second argument in the tax and transfer function takes $n_j = 0$. The budget constraint excludes explicit income taxation as the replacement rate w_R is already net of taxes, thus. Time endowment can be allocated between leisure and home production:

$$\bar{T} = l_{igj} + q_{igj} \tag{22}$$

Retiree couples take as given their retirement state space Ω_i^R defined as:

$$\Omega_i^R \equiv \{H_{ifJ+1}, H_{imJ+1}, o_{if}, o_{im}\} \tag{23}$$

The retirement state space is a simplified version of the pre-retirement state space. In retirement, face no workplace uncertainty, and do not make decisions about market work or workplace location. However, their retirement income depends on their final accumulated human capital level and occupation, both of which remain part of the state space. Define $\iota_{ij}^R \equiv \{c_{ifj}, c_{imj}, q_{ifj}, q_{imj}\}$ the vector of variables over which the household maximizes in period j. The Bellman equation for a retiree couple i in period j is given by:

$$V_j^R(\Omega_i^R) = \max_{\iota_j^R} \quad u_f(c_{ifj}, l_{ifj}, Q_{ij}, n_j, o_{if}) + u_m(c_{imj}, l_{imj}, Q_{ij}, n_j, o_{im}) + \beta V_{j+1}^R(\Omega_i^R), \tag{24}$$

where β is a discount factor. Couples maximize the Bellman equation subject to their joint retirement budget constraint and individual time constraints.

B.2 Adding Taste Shocks

Couples face two distinct decisions: (i) the initial occupation choice for both spouses at the start of $j = 1$, and (ii) the workplace location decision for one or both spouses at each life stage, provided they have the flexibility to choose (i.e., have a work-from-home opportunity). A standard way to handle discontinuities in discrete choice models is to introduce choice-specific, independent, and identically distributed random taste shocks. These shocks smooth the decision probabilities around discontinuities, generating more realistic distributions of types across choices and preventing large calibration updates in response to small parameter changes (see, e.g., Iskhakov et al. 2017). Let $\vec{\epsilon}_o$ and $\vec{\epsilon}_{pj}$ denote the vectors of choice-specific taste shocks for occupation and workplace location choices, respectively, with corresponding scaling parameters σ_{ϵ_o} and σ_{ϵ_p}. These parameters govern the relative importance of the taste shocks in utility. Both $\vec{\epsilon}_o$ and $\vec{\epsilon}_{pj}$ are assumed to follow an Extreme Value Type I distribution and enter the utility function in an additively separable, choice-specific manner.

For ease of notation, I omit the couple index i henceforth. Let the joint flexibility state of the spouses be denoted by $X_f X_m \in \{II, FF, FI, IF\}$, where X_f and X_m represent the female's and male's flexibility states, respectively. The symbol I indicates "inflexible" (i.e., without a work-from-home opportunity), and F denotes "flexible" (i.e., with a work-from-home opportunity).

Workplace Taste Shocks With the presence of discrete workplace taste shocks, the value function for some flexibility state $X_f X_m$, state vector Ω_j, and taste shock vector draw $\vec{\epsilon}_{pj}$ in life-stage j rewrites as:

$$V_j^{X_f X_m}(\Omega_j, \vec{\epsilon}_{pj}) = \begin{cases} \max\{\, v_j(\Omega_j|d_j) + \sigma_\epsilon \epsilon_{pj}(d_j) \,\}_{d_j \in D^{X_f X_m}} & , X_f X_m \in \{FF, FI, IF\} \\ v_j(\Omega_j|(onsite, onsite)) & , X_f X_m \in \{II\}\,. \end{cases} \tag{25}$$

For each workplace location choice pair $d_j = (p_{fj}, p_{mj})$ from the flexibility state–specific choice set $D^{X_f X_m}$, the couple draws a random shock $\epsilon_{pj}(d_j)$ that enters the utility function in an additively separable manner. The term $v_j(\Omega_t|d_j)$ is the Bellmann equation in life-stage j for a *given* discrete choice d_j. Formally:

$$\begin{aligned} v_j(\Omega_j|d_j) = \max_{\iota_j} \quad & u_f(c_{fj}, l_{fj}, Q_j, n_j, o_f) + u_m(c_{mj}, l_{mj}, Q_j, n_j, o_m) \\ & + \beta \Big\{ (1-\rho_{fj})(1-\rho_{mj})\, v_{j+1}(\Omega_{j+1}|(onsite, onsite)) \\ & + \quad (1-\rho_{fj})\rho_{mj}\, \mathbb{E}_{\epsilon_p} V_{j+1}^{IF}(\Omega_{j+1}, \vec{\epsilon}_{pj+1}) \\ & + \quad \rho_{fj}(1-\rho_{mj})\, \mathbb{E}_{\epsilon_p} V_{j+1}^{FI}(\Omega_{j+1}, \vec{\epsilon}_{pj+1}) \\ & + \quad \rho_{fj}\rho_{mj}\, \mathbb{E}_{\epsilon_p} V_{j+1}^{FF}(\Omega_{j+1}, \vec{\epsilon}_{pj+1}) \Big\}, \end{aligned} \tag{26}$$

where ρ_{fj} and ρ_{mj} are the respective arrival rates of a WfH opportunity of the female and male spouse.

With taste shocks, the Bellman equation is modified to account for the expectation operator in future taste shocks $\mathbb{E}_{\epsilon_p} V_{j+1}^{X_f X_m}$. Since the workplace choice-specific preference shocks are independent Extreme Value Type I (Gumbel) distributed random variables, $\mathbb{E}_{\epsilon_p} V_{j+1}^{X_f X_m}$ is given by the well-known *logsum* formula (Iskhakov et al. 2017):

$$\begin{aligned}
\mathbb{E}_{\epsilon_p} V_{j+1}^{IF}(\Omega_{j+1}, \vec{\epsilon}_{pj+1}) &= \sigma_{\epsilon_p} \log \left\{ \sum_{\substack{p_{fj+1}=\{onsite\} \\ p_{mj+1}=\{onsite,WfH\}}} \exp\left[\frac{v_{j+1}^{IF}(\Omega_{j+1}|(p_{fj+1}, p_{mj+1}))}{\sigma_{\epsilon_p}}\right] \right\} \\
\mathbb{E}_{\epsilon_p} V_{j+1}^{FI}(\Omega_{j+1}, \vec{\epsilon}_{pj+1}) &= \sigma_{\epsilon_p} \log \left\{ \sum_{\substack{p_{fj+1}=\{onsite,WfH\} \\ p_{mj+1}=\{onsite\}}} \exp\left[\frac{v_{j+1}^{FI}(\Omega_{j+1}|(p_{fj+1}, p_{mj+1})}{\sigma_{\epsilon_p}}\right] \right\} \\
\mathbb{E}_{\epsilon_p} V_{j+1}^{FF}(\Omega_{j+1}, \vec{\epsilon}_{pj+1}) &= \sigma_{\epsilon_p} \log \left\{ \sum_{\substack{p_{fj+1}=\{onsite,WfH\} \\ p_{mj+1}=\{onsite,WfH\}}} \exp\left[\frac{v_{j+1}^{FF}(\Omega_{j+1}|(p_{fj+1}, p_{mj+1})}{\sigma_{\epsilon_p}}\right] \right\}.
\end{aligned} \tag{27}$$

The corresponding choice probabilities for the discrete workplace choices in flexibility state $X_f X_m$ are standard logits:

$$P^{XX}((p_{fj}, p_{mj})|\Omega_j) = \frac{\exp\left(v_j^{XX}(\Omega_j|(p_{fj}, p_{mj}))/\sigma_{\epsilon_p}\right)}{\sum_{\tilde{p}_{fj}, \tilde{p}_{mj} \in D^{X_f X_m}} \exp\left(v_j^{XX}(\Omega_j|(\tilde{p}_{fj}, \tilde{p}_{mj}))/\sigma_{\epsilon_p}\right)} \tag{28}$$

For each discrete choice set $D^{X_f X_m}$ over workplace location periods in period j, agents determine their mixed strategy over the discrete choices as described in Equation 32. For given type Ω_j couples will have the same mixed strategy.

Initial Occupation Taste Shocks Before the realization of the flexibility state, couples make their joint occupational choice, given their ex-ante heterogeneity in educational attainment. For this initial occupation decision, each couple receives a one-time, i.i.d. preference shock specific to each occupation pair (or a vector of taste shocks) in the first period. Let $\tilde{\Omega}$ denote the subset of the state vector excluding both spouses' occupations. The choice problem can then be written as:

$$\begin{aligned}
V_1(\Omega_1, \vec{\epsilon}_o) = \max \Big\{ \big\{ & \rho_{fj}\rho_{mj}\, \mathbb{E}_{\epsilon_p} V_1^{FF}(\tilde{\Omega}_1|o_f, o_m) \\
& + (1-\rho_{fj})(1-\rho_{mj})\, V_1^{II}(\tilde{\Omega}_1|o_f, o_m) \\
& + (1-\rho_{fj})\rho_{mj}\, \mathbb{E}_{\epsilon_p} V_1^{FI}(\tilde{\Omega}_1|o_f, o_m) \\
& + \rho_{fj}(1-\rho_{mj})\, \mathbb{E}_{\epsilon_p} V_1^{IF}(\tilde{\Omega}_1|o_f, o_m) \\
& + \sigma_{\epsilon_o}\epsilon_o(o_f, o_m) \big\}_{\substack{o_f=\{abstract,routine\} \\ o_m=\{abstract,routine\}}} \Big\}
\end{aligned} \tag{29}$$

Thus, in the first period ($j = 1$), prior to the realization of the flexibility state $X_f X_m$, the couple maximizes over the four possible occupation pairs, taking into account the choice-specific taste shock $\epsilon_o(o_f, o_m)$, which enters utility in an additively separable manner. Taking expectations over the possible flexibility states using the operator $\mathbb{E}_{X_f X_m}$ and applying the Law of Iterated Expectations together with the *logsum* formula yields:

$$\Leftrightarrow V_1(\Omega_0, \vec{\epsilon}_o) = \max \left\{ \left\{ \mathbb{E}_{X_f X_m} \mathbb{E}_{\epsilon_p} V_1^{X_f X_m}(\tilde{\Omega}_1 | o_f, o_m) + \sigma_{\epsilon_o} \epsilon_o(o_f, o_m) \right\}_{\substack{o_f = \{abstract, routine\} \\ o_m = \{abstract, routine\}}} \right\} \tag{30}$$

and

$$\mathbb{E}_{\epsilon_o} V_1(\Omega_0, \vec{\epsilon}_o) = \sigma_{\epsilon_o} \log \left\{ \sum_{\substack{o_f = \{abstract, routine\} \\ o_m = \{abstract, routine\}}} \exp \left(\frac{\mathbb{E}_{X_f X_m} \mathbb{E}_{\epsilon_p} V_1^{X_f X_m}(\tilde{\Omega}_1 | o_f, o_m)}{\sigma_{\epsilon_o}} \right) \right\}. \tag{31}$$

The resulting choice probabilities for the discrete occupation-pair choices take the standard logit form:

$$P(o_f, o_m | \tilde{\Omega}_1) = \frac{\exp \left(\mathbb{E}_{X_f X_m} \mathbb{E}_{\epsilon_p} V_1^{X_f X_m}(\tilde{\Omega}_1 | o_f, o_m) / \sigma_{\epsilon_o} \right)}{\sum_{\substack{\tilde{o}_f = \{abstract, routine\} \\ \tilde{o}_m = \{abstract, routine\}}} \exp \left(\mathbb{E}_{X_f X_m} \mathbb{E}_{\epsilon_p} V_1^{X_f X_m}(\tilde{\Omega}_1 | \tilde{o}_f, \tilde{o}_m) / \sigma_{\epsilon_o} \right)}. \tag{32}$$

C Model Calibration

C.1 Joint Initial Spousal Human Capital Distribution

To estimate the initial human capital distribution in my model, I follow a two-step process. First, I estimate the joint education distribution of married couples. Second, I map each education group onto the human capital grid of my model.

Estimating the Joint Initial Education Distribution To estimate the initial joint distribution of education among couples, I use data from the PSID, restricting the sample as described previously in Appendix A. In this dataset, I observe the education levels of both spouses, which I categorize into three groups: (1) "no college", (2) "some college but no degree," and (3) "at least a college degree." To align with the first period of my model, I focus on young married couples aged 25–29 who are not currently enrolled as students and have no missing education information. This results in a sample of 1,637 unique couples. Using the provided statistical weights (based on the husband), I compute the matrix of shares for each education group pair combination of spouses. The resulting joint distribution is illustrated in Figure 6b.

Mapping Education on the Human Capital Grid In order, to map the three education groups onto the human capital grid let me introduce the following notation. At point $j = 1$, de-

note the corresponding (unobserved) initial human capital levels for each education group as $\{H_{no\,college},\, H_{some\,college},\, H_{college}\}$. Let the human capital grid take the form $\{H_{min}, ..., H_{max}\}$, where I normalize, without loss of generality, $H_{min} = 1 = H_{no\,college}$. Recall, with simplified notation, that the wage process for occupation o, workplace p and human capital level H of spouse g in couple i at age j is:

$$w_{igj} = \phi_o(1 + \delta(p_{igj}))\, H_{igj}.$$

Thus, at the onset of a worker's career their wage is proportional to their initial human capital $H_{educ} \in \{H_{no\,college},\, H_{some\,college},\, H_{college}\}$:

$$w_{ig1} = \phi_o(1 + \delta(p_{ig1}))\, H_{educ}.$$

Taking the logs we can rewrite as:

$$\ln(w_{ig1}) = \ln(\, \phi_o(1 + \delta(p_{ig1}))\,) \,+\, \ln(H_{educ}).$$

This can be rewritten as an estimable regression, where the first term is captured by variation in occupation and workplace location, while the second term is captured through education dummies. To avoid perfect co-linearity, I omit one education group—specifically, the *no college* group—which is normalized to 1 without loss of generality. The regression reads as:

$$\Leftrightarrow \ln(w_{ig1}) = \beta_0 + \beta_1 o_{ig1} + \beta_2 p_{ig1} + \beta_3 o_{ig1} \,\times\, p_{ig1} + \beta_4 \text{College}_{ig1} + \beta_5 \text{Some college}_{ig1} + \epsilon_{igj}$$

Hence,

$$\ln(H_{college}) = \beta_4 + \ln(1) = \beta_4$$

$$\Leftrightarrow\; H_{college} = \exp(\beta_4)$$

and

$$\ln(H_{some_college}) = \beta_5 + \ln(1) = \beta_5$$

$$\Leftrightarrow\; H_{some_college} = \exp(\beta_5).$$

I assume that wages at the onset of a career can be approximated by a share initial human capital within an education group, alongside their occupation and workplace location. Assuming that young workers' initial wages at the start of their careers are proportional to their educational attainment, and normalizing the human capital grid level for one education group (e.g., the *no college* group) without loss of generality, I leverage the relative differences in mean observed wages across education groups—conditional on workplace and occupation—to infer the implied human capital levels for the model.[41]

[41] It is important to note that the coefficients derived are not equivalent to the college wage premium, typically defined as the percentage difference between the average wages of workers with a four-year college degree and those with a

Table 41: Regression Results

	Coefficient	Std. Err.	P>|t|	[95% Conf. Interval]	
abstract	0.2625	0.0096	0.000	0.2436	0.2814
WfH	0.1559	0.0196	0.000	0.1175	0.1944
Abstract× WfH	0.1415	0.0292	0.000	0.0842	0.1987
Some college	0.1411	0.0098	0.000	0.1219	0.1603
College	0.2979	0.0086	0.000	0.2811	0.3147
Constant	2.5255	0.0052	0.000	2.5152	2.5358

Note: The table display mean wage, standard errors by education and occupation group and resulting human capital mapping by education. The moments are computed in SIPP (2013-2016) on married couples, age 25-29, that work onsite, accounting for statistical weights and excluding wages that exceed three standard deviations of the mean.

To ensure consistency with the first period of my model, I restrict the sample to workers aged 25–29, a group that is no longer enrolled in education. Table 41 presents the estimated coefficients, which yield the mapping $\{H_{\text{no college}}, H_{\text{some college}}, H_{\text{college}}\} = \{1, 1.15, 1.35\}$. These results indicate that, at ages 25–29, workers with a college degree have 35% higher human capital levels than those without a college degree, while workers with some college education exhibit 15% higher human capital levels than those with no college education.

high school diploma. Instead, my comparison focuses on workers within the same occupation and workplace location. Furthermore, as individuals self-select into different educational groups based on unobserved characteristics, the inferred human capital level can serve as an auxiliary variable, reflecting differences in both educational attainment and innate ability.

D Model Results

D.1 Model Results

Table 42: Steady-state Comparison of Male Labor Outcomes (Aggregate Effects)

Δ (in %)			Δ (in ppt.)
Hourly wages	Market hours	Labor earnings	Earnings growth between age 25-40
-1.17	-0.49	-2.48	+2.30

Note: The table reports the average percentage change in men's aggregate labor outcomes—hourly wages, market hours, and labor earnings (the product of the two)—between the old and new steady states.

Table 43: Steady-state comparison of female labor outcomes (occupation switcher)

Sample selection			Δ (in %)			Δ (in ppt.)	
Occ. stayer		Occ. switcher	Hourly	Market	Labor	Earnings growth	Share (in %)
own WfH	spousal WfH	own	wages	hours	earnings	between age 25-40	
		✓	+76.63	+75.94	+209.97	+39.93	0.09
✓		✓	+69.90	+74.60	+196.02	+35.58	1.07
	✓	✓	+74.45	+123.96	+285.52	+48.23	0.20
✓	✓	✓	+68.75	+118.73	+263.48	+48.04	1.58

Note: The table shows the average percentage change in women's labor outcomes—hourly wages, market hours, and labor earnings (the product of the two)—between the old and new steady states. To isolate the role of increased WfH opportunities, I compare the same couples across environments that differ only in the availability of WfH. Specifically, steady-state outcomes are compared between female *twins*, defined as women (and their spouses) with identical initial human capital endowments and identical realizations of exogenous shocks. I look at changes by subgroups depending on women's own WfH take-up and their spouses, as well on wether they switched their occupation group.

Table 44: Steady-state comparison of female labor outcomes (Whole Sample)

Sample selection			**Δ (in %)**			Δ (in ppt.)	
Occ. stayer		Occ. switcher	Hourly	Market	Labor	Earnings growth	Share (in %)
own WfH	spousal WfH	own	wages	hours	earnings	between age 25-40	
			+0.73	+0.32	+0.62	-0.03	4.7
✓			-2.36	+2.02	-1.77	+1.11	16.2
	✓		+1.57	+5.11	+4.97	+3.86	24.0
✓	✓		-0.15	+5.85	+1.79	+9.61	49.5
		✓	+69.25	+105.17	+243.05	+44.92	4.6

Note: The table shows the average percentage change in women's labor outcomes—hourly wages, market hours, and labor earnings (the product of the two)—between the old and new steady states. To isolate the role of increased WfH opportunities, I compare the same couples across environments that differ only in the availability of WfH. Specifically, steady-state outcomes are compared between female *twins*, defined as women (and their spouses) with identical initial human capital endowments and identical realizations of exogenous shocks. I look at changes by subgroups depending on women's own WfH take-up and their spouses, as well on wether they switched their occupation group.

Table 45: Steady-state Comparison of Ex-ante Couple Welfare

Subgroup			**Δ (in %)**	
Occ. stayer		Occ. switcher	Welfare	Share (in %)
Own WfH	Spousal WfH			
			+4.260	4.7
✓			+4.279	12.2
	✓		+4.275	18.4
✓	✓		+4.281	19.0
		✓	+4.297	2.9
Aggregate Effect			+4.287	100

Note: The table shows the average percentage change on couple's welfare. To isolate the role of increased WfH opportunities, I compare the same couples across environments that differ only in the availability of WfH. Specifically, steady-state outcomes are compared between female *twins*, defined as women (and their spouses) with identical initial human capital endowments and identical realizations of exogenous shocks. I look at changes by subgroups depending on women's own WfH take-up and their spouses, as well on wether they switched their occupation group.

Table 46: Steady-state comparison of aggregates and gender gaps - A decomposition

		Δ relative to old steady-state (in %)		
		Gender Gaps in		
	Output	Hourly wages	Labor Earnings	Earnings growth by 40
Main counterfactual	+0.47	-2.85	-7.40	-16.64
(1) No WfH penalties	+0.16	-2.73	-7.54	-16.42
(2) No GE	+0.88	-2.21	-6.37	+14.48
(3) No occ. change	-0.91	-0.32	-1.80	-4.94

Note: The table reports aggregate percentage changes in output and gender gaps in labor outcomes between the old steady state and the main counterfactual scenario with increased WfH opportunities, as well as counterfactual new steady-states where single model ingredients are shut off. Results are shown for the main counterfactual as well as for the decomposition exercises summarized in Table 30.