

Work From Home, Worker Interactions, and Economic Growth

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Abstract

This paper applies the dynamic knowledge diffusion model developed by Lucas and Moll (2014) to examine how worker productivity distribution evolves and how long-run growth responds to the shift toward hybrid work environments. In the model, workers differ in their productivity and allocate time between working from home (WFH) and working on-site (WOS). Productivity improves only through learning from higher-productivity workers. I incorporate a learning probability kernel based on relative productivity and empirical rate of returns of face-to-face spillovers to better capture heterogeneity in knowledge transmission. The allocation of time between remote and on-site work determines both the current level of output and the economy's long-run growth path. Through numerical simulations, I characterize the balanced growth equilibrium under various hybrid work intensities. Furthermore, I compare decentralized outcomes with the socially optimal solution that internalizes the positive externalities of knowledge spillovers. The findings contribute to the ongoing policy debate on the optimal design of remote work in the post-pandemic economy.

Keywords: working from home, hybrid working arrangement, interaction-based endogenous growth, knowledge spillover through interaction, productivity dynamics

1 Introduction

The COVID-19 pandemic has profoundly transformed our lives, and the shift toward working from home (WFH) is one of its most enduring legacies. Although the pandemic has subsided, working arrangements have not reverted to their pre-pandemic norms. Figure 1 illustrates the historical trend of WFH since 1965. As of July 2025, 27.3% of full workdays in the U.S. are conducted from home, which translates to an average of 1.37 days per week ((Barrero et al., 2021b)). This figure is more than sixty times higher than the pre-pandemic average of 0.02 days (0.4%). A growing body of research argues that this structural change is here to stay ((Barrero et al., 2021b; Bick et al., 2021)).¹

While the rapid adoption of WFH is evident, its productivity effects remain controversial. Many workers report benefits such as reduced commuting time and greater leisure, often claiming that they are more productive at home. For instance, survey data from Barrero et al. (2021b) indicated that 39.2% of respondents experienced increased productivity when working remotely, compared to only 15.2% who reported a negative impact.

However, these positive assessments are not universal. Managerial-level employees often report declines in productivity, citing increased coordination and management costs associated with remote work ((Bloom et al., 2023)). Young professionals, particularly early-career workers, also report challenges in acquiring tacit knowledge due to limited face-to-face interactions ((Goldberg and Casselman, 2023)). Empirical evidence from Emanuel et al. (2023) supports this concerns, showing that mentoring and feedback significantly declined for remote workers in a Fortune 500 tech firm: A decrease in task-related feedback was especially apparent for young female workers.

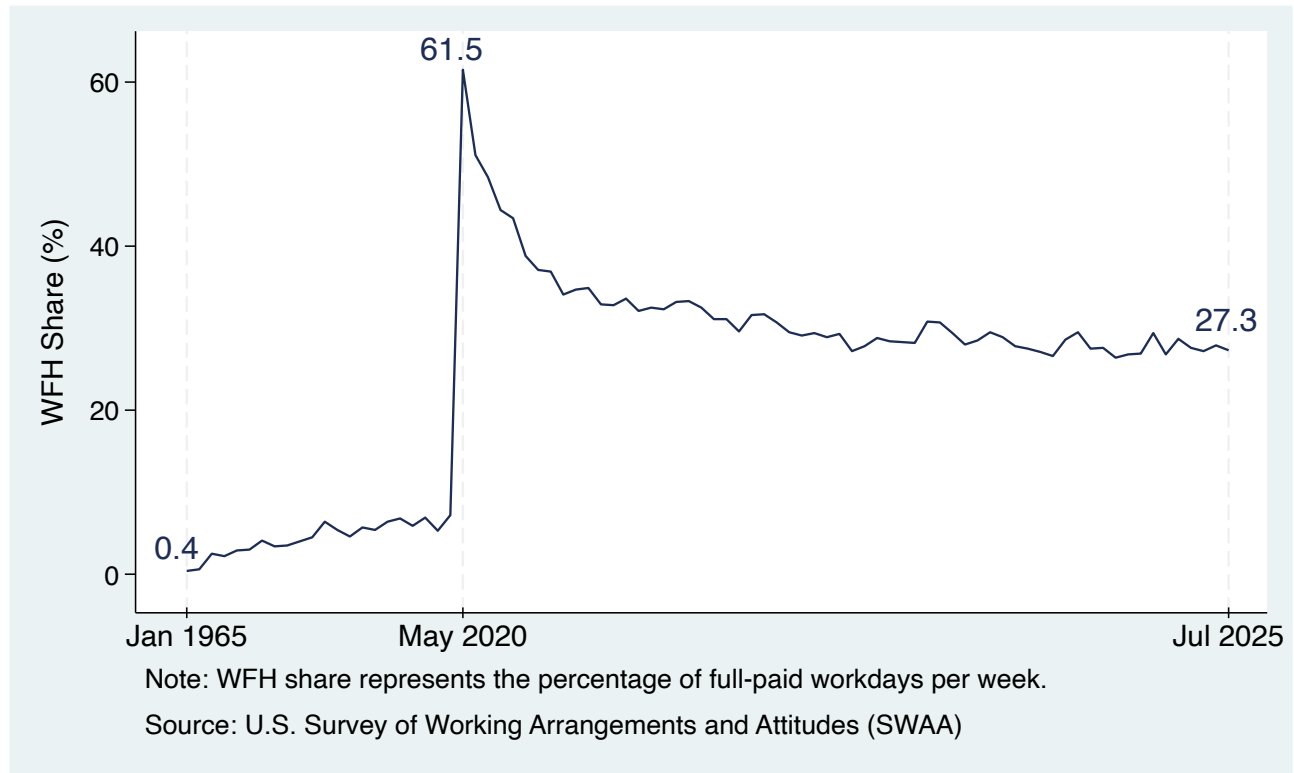
Furthermore, after several months of the WFH experiment, some firms have called workers back to the office. Although we do not yet have a complete data analysis, these firms may internally have found some drawbacks of WFH. Although there exist many anecdotal and survey literature on WFH, they mostly focus on short-term analysis. Without a formal analytical framework, it remains difficult to evaluate the long-run implications of WFH on productivity and growth.

The purpose of this research is to develop a framework that analyzes the effect of a hybrid working environment and to investigate its impact on productivity and economic growth. The main question is how the WFH affects workers' productivity, long-run growth and, ultimately, welfare. We also consider the question of whether the current 27.3% of workdays represent a

¹These studies highlight multiple factors behind this persistence: (i) the actual WFH experience exceeded expectations for both workers and employers; (ii) technological improvements and targeted investments have facilitated remote work; (iii) the stigma associated with WFH has diminished; and (iv) concerns about health risks and infection continue to influence preferences. In short, the long-term shift toward hybrid work reflects both preference changes on the household side and technological advances on the production side.

56 socially optimal allocation.

Figure 1: WFH trend



57 **Related Literature** This paper builds upon two strands of literature. Firstly, it contributes
58 to the growing literature on the roles and impacts of WFH, especially in the post-pandemic
59 economy. Several studies, including Barrero et al. (2021a), Barrero et al. (2021b), Barrero et al.
60 (2023), Bick et al. (2021), Aksoy et al. (2022), Aksoy et al. (2025), have shown that the transition
61 in working arrangement is likely to be permanent and pervasive, especially among college-
62 educated workers and in knowledge-intensive industries. These papers emphasize that WFH
63 improves aggregate productivity primarily through reduced commuting time and improved job
64 matching. Eberly et al. (2021) highlights WFH as a form of 'potential capital,' which enhances
65 resilience by diversifying working arrangements against negative shocks to the economy.

66 A growing body of policy-focused studies further underscores the macroeconomic signifi-
67 cance of WFH. For example, the U.S. Government Accountability Office (2025) evaluates that
68 mandatory full-return-to-office policies may hinder labor market efficiency. In the general equi-
69 librium context, Behrens et al. (2021) have investigated the effects of WFH on growth and
70 inequality. Bagga et al. (2023) have shown that preference shock toward remote work is the
71 main factor explaining the unconventional pattern of labor market reallocation post-COVID
72 period.

Secondly, from a theoretical standpoint, this paper is related to interaction-based growth theory and knowledge spillovers. Akcigit et al. (2018); Lucas and Moll (2014); Perla and Tonetti (2014) establish models in which innovation and knowledge diffusion occur through interactions among heterogeneous agents Jarosch et al. (2021) provide econometric estimates on the value of learning from coworkers at the work site, while Atkin et al. (2022) leverage cellphone-based location data to quantify the granular return to face-to-face interactions in Silicon Valley. Similarly, Kerr and Robert-Nicoud (2020) and Emanuel et al. (2023) show that the productivity of workers in high-skill tech sectors is amplified by physical proximity to knowledgeable peers.

Among these, Lucas and Moll (2014) is the most relevant for this paper. I adapt their knowledge diffusion framework to investigate the productivity implications of reduced face-to-face interaction under remote work. In contrast to the existing model that centers on aggregate output maximization, our framework incorporates a utility maximization problem at the individual level. Moreover, I introduce a micro-founded learning probability function, informed by empirical estimates from Atkin et al. (2022), to capture how the effectiveness of knowledge transmission depends on both proximity and the productivity distance between agents.

Taken together, this paper bridges the empirical insights on WFH with the theoretical literature on interaction-based growth model that reveals heterogeneous productivity and welfare outcomes arising from differential access on in-person interactions.

The rest of this paper is organized as follows. Section 2 presents the model and establishes an equilibrium concept in the decentralized economy. In Section 3, the computation strategy and quantitative results are given. In Section 4, I solve social planner’s problem and compare the results from the decentralized economy outcome. Section 5 concludes.

2 Model

This section introduces a continuous-time model of endogenous growth driven by knowledge spillovers through worker interactions. The structure is based on Lucas and Moll (2014), with a critical modification to incorporate hybrid work arrangements. Workers divide their labor time between working on site and working from home, and learning opportunities arise from interactions in both settings, though with differing probabilities.

2.1 Environment

Time is continuous. At initial time 0, each worker's productivity level $\tilde{z} \in \mathbb{R}_+$ is randomly, exogenously drawn from a cumulative productivity distribution $F(z, 0)$, defined as:

$$F(z, 0) = \Pr\{\tilde{z} \leq z \text{ at date } 0\}.$$

We assume that the initial cumulative distribution $F(z, 0)$ has a Pareto tail.²

ASSUMPTION 1. *Pareto Tail*

There exist $k, \theta > 0$ such that

$$\lim_{z \rightarrow \infty} \frac{1 - F(z, 0)}{z^{-1/\theta}} = k.$$

I further assume that productivity specifically follows a Fréchet distribution as a Fréchet distribution has a Pareto tail.

ASSUMPTION 2. *Fréchet Distribution*

$$\begin{aligned} F(z, 0) &= \Phi_0(z) = e^{-kz^{-1/\theta}}. \\ f(z, 0) &= \phi_0(z) = \frac{k}{\theta} z^{-1/\theta-1} e^{-kz^{-1/\theta}}. \end{aligned}$$

The productivity level z determines the worker's individual output and influences their ability to contribute to the productivity growth of others through interactions.

Each worker allocates their unit time available between working from home (WFH) and working on-site (WOS). Let $h(z, t) \in [0, 1]$ denote the fraction of time a worker of type z devotes to WFH at time t . Then $1 - h(z, t)$ represents the corresponding time spent WOS.

Production Consistent with Lucas and Moll (2014), each worker produces output using their individual productivity and a fixed amount of labor. Individual output per labor at time t is given by:

$$y(t) = z(t) \text{ for all } t.$$

The per capita production in the economy is:

$$Y(t) = \int_0^\infty y(t) f(z, t) dz \text{ for all } t$$

²I impose the Pareto tail assumption for the following two reasons: (i) theoretically speaking, a Pareto tail is necessary in a perpetual growth model, and (ii) empirically speaking, wage distribution exhibits a Pareto tail.

120 where $f(z, t) = \frac{\partial F(z, t)}{\partial z}$ denotes the cross-sectional productivity density function at time t .

121 The productivity distribution evolves endogenously over time as workers engage in learning
 122 through interactions. A worker of type z can improve their productivity by meeting and learning
 123 from a more productive worker with productivity $y > z$. The law of motion of productivity
 124 distribution is derived in Section 2.2.

125 **Meeting and Learning** Learning occurs stochastically upon meetings. Meetings among
 126 workers also occur randomly, with the meeting probability depending on whether workers are
 127 on-site or remote. Let α_o and α_h denote these probabilities, respectively.

128 We define the meeting probability function for a worker of type z , denoted by $\alpha(h(z, t))$, as
 129 a decreasing function of their work-from-home (WFH) share:

$$\alpha(h(z, t)) = (\alpha_o - \alpha_h)(1 - h(z, t))^\eta + \alpha_h,$$

130 where $\alpha_o \in (0, 1]$ represents the meeting probability under full on-site work, and $\alpha_h \in (0, \alpha_o)$
 131 under full remote work. The function smoothly interpolates between these two extremes. The
 132 curvature parameter $\eta > 0$ governs the sensitivity of meeting probability to on-site work inten-
 133 sity.³

134 2.2 Evolution of Productivity Distribution

135 This section characterizes the evolution of the productivity distribution over time, capturing
 136 how each worker improves one's productivity by learning from others. The model builds upon
 137 the learning dynamics introduced by Lucas and Moll (2014), while implementing a more realistic
 138 *partial learning rule* that allows for gradual and stochastic updates in productivity, rather than
 139 instantaneous jumps to the higher productivity level.

140 **Stochastic Partial Learning** Workers improve their productivity through stochastic inter-
 141 actions. Upon meeting a more productive worker with productivity level $y \geq z > 0$, a worker
 142 of type z partially updates her productivity according to the partial learning rule as follows:

$$z' = T(z, y) := (1 - \lambda(z, y)) \cdot z + \lambda(z, y) \cdot y,$$

³When $\eta = 1$ the meeting probability increases linearly with on-site work. When $\eta > 1$, the gains from on-site work are convex, which means that the interaction benefits increase more rapidly as workers spend more time on-site. Conversely, when $\eta < 1$, the meeting function exhibits diminishing returns: even limited on-site presence (e.g., occasional office visits) can capture most of the interaction benefits. This curvature allows the model to flexibly reflect different degrees of complementarity between physical presence and knowledge diffusion.

143 where $\lambda(z, y) \in (0, 1)$ governs the intensity of learning. We assume

$$\lambda(z, y) = \underline{\lambda} + (1 - \underline{\lambda}) \left(\frac{y}{z} \right)^{-\kappa}, \quad \underline{\lambda} \in (0, 1), \quad \kappa > 0.$$

144 This formulation implies that productivity improvements depend on the relative distance be-
 145 tween workers. As the productivity gap widens, learning becomes more ineffective. This mod-
 146 ifies the seminary Lucas and Moll (2014), where productivity jumps instantaneously to the
 147 higher level upon meeting. Our approach reflects more realistic workplace learning, where
 148 knowledge increment takes place as gradual increment. Note that we denote $\underline{\lambda}$ as the minimum
 149 learning intensity, which ensures that even the least productive agents have a strictly positive
 150 probability of upgrading their productivity through partial learning.

151 **Law of Motion of Productivity Density Distribution** Let $f(z, t)$ denote the density
 152 of workers with productivity z at time t . In this economy, productivity density distribution
 153 evolves as follows:

$$\begin{aligned} \frac{\partial f(z, t)}{\partial t} = & \underbrace{-\alpha(h(z, t))f(z, t) \int_{y>z} f(y, t) dy}_{\text{outflow}} \\ & + \underbrace{\int_{y \leq z} \alpha(h(y, t))f(y, t) \left[\int_{z' \geq z} f(z', t) \delta(z - T(y, z')) dz' \right] dy}_{\text{inflow}}. \end{aligned} \quad (1)$$

154 The first term on the right hand side represents *outflow* from productivity z . This term reflects
 155 the loss of mass at productivity level z due to upward transitions. A z -type worker can meet a
 156 more productive worker ($y > z$) and move to a higher productivity level $z' > z$, reducing the
 157 density at z .

158 The second term on the right hand side of the law of motion equation represents *inflow*
 159 to productivity z . This term captures the gain of mass at productivity level z from workers
 160 of lower productivity $y \leq z$ who learn and improve *exactly* to z . The detailed derivation is
 161 provided in Appendix A.1.

162 2.3 Household Problem

163 At each time t , we assume that workers have the option to choose between WFH and WOS.
 164 Each worker chooses optimal WFH intensity $h(z, t) \in [0, 1]$ to maximize one's lifetime utility.
 165 The instantaneous utility function is given by:

$$u(z, t) = c(z, t) + z(t) \log l(z, t)$$

166 where $c(z, t)$ denotes consumption and $l(z, t)$ denotes leisure. The utility function assumes that
 167 workers are risk-neutral in consumption but exhibit risk aversion in leisure, which is scaled by
 168 their productivity level $z(t)$.

169 Leisure is constructed as:

$$l(z, t) = 1 - L - (1 - h(z, t))\chi - \frac{\epsilon}{2}h(z, t)^2$$

170 where L is the fixed amount of labor, χ denotes commuting cost when a worker works on site,
 171 ϵ inefficiency of setting up office when a worker works at home.

172 Notice that the partial derivative of leisure with respect to WFH ratio $h(z, t)$ captures the
 173 trade-off effects of WFH:

$$\frac{\partial l(z, t)}{\partial h(z, t)} = \chi - \epsilon h(z, t).$$

174 In other words, workers, when they work at home, can enjoy additional leisure by saving
 175 commuting time, which is linear in χ . However, at the same time, they also have to give up a
 176 certain amount of leisure due to distractions and inefficiency caused by WFH working setup,
 177 which is convexly increasing in WFH ratio $h(z, t)$.

178 Further assuming that $c(z, t) = y(t) = z(t)$ in equilibrium, we can rewrite the instantaneous
 179 utility function:

$$u(z, t) = z(t) + z(t) \log(1 - L - (1 - h(z, t))\chi - \frac{\epsilon}{2}h(z, t)^2).$$

180 For any policy $h(z, t)$ with given z , $V^h(z, t)$ is the household's discounted expected lifetime
 181 utility:

$$V^h(z, t) = \mathbb{E} \left[\int_t^\infty e^{-\rho(\tau-t)} u(\tilde{z}(\tau), \tau) d\tau \mid \tilde{z}(t) = z \right].$$

182 The workers want to choose policy $h(z, t)$ so as to maximize $V^h(z, t)$. The optimal value function
 183 $V(z, t) = \max_h V^h(z, t)$ satisfies the dynamic programming principle, which leads to the HJB
 184 equation as follows:

$$\begin{aligned}
\rho V(z, t) &= \max_{h \in [0, 1]} \left\{ \underbrace{u(z, t)}_{\text{current flow utility}} + \underbrace{\frac{\partial V(z, t)}{\partial t}}_{\text{explicit time variation}} + \underbrace{\alpha(h(z, t)) \int_z^\infty [V(T(z, y), t) - V(z, t)] f(y, t) dy}_{\text{expected gain from learning via meetings}} \right\} \\
&= \max_{h \in [0, 1]} \left\{ z + z \log(1 - L - (1 - h(z, t))\chi - \frac{\epsilon}{2} h(z, t)^2) + \frac{\partial V(z, t)}{\partial t} \right. \\
&\quad \left. + \alpha(h(z, t)) \int_z^\infty [V(T(z, y), t) - V(z, t)] f(y, t) dy \right\}.
\end{aligned} \tag{2}$$

185 The formal derivation of the HJB equation is provided in Appendix A.2. The left-hand side,
186 $\rho V(z, t)$, represents the required flow return that makes the continuation value $V(z, t)$ consistent
187 with discounting at rate ρ .

188 The first term inside the braces, $u(z, t)$, is the instantaneous utility from current consump-
189 tion and leisure given the worker's time-allocation choice $h(z, t)$.

190 The second term, $\partial V(z, t)/\partial t$, captures explicit time variation in the value function that
191 arises when the aggregate environment evolves over time, for example through changes in
192 the cross-sectional productivity distribution $f(\cdot, t)$ or in equilibrium objects pinned down by
193 that distribution. In stationary environments (e.g., along a balanced growth path), this term
194 typically vanishes.

195 The final term reflects learning through stochastic meetings. Meetings arrive at Poisson
196 rate $\alpha(h(z, t))$. Conditional on a meeting, the worker encounters a more productive peer with
197 productivity $y > z$ drawn from the current distribution $f(y, t)$. Under the partial-learning
198 rule, the worker's productivity updates to $T(z, y)$, implying a change in continuation value
199 from $V(z, t)$ to $V(T(z, y), t)$. The integral therefore aggregates the expected value gain from
200 potential learning opportunities across all higher-productivity counterparts, weighted by their
201 density in the economy.

202 2.4 Equilibrium

203 **DEFINITION 1.** (*Equilibrium*) Given the initial distribution $f(z, 0)$, an equilibrium is a triple
204 (f, V, h) such that (i) given h , f satisfies its law of motion equation (1) for all (z, t) ; (ii) given
205 f , V satisfies HJB equation (2); and (iii) $h(z, t)$ attains the utility maximum for all (z, t) .

206 **DEFINITION 2.** (*BGP Equilibrium*) A balanced growth path (BGP) equilibrium is an equi-

207 *librium with a constant γ and a triple of functions (ϕ, v, σ) on $\mathbf{R}_+$ such that*

$$f(z, t) = e^{-\gamma t} \phi(ze^{-\gamma t}), \quad (3)$$

$$V(z, t) = e^{\gamma t} v(ze^{-\gamma t}), \quad (4)$$

$$h(z, t) = \sigma(ze^{-\gamma t}) \quad (5)$$

208 *for all (z, t) and (f, V, h) is an equilibrium with the initial condition $f(z, 0) = \phi(z)$.*

209 On a BGP equilibrium, productivity density function f grows as a traveling wave, main-
 210 taining its shape. To normalize productivity level, we use a normalized productivity $x \equiv ze^{-\gamma t}$.
 211 The value function V grows at a rate of γ , and optimal WFH ratio $h(z, t)$ does not change.

212 **LEMMA 1.** *Homogeneity of Degree One of Learning Update Rule.*

213 *The learning update rule $T(z, y)$ is homogeneous of degree one, i.e.,*

$$T(nz, ny) = nT(z, y) \quad \text{for any } n > 0.$$

214 *Proof.* Recall that $T(z, y) = (1 - \lambda(z, y))z + \lambda(z, y)y$, $y \geq z > 0$ where the learning weight
 215 depends only on the relative productivity gap:

$$\lambda(z, y) = \underline{\lambda} + (1 - \underline{\lambda}) \left(\frac{y}{z} \right)^{-\kappa}, \quad \underline{\lambda} \in (0, 1), \kappa > 0.$$

216 In other words,

$$\begin{aligned} \lambda(nz, ny) &= \underline{\lambda} + (1 - \underline{\lambda}) \left(\frac{ny}{nz} \right)^{-\kappa} \\ &= \underline{\lambda} + (1 - \underline{\lambda}) \left(\frac{y}{z} \right)^{-\kappa} \\ &= \lambda(z, y) \end{aligned}$$

217 Therefore,

$$\begin{aligned} T(nz, ny) &= (1 - \lambda(nz, ny))(nz) + \lambda(nz, ny)(ny) \\ &= n(1 - \lambda(z, y))z + n\lambda(z, y)y \\ &= n\{(1 - \lambda(z, y))z + \lambda(z, y)y\} \\ &= nT(z, y) \end{aligned}$$

218 which proves the claim. □

219 To investigate the equilibrium on the balanced growth path, let us restate each function
 220 in terms of BGP form. Note that I repeatedly use a change-of-variables argument under the

221 BGP scaling. For completeness, Appendix A.3 and A.4 prove the key transformations used to
 222 rewrite the law of motion of productivity density distribution and household's HJB equation in
 223 stationary form.

224 From (3) by definition and by construction,

$$\begin{aligned}\frac{\partial f(z, t)}{\partial t} &= -\gamma e^{-\gamma t} \phi(z e^{-\gamma t}) + e^{-\gamma t} \phi'(z e^{-\gamma t}) (-\gamma z e^{-\gamma t}) \\ &= -\gamma e^{-\gamma t} \phi(x) - e^{-\gamma t} \gamma x \phi'(x)\end{aligned}\tag{6}$$

225 where $x \equiv z e^{-\gamma t}$ denotes the normalized productivity.

226 Rewriting the right-hand side of equation (1) on a BGP,

$$\begin{aligned}\frac{\partial f(z, t)}{\partial t} &= -e^{-\gamma t} \alpha(\sigma(x)) \phi(x) \int_x^\infty \phi(s) ds \\ &\quad + e^{-\gamma t} \int_0^x \alpha(\sigma(s)) \phi(s) \left[\int_x^\infty \phi(r) \delta_D(x - T(s, r)) dr \right] ds\end{aligned}\tag{7}$$

227 Equating (6) and (7), and crossing out $e^{-\gamma t}$ from both sides, we have

$$-\gamma \phi(x) - \gamma x \phi'(x) = -\alpha(\sigma(x)) \phi(x) \int_x^\infty \phi(s) ds + \int_0^x \alpha(\sigma(s)) \phi(s) \left[\int_x^\infty \phi(r) \delta_D(x - T(s, r)) dr \right] ds.\tag{8}$$

228 Likewise, the HJB equation (2) can be rewritten as

$$(\rho - \gamma)v(x) - x + \gamma x v'(x) = \max_{\sigma \in [0, 1]} \left\{ x \log l(\sigma(x)) + \alpha(\sigma(x)) \int_x^\infty \left[v(T(x, s)) - v(x) \right] \phi(s) ds \right\}.\tag{9}$$

229 2.5 BGP Growth Rate

230 Total production on a BGP is

$$\begin{aligned}Y(t) &= \int_0^\infty z(t) f(z, t) dz \\ &= \int_0^\infty e^{\gamma t} x e^{-\gamma t} \phi(x) e^{\gamma t} dx \\ &= e^{\gamma t} \int_0^\infty x \phi(x) dx.\end{aligned}$$

231 Total production grows at the rate of γ on a BGP.

232 **LEMMA 2.** *BGP Growth Rate.*

233 *Under the Assumptions 1 and 2, BGP growth rate is pinned down as*

$$\gamma = \theta \underline{\lambda}^{\frac{1}{\theta}} \int_0^\infty \alpha(\sigma(y)) \phi(y) dy. \quad (10)$$

234 Refer to the Appendix A.5 for a rigorous proof. Also note that the BGP growth rate γ boils
235 down to Lucas and Moll (2014) case when $\underline{\lambda} = 1$, which means the extreme value jump case.

236 **3 Quantitative Analysis**

237 **3.1 Computation Strategy**

238 Recall the HJB equation (9). Define the function

$$S(x) = \int_x^\infty \left[v(T(x, s)) - v(x) \right] \phi(s) ds.$$

239 Then, the first-order condition for $\sigma(x)$ is

$$\frac{x(\chi - \epsilon\sigma(x))}{1 - L - (1 - \sigma(x))\chi - \frac{\epsilon}{2}\sigma^2} + \alpha'(\sigma(x))S(x) \begin{cases} \leq 0, & \text{if } \sigma(x) = 0, \\ = 0, & \text{if } 0 < \sigma(x) < 1, \\ \geq 0, & \text{if } \sigma(x) = 1. \end{cases} \quad (11)$$

240 For a specific functional form of α function, we use $\alpha(\sigma(x)) = (\alpha_o - \alpha_h)((1 - \sigma(x))^\eta + \alpha_h$
241 where α_o denotes the meeting probability of workers in office and α_h the meeting probability
242 of workers at home. For the specific numerical value, we use the estimated meeting probability
243 values from Atkin et al. (2022).

244 Next, consider the productivity distribution function (8). Rewrite the equation (8) as

$$-\gamma\phi(x) - \gamma x\phi'(x) = -\alpha(\sigma(x))\phi(x)[1 - \Phi(x)] + \phi(x)\psi(x) \quad (12)$$

245 where

$$\psi(x) = \int_0^x \alpha(\sigma(s))\phi(s) \left[\int_x^\infty \phi(r)\delta_D(s - T(s, r)) dr \right] ds \quad (13)$$

$$\Phi(x) = \int_0^x \phi(s) ds. \quad (14)$$

246 To carry out the Bellman function iteration and distribution iteration, I apply a finite
247 difference method on a grid $(x_1, x_2, \dots, x_i, \dots, x_I)$ of I values. The specific parameter values
248 that I chose are given in Table 1.

Table 1: Parameterization and Source of Identification

Parameter	Value	Classification	Interpretation and Source
α_o	0.305	Literature-informed assumption	Meeting arrival rate in on-site working arrangement motivated by Atkin et al. (2022)
α_h	0.076	Literature-informed assumption	Meeting arrival rate in remote working arrangement motivated by Atkin et al. (2022)
η	1.1834	Conditional calibration	Jointly chosen with $\underline{\lambda}$ to approximately match aggregate WFH and annual growth rate
$\underline{\lambda}$	0.41145	Conditional calibration	Minimum fraction of a productivity gap learned per productive encounter; jointly chosen with η
κ	1	Exogenous assumption	Curvature of partial learning with respect to the productivity gap
χ	0.05	Literature-anchored calibration	72 minutes of commute-time savings divided by 24 hours, using Aksoy et al. (2023)
ϵ	0.05	Exogenous assumption	Convex WFH time-equivalent cost
ρ	0.05	Exogenous assumption	Conventional annual continuous-time discount rate.
θ	0.5	Literature-informed proxy	Implies productivity-tail Pareto exponent $1/\theta = 2$; motivated by evidence on the US labor-income tail Lee et al. (2022)
L	1/3	Normalization	Eight work hours out of a 24-hour daily time endowment.

Notes. No structural parameter is estimated directly by econometric methods in the current specification. The meeting arrival rate in each working arrangement, 0.305 and 0.076, was estimated within 30-minute time window. The model takes them as same as annual intensities.

Table 2: Quantitative Results

Moment	Target	Model
Mean WFH share	27.30%	27.1994%
Annual productivity growth	2.00%	2.0021%

3.2 Quantitative Results

Figure 2 shows the competitive equilibrium of WFH ratio on the BGP. Note that WFH ratio is weakly increasing in relative productivity. This is because a worker with higher productivity has smaller room to improve their productivity, thus less incentive to meet others in person compared to the cost of commuting, and prefers to work from home. This result coincides with the results from Emanuel et al. (2023), which shows that younger workers with lower productivity prefer face-to-face interaction. The model-generated average WFH ratio is 27.19% and economic growth rate on the BGP γ is 2%.

Figure 2: Optimal Work-from-Home Policy in the Decentralized Economy

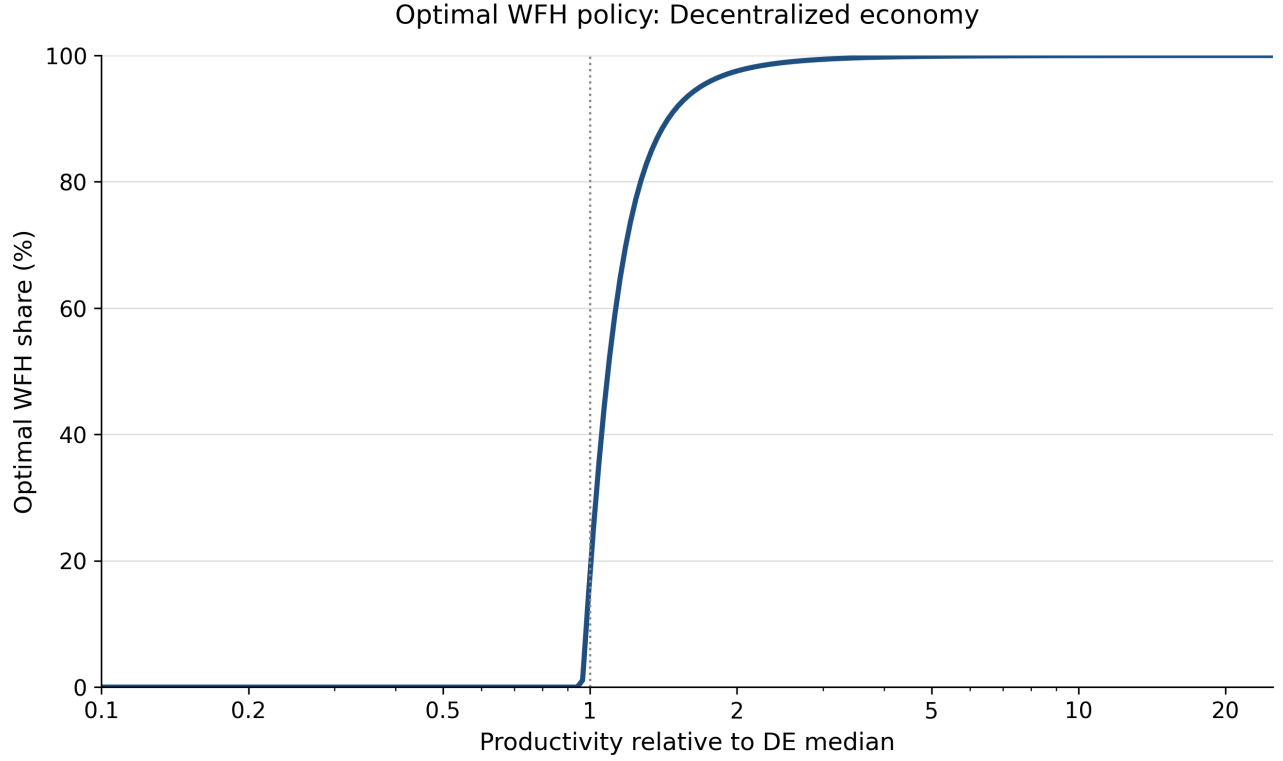


Table 3: Quantitative Results

Moment	Target	Model
Average WFH share	27.30%	27.1994%
Annual productivity growth	2.00%	2.0021%

Table 4: Long-run Productivity Growth Under Mandated Work Arrangements

Allocation	Average WFH share (%)	Annual BGP growth (%)
100% WFH mandated	100	0.643
Decentralized equilibrium	27.199	2.002
100% WOS mandated	0	2.581

Notes: The forced cases impose $h(z) = 1$ or $h(z) = 0$ for all workers and jointly re-solve the stationary finite-volume productivity distribution. The growth rates are permanent BGP comparisons, not dynamic transition effects. The difference between 100% WOS and 100% WFH is 1.938 percentage points per year. Forced policies do not mean welfare optimal.

Table 3 summarizes the quantitative results of the model calibration and compares the results with the targeted moments.

Counterfactual Analysis I also conduct a couple of counterfactual experiments by fixing WFH ratio as 0% (fully on-site scenario) and 100% (fully remote scenario). Table 4 shows that

261 if every worker works on site, BGP economic growth rate is 2.581%. On the other hand, if
 262 every worker works at home, BGP economic growth rate plummets to 0.643%.

263 4 The Planner Problem

264 Notice that, in the decentralized economy, each agent does not consider the positive externalities
 265 of his own knowledge for others when he chooses the optimal WFH ratio. In this section,
 266 we investigate how a benevolent planner would allocate time, accommodating this positive
 267 externality problem. The objective function of the social planner is to maximize total utility
 268 in the economy.

$$W[f(\cdot, t)] = \max_h \int_t^\infty e^{-\rho(\tau-t)} \int_0^\infty u(z, t) f(z, \tau) dz d\tau$$

269 subject to the law of motion for f as in the equation (2). Note that, unlike the decentralized
 270 economy where the state variable is the specific individual's productivity z , the state variable
 271 in the social planner's problem is the productivity distribution $f(\cdot, t)$ as a whole.

272 Define the *marginal social value* of a type z as

$$w(z, t) = \frac{d W[f(\cdot, t)]}{d f(\cdot, t)}.$$

273 Marginal social value of a type z measures the contribution of a worker with productivity z
 274 to aggregate discounted welfare. It satisfies the HJB equation:

$$\begin{aligned} \rho w(z, t) = \max_{h \in [0, 1]} \left\{ u(z, t) + \frac{\partial w(z, t)}{\partial t} + \underbrace{\alpha(h(z, t)) \int_z^\infty [w(T(z, z'), t) - w(z, t)] f(z', t) dz'}_{\text{expected gain from learning via meetings}} \right. \\ \left. + \underbrace{\int_0^z \alpha(h(y, t)) [w(T(y, z)) - w(y, t)] f(y, t) dy}_{\text{positive externality value of knowledge spillover}} \right\}. \quad (15) \end{aligned}$$

275 The detailed derivation is available in Appendix B.1.

276 **DEFINITION 3.** (*Pareto Efficient Allocation*) Given the initial distribution $f(z, 0)$, a Pareto
 277 efficient allocation is a triple (f, w, h) such that (i) given h , f satisfies (2) for all (z, t) ; (ii)
 278 given f , w satisfies (15); and (iii) $h(z, t)$ attains the social welfare maximization for all (z, t) .

279 **DEFINITION 4.** (*BGP Pareto Efficient Allocation*) A balanced growth path (BGP) Pareto
 280 efficient allocation is an allocation with a constant γ and a triple of functions (ϕ, ω, ζ) on $\mathbf{R}_+$

281 *such that*

$$f(z, t) = e^{-\gamma t} \phi(ze^{-\gamma t}), \quad (16)$$

$$w(z, t) = e^{\gamma t} \omega(ze^{-\gamma t}), \quad (17)$$

$$h(z, t) = \zeta(ze^{-\gamma t}) \quad (18)$$

282 *for all (z, t) and (f, w, h) is an allocation with the initial condition $f(z, 0) = \phi(z)$.*

283 The fundamental insight of each function is the same as the decentralized equilibrium: on
 284 a BGP, productivity density function $f(z, t)$ is a traveling wave maintaining a same shape,
 285 marginal social value $\omega(z, t)$ grows at a rate of γ , and optimal time allocation spent on WFH
 286 $h(z, t)$ does not change.

287 As in the case of a decentralized economy, restating the social planner's problem in terms
 288 of normalized productivity $x \equiv ze^{-\gamma t}$, a BGP Bellman equation is

$$\begin{aligned} & (\rho - \gamma)\omega(x) + \gamma x \omega'(x) \\ &= \max_{\zeta(x) \in [0, 1]} \left\{ x + x \log(1 - L - (1 - \zeta)\kappa - \frac{\lambda}{2}\zeta(x)^2) \right. \\ & \quad \left. + \alpha(\zeta(x)) \int_x^\infty [\omega(T(x, s)) - \omega(x)] \phi(s) ds + \int_0^x \alpha(\zeta(r)) [\omega(T(r, x)) - \omega(r)] \phi(r) dr \right\}. \end{aligned} \quad (19)$$

289 and the productivity density distribution on a BGP follows the law of motion equation (8).

290 **4.1 Computation Strategy**

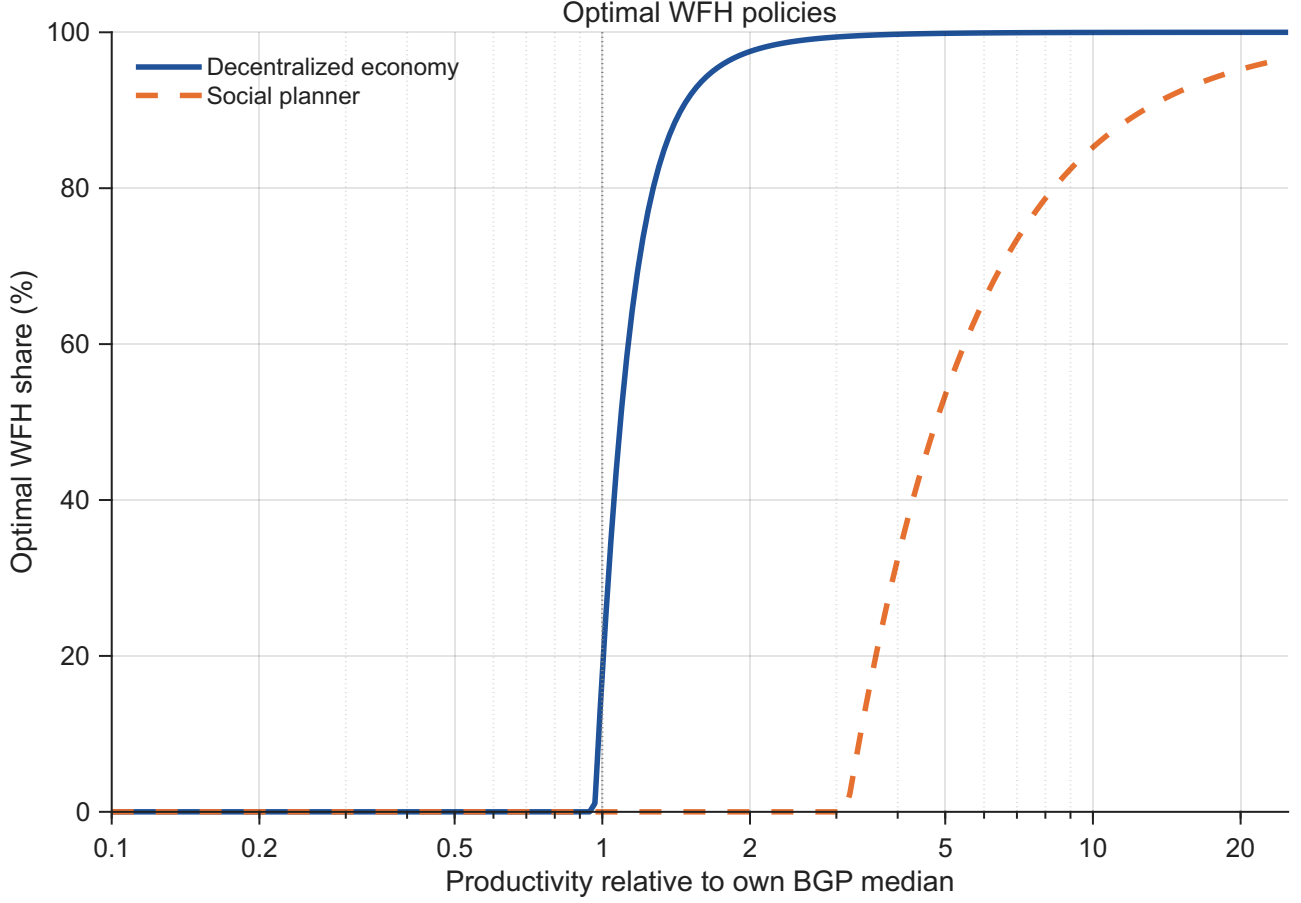
291 We apply the finite difference method, which is the same computation method used in the
 292 decentralized economy. Recall the HJB equation for social planner (19) in a BGP form:

$$(\rho - \gamma)\omega(x) + \gamma x \omega'(x) = \max_{\zeta(x) \in [0, 1]} \left\{ x + x \log(1 - L - (1 - \zeta(x))\kappa - \frac{\lambda}{2}\zeta(x)^2) + \alpha(\zeta(x))S(x) + R(x) \right\},$$

293 where $S(x)$ and $Q(x)$ are defined as

$$\begin{aligned} S(x) &\equiv \int_x^\infty [\omega(T(x, s)) - \omega(x)] \phi(s) ds, \\ R(x) &\equiv \int_0^x \alpha(\zeta(r)) [\omega(T(r, x)) - \omega(r)] \phi(r) dr. \end{aligned}$$

Figure 3: Optimal Work-from-Home Allocation by Social Planner



294 The first-order condition for $\zeta(x)$ is

$$\frac{x(\kappa - \epsilon\zeta(x))}{1 - L - (1 - \zeta(x))\kappa - \frac{\lambda}{2}\zeta(x)^2} + \alpha'(\zeta(x))S(x) \begin{cases} \leq 0 & \text{if } \zeta(x) = 0, \\ = 0 & \text{if } 0 < \zeta(x) < 1, \\ > 0 & \text{if } \zeta(x) = 1. \end{cases}$$

295 4.2 Quantitative Results

296 Figure 3 shows the optimal WFH allocation on the BGP chosen by social planner. The social
 297 planner's Pareto efficient allocation shifts the optimal WFH choices rightward. The figure says
 298 that a certain amount of workers, whose relative productivities lie between the median and
 299 the 3.15 times and who choose to work hybrid in a decentralized economy, are now encour-
 300 aged to work on-site in the social planner's case. The average WFH ratio is 0.0358% when
 301 workers internalize the value of externality. Economic growth rate γ is 2.58%, higher than the
 302 decentralized case.

303 Table 5 compares the major variables of interest in the decentralized economy and social

Table 5: Comparison between Decentralized Outcome and Social Planner Allocation

Allocation	Average WFH share (%)	Annual BGP growth (%)
Decentralized equilibrium	27.1994	2.0021
Social planner allocation	0.0358	2.5809

planner allocation.

4.3 Policy Discussion

How can decentralized economy achieve the Pareto efficient allocation? To internalize the positive externalities of working on-site, the government can incentivize office workers or penalize workers at home. Considering the robust preference for working from home, incentivizing working onsite would be more feasible than penalizing the WFH. In particular, policies that reduce commuting time may increase workers' incentives to work on-site.

An example of existing policies is the *Live Near Your Work* program offered by Johns Hopkins University in partnership with Baltimore City, which provides financial assistance to employees purchasing homes in designated neighborhoods near their workplaces. Another example is the U.S. *Federal Transit Benefit Program*, which provides eligible federal employees with subsidies for public transportation expenses associated with commuting to work, subject to a monthly limit of \$340 in 2026. Although primarily designed to promote public transportation use, this program also reduces the monetary cost of commuting.

In the model, reductions in commuting time correspond to a decrease in the commuting cost parameter χ , making on-site work more attractive to workers. Monetary commuting subsidies could operate through a similar incentive channel. By reducing the private cost of working on-site, these policies could encourage face-to-face interactions, strengthen knowledge spillovers, and promote long-run productivity growth. Policy instruments encouraging skillful workers to work on site are also required.

5 Conclusion

This paper examines the long-run effects of hybrid working arrangements. Since the transition in the working environment is relatively new, there are not enough time series data to look at. To deal with this difficulty, we approach the research question from the theoretical side. The model is mainly based on Lucas and Moll (2014), with two adjustments: (i) utility maximizing objective function and (ii) micro-founded meeting probability function.

In modeling the effects of WFH, we consider a simple trade-off. The benefit of WFH is saving

commuting time, which increases leisure time. The cost of WFH is the reduced face-to-face meeting probability, leading to a forgone learning opportunity from others.

Quantitative results show that the BGP WFH ratio is 27.19% in the decentralized economy and 0.036% in the social planner's case. Economic growth rate is 2% in the decentralized economy and 2.58% in the social planner's case. The optimal time allocation for WFH is heterogeneous in worker's productivity: Lower-productivity workers choose to work on site; Higher-productivity workers choose to work from home.

The contribution of this paper would be twofold: (i) to conduct research on WFH beyond anecdotal and survey-oriented approach; (ii) to examine the long-run effects of WFH despite the lack of sufficient time series data to look at.

This research has several limitations. Further rigorous empirical analysis is called for to corroborate the results of this study. Also, once more data about the transition in the working arrangement has accumulated, we can implement more granular and data-oriented empirical research and compare the results from the theoretical experiments.

For future research, a better understanding of the nature of face-to-face interaction and learning process among people will help appropriately adjust the evolution of productivity distribution.

Appendix A Decentralized Economy

A.1 Law of Motion of Productivity Density Distribution

Fix $z > 0$. A worker who is below z at time t remains below z at time $t + \Delta$ if either (i) she does not meet anyone during $(t, t + \Delta)$, or (ii) she meets someone but the post-meeting productivity remains below z . Conditioning on the initial productivity level $\tilde{z} \leq z$ and using the Poisson approximation gives

$$F(z, t + \Delta) = \int_0^z f(\tilde{z}, t) \left[\underbrace{\left(1 - \alpha(h(\tilde{z}, t))\Delta\right)}_{\text{no meeting}} + \underbrace{\alpha(h(\tilde{z}, t))\Delta \int_0^\infty f(y, t) \mathbf{1}\{T(\tilde{z}, y) \leq z\} dy}_{\text{meet but stay} \leq z} \right] d\tilde{z}.$$

Subtracting $F(z, t) = \int_0^z f(\tilde{z}, t) d\tilde{z}$ from both sides and dividing by Δ yields

$$\frac{F(z, t + \Delta) - F(z, t)}{\Delta} = - \int_0^z \alpha(h(\tilde{z}, t)) f(\tilde{z}, t) d\tilde{z} + \int_0^z \alpha(h(\tilde{z}, t)) f(\tilde{z}, t) \left[\int_0^\infty f(y, t) \mathbf{1}\{T(\tilde{z}, y) \leq z\} dy \right] d\tilde{z}.$$

Letting $\Delta \rightarrow 0$ and rearranging terms, we obtain

$$\begin{aligned} \frac{\partial F(z, t)}{\partial t} &= \int_0^z \underbrace{\alpha(h(\tilde{z}, t)) f(\tilde{z}, t)}_{A(\tilde{z}, t)} \left[\underbrace{\int_0^\infty f(y, t) \mathbf{1}\{T(\tilde{z}, y) \leq z\} dy}_{B(\tilde{z}, z, t)} - 1 \right] d\tilde{z}. \\ &= \int_0^z H(\tilde{z}, z, t) d\tilde{z} \end{aligned} \tag{20}$$

where $H(\tilde{z}, z, t) := A(\tilde{z}, t)[B(\tilde{z}, z, t) - 1]$

Using $f(z, t) = \partial F(z, t) / \partial z$ and exchanging derivatives $\partial t \partial z = \partial z \partial t$, we have

$$\frac{\partial f(z, t)}{\partial t} = \frac{\partial}{\partial z} \left(\frac{\partial F(z, t)}{\partial t} \right).$$

Differentiating (20) with respect to z , we obtain

$$\frac{\partial f(z, t)}{\partial t} = \frac{\partial}{\partial z} \int_0^z H(\tilde{z}, z, t) d\tilde{z} = H(z, z, t) + \int_0^z \frac{\partial H(\tilde{z}, z, t)}{\partial z} d\tilde{z}. \tag{21}$$

To begin with the first term on the right hand side,

$$\begin{aligned} H(z, z, t) &= A(z, t)[B(z, z, t) - 1] \\ &= \alpha(h(z, t)) f(z, t) \left[\int_0^\infty f(y, t) \mathbf{1}\{T(z, y) \leq z\} dy - 1 \right]. \end{aligned}$$

360 Note that the bracket term in the above equation can be rewritten as

$$\begin{aligned} \int_0^\infty f(y, t) \mathbf{1}\{T(z, y) \leq z\} dy - 1 &= -(1 - \int_0^\infty f(y, t) \mathbf{1}\{T(z, y) \leq z\} dy) \\ &= - \int_0^\infty f(y, t) \mathbf{1}\{T(z, y) > z\} dy. \end{aligned}$$

361 Also note that by the partial learning rule,

$$T(y, z) = \begin{cases} z' > z, & \text{if } y > z \\ z' \leq z, & \text{if } y \leq z. \end{cases}$$

362 Hence,

$$\mathbf{1}\{T(z, y) > z\} = \mathbf{1}\{y > z\}.$$

363 Therefore,

$$H(z, z, t) = -\alpha(h(z, t))f(z, t) \int_{y>z} f(y, t) dy. \quad (22)$$

364 Next, regarding the second term in the equation (21),

$$\frac{\partial H(\tilde{z}, z, t)}{\partial z} = A(\tilde{z}, t) \frac{\partial B(\tilde{z}, z, t)}{\partial z}.$$

365 Note that

$$\begin{aligned} \frac{\partial}{\partial z} B(\tilde{z}, z, t) &= \int_0^\infty f(y, t) \frac{\partial}{\partial z} \mathbf{1}\{T(\tilde{z}, y) \leq z\} dy \\ &= \int_0^\infty f(y, t) \delta(z - T(\tilde{z}, y)) dy. \end{aligned}$$

366 where $\delta(z - T(\tilde{z}, y))$ is a Dirac delta, a generalized function that picks out contribution from the
367 event $z = T(\tilde{z}, y)$ when integrated. Therefore, the second term in the equation (21) becomes

$$\int_0^z \alpha(h(\tilde{z}, t))f(\tilde{z}, t) \left[\int_0^\infty f(y, t) \delta(z - T(\tilde{z}, y)) dy \right] d\tilde{z}. \quad (23)$$

368 Renaming of the dummy variables for the consistency of notations with the main part, the
369 equation (23) can be rewritten as

$$\int_0^z \alpha(h(y, t))f(y, t) \left[\int_0^\infty f(z', t) \delta(z - T(y, z')) dz' \right] dy. \quad (24)$$

370 For $y \leq z$, for partial learning results to be exactly same as z , the effective integral in the

371 bracket of equation(24) remains as

$$\int_{z' \geq z} f(z', t) \delta(z - (T(y, z'))) dz'.$$

372 Then the second term in the equation (21) becomes

$$\int_{y < z} \alpha(h(y, t)) f(y, t) \int_{z' \geq z} f(z', t) \delta(z - (T(y, z'))) dz' dy. \quad (25)$$

373 Finally, putting the equations (22) and (25) together, we get the law of motion equation of
374 productivity density distribution function:

$$\begin{aligned} \frac{\partial f(z, t)}{\partial t} = & -\alpha(h(z, t)) f(z, t) \int_{y > z} f(y, t) dy \\ & + \int_{y \leq z} \alpha(h(y, t)) f(y, t) \left[\int_{z' \geq z} f(z', t) \delta(z - T(y, z')) dz' \right] dy. \end{aligned}$$

375 **A.2 Household HJB Equation**

376 This appendix derives the Hamilton-Jacobi-Bellman (HJB) equation for the worker's optimal
377 WFH policy.

378 Recall that the discounted expected lifetime utility (conditional on $\tilde{z}(t) = z$) is

$$V^h(z, t) := \mathbb{E} \left[\int_t^\infty e^{-\rho(\tau-t)} u(\tilde{z}(\tau), \tau) d\tau \mid \tilde{z}(t) = z \right], \quad (26)$$

379 where $\rho > 0$ is the discount rate. The optimal value function is $V(z, t) = \max_h V^h(z, t)$.

380 Consider a short time interval $[t, t + \Delta]$ with $\Delta > 0$. By splitting the integral in the equation
381 (26) at $t + \Delta$,

$$V^h(z, t) = \mathbb{E} \left[\int_t^{t+\Delta} e^{-\rho(\tau-t)} u(\tilde{z}(\tau), \tau) d\tau + e^{-\rho\Delta} V^h(\tilde{z}(t + \Delta), t + \Delta) \mid \tilde{z}(t) = z \right].$$

382 Optimizing over h yields the dynamic programming principle for the optimal value function:

$$V(z, t) = \max_{h \in [0, 1]} \mathbb{E} \left[\underbrace{\int_t^{t+\Delta} e^{-\rho(\tau-t)} u(\tilde{z}(\tau), \tau) d\tau}_{\text{short term pay-off}} + \underbrace{e^{-\rho\Delta} V(\tilde{z}(t + \Delta), t + \Delta)}_{\text{continuation value}} \mid \tilde{z}(t) = z \right]. \quad (27)$$

383 Regarding the first term in the bracket of the equation (27), applying the Taylor expansion,

384 we get:

$$\begin{aligned}
e^{-\rho\Delta}u(z, t + \Delta) &\approx (1 - \rho\Delta + O(\Delta^2)) \left(u(z, t) + \frac{\partial u(z, t)}{\partial t} \Delta + O(\Delta^2) \right) \\
&\approx u(z, t) + \frac{\partial u(z, t)}{\partial t} \Delta - \rho u(z, t) \Delta - \rho \frac{\partial u(z, t)}{\partial t} \Delta^2 \\
&= u(z, t) + \left[\frac{\partial u(z, t)}{\partial t} - \rho u(z, t) \right] \Delta + O(\Delta^2)
\end{aligned}$$

385 Then the first term can be rewritten as:

$$\begin{aligned}
&\int_t^{t+\Delta} \left(u(z, t) + \left[\frac{\partial u(z, t)}{\partial t} - \rho u(z, t) \right] \Delta + O(\Delta^2) \right) d\tau \\
&= u(z, t) \int_t^{t+\Delta} d\tau + \left[\frac{\partial u(z, t)}{\partial t} - \rho u(z, t) \right] \int_t^{t+\Delta} (\tau - t) d\tau + \int_t^{t+\Delta} O(\Delta^2) \tau \\
&= u(z, t) \Delta + \frac{\Delta^2}{2} \left[\frac{\partial u(z, t)}{\partial t} - \rho u(z, t) \right] + O(\Delta^3) \\
&\approx u(z, t) \Delta + o(\Delta)
\end{aligned} \tag{28}$$

386 Now, we next consider the continuation value at $t + \Delta$. Note that expected continuation
387 value of the equation (27) is a probability-weighted average of the values associated with two
388 possible events: whether a meeting occurs during the interval $[t, t + \Delta]$ or not. If no meeting
389 occurs, the worker's productivity remains at z , and the continuation value is $V(z, t + \Delta)$. If a
390 meeting occurs, the worker's post-meeting productivity depends on the productivity y of the
391 encountered worker, resulting in the continuation value $V(T(z, y), t + \Delta)$. Hence, we get:

$$\begin{aligned}
&\mathbb{E}[V(\tilde{z}(t + \Delta), t + \Delta) \mid \tilde{z}(t) = z] \\
&= \underbrace{(1 - \alpha\Delta)V(z, t + \Delta)}_{\text{No meeting}} + \underbrace{\alpha\Delta \int_0^\infty V(T(z, y), t + \Delta) f(y, t) dy}_{\text{Meeting}} + o(\Delta)
\end{aligned} \tag{29}$$

392 where $\alpha = \alpha(h(z, t))$ and $T(z, y)$ denotes the post-meeting productivity.

393 As for the second term in the above equation,

$$\begin{aligned}
\int_0^\infty V(T(z, y), t + \Delta) f(y, t) dy &= V(z, t + \Delta) \int_0^z f(y, t) dy + \int_z^\infty V(T(z, y), t + \Delta) f(y, t) dy \\
&= V(z, t + \Delta) \left(1 - \int_z^\infty f(y, t) dy \right) + \int_z^\infty V(T(z, y), t + \Delta) f(y, t) dy
\end{aligned}$$

394 Substituting this into (29) and rearranging terms yield:

$$\begin{aligned} \mathbb{E}[V(\tilde{z}(t + \Delta), t + \Delta) \mid \tilde{z}(t) = z] &= V(z, t + \Delta) \\ &+ \alpha \Delta \int_z^\infty (V(T(z, y), t + \Delta) - V(z, t + \Delta)) f(y, t) dy + o(\Delta). \end{aligned} \quad (30)$$

395 Insert (28) and (30) into the optimal dynamic programming principle (27):

$$\begin{aligned} V(z, t) = \max_{h \in [0, 1]} & \left\{ u(z, t) \Delta + e^{-\rho \Delta} [V(z, t + \Delta) \right. \\ & \left. + \alpha(h(z, t)) \Delta \int_z^\infty (V(T(z, y), t + \Delta) - V(z, t + \Delta)) f(y, t) dy] \right\}. \end{aligned}$$

396 To derive the HJB equation, we express the continuation value at $t + \Delta$ in terms of the current
 397 value $V(z, t)$ and its change over the short interval Δ . Holding productivity z fixed, a first-order
 398 Taylor expansion gives $V(z, t + \Delta) = V(z, t) + \frac{\partial V(z, t)}{\partial t} \Delta + o(\Delta)$ and dropping $o(\Delta)$ terms gives:

$$\begin{aligned} V(z, t) = \max_{h \in [0, 1]} & \left\{ u(z, t) \Delta + (1 - \rho \Delta) \left[V(z, t) + \frac{\partial V(z, t)}{\partial t} \Delta \right. \right. \\ & \left. \left. + \alpha(h(z, t)) \Delta \int_z^\infty (V(T(z, y), t + \Delta) - V(z, t + \Delta)) f(y, t) dy \right] \right\}. \end{aligned}$$

399 After canceling $V(z, t)$ from both sides, dividing by Δ , and letting $\Delta \rightarrow 0$, we obtain the HJB
 400 equation:

$$\rho V(z, t) = \max_{h \in [0, 1]} \left\{ u(z, t) + \frac{\partial V(z, t)}{\partial t} + \alpha(h(z, t)) \int_z^\infty (V(T(z, y), t) - V(z, t)) f(y, t) dy \right\}.$$

401 This is equation (2) in the main text.

402 **A.3 Law of Motion of Productivity Density Function on a BGP**

403 This appendix derives the law of motion of productivity density distribution along a BGP.
 404 Starting from equation (1), we transform the outflow and inflow terms using the BGP scaling
 405 conditions.

406 Recall that, on a BGP, the productivity density and the optimal WFH policy satisfy:

$$f(z, t) = e^{-\gamma t} \phi(x), \quad h(z, t) = \sigma(x), \quad x = ze^{-\gamma t}.$$

Also, recall that the original law of motion is given by:

$$\frac{\partial f(z, t)}{\partial t} = -\alpha(h(z, t))f(z, t) \int_z^\infty f(y, t) dy + \int_0^z \alpha(h(y, t))f(y, t) \left[\int_z^\infty f(z', t) \delta_D(z - T(y, z')) dz' \right] dy.$$

where δ_D denotes the Dirac delta function.

First, consider the outflow term,

$$-\alpha(h(z, t))f(z, t) \int_z^\infty f(y, t) dy.$$

To transform the integral, also define $s = ye^{-\gamma t}$. Then it follows that

$$y = e^{\gamma t} s, \quad dy = e^{\gamma t} ds.$$

The lower integration bound $y = z$ becomes $s = x$. Therefore,

$$\int_z^\infty f(y, t) dy = \int_x^\infty e^{-\gamma t} \phi(s) e^{\gamma t} ds.$$

Substituting these expressions into the original outflow term yields:

$$\begin{aligned} -\alpha(h(z, t))f(z, t) \int_z^\infty f(y, t) dy &= -\alpha(\sigma(x))e^{-\gamma t} \phi(x) \int_x^\infty e^{-\gamma t} \phi(s) e^{\gamma t} ds \\ &= -\alpha(\sigma(x))e^{-\gamma t} \phi(x) \int_x^\infty \phi(s) ds. \end{aligned}$$

Next, consider the inflow term,

$$\int_0^z \alpha(h(y, t))f(y, t) \left[\int_z^\infty f(z', t) \delta_D(z - T(y, z')) dz' \right] dy.$$

To express this term in normalized productivity, define

$$s = ye^{-\gamma t}, \quad r = z'e^{-\gamma t},$$

where s and r represent the normalized productivity levels of the learning worker and the encountered worker, respectively.

These changes of variables imply

$$y = e^{\gamma t} s, \quad z' = e^{\gamma t} r,$$

and

$$dy = e^{\gamma t} ds, \quad dz' = e^{\gamma t} dr.$$

419 The integration bounds also transforms as:

$$0 \leq y \leq z \implies 0 \leq s \leq x,$$

420 and

$$z' \geq z \implies r \geq x.$$

421 Applying these transformations, the inflow term can be rewritten as:

$$\begin{aligned} & \int_0^z \alpha(h(y, t)) f(y, t) \left[\int_z^\infty f(z', t) \delta_D(z - T(y, z')) dz' \right] dy \\ &= \int_0^x \alpha(\sigma(s)) e^{-\gamma t} \phi(s) \left[\int_x^\infty e^{-\gamma t} \phi(r) \delta_D(e^{\gamma t} x - T(e^{\gamma t} s, e^{\gamma t} r)) e^{\gamma t} dr \right] e^{\gamma t} ds \\ &= \int_0^x \alpha(\sigma(s)) \phi(s) \left[\int_x^\infty \phi(r) \delta_D(e^{\gamma t} x - T(e^{\gamma t} s, e^{\gamma t} r)) dr \right] ds \\ &= \int_0^x \alpha(\sigma(s)) \phi(s) \left[\int_x^\infty \phi(r) \delta_D(e^{\gamma t} x - e^{\gamma t} T(s, r)) dr \right] ds \quad \text{by LEMMA 1.} \end{aligned}$$

422 We now use the scaling property of the Dirac delta function:

$$\delta_D(aq) = \frac{1}{|a|} \delta_D(q), \quad a \neq 0.$$

423 Since $e^{\gamma t} > 0$, it follows that

$$\begin{aligned} \delta_D(e^{\gamma t} x - e^{\gamma t} T(s, r)) &= \delta_D(e^{\gamma t} (x - T(s, r))) \\ &= \frac{1}{e^{\gamma t}} \delta_D(x - T(s, r)). \end{aligned}$$

424 Substituting this result into the transformed inflow term, we obtain:

$$e^{-\gamma t} \int_0^x \alpha(\sigma(s)) \phi(s) \left[\int_x^\infty \phi(r) \delta_D(x - T(s, r)) dr \right] ds.$$

425 Combining the transformed outflow and inflow expressions gives the equation (7) in the main
426 text.

427 A.4 Household HJB Equation on a BGP

428 This appendix derives the household HJB equation along a BGP. Starting from equation (2),
429 we transform the flow utility, the time derivative of the value function, and the expected gains
430 from learning from others using normalized productivity scales.

Recall that the household HJB equation is:

$$\rho V(z, t) = \max_{h(z, t)} \left\{ z + z \log l(h(z, t)) + \frac{\partial V(z, t)}{\partial t} + \alpha(h(z, t)) \int_z^\infty [V(T(z, y), t) - V(z, t)] f(y, t) dy \right\}.$$

On a BGP, the value function, productivity density, and optimal WFH policy satisfy:

$$V(z, t) = e^{\gamma t} v(x), \quad f(z, t) = e^{-\gamma t} \phi(x), \quad h(z, t) = \sigma(x), \quad x = e^{-\gamma t} z.$$

First, consider the instantaneous utility,

$$z + z \log l(h(z, t)).$$

Since $z = e^{\gamma t} x$, it follows that

$$e^{\gamma t} x + e^{\gamma t} x \log l(\sigma(x)).$$

Thus, the flow utility is proportional to $e^{\gamma t}$, with normalized flow utility $x + x \log l(\sigma(x))$.

Next, consider the time derivative term. To differentiate the value function with respect to t , we apply the chain rule:

$$\frac{\partial V(z, t)}{\partial t} = \frac{\partial e^{\gamma t} v(e^{-\gamma t} z)}{\partial t} = \gamma e^{\gamma t} v(x) - e^{\gamma t} \gamma x v'(x).$$

We now transform the expected learning gain. Define the normalized productivity of the encountered worker as $s = ye^{-\gamma t}$. It follows that

$$y = e^{\gamma t} s, \quad dy = e^{\gamma t} ds.$$

The lower integration bound $y = z$ becomes $s = x$, so the integral is now taken over $s \in [x, \infty)$.

$$\begin{aligned} \int_z^\infty [V(T(z, y), t) - V(z, t)] f(y, t) dy &= \int_x^\infty [V(T(e^{\gamma t} x, e^{\gamma t} s)) - e^{\gamma t} v(x)] e^{-\gamma t} \phi(s) e^{\gamma t} ds \\ &= \int_x^\infty [V(e^{\gamma t} T(x, s)) - e^{\gamma t} v(x)] \phi(s) ds \quad \text{by LEMMA 1.} \end{aligned}$$

Note that using the BGP value-function scaling,

$$V(T(z, y), t) = e^{\gamma t} v(T(z, y)e^{-\gamma t}) \implies V(e^{\gamma t} T(x, s), t) = e^{\gamma t} v(T(x, s)).$$

Thus, the difference in continuation values can be expressed as

$$e^{\gamma t} (v(T(x, s)) - v(x)).$$

443 Substituting these expressions into the expected learning gain yields:

$$e^{\gamma t} \int_x^\infty [v(T(x, s)) - v(x)] \phi(s) ds.$$

444 We now substitute the transformed expressions into the original HJB equation:

$$\begin{aligned} \rho e^{\gamma t} v(x) = \max_{\sigma(x)} & \left\{ e^{\gamma t} x + e^{\gamma t} x \log l(\sigma(x)) + \gamma e^{\gamma t} v(x) - e^{\gamma t} \gamma x v'(x) \right. \\ & \left. + \alpha(\sigma(x)) e^{\gamma t} \int_x^\infty [v(T(x, s)) - v(x)] \phi(s) ds \right\}. \end{aligned}$$

445 Canceling out $e^{\gamma t}$ from both sides and rearranging terms, we obtain equation (9) in the main
446 text.

447 A.5 BGP Growth Rate

448 The proof follows the standard upper-tail (threshold-crossing) argument used in Lucas and Moll
449 (2014) models, and adapts it to the present setting in which the meeting intensity depends on
450 the worker's WFH choice. Fix a threshold $z > 0$ and consider the mass of workers with
451 productivity at most z , namely $F(z, t)$.

452 Over a short interval $(t, t + \Delta)$, a worker with current productivity $\tilde{z} \leq z$ remains below z if
453 either (i) no meeting occurs, or (ii) a meeting occurs but the realized post-meeting productivity
454 does not exceed z . To obtain a tractable expression for the leading-order change in $F(z, t)$, we
455 use a sufficient condition for crossing above z that holds uniformly for all $\tilde{z} \leq z$.

456 Since $\lambda(\tilde{z}, y) \geq \underline{\lambda}$ and $\tilde{z} \geq 0$,

$$T(\tilde{z}, y) = (1 - \lambda)\tilde{z} + \lambda y \geq \lambda y \geq \underline{\lambda} y.$$

457 Hence, whenever $y > z/\underline{\lambda}$, the worker's post-meeting productivity exceeds z for any $\tilde{z} \leq z$:

$$y > z/\underline{\lambda} \quad \Rightarrow \quad T(\tilde{z}, y) > z.$$

458 Meetings arrive as a Poisson process with intensity $\alpha(h(\tilde{z}, t))$. Thus, the probability of
459 (at least one) meeting over $(t, t + \Delta)$ is $\alpha(h(\tilde{z}, t))\Delta + o(\Delta)$. Conditional on a meeting, the
460 probability that the encountered peer has productivity $y > z/\underline{\lambda}$ is $1 - F(z/\underline{\lambda}, t)$. Therefore, for
461 a given type $\tilde{z} \leq z$, the probability of crossing above z over $(t, t + \Delta)$ is

$$\alpha(h(\tilde{z}, t))\Delta [1 - F(z/\underline{\lambda}, t)] + o(\Delta).$$

462 Aggregating across $\tilde{z} \leq z$ yields the total mass leaving the set $\{\tilde{z} \leq z\}$:

$$\Delta [1 - F(z/\underline{\lambda}, t)] \int_0^z \alpha(h(u, t)) f(u, t) du + o(\Delta).$$

463 Hence,

$$F(z, t + \Delta) = F(z, t) - \Delta [1 - F(z/\underline{\lambda}, t)] \int_0^z \alpha(h(u, t)) f(u, t) du + o(\Delta).$$

464 Dividing by Δ and letting $\Delta \rightarrow 0$ gives

$$\frac{\partial F(z, t)}{\partial t} = -[1 - F(z/\underline{\lambda}, t)] \int_0^z \alpha(h(u, t)) f(u, t) du. \quad (*)$$

465 Now impose the BGP scaling $F(z, t) = \Phi(x)$ with $x = ze^{-\gamma t}$, and $f(z, t) = e^{-\gamma t} \phi(x)$. Then

$$\frac{\partial F(z, t)}{\partial t} = -\gamma x \phi(x).$$

466 Using the change of variables $s = ue^{-\gamma t}$, the integral on the right-hand side of $(*)$ becomes

$$\int_0^z \alpha(h(u, t)) f(u, t) du = \int_0^x \alpha(\sigma(s)) \phi(s) ds,$$

467 and $1 - F(z/\underline{\lambda}, t) = 1 - \Phi(x/\underline{\lambda})$. Therefore, $(*)$ can be written as

$$\gamma x \phi(x) = [1 - \Phi(x/\underline{\lambda})] \int_0^x \alpha(\sigma(s)) \phi(s) ds. \quad (**)$$

468 Finally, take $x \rightarrow \infty$ and use the Pareto tail and Frechet distribution assumption. We have

$$1 - \Phi(x/\underline{\lambda}) \sim \underline{\lambda}^{1/\theta} k x^{-1/\theta}, \quad x \phi(x) \sim \frac{1}{\theta} k x^{-1/\theta}$$

469 and $\int_0^x \alpha(\sigma(s)) \phi(s) ds \rightarrow \int_0^\infty \alpha(\sigma(s)) \phi(s) ds$. Dividing both sides of $(**)$ by $k x^{-1/\theta}$ and letting

470 $x \rightarrow \infty$ yields

$$\gamma \cdot \frac{1}{\theta} = \underline{\lambda}^{1/\theta} \int_0^\infty \alpha(\sigma(s)) \phi(s) ds,$$

471 which implies

$$\gamma = \theta \underline{\lambda}^{1/\theta} \int_0^\infty \alpha(\sigma(s)) \phi(s) ds.$$

Appendix B Social Planner's Case

B.1 Marginal Social Value HJB Equation

This appendix provides a derivation of HJB equation for marginal social value. Recall that social planner's value function is

$$W[f(\cdot, t)] = \max_h \int_t^\infty e^{-\rho(\tau-t)} U(\tau) d\tau$$

where

$$U(t) = \int_0^\infty u(z, t) f(z, t) dz.$$

Applying dynamic programming principle, we can rewrite social planner's value function as

$$W[f(\cdot, t)] = \max_h \left\{ \int_t^{t+\Delta} e^{-\rho(\tau-t)} U(\tau) d\tau + e^{-\rho\Delta} W[f(\cdot, t + \Delta)] \right\}.$$

For small enough Δ close to zero, the changes in the productivity distribution and the optimal policy for WFH ratio contribute only higher-order terms to the integral. Hence, the instantaneous social utility accumulated over this short interval can be approximated by

$$\begin{aligned} \int_t^{t+\Delta} e^{-\rho(\tau-t)} U(\tau) d\tau &= \Delta U(t) + o(\Delta) \\ &\approx \Delta \int_0^\infty u(z, t) f(z, t) dz. \end{aligned}$$

For continuation value, taking Taylor approximation to discount factor gives us

$$\begin{aligned} e^{-\rho\Delta} &= 1 - \rho\Delta + o(\Delta). \\ &\approx 1 - \rho\Delta. \end{aligned}$$

Similarly, taking Taylor approximation to the social value function, we have:

$$\begin{aligned} W[f(\cdot, t + \Delta)] &= W[f(\cdot, t)] + \Delta \int_0^\infty \frac{\delta W[f(z, t)]}{\delta f(z, t)} \frac{\partial f(z, t)}{\partial t} dz + o(\Delta) \\ &\approx W[f(\cdot, t)] + \Delta \int_0^\infty w(z, t) \dot{f}(z, t) dz. \end{aligned}$$

483

Substituting these values into the original value function rearranging terms, we obtain:

$$\begin{aligned}
W[f(\cdot, t)] &= \max_h \left\{ \Delta U(t) + (1 - \rho\Delta) \left[W[f(\cdot, t)] + \Delta \int_0^\infty w(z, t) \dot{f}(z, t) dz \right] \right\} \\
&= W[f(\cdot, t)] + \Delta \max_h \left\{ U(t) - \rho W[f(\cdot, t)] + \int_0^\infty w(z, t) \dot{f}(z, t) dz \right\} + o(\Delta) \\
&\approx W[f(\cdot, t)] + \Delta \max_h \left\{ U(t) - \rho W[f(\cdot, t)] + \int_0^\infty w(z, t) \dot{f}(z, t) dz \right\}.
\end{aligned}$$

484

Subtracting $W[f(\cdot, t)]$ from both sides, dividing by Δ , and rearranging terms, we get:

$$\rho W[f(\cdot, t)] = \max_h \left\{ \int_0^\infty u(z, t) f(z, t) dz + \int_0^\infty w(z, t) \dot{f}(z, t) dz \right\}. \quad (31)$$

485

For the second term in the right hand side, note that $\dot{f}(z, t) = \frac{\partial f(z, t)}{\partial t}$, which is equation (1),

486

the law of motion of productivity density function. Plug equation (1) in to the term to get

$$\begin{aligned}
&\int_0^\infty w(z, t) \dot{f}(z, t) dz \\
&= \int_0^\infty w(z, t) \left(-\alpha(h(z, t)) f(z, t) \int_z^\infty f(y, t) dy + \int_0^z \alpha(h(y, t)) f(y, t) \left[\int_z^\infty f(z', t) \delta_D(z - T(y, z')) dz' \right] dy \right) dz \\
&= \underbrace{- \int_0^\infty \alpha(h(z, t)) w(z, t) f(z, t) \int_z^\infty f(y, t) dy dz}_{\text{outflow}} \\
&\quad + \underbrace{\int_0^\infty w(z, t) \int_0^z \alpha(h(y, t)) f(y, t) \left[\int_z^\infty f(z', t) \delta_D(z - T(y, z')) dz' \right] dy dz}_{\text{inflow}}.
\end{aligned}$$

487

Regarding the inflow term, changing the order of integration yields

$$\begin{aligned}
&\int_0^\infty w(z, t) \int_0^z \alpha(h(y, t)) f(y, t) \left[\int_z^\infty f(z', t) \delta_D(z - T(y, z')) dz' \right] dy dz \\
&= \int_0^\infty \int_y^\infty \alpha(h(y, t)) f(y, t) f(z', t) \left[\int_y^{z'} w(z, t) \delta_D(z - T(y, z')) dz \right] dz' dy \\
&= \int_0^\infty \int_y^\infty \alpha(h(y, t)) f(y, t) f(z', t) w(T(y, z'), t) dz' dy \quad \text{by sifting property of Dirac delta function.}
\end{aligned}$$

488

Changing the dummy variables in the outflow term by using z' and y and taking outflow

and inflow equations together, we obtain

$$\begin{aligned}
& \int_0^\infty w(z, t) \dot{f}(z, t) dz \\
&= - \int_0^\infty \int_y^\infty \alpha(h(y, t)) f(y, t) f(z', t) w(y, t) dz' dy \\
&+ \int_0^\infty \int_y^\infty \alpha(h(y, t)) f(y, t) f(z', t) w(T(y, z'), t) dz' dy \\
&= \int_0^\infty \int_y^\infty \alpha(h(y, t)) f(y, t) f(z', t) [w(T(y, z'), t) - w(y, t)] dz' dy
\end{aligned} \tag{32}$$

Taking all the pieces together and taking a functional derivative with respect to $f(z, t)$, equation (31) is rewritten as

$$\rho w(z, t) = \max_h \left\{ u(z, t) + \frac{\delta}{\delta f(z, t)} \int_0^\infty \int_y^\infty \alpha(h(y, t)) f(y, t) f(z', t) [w(T(y, z'), t) - w(y, t)] dz' dy \right\}.$$

Note that when we differentiate the planner's HJB equation, we apply the envelope theorem by holding the optimal WFH policy fixed. Although the optimal policy, and hence the meeting intensity, may depend indirectly on the productivity distribution, the effects operating through changes in the optimal policy vanish by the planner's first-order condition. Therefore, the meeting intensity $\alpha(h(y, t))$ is treated as fixed when taking the functional derivative. Therefore, the second term in the right hand side of the above equation becomes

$$\begin{aligned}
& \frac{\delta}{\delta f(z, t)} \int_0^\infty \int_y^\infty \alpha(h(y, t)) f(y, t) f(z', t) [w(T(y, z'), t) - w(y, t)] dz' dy \\
&= \int_0^\infty \alpha(h(y, t)) \frac{\delta f(y, t)}{\delta f(z, t)} \int_y^\infty f(z', t) \Delta w(y, z', t) dz' dy + \int_0^\infty \alpha(h(y, t)) f(y, t) \int_y^\infty \frac{\delta f(z', t)}{\delta f(z, t)} \Delta w(y, z', t) dz' dy \\
&+ \int_0^\infty \alpha(h(y, t)) f(y, t) \int_y^\infty f(z', t) \frac{\delta \Delta w(y, z', t)}{\delta f(z, t)} dz' dy
\end{aligned} \tag{33}$$

where $\Delta w(y, z', t) = w(T(y, z'), t) - w(y, t)$.

The first term in equation (33) can be rewritten as

$$\begin{aligned}
& \int_0^\infty \alpha(h(y, t)) \frac{\delta f(y, t)}{\delta f(z, t)} \int_y^\infty f(z', t) \Delta w(y, z', t) dz' dy \\
&= \int_0^\infty \alpha(h(y, t)) \delta_D(y - z) \int_y^\infty f(z', t) \Delta w(y, z', t) dz' dy \\
&= \alpha(h(z, t)) \int_z^\infty f(z', t) [w(T(z, z'), t) - w(z, t)] dz'.
\end{aligned}$$

500 The second term becomes

$$\begin{aligned}
& \int_0^\infty \alpha(h(y, t)) f(y, t) \int_y^\infty \frac{\delta f(z', t)}{\delta f(z, t)} \Delta w(y, z', t) dz' dy \\
&= \int_0^\infty \alpha(h(y, t)) f(y, t) \int_y^\infty \delta_D(z' - z) \Delta w(y, z', t) dz' dy \\
&= \int_0^\infty \alpha(h(y, t)) f(y, t) \mathbf{1}_{\{y < z\}} \Delta w(y, z, t) dy \\
&= \int_0^z \alpha(h(y, t)) f(y, t) [w(T(y, z), t) - w(y, t)] dy.
\end{aligned}$$

501 The third term becomes

$$\begin{aligned}
& \int_0^\infty \alpha(h(y, t)) f(y, t) \int_y^\infty f(z', t) \frac{\delta \Delta w(y, z', t)}{\delta f(z, t)} dz' dy \\
&= \int_0^\infty \alpha(h(y, t)) f(y, t) \int_y^\infty f(z', t) \left[\frac{\delta w(T(y, z'), t)}{\delta f(z, t)} - \frac{\delta w(y, t)}{\delta f(z, t)} \right] dz' dy \\
&= \int_0^\infty \frac{\delta w(q, t)}{\delta f(z, t)} \dot{f}(q, t) dq \quad \text{by the result of equation (32)} \\
&= \int_0^\infty \frac{\delta w(z, t)}{\delta f(q, t)} \dot{f}(q, t) dq \\
&= \frac{\partial w(z, t)}{\partial t}.
\end{aligned}$$

502 Taking pieces together, we get equation (15) in the main text.

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