The Great Re-Valuation: Preferences, Technology, and the Rise of Remote Work

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Write the final abstract based on the estimated results. Should cover: Motivation (post-pandemic shift), Question (Preferences vs. Technology), Method (Structural search model with heterogeneity), Estimation (SMM on 2019 vs. 2024), Key Finding (Preference shock dominates), and Contribution (Structural decomposition).

1 Introduction

he COVID-19 pandemic reshaped the landscape of work almost overnight, catapulting remote and hybrid work arrangements from niche to mainstream. By 2024, nearly 30% of U.S. workdays were performed remotely—over four times the pre-pandemic share (Barrero, Bloom, and Davis, 2023). This dramatic shift presents a puzzle: while remote work is clearly valued by workers, it has not led to a universal wage penalty, and the productivity implications remain ambiguous.

Our research question is straightforward: to what extent did the recent "great re-valuation" of remote work stem from shifts in worker preferences versus advances in technology? And how does the pattern of matching between workers and firms help explain the observed patterns in wages and work arrangements?

To answer these questions, we develop and estimate a general equilibrium search model with heterogeneity in worker skills, firm remote-work efficiency, and idiosyncratic worker tastes. A key innovation of our empirical approach is a novel, continuous measure of occupational teleworkability, which we construct using machine learning techniques. This index allows for a more nuanced identification of firm-level remote efficiency and sorting patterns than the binary measures used in prior work CITE. We estimate the model's parameters using the Simulated Method of Moments (SMM) on rich microdata from 2019 and 2024 to quantify the relative contributions of preference and technology shocks. Our estimates reveal that the primary driver of the shift to remote work has been

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Case 1: Preferences Dominate

a profound re-valuation of in-office time by workers. We estimate a $X\%$ increase in the parameter governing the disutility of commuting and in-office presence, an effect that is over N times larger than the concurrent $Y\%$ increase we estimate in the parameter for remote work technology. This indicates that the "great re-valuation" is fundamentally a story about evolving worker preferences, which reshaped the equilibrium sorting of workers to firms and the resulting wage and work arrangements.

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Case 2: Technology Dominates

a significant technological shock that enhanced the viability of remote work. We estimate a $X\%$ increase in the parameter governing the relative productivity of remote technology, an effect that is over N times larger than the modest $Y\%$ shift we estimate in the parameter for worker preferences. This suggests that the "great re-valuation" is fundamentally a story about technological adoption, which reshaped the equilibrium sorting of workers to firms and the resulting wage and work arrangements.

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2 Data and Stylized Facts of the Post-Pandemic Labor Market

2.1 Empirical Evidence: Three Puzzles Motivating a Structural Approach

- [cite_start]**Narrative Introduction (Revised):** *(Applying the "Punchline First" principle [cite: 55, 231])* Start by stating the section's main conclusion directly. For example: "This section presents three key empirical puzzles of the post-pandemic labor market. First, the adoption of flexible work is highly stratified by education and occupation. Second, wages exhibit a complex, concave relationship with an occupation's potential for remote work, even after conditioning on rich observable characteristics. Third, we document powerful sorting between highly educated workers and remote-friendly occupations. We argue that these facts, taken together, are difficult to reconcile with a simple framework and point toward a deeper sorting mechanism based on latent worker skill. This evidence forms the empirical foundation that our structural model is designed to explain. Our analysis primarily relies on data from the Current Population Survey (CPS)."

2.1.1 Data, Sample Construction, and Limitations

- [cite_start]**Goal:** Describe the data, sample selection, and transparently address any limitations to build credibility[cite: 209].
- **Content:**
  - **Data Source:** Describe the Current Population Survey (CPS), the supplements used (e.g., ASEC), and the sample years (e.g., 2019, 2022-2024).
  - [cite_start]**Justification and Limitations:** *(New subsection to boost credibility)* Briefly explain *why* the CPS is the appropriate dataset for this analysis (e.g., large sample size, detailed demographics). Then, be transparent about its limitations (e.g., "We acknowledge that the CPS questions on remote work are self-reported and may contain measurement error. Furthermore, our wage measure does not include non-wage benefits, which may be an important margin of adjustment.").
  - **Sample Selection:** Detail the filters applied to the raw data (e.g., full-time workers, age 25-64, non-military, etc.).
  - [cite_start]**Table 1: Summary Statistics of the Analysis Sample (2024):** *(Title revised to be more descriptive [cite: 247])*
    * **Content:** Present weighted means and standard deviations for key variables (age, education, log wage, shares by sex/race).
    * [cite_start]**Notes:** *(Ensure the table is self-contained [cite: 243][cite_start])* The notes should define all variables, state the data source (CPS ASEC), and specify the sample restrictions and application of survey weights, ensuring replicability[cite: 197].

2.1.2 Measuring Occupational Amenability to Remote Work (ψ)

- **Goal:** Introduce the key explanatory variable (ψ) and document its strong correlation with other key worker and job characteristics, highlighting the primary empirical challenge.
- **Narrative:** Explain that a quantitative measure of an occupation's intrinsic suitability for remote work is needed.
- **Construction of ψ:**
  - **Methodology:** Briefly explain the construction methodology (e.g., following Dingel and Neiman (2020)).
  - **Interpretation:** State clearly that ψ is a continuous [0, 1] index.
- **Figure 1: The Skewed Distribution of Remote-Work Potential:** *(Title revised for clarity)*
  - **Content:** A density plot of the ψ index across occupations, weighted by employment.
  - **Takeaway:** Emphasize the concentration, e.g., "The potential for remote work is a scarce occupational feature. Over half of all workers are in occupations with $\psi < 0.2$."
- **Table 2: Worker and Job Characteristics by ψ Quantile:**
  - **Content:** Show average education, wages, and industry composition for workers in Low-ψ, Mid-ψ, and High-ψ occupations.
  - [cite_start]**Takeaway and Narrative Framing:** Frame this table as demonstrating the core challenge of confounding variables[cite: 221]. State clearly: "This table reveals the central empirical challenge that motivates our structural approach. High-ψ occupations are not randomly assigned; they are disproportionately held by higher-educated workers in higher-paying industries. This demonstrates that simple OLS regressions of wages on remote work status would be severely biased by worker and firm selection."

2.1.3 The Three Puzzles

- **Goal:** Present the key empirical patterns as distinct puzzles that the model must explain. [cite_start]This turns the section into a compelling narrative[cite: 359].

- **Puzzle 1: The Stratification of Work Arrangements.**
  - **Figure 2: The Post-Pandemic Rise of Hybrid and Remote Work:** Time-series plot (2019-2024) of In-Person, Hybrid, and Full-Remote work shares.
  - **Figure 3: Remote and Hybrid Work are Dominated by the Highly Educated in High-ψ Jobs:** The two-panel bar chart.
  - **Narrative:** "The first puzzle is the sharp stratification of who performs flexible work. It is not a widespread phenomenon but one concentrated in a specific corner of the labor market."
- **Puzzle 2: The Concave Wage Profile.**
  - **Figure 4: The Non-Linear Relationship Between Wages and Occupational Flexibility:** Binned scatter plot of residual log wage against your ψ or α index.
  - **Table 3: OLS and Fixed-Effects Estimates of the Wage-ψ Profile:** The key regression table showing ψ (positive) and ψ^2 (negative) coefficients.
  - **Narrative:** "The second puzzle lies in the wage structure. After controlling for an extensive set of worker and job characteristics, we find a positive but concave relationship between wages and an occupation's remote-work potential. This suggests a premium that diminishes at higher levels, a pattern that simple theories of compensating differentials struggle to explain."
- **Puzzle 3: Powerful Sorting on Unobservables.**
  - **Figure 5: Strong Assortative Matching on Education:** Scatter plot showing the positive correlation between worker education and their occupation's average ψ.
  - **Table 4: Evidence of a Sorting Premium:** *(Revised framing)* Your key regression table.
  - **Narrative Framing:** Be precise about what this regression shows. "The final puzzle points to the importance of unobserved factors. The strong positive sorting between worker education and occupational ψ is striking. More importantly, even *within the subsample of workers in flexible jobs*, we find a significant wage premium associated with being in a high-ψ occupation after controlling for education (Table 4). This is not a causal estimate of a 'return to ψ,' but rather evidence consistent with a sorting mechanism where higher-skilled workers (both observably and unobservably) sort into high-ψ jobs.

This is the final piece of evidence our model must rationalize." [cite_start]This framing shows intellectual honesty and clearly defines the purpose of the regression[cite: 223].

2.1.4 Synthesizing the Puzzles and Motivating the Structural Model

- **Goal:** Summarize and make the case for your model.
- **Narrative:** Your original paragraph is excellent and already aligns perfectly with the guide's principles. It masterfully summarizes the puzzles and pivots to the solution. I would only suggest a slightly more active title for the subsection. > "The empirical evidence points to a complex new equilibrium. Remote work is concentrated among the highly educated in specific occupations and is associated with a positive, concave wage profile that persists after controlling for these observable characteristics. The strong assortative matching suggests the presence of a deeper, unobserved factor driving these patterns. To simultaneously rationalize the distribution of work arrangements, the complex wage structure, and the powerful sorting dynamics, we develop and estimate a structural search model. The model's central mechanism is the interaction between a latent, continuously distributed worker skill, h, and the observable occupational technology, ψ, which jointly determine productivity, wages, and the choice of workplace flexibility."

3 A Model of Labor Search with Heterogeneous Preferences for Workplace Flexibility

Statement of purpose...

We consider a labor market populated by a continuum of firms and infinitely lived, risk-neutral workers. This framework abstracts from life-cycle and precautionary savings motives to focus solely on the trade-offs inherent in job search and workplace arrangements. Heterogeneity is central to our analysis: workers differ in their skill level, $h \in \mathcal{H}$, which determines their baseline productivity, while firms differ in their remote work efficiency, $\psi \in \Psi$. This parameter primarily reflects occupation-level characteristics that determine a job's suitability for remote work, but it also encompasses firm-specific factors like technological infrastructure and organizational capacity.

The measure of unemployed workers of skill level h is denoted $u(h)$, creating an aggregate stock of job seekers $L = \int_{\mathcal{H}} u(h)dh$. Similarly, the measure of vacancies posted for type-ψ jobs is $v(\psi)$, which aggregates to a total of $V = \int v(\psi)d\psi$ job opportunities. This supply of vacancies is determined by a free-entry condition, where firms can create and post jobs a cost $\kappa(v)$, doing so until the expected value of filling a position equals the cost of posting. Looking for a job is a time consuming effort, something we characterized by assuming search and matching frictions. A standard constant-returns-to-scale matching function, $M(L, V)$, governs the meeting process between unemployed workers and vacancies. This process determines the key outcomes of the search process: the job-finding rate for workers, $p(\theta)$, and the vacancy-filling rate for firms, $q(\theta)$, both of which depend on the aggregate labor market tightness, $\theta = V/L$.

Worker preferences over wage and remote work bundles $\{(w, \alpha)\}_{\mathbb{R}_+ \times [0,1]}$ continuously differentiable and concave to ensure well-behaved optimization. We make two standard assumptions: utility is strictly increasing in wages ($u_w > 0$), as workers prefer more consumption, and it is also increasing in the remote work share ($u_\alpha > 0$), reflecting the direct value workers place on the flexibility and amenities associated with working from home.

A key assumption governs the trade-off between these two goods: we assume the Marginal Rate of Substitution remote work and wages: $MRS_{\alpha,w} = u_\alpha/u_w$, is *increasing* in α. In economic terms, this means that as a worker's remote share increases, they require progressively larger wage compensation to give up an additional unit of remote work. This non-standard assumption is designed to capture real-world phenomena that can lead to a preference for corner solutions (either fully in-person or fully remote). For example, it can reflect significant lifestyle adjustments that make a fully remote setup particularly valuable once established, or the presence of high fixed costs (e.g., commuting, separate childcare arrangements) associated with even a single day of in-office presence, which can make hybrid schedules less desirable.THERE IS DATA IN SWAA TO BACK THIS UP SHOULD HAVE A FOOTNOTE HERE.

The Production technology Y, depends on the remote work share α, the worker's skill h, and the firm/occupation's remote conduciveness ψ. The production function takes the form of a linear combination of output from in-person and remote work:

$$Y(\alpha \mid \psi, h) = A(h) \cdot ((1 - \alpha) + \alpha \cdot g(h, \psi)) \tag{1}$$

Here, $A(h) = A_0 + A_1 h$ is the baseline output of a worker with skill h in a fully in-person setting, with $A'(h) > 0$. Notice that the only source of heterogeneity on the firm side is the parameter ψ, which captures the firm's remote work efficiency, therefore for full-in person arrangements ($\alpha = 0$), the sole determinant of output is worker skill.

Remote work productivity is scaled by an efficiency adjustment factor, $g(h, \psi)$, which we specify with a flexible functional form:

$$g(h, \psi) = \psi_0 \cdot h^{\phi} \cdot \psi^{\nu} \tag{2}$$

n this specification, ψ_0 is a baseline technology parameter for remote productivity across the economy, while ϕ and ν are the output elasticities with respect to worker skill and firm remote work efficiency respectively. We assume $\psi > 0$ and $\nu > 0$. The assumption that remote productivity increases with worker skill ($\phi > 0$) is motivated by the idea that higher-skilled workers often engage in tasks requiring greater autonomy and self-direction—traits that are highly complementary to the remote work environment. Furthermore, their work may be less reliant on physical co-location for supervision and execution compared to more routine tasks.

Crucially, this functional form implies a positive cross-partial derivative ($g_{h\psi} > 0$), meaning there is a **complementarity** between worker skill and firm remote efficiency. This complementarity is the central force that will drive assortative matching in the model, creating a tendency for high-skill workers to sort into firms that are most efficient at remote work.

3.1 Deterministic Choice of Flexibility: A Benchmark

To build intuition for the core trade-offs governing workplace flexibility, we first analyze a simplified benchmark model where the choice of work arrangement is **fully deterministic**. This approach allows us to isolate the fundamental economic forces driven by technology and preferences before we introduce additional sources of heterogeneity.

For any given work arrangement, α, the total flow surplus of a match is the sum of the firm's profit and the worker's utility. The firm's per-period profit is its output net of the wage paid, $\Pi(h, \psi \mid w, \alpha) = Y(h, \psi \mid \alpha) - w$. The worker's utility, given our quasi-linear specification, is their wage net of the non-pecuniary cost of in-office work, $u(w, \alpha) = w - c(1 - \alpha)$. The joint surplus, $J(\alpha)$, is therefore:

$$\pi(h, \psi \mid \alpha) = \Pi(h, \psi \mid w, \alpha) + u(w, \alpha) = \Big(Y(h, \psi \mid \alpha) - w\Big) + \Big(w - c(1 - \alpha)\Big) \tag{3}$$

As the wage, w, is a pure intra-match transfer, it cancels out. This leaves the joint surplus dependent only on the match's total output and the worker's non-pecuniary cost.

We assume the wage is determined by generalized Nash bargaining between the firm and the worker. This bargaining framework implies that the match operates under an **efficient contract**, which separates the problem into two parts: an efficiency decision and a distributional decision. First, the remote work share, α is chosen jointly to maximize the total surplus generated by the match. Second, this maximized surplus is divided between the worker and the firm according to their exogenous bargaining power ξ. With our choice of quasi-linear utility, the wage acts as the endogenous transfer that facilitates this division. This efficient contracting structure allows us to solve for the optimal work arrangement by first focusing on the joint surplus maximization given by equation Equation 3:

$$\pi = \max_{\alpha \in [0,1]} \quad \Big\{ Y(\alpha \mid \psi, h) - c(\alpha) \Big\} \tag{4}$$

The solution to problem Equation 4 reveals that the optimal work arrangement, $\alpha^*(\psi, h)$, partitions the market into three distinct regimes based on the firm's remote efficiency ψ, , relative to two skill-dependent thresholds, $\underline{\psi}(h)$ and $\overline{\psi}(h)$:

$$\alpha^*(\psi, h) = \begin{cases} 0 & \text{if } \psi \leq \underline{\psi}(h) \quad \text{(Full In-Person)} \\ 1 - \left[\frac{A_1 h (1 - g(\psi, h))}{c_0} \right]^{\frac{1}{\chi}} & \text{if } \underline{\psi}(h) < \psi < \overline{\psi}(h) \quad \text{(Hybrid)} \\ 1 & \text{if } \psi \geq \overline{\psi}(h) \quad \text{(Full Remote)} \end{cases} \tag{5}$$

These thresholds represent economic tipping points where the trade-off between **production efficiency and worker amenities** dictates the optimal work arrangement. The worker always values the non-pecuniary benefits of remote work, while the firm is focused on the impact on output, which may be positive or negative.

- For firms with low remote efficiency ($\psi \leq \underline{\psi}\ (h)$), the **productivity loss** from remote work is too severe. Although the worker desires the remote work amenity, the firm cannot afford to grant this preference because the marginal drop in output is greater than the worker's marginal valuation for it. Thus, the match defaults to a fully in-person arrangement.
- Conversely, for firms with very high efficiency ($\psi \geq \overline{\psi}(h)$), remote work may be so productive that it generates a **"productivity premium."** In this scenario, maximizing output and

satisfying the worker's desire for remote work are aligned, making a fully remote arrangement the optimal choice for the match.

- **Hybrid work** emerges for the intermediate firms where a clear trade-off exists. These firms are willing to "sell" the remote work amenity to the worker, accepting a modest productivity loss (or smaller gain) up to the point where the marginal cost in terms of output exactly equals the worker's marginal non-pecuniary benefit.

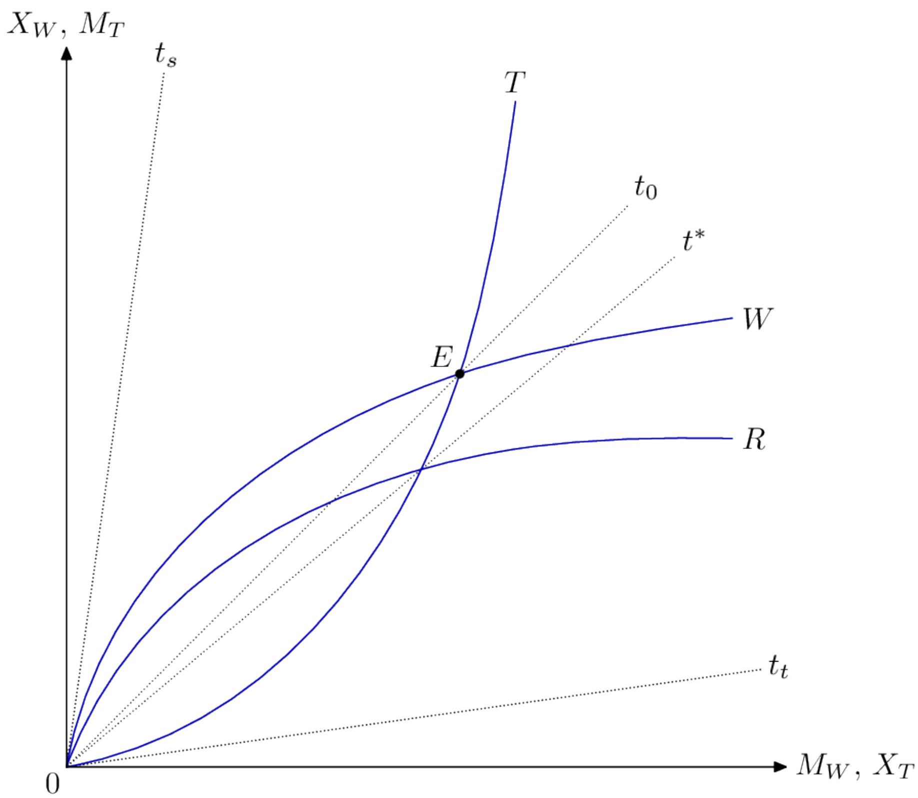

Figure 1: Optimal Work Arrangements in the Deterministic Benchmark. The figure illustrates how the optimal remote work share, α^*, depends on worker skill (h) and firm remote efficiency (ψ). The market is partitioned into three regimes by two skill-dependent thresholds, $\underline{\psi}(h)$ and $\overline{\psi}(h)$. Matches falling below the lower threshold are fully in-person, matches above the upper threshold are fully remote, and matches between the thresholds adopt a hybrid arrangement.

This deterministic model provides sharp predictions: for any given worker, only firms within a specific range of remote efficiency will offer a hybrid arrangement. However, this stark segmentation is at odds with the smooth distribution of work arrangements observed in the data. This motivates the introduction of idiosyncratic preferences, which allows for a richer and more realistic pattern of matching.

3.2 The Full Model with Idiosyncratic Preferences

The deterministic benchmark provides sharp predictions but cannot account for the smooth distribution of work arrangements observed in the data. To capture this rich heterogeneity, we extend the model by introducing idiosyncratic worker preferences. We posit that a worker only discovers their true preference for a specific work arrangement after a match is formed. Factors such as the actual commute, the specific in-office culture, or the suitability of their home environment for work are not fully known ex-ante. This uncertainty is captured by an idiosyncratic taste shock.

For a given contract (w, α), a worker's realized utility is the sum of their deterministic utility and this stochastic taste shock:

$$u(w, \alpha; \varepsilon) = w - c(1-\alpha) + \mu \cdot \varepsilon(\alpha) \tag{6}$$

Here, $\varepsilon(\alpha)$ is the realization of the taste shock for a remote share α, and μ is a scale parameter governing its importance. Analogous to the deterministic model, the total **realized joint surplus** for a given arrangement and taste shock, is the sum of the firm's profit and the worker's realized utility. The wage remains a pure transfer and cancels out, leaving the surplus dependent only on the physical aspects of the match and the worker's non-pecuniary utility. Following the discrete choice literature, we assume $\varepsilon(\alpha)$ follows a Type I Extreme Value (Gumbel) process.

Before the idiosyncratic taste shocks are realized, the firm and worker jointly maximize the expected value of their match. This value, known as the "inclusive value," accounts for the option to choose the best possible work arrangement once the shocks are revealed. The ex-ante joint maximization problem is:

$$\pi(h, \psi) = \max_{\alpha \in [0,1]} \mathbb{E}_{\varepsilon} \left[\underbrace{Y(\alpha \mid \psi, h) - c(\alpha)}_{V(h,\psi|\alpha)} + \mu \cdot \varepsilon(\alpha) \right] \tag{7}$$

Where $V(h, \psi; \alpha)$ denote the deterministic component of the joint value of the match. A well-known result from the discrete choice literature is that when the shocks $\varepsilon(\alpha)$ are drawn from a Type I Extreme Value (Gumbel) distribution, this maximization problem has a convenient closed-form solution. The maximized expected surplus of the match is given by the log-sum integral:

$$\pi(h, \psi) = \mu \ln \left(\int_0^1 \exp\left(\frac{V(h, \psi; \alpha)}{\mu} \right) d\alpha \right) \tag{8}$$

This inclusive value is the fundamental object that enters the equilibrium Bellman equations that we define next. We define the flow surplus of the match, $s(h, \psi)$, as this value net of the worker's outside option, their flow unemployment benefit $b(h)$:

$$s(h, \psi) = \left[\mu \ln \left(\int_0^1 \exp\left(\frac{V(h, \psi; \alpha)}{\mu} \right) d\alpha \right) \right] - b(h) \tag{9}$$

This expected flow surplus, $s(h, \psi)$, is the fundamental object that determines the value of a match in the full equilibrium.

A direct consequence of this framework is that the choice of α becomes probabilistic. The probability that a specific arrangement α is chosen for a match (h, ψ) follows the continuous logit formula:

$$p(\alpha \mid h, \psi) = \frac{\exp\left(V(h, \psi; \alpha)\mu^{-1}\right)}{\int_0^1 \exp\left(V(h, \psi; a)\mu^{-1}\right) da} \tag{10}$$

This structure provides the link between the two versions of the model: the hard thresholds of the deterministic benchmark now become the central inflection points of the smooth choice probabilities in the full model. The scale parameter, μ, governs how "blurry" or "soft" these thresholds are.

3.3 Equilibrium

A steady-state equilibrium is characterized by a set of value functions for workers and firms, optimal vacancy posting by firms, and worker flows that are balanced. These components are mutually consistent and determine the aggregate state of the labor market. ### Value Functions and Surplus

The equilibrium is defined by the lifetime values for workers and firms in different states. We begin by defining the value of an ongoing match and the value of unemployment, and from these, we derive the Bellman equation for the match surplus, $S(h, \psi)$, which will be shown to be the central object that characterizes the equilibrium.

The joint value of a match, $J(h, \psi)$, is the present discounted value of all future returns. It is composed of the current period's expected flow surplus, $s(h, \psi) + b(h)$, plus the discounted continuation value. With probability $(1 - \delta)$, the match survives and retains its value, and with probability δ, it is destroyed and the worker's value reverts to that of unemployment, $U(h)$[1]. This gives the Bellman equation:

$$J(h, \psi) = (\pi(h, \psi) - b(h)) + \beta \left[(1 - \delta)J(h, \psi) + \delta U(h)\right] \tag{11}$$

The value of unemployment for a worker of type h, $U(h)$, consists of the current flow benefit, $b(h)$, plus the expected value from job search. With probability $p(\theta)$, the worker contacts a firm, and with probability $(1 - p(\theta))$, they remain unemployed. The value of a new match to a worker, $W(h, \psi')$, is determined by our **Nash bargaining** assumption, which dictates that the worker receives their outside option, $U(h)$, plus a share ξ of the total match surplus, $S(h, \psi')$. A match is only formed if the surplus is positive. This gives the Bellman equation for unemployment:

$$U(h) = b(h) + \beta \left[p(\theta)\mathbb{E}_{\psi'} \left[\max\{W(h, \psi'), U(h)\}\right] + (1 - p(\theta))U(h)\right] \tag{12}$$

Substituting $W(h, \psi') = U(h) + \xi S(h, \psi')$ and simplifying yields:

$$U(h) = b(h) + \beta U(h) + \beta p(\theta)\xi \int \max\{0, S(h, \psi')\}d\Gamma_v(\psi') \tag{13}$$

The total match surplus is the net value created by the match, defined as $S(h, \psi) \equiv J(h, \psi) - U(h)$. We can derive its Bellman equation by subtracting the equation for $U(h)$ from the one for $J(h, \psi)$, which after rearranging highlights that the worker's expected gain from search acts as an effective opportunity cost for the match:

$$S(h, \psi) = s(h, \psi) + \beta(1 - \delta)S(h, \psi) - \beta p(\theta)\xi \int \max\{0, S(h, \psi')\}d\Gamma_v(\psi') \tag{14}$$

Solving for $S(h, \psi)$ gives the final expression:

$$S(h, \psi) = \frac{s(h, \psi) - \beta p(\theta)\xi \int \max\{0, S(h, \psi')\}d\Gamma_v(\psi')}{1 - \beta(1 - \delta)} \tag{15}$$

This derivation highlights a key insight: the surplus equation is the only object needed to solve for the equilibrium. Because the term $\max\{0, S(h, \psi')\}$ appears inside the integral, the sign of the surplus itself determines the set of viable matches that will form. A negative surplus means the parties are better off separated, and no match is created. Therefore, $S(h, \psi)$ is a sufficient statistic that fully encodes the equilibrium matching decisions.

[1]We assume that free entry make the value for a firm of a dicontinued match equal to zero

3.3.1 Vacancy Creation and Market Tightness

The number of vacancies is determined by firms' profit maximization. Firms post vacancies for a type-ψ job until the marginal cost of posting, κ'(v), equals the expected marginal benefit. The benefit of posting depends on the probability of filling the vacancy, $q(\theta)$, and the firm's expected share of the surplus, $(1-\xi)S(h,\psi)$, averaged over the distribution of workers it might meet. This gives the vacancy creation condition:

$$c'(v(\psi)) = q(\theta)(1-\xi)\int_h \max\{0, S(h,\psi)\}\frac{u(h)}{L}dh \tag{16}$$

This set of decisions, aggregated across all firm types, endogenously determines the total stock of vacancies V and thus the equilibrium market tightness θ.

3.3.2 Steady-State Flows

In a steady-state equilibrium, the flows of workers between employment and unemployment are balanced. The total number of workers who lose their jobs *(job destruction)* must equal the total number of unemployed workers who find new, acceptable jobs *(job creation)*. This condition, $\delta \cdot N_{\text{emp}} = p(\theta) \cdot N_{\text{unemp}} \cdot \mathbb{P}(\text{Accept})$, where N denotes the mass of workers, closes the model by determining the equilibrium distributions of employed and unemployed workers for each skill type, $n(h,\psi)$ and $u(h)$.

3.4 Wage Determination

With the expected surplus of the match, $s(h,\psi)$, determined, the wage serves as the transfer that divides the realized proceeds. It is best understood not as a single number but as a **contingent contract** agreed upon at the start of the match. In each period, after the worker's idiosyncratic taste shock $\varepsilon(\alpha)$ is realized, the specific remote work share α^* is chosen to maximize the realized joint surplus. The wage, $w(\alpha^*)$, is then paid according to the pre-agreed contract to ensure the division of surplus aligns with the parties' bargaining powers.

To derive the wage, we start with the Bellman equation for the worker's value in an ongoing match, $W(h,\psi)$. This value is the sum of the current period's flow utility and the discounted continuation value, accounting for the probabilities of the match surviving $(1-\delta)$ or being destroyed (δ):

$$W(h, \psi) = (w - c(1 - \alpha^*)) + \beta(1 - \delta)W(h, \psi) + \beta\delta U(h) \tag{17}$$

Rearranging this asset-pricing equation, we can solve for the flow utility that the wage must generate in each period to support the lifetime value $W(h, \psi)$:

$$w - c(1 - \alpha^*) = (1 - \beta(1 - \delta))W(h, \psi) - \beta\delta U(h) \tag{18}$$

From our Nash bargaining assumption, we know the worker's equilibrium lifetime value is their outside option plus their bargained share of the total match surplus: $W(h, \psi) = U(h) + \xi S(h, \psi)$. To find the equilibrium wage, $w^*(h, \psi)$, we substitute this bargained value into the expression for the required flow utility. The quasi-linearity of preferences allows us to then simply solve for the optimal wage. This final expression clearly separates the wage into two economically distinct components:

$$w^*(h, \psi) = \underbrace{((1 - \beta(1 - \delta))\,[U(h) + \xi S(h, \psi)] - \beta\delta U(h))}_{\text{Base Wage}} + \underbrace{c_0 \frac{(1 - \alpha^*(h, \psi))^{1+\chi}}{1 + \chi}}_{\text{Compensating Differential}} \tag{19}$$

1. **Base Wage**: The monetary payment required to deliver the worker their bargained share of the match surplus, net of continuation values.
2. **Compensating Differential**: An additional, separate payment that exactly reimburses the worker for the non-pecuniary disutility associated with the fraction of time, $(1-\alpha^*)$, they are required to spend in the office. This term is zero for a fully remote worker.

4 Estimation Strategy

4.0.1 Calibration of Unemployment Value $b(h)$: A Summary

This section outlines the calibration strategy for the flow value of unemployment, $b(h)$. We depart from a simple constant replacement rate of wages and instead adopt a more theoretically consistent approach that accounts for the non-pecuniary amenities central to our model.

- **Economic Rationale:** In a model where a job's value includes both a wage and a significant amenity component (from the choice of remote work), the worker's outside option should reflect the total utility of employment, not just the wage. A worker's decision to accept a job is based on the total surplus $S(h, \psi)$, which encapsulates both pecuniary and non-pecuniary gains. Therefore, the value of non-market time (leisure, home production) should be benchmarked against this total expected gain from employment.

- **Functional Form ("Surplus Replacement Rate"):** We model the flow value of unemployment for a worker of skill h as a fraction of the expected utility gain they would receive from finding a job. This gain is their share (ξ) of the expected total match surplus ($E[S|h]$).

$$b(h) = b \cdot \xi \cdot \mathbb{E}_{\psi}[S(h, \psi)]$$

- **Parameter Interpretation:** The single parameter to be calibrated, b, now has a sharp economic interpretation: it is the **value of non-market time as a fraction of the value of market time.** It represents how valuable leisure and home production are relative to the surplus generated in a formal job.
- **Endogenous Calculation:** $b(h)$ is not a fixed primitive. It is an **endogenous object** calculated within the model's equilibrium. In each iteration of the solver, the model uses the current state of the economy (the surplus matrix S and the vacancy distribution Γ) to compute the expected surplus for each worker type, $E[S|h]$, and then updates the $b(h)$ vector accordingly. This creates a realistic general equilibrium feedback loop.
- **Calibration Strategy for b:** The parameter b is not directly observable. We will calibrate it externally based on standard values from the search and home production literature.
  - **Target Value:** A standard value for the ratio of the value of non-market time to market time is approximately **0.5**. This is a common benchmark in quantitative macroeconomics.
  - **Justification:** This value is consistent with a wide range of microeconomic estimates and is a standard choice in models that require a calibration for the value of leisure (e.g., Hall and Milgrom, 2008). We will set $b = 0.5$ in our baseline calibration.

4.0.2 Why the Aggregate Approximation is Sufficient for Calibrating

Given that is part of your "Group 1: Externally Calibrated Parameters," the aggregate approximation method is a great choice for the following reasons:

1. **It's Disciplined by Data:** You are not just picking a number like `0.5` out of thin air. Your procedure uses high-quality, aggregate data from JOLTS and published research on labor flows. This makes your choice of transparent and grounded in empirical evidence.

2. **It Captures the Right Magnitude:** While the approximation might miss some of the subtle cyclical or cross-sectional variation, it will get you into the correct **economic ballpark**. The literature consistently finds that the matching elasticity is somewhere between 0.3 and 0.7. Your method will almost certainly produce a value in this range, which is the primary goal of a calibration.

3. **It's a Common Practice:** Using this type of informed approximation for calibrated parameters is a standard and well-accepted practice in quantitative macroeconomics. You are on solid methodological ground.

4. **The Burden of Proof is Lower:** Since you are not claiming to have a new, superior estimate of the matching elasticity (it's not the main contribution of your paper), you don't need to use the absolute state-of-the-art, microdata-intensive method. You just need to demonstrate that you have chosen a reasonable value based on a transparent procedure.

4.0.3 How to Justify This in Your Paper

This is the most important part. You need to be clear and upfront about your methodology in the calibration section of your paper.

Here is a template for how you would write this up:

Parameter (Matching Elasticity): The elasticity of the matching function, , is a crucial parameter governing the efficiency of the search process. While a wide range of estimates exist in the literature, we calibrate this parameter using a procedure that reflects the aggregate dynamics of the U.S. labor market. We construct a state-level panel of monthly hires, vacancies, and unemployment from 2001 to 2024. State-level vacancy and unemployment data are taken directly from the JOLTS and LAUS programs, respectively. As state-level U-to-E flows are not directly published, we approximate them by multiplying the total state-level hires from JOLTS (`H_it`) by the national, time-varying share of hires that come from unemployment, which we calculate from the aggregate CPS labor force flow data. This approach, while abstracting from state-level heterogeneity in flow shares, allows us to capture the crucial business-cycle variation in hiring sources. We then estimate the standard panel fixed-effects model of Hall and Schulhofer-Wohl (2018):

$$\ln(f_{it}) = \delta_i + \delta_t + (1 - \gamma_1)\ln(\theta_{it}) + \varepsilon_{it}$$

This procedure yields an estimate of ˆ **`= [Your Value]`**, which we use in our baseline calibration. This value is consistent with recent estimates in the literature.

Why this justification is strong: * It is **transparent** about the approximation being made. * It **justifies** the approximation by highlighting that it still captures the important time-series variation. * It **cites** the state-of-the-art methodology (HSW) that it is based on. * It **benchmarks** the final result against the broader literature.

Conclusion:

Yes, for the purpose of **calibration**, your proposed aggregate method is not just sufficient; it is a good, pragmatic, and defensible choice. It provides a data-driven value for without requiring the massive overhead of a full microdata-based estimation for what is ultimately a background parameter in your study. You can proceed with this plan with confidence.

- ☐ **4.1. Overview:** Describe the SMM approach and the two-stage estimation strategy.
- ☐ **4.2. Identification:**
  - ☐ Insert the main identification table linking parameters to moments.
  - ☐ Write a paragraph for each parameter (or group of parameters) justifying the choice of moment, referencing the detailed analysis in Appendix B.

5 Results

- ☐ **5.1. Parameter Estimates:**
  - ☐ Insert the main table of estimated parameters for 2019 and 2024.
  - ☐ Discuss the statistical significance of the changes.

- ☐ **5.2. The Anatomy of the "Great Re-Valuation":**
  - ☐ Interpret the large change in c_0 in monetary terms.
  - ☐ Contrast this with the smaller changes in technology parameters (ν, ψ_0).
  - ☐ Discuss the implications of the changes in ξ and ϕ.
- ☐ **5.3. Model Fit:**
  - ☐ Insert the table comparing data moments to simulated moments.
  - ☐ Discuss how well the model replicates the stylized facts from Section 2.
- ☐ **In the subsection where you present your new visualizations:**
  - ☐ **TODO:** When presenting the **"S-Curve" plot of** $E[\alpha]$, write: "As shown in Figure X, the model generates a smooth S-shaped relationship between firm efficiency and the expected remote share. The 'liftoff' and 'saturation' points of these curves correspond closely to the analytical thresholds derived in our deterministic benchmark (Section 3.2), illustrating how preference heterogeneity smooths the sharp predictions of the simpler model."
  - ☐ **TODO:** When presenting the **"Heatmap of Var**(α)**"**, write: "Figure Y visualizes the heterogeneity of choice across the equilibrium. The bright diagonal ridge, indicating high variance in work arrangements, is centered precisely in the 'hybrid' region defined by the deterministic thresholds, $\underline{\psi}(h)$ and $\overline{\psi}(h)$."

6 Counterfactuals

- ☐ **Introduction:** Briefly state the purpose of this section: to use the estimated structural model to perform experiments that are impossible with reduced-form methods, allowing us to decompose the key economic forces at play.
- ☐ **6.1. Counterfactual 1: Decomposing the Drivers of the New Equilibrium**
  - ☐ **State the Question:** What were the relative contributions of the preference shock versus the technology shock in shaping the 2024 labor market?
  - ☐ **Experiment A (Preference Shock Only):**

- ☐ **Method:** Re-solve the model using the estimated **2024 preference parameters** (c_0, μ, χ) but holding all other parameters (especially technology: ψ_0, ν, ϕ) at their estimated **2019 levels**.
- ☐ **Report Key Outcomes:** Report the model-predicted shares of in-person/hybrid/remote work, average α, and aggregate productivity.

☐ **Experiment B (Technology Shock Only):**

- ☐ **Method:** Re-solve the model using the estimated **2024 technology parameters** (ψ_0, ν, ϕ) but holding all other parameters (especially preferences: c_0, μ, χ) at their estimated **2019 levels**.
- ☐ **Report Key Outcomes:** Report the same set of outcomes as in Experiment A.

☐ **Present the Results:**

- ☐ **Create a summary table or bar chart.** The columns should be: "Actual 2019", "Actual 2024", "CF A: Pref. Shock Only", "CF B: Tech. Shock Only". The rows should be the key outcomes.
- ☐ **Write the narrative:** Explain what the results show. (e.g., "As shown in Figure X, the preference shock alone can explain approximately 85% of the observed shift in the share of remote work, while the technology shock accounts for only 15%…").

☐ 6.2. Counterfactual 2: Quantifying the Importance of Sorting

☐ **State the Question:** How important is the assortative matching of high-skill workers to high-efficiency firms in generating the observed outcomes?

☐ **Method:** Take the fully estimated **2024 model** and re-solve it after "turning off" the skill-remote complementarity by setting the sorting parameter $\phi = 0$.

☐ **Report Key Outcomes:**

- ☐ How much does the average remote share (`mean_alpha`) fall?
- ☐ What happens to the WFH wage premium? (Calculate the conditional wage difference in the simulation).
- ☐ Does overall wage inequality (`var_logwage`) change?

☐ **Write the narrative:** Explain the results. (e.g., "We find that eliminating the sorting channel reduces the share of remote work by X percentage points and completely flattens the WFH wage premium, highlighting that sorting is a crucial mechanism…").

A Appendix

A.0.1 Model Derivations

- ☐ **A.1. The Deterministic Benchmark Model ($\mu \to 0$)**
  - ☐ State the joint surplus maximization problem.
  - ☐ Derive the First-Order Condition for the interior α^*.
  - ☐ Derive the analytical threshold functions $\underline{\psi}(h)$ and $\overline{\psi}(h)$.
  - ☐ Prove the properties of the optimal remote policy (monotonicity of thresholds with respect to h).
- ☐ **A.2. The Full Model with Gumbel Shocks**
  - ☐ State the choice problem with the Gumbel shock.
  - ☐ Derive the expression for the expected flow surplus, $E[s(h, \psi)]$, showing the log-sum-exp (integral) form.
- ☐ **A.3. Equilibrium Objects**
  - ☐ Derive the worker's Value of Unemployment $U(h)$.
  - ☐ Derive the recursive expression for the Match Surplus $S(h, \psi)$.
  - ☐ Derive the full Equilibrium Wage equation $w(h, \psi)$.
  - ☐ Derive the Free Entry Condition and the expression for Market Tightness θ.
- ☐ **A.X. Proof of Convergence to the Deterministic Limit**
  - ☐ **TODO:** Write out the formal mathematical proof we discussed.
  - ☐ **TODO:** Start with the log-sum-exp formula for the expected surplus.
  - ☐ **TODO:** Use the logic of Laplace's Method to show that as $\mu \to 0$, the expected surplus converges to the maximized surplus of the deterministic model.
  - ☐ **TODO:** Show that the probability density $P(\alpha)$ converges to a Dirac delta function at the deterministic α^*, and therefore $E[\alpha]$ converges to α^*.

Of course. This is the perfect way to ensure your paper is transparent and reproducible. A detailed appendix that formally defines the model's moments is a sign of high-quality research.

Here is a comprehensive summary of the moment computations, written in Markdown and suitable for direct inclusion in your paper's technical appendix. It incorporates the final, most sophisticated logic we developed, using probabilistic weighting instead of hard masks.

A.0.2 Appendix C: Computation of Model-Generated Moments

This appendix provides the formal mathematical definitions for the model-generated moments used in the Simulated Method of Moments (SMM) estimation. These are the theoretical counterparts to the empirical moments described in the main text.

Given the model's structure with a continuous choice of remote work share, , subject to an idiosyncratic Gumbel taste shock, the model's moments are computed as expectations. These expectations are taken over both the steady-state equilibrium distribution of employed workers, `n(h, )`, and the conditional probability distribution of work arrangements, `p( | h, )`.

A.0.2.1 Core Objects

The calculation of all moments relies on three fundamental objects from the solved model:

1. **The Employment Distribution, `n(h, )`:** The steady-state mass of employed workers in a match of type `(h, )`. The total mass of employed workers is `L_e =  n(h, ) dh d`.

2. **The Deterministic Value Function, `V(h, ; )`:** The value of a match for a given choice of , before the idiosyncratic taste shock is realized.

$$V(h, \psi; \alpha) = Y(h, \psi; \alpha) - c(1 - \alpha)$$

   where `Y` is the output function and `c` is the baseline in-office disutility function.

3. **The Conditional PDF of , `p( | h, )`:** The probability density function for the choice of in a given `(h, )` match, derived from the continuous logit framework:

$$p(\alpha \mid h, \psi) = \frac{\exp(V(h, \psi; \alpha)/\mu)}{\int_0^1 \exp(V(h, \psi; \alpha')/\mu) d\alpha'}$$

   where is the scale of the Gumbel taste shocks.

A.0.2.2 1. Unconditional Moments

These moments are calculated over the entire population of valid employed workers.

- **Mean of Log Wages:** The expectation of the conditional expected log wage, taken over the employment distribution.

$$\mathbb{E}[\log(w)] = \frac{1}{L_e} \iint \mathbb{E}[\log(w) \mid h, \psi] \cdot n(h, \psi) \, dh \, d\psi$$

  where the conditional expectation is:

$$\mathbb{E}[\log(w) \mid h, \psi] = \int_0^1 \log(w(h, \psi; \alpha)) \cdot p(\alpha \mid h, \psi) \, d\alpha$$

- **Variance of Log Wages:** Calculated using the law of total variance or directly as $\mathbb{E}[(\log w)^2] - (\mathbb{E}[\log w])^2$. The expectation of the squared term is:

$$\mathbb{E}[(\log w)^2] = \frac{1}{L_e} \iint \left(\int_0^1 (\log(w(h, \psi; \alpha)))^2 \cdot p(\alpha \mid h, \psi) \, d\alpha \right) \cdot n(h, \psi) \, dh \, d\psi$$

- **Mean and Variance of Alpha:** Calculated using the same logic as the wage moments, substituting   for `log(w)`.

$$\mathbb{E}[\alpha] = \frac{1}{L_e} \iint \left(\int_0^1 \alpha \cdot p(\alpha \mid h, \psi) \, d\alpha \right) \cdot n(h, \psi) \, dh \, d\psi$$

$$\mathrm{Var}(\alpha) = \mathbb{E}[\alpha^2] - (\mathbb{E}[\alpha])^2$$

A.0.2.3 2. Work Arrangement Shares

The shares are the expectation of the conditional probability of falling into a specific work arrangement category. The categories are defined by a tolerance, `_tol` (e.g., 0.1).

- **In-Person Share:**

$$\text{Share}_{\text{In-Person}} = \frac{1}{L_e} \iint \mathbb{P}(\text{In-Person} \mid h, \psi) \cdot n(h, \psi) \, dh \, d\psi$$

where the conditional probability is the integral of the PDF over the in-person range:

$$\mathbb{P}(\text{In-Person} \mid h, \psi) = \int_0^{\alpha_{tol}} p(\alpha \mid h, \psi)\, d\alpha$$

- **Remote Share:** Calculated analogously over the remote range.

$$\mathbb{P}(\text{Remote} \mid h, \psi) = \int_{1-\alpha_{tol}}^{1} p(\alpha \mid h, \psi)\, d\alpha$$

- **Hybrid Share:** Calculated as the residual: `1 - Share_In-Person - Share_Remote`.

A.0.2.4 3. Conditional Moments

These moments are calculated over specific subsamples of the employed population.

- **Difference in Average Remote Share (`diff_alpha_high_lowpsi`):** This is the difference between the conditional expectation of for high- and low- firms. The expectation for a group `Q` (e.g., in the top quartile) is:

$$\mathbb{E}[\alpha \mid \psi \in Q] = \frac{\iint_{\psi \in Q} \mathbb{E}[\alpha \mid h, \psi] \cdot n(h, \psi)\, dh\, d\psi}{\iint_{\psi \in Q} n(h, \psi)\, dh\, d\psi}$$

- **Compensating Wage Differential (`diff_logwage_inperson_remote`):** This is the difference between the conditional expectation of log wages for in-person and remote workers. The expectation for a group `J` (e.g., In-Person) is:

$$\mathbb{E}[\log(w) \mid J] = \frac{\mathbb{E}[\log(w) \cdot \mathbf{I}(J)]}{\mathbb{P}(J)}$$

  where the denominator is the share of workers in group `J`, and the numerator is the total expectation of the partial expectation:

$$\mathbb{E}[\log(w) \cdot \mathbf{I}(J)] = \frac{1}{L_e} \iint \left(\int_{\alpha \in J} \log(w(\alpha)) \cdot p(\alpha \mid h, \psi)\, d\alpha \right) \cdot n(h, \psi)\, dh\, d\psi$$

- **Wage Premium & Slope (`wage_premium_high_psi`, `wage_slope_psi`):** These are calculated using the same conditional expectation logic as the compensating differential, but the conditioning set is `J = {(\alpha, \psi) | \alpha >  _tol, \psi   Q}`. For example:

$$\mathbb{E}[\log(w) \mid \text{RH}, \psi \in Q_{\text{High}}] = \frac{\mathbb{E}[\log(w) \cdot \mathbf{I}(\text{RH}) \cdot \mathbf{I}(\psi \in Q_{\text{High}})]}{\mathbb{P}(\text{RH}, \psi \in Q_{\text{High}})}$$

A.0.2.5 4. Aggregate and Search Moments

These moments are direct outputs of the solved model's equilibrium.

- **Aggregate Productivity (`agg_productivity`):** The employment-weighted average of expected output per match.

$$\text{Agg. Prod.} = \frac{1}{L_e} \iint \mathbb{E}[Y(h, \psi; \alpha) \mid h, \psi] \cdot n(h, \psi) \, dh \, d\psi$$

- **Market Tightness (`market_tightness`):** The equilibrium vacancy-to-unemployment ratio, , from the solved model.
- **Job Finding Rate (`job_finding_rate`):** The equilibrium job finding rate, `p`, from the solved model.

B Identification Strategy

The parameters are divided into two groups. The first group consists of parameters that are set externally, based on standard values in the literature or straightforward calculations from aggregate data. The second group contains the core parameters that are estimated jointly to match a set of key moments that characterize the labor market in each period.

B.1 Group 1: Externally Calibrated Parameters

These parameters are generally considered to be stable structural parameters or are easily pinned down from aggregate statistics. The following table summarizes these parameters along with their values for 2019 and 2024.

Parameter	Description	Source/Target	2019 Value	2024 Value
β	Discount Factor	Matches a 5% annual real interest rate. Standard in macro models (Lise and Robin, 2017; Bagga et al., 2024).	0.996	0.996
γ_0	Matching Efficiency	Set to 1 as a normalization. The level of matching is absorbed by other parameters, primarily vacancy costs.	1.0	1.0
γ_1	Matching Elasticity	Common value in the search and matching literature (Petrongolo and Pissarides, 2001).	0.5	0.5
ξ	Worker Bargaining Power	Standard value implying equal surplus sharing (Shimer, 2005).	0.5	0.5
δ	Exogenous Separation Rate	Matches the average monthly Layoffs and Discharges rate, calculated from JOLTS data for the target year.	0.012	0.011
κ_1	Vacancy Cost Convexity	Imposes a standard quadratic cost function, $c(v) = \frac{\kappa_0}{2}v^2$	1.0	1.0

B.2 Group 2: Internally Estimated Parameters

These parameters are estimated jointly for each period (2019 and 2024) using the Simulated Method of Moments (SMM). The goal is to choose the parameter values that minimize the distance between moments generated by the model and their counterparts in the data for each specific year. This allows us to see which parameters have changed following the pandemic.

B.2.1 Worker Skill (h) Distribution

- **Functional Form Assumption:** Following Lise and Robin (2017), we assume a flexible parametric form for the unobserved distribution of worker skill. Specifically, worker skill h is assumed to be drawn from a Beta distribution with shape parameters $a_h > 0$ and $b_h > 0$:

$$h \sim \text{Beta}(a_h, b_h)$$

- **Identification Rationale:** The parameters (a_h, b_h) are identified by matching the moments of the unconditional wage distribution in the model to the data. The shape of the skill distribution is the primary source of wage dispersion in the model. A distribution of h with a higher mean will raise the average wage, while a higher variance in h will, all else equal, increase wage inequality.

  - **Moment 1: Average Wage Level:** This moment pins down the central tendency of the skill distribution.

    * **Data Moment:** The sample mean of log hourly wages for all employed workers in the target year.
$$\text{Moment}_1^{\text{Data}} = \frac{1}{N}\sum_{i=1}^{N}\log(w_i)$$

    * **Model Counterpart:** The theoretical expectation of log wages in the model's steady state. This is calculated by integrating over the equilibrium distribution of employed workers, $n(h, \psi)$, and the conditional distribution of work arrangements, $p(\alpha \mid h, \psi)$.
$$\text{Moment}_1^{\text{Model}}(a_h, b_h, \dots) = \iint \mathop{\mathbb{E}}_{\alpha}[\log(w(h, \psi; \alpha))]n(h, \psi)\, dF_h\, dF_\psi$$

  - **Moment 2: Wage Inequality:** This moment pins down the dispersion of the skill distribution.

    * **Data Moment:** The sample variance of log hourly wages for all employed workers in the target year.
$$\text{Moment}_2^{\text{Data}} = \frac{1}{N-1}\sum_{i=1}^{N}(\log(w_i) - \overline{\log(w)})^2$$

    * **Model Counterpart:** The theoretical variance of log wages in the model's steady state.
$$\text{Moment}_2^{\text{Model}}(a_h, b_h, \dots) = \mathbb{E}\left[(\log(w^*) - \mathbb{E}[\log(w^*)])^2\right]$$

  - **Joint Identification:** The mean and variance of the Beta distribution are known functions of its shape parameters:
$$\mathbb{E}[h] = \frac{a_h}{a_h + b_h} \quad \text{and} \quad \text{Var}(h) = \frac{a_h b_h}{(a_h + b_h)^2(a_h + b_h + 1)}$$

While the mapping from these theoretical moments of h to the moments of the log wage distribution is complex, the intuition is direct. The SMM estimator will adjust a_h and b_h to find the unique shape of the skill distribution that, when filtered through the model's sorting, choice, and wage-setting mechanisms, best replicates the observed mean and variance of wages. Even in the continuous logit model, where wages depend on the chosen α, the fundamental driver of a worker's productivity and surplus-generating potential remains their skill h, preserving this identification channel. For example, to match a high level of wage inequality (a high $\mathrm{Var}(\log(w))$), the estimator will need to choose a_h and b_h that imply a high $\mathrm{Var}(h)$.

B.2.2 In-Office Cost and Preference Heterogeneity (c_0, χ, μ)

These three parameters jointly define worker preferences over work arrangements. The deterministic part of the in-office disutility is specified by the function $c(1-\alpha) = c_0\frac{(1-\alpha)^{1+\chi}}{1+\chi}$, while μ governs the scale of idiosyncratic taste shocks around this baseline. While they are estimated together, they are identified by distinct features of the data: - c_0 governs the overall **scale** or average "price" of the remote work amenity. - χ governs the **curvature** of the cost, which shapes the incentives for corner vs. interior solutions. - μ governs the **dispersion** of preferences, which determines how much choices deviate from the deterministic optimum.

To separately identify these three parameters, we require three distinct moments that are uniquely sensitive to each one.

- **Identification of the Scale Parameter (c_0)**: The scale parameter c_0 is primarily identified by the **average compensating wage differential** between in-person and remote work. It directly scales the monetary compensation a worker receives for the disutility of their chosen work arrangement.
  - **Mechanism:** In the continuous logit model, the wage paid to a worker in a match (h, ψ) who has chosen arrangement α is:

$$w(h, \psi; \alpha) = \underbrace{\text{Base Wage}(h, \psi)}_{\text{From surplus split}} + \underbrace{c_0\frac{(1-\alpha)^{1+\chi}}{1+\chi}}_{\text{Compensation for in-office disutility}}$$

The "Base Wage" component depends on the total expected surplus. The second term is the compensating differential. The average observed wage gap between groups is therefore a direct reflection of the average compensation paid, which is scaled by c_0.

  - **Identification Argument:** Holding the distribution of choices constant, a larger observed wage premium for in-person work requires a larger c_0 for the model to generate the necessary compensation. While the choice of α is itself endogenous, c_0 remains the primary parameter governing the magnitude of this wage-arrangement relationship.
  - **Data Moment:** The estimated coefficient, $\hat{\beta}_2$, from a Mincer-style wage regression with dummy variables for work arrangements, where "Fully Remote" is the omitted reference category:

$$\log(w_i) = \beta_0 + \beta_1 \mathbf{I}(\text{Hybrid}_i) + \beta_2 \mathbf{I}(\text{In-Person}_i) + \mathbf{X}_i'\Gamma + \varepsilon_i$$

  - **Model Counterpart:** The analogous regression coefficient, $\hat{\beta}_{2,\text{sim}}$, estimated from a large cross-section of simulated data generated by the model.

- **Identification of the Curvature Parameter (χ):** The curvature parameter χ is primarily identified by the **share of workers in corner solutions, specifically the share that is fully remote ($\alpha = 1$)**. It determines how quickly the marginal disutility of in-office work changes, thereby shaping the desirability of full vs. partial remote work.

  - **Mechanism:** A high χ makes the deterministic value function $V(h, \psi; \alpha)$ highly convex in α (as a function of in-office time $1 - \alpha$). This creates a strong incentive to "snap" to a corner solution. For matches where remote work is productive ($g(h, \psi) > 1$), a high χ makes the final step from $\alpha = 0.99$ to $\alpha = 1$ very attractive.
  - **Identification Argument:** The model's predicted share of workers who choose $\alpha = 1$ is highly sensitive to χ. While other parameters influence *which* matches are candidates for remote work, χ has a disproportionate effect on whether those candidates choose a full or partial arrangement. To match a large observed share of fully remote workers, the estimation must select a high value for χ.
  - **Data Moment:** The share of the employed workforce in fully remote work arrangements.
  - **Model Counterpart:** The share of simulated workers in the model's steady state for whom the drawn work arrangement α is equal to 1 (or within a small tolerance, e.g., $\alpha > 0.95$).

- **Identification of the Taste Dispersion Parameter (μ):** The scale parameter μ is primarily identified by the **share of workers in hybrid arrangements**. It determines the degree of randomness in choices, and therefore the prevalence of interior solutions that deviate from the deterministic corners.

- **Mechanism:** The deterministic value function $V(h, \psi; \alpha)$ is often bimodal (with peaks at $\alpha = 0$ and $\alpha = 1$). In the absence of taste shocks ($\mu = 0$), all choices would be at these corners. The parameter μ "smears out" these choices. A larger μ implies more significant taste shocks, making it more likely that a worker will choose an interior "hybrid" α even if the deterministic optimum is at a corner.
- **Identification Argument:** The model's predicted share of workers in hybrid arrangements is highly sensitive to μ. To match a large observed share of hybrid workers in the data, the estimation must select a high value for μ, indicating significant preference heterogeneity.
- **Data Moment:** The share of the employed workforce in hybrid work arrangements.
- **Model Counterpart:** The share of simulated workers in the model's steady state for whom the drawn work arrangement α is an interior solution (e.g., $0.05 < \alpha < 0.95$).
- **TODO:** "The Gumbel scale parameter μ is strongly identified by the variance of remote work (var_α), as shown in its sharp likelihood profile (Figure B.X). The estimated value of μ is an empirical measure of the importance of idiosyncratic preferences. It quantifies how 'blurry' the decision margins are in the real world, telling us how far the true data generating process is from the simplified, deterministic benchmark."

Joint Identification: The parameters c_0, χ, and μ are disentangled by targeting three distinct moments: 1. The **wage gap** between remote and in-person workers identifies the scale of the amenity value, c_0. 2. The **share of fully remote workers** identifies the preference curvature, χ, which drives corner solutions. 3. The **share of hybrid workers** identifies the taste dispersion, μ, which drives interior solutions. - By forcing the model to match the "price" (wage gap), the "corner quantity" (full remote share), and the "interior quantity" (hybrid share) simultaneously, the estimator can separately identify the scale c_0, the curvature χ, and the dispersion μ.

B.2.3 Production Function (ψ_0, ϕ, ν)

These parameters jointly determine the output of a worker-firm match. Their identification relies on the wage distribution and the distribution of work arrangements, conditional on firm and worker types.

Remote Productivity Parameters (ψ_0, ν) These parameters govern the level and dispersion of remote work productivity. - **Mechanism:** These parameters enter the production function via the relative remote productivity term, $g(h, \psi) = \psi_0 \exp(\nu\psi + \phi h)$. This term shapes the deterministic value function $V(h, \psi; \alpha)$ and, consequently, the flow surplus $s(h, \psi)$ and the total surplus $S(h, \psi)$. Since the wage is an increasing function of the surplus, the properties of $g(h, \psi)$ directly map to the properties of wages.

- **Identification Argument:**
  1. **Firm-Remote Complementarity (ν):** This elasticity is identified by the **slope of the wage-efficiency profile**, which we measure in the data by the **correlation between firm efficiency ψ and wages**. Formally, the parameter ν directly scales the sensitivity of the flow surplus, $s(h, \psi)$, to changes in ψ. A steeper observed wage profile in the data therefore requires a higher ν in the model to generate a sufficiently strong surplus response. (A formal proof is provided in Appendix Rigorous Justification for the Wage-Efficiency Profile).
     - **Data Moment:** The estimated coefficient, $\hat{\beta}_1$, from a Mincer-style wage regression that estimates the semi-elasticity of wages with respect to the firm's remote work efficiency, ψ, after controlling for observable worker characteristics:

$$\log(w_i) = \beta_0 + \beta_1 \psi_i + \mathbf{X}_i' \Gamma + \varepsilon_i$$

     - **Model Counterpart:** The analogous regression coefficient, $\hat{\beta}_{1,\text{sim}}$, estimated from a large cross-section of simulated data generated by the model.
  2. **Remote Productivity Scale (ψ_0):** Given the slope ν, the scale ψ_0 is identified by the **average wage premium** of high-ψ firms over low-ψ firms. This moment pins down the overall level of the remote productivity advantage.
     - **Mechanism:** The parameter ψ_0 acts as a level shifter on the relative productivity term $g(h, \psi)$. This directly scales the flow surplus $s(h, \psi)$ and, consequently, the average wage for any given ψ. The parameter ν determines *how much steeper* the wage-ψ profile is, while ψ_0 shifts the entire profile up or down.
     - **Identification:** To match a large average wage premium in the data for high-ψ

firms, the estimator must choose a sufficiently large ψ_0 to scale up the productivity advantage of these firms.

- **Data Moment:** The estimated **average wage premium** for firms with high remote-work efficiency, controlling for worker characteristics. This is captured by the coefficient on a dummy variable in a Mincer-style wage regression:

$$\log(w_i) = \beta_0 + \beta_1 \mathbf{I}(\psi_i \in \text{High}) + \mathbf{X}_i'\Gamma + \varepsilon_i$$

- **Model Counterpart:** The analogous regression coefficient, $\hat{\beta}_{1,\text{sim}}$, estimated from a large cross-section of simulated data generated by the model.

Skill-Remote Complementarity (ϕ) This is a key parameter of interest, determining whether worker skill and firm remote technology are complements or substitutes. - **Mechanism:** The parameter ϕ governs the **cross-partial derivative** of the deterministic value function, which determines the nature of sorting in the market.

$$\frac{\partial^2 V(h,\psi;\alpha)}{\partial h \partial \psi} \propto \phi$$

- If $\phi > 0$ **(Complements)**, high-skill workers are disproportionately more productive in high-ψ firms, creating gains from **positive assortative matching**. - If $\phi < 0$ **(Substitutes)**, high-skill workers' advantage is diminished in high-ψ firms, creating gains from **negative assortative matching**. - **Identification Argument:** The parameter ϕ is identified by the **sorting pattern between worker skill h and firm efficiency ψ**. We use the conditional distribution of work arrangements as the primary identifying moment. - **The Logic:** Sorting not only affects wages but also the **distribution of chosen work arrangements**. The probability of choosing a high α is increasing in the deterministic value $V(h,\psi;\alpha)$. - If $\phi > 0$ **(Complements)**, high-h workers sort into high-ψ firms. In these matches, the term $g(h,\psi)$ is particularly large, making the deterministic value of remote work high. This pushes the entire probability distribution $p(\alpha \mid h,\psi)$ to the right, increasing the average chosen α. - Therefore, ϕ is identified by how the **average share of remote work, $\mathbb{E}[\alpha]$, differs across firms with high and low ψ**. - **The Data Moment:** We compute the average share of remote work (e.g., average days worked from home) for workers in high-ψ firms and low-ψ firms and take the difference:

$$\text{Moment}_{\text{Data}} = \mathbb{E}[\alpha \mid \psi \in \text{High Quantile}] - \mathbb{E}[\alpha \mid \psi \in \text{Low Quantile}]$$

- **The Model Counterpart:** We simulate the model and compute the same conditional difference in the average drawn α.

B.2.4 Search & Matching

- **Vacancy Cost Scale (κ_0):** This parameter governs the overall cost of posting vacancies and is the primary determinant of the number of vacancies firms create in equilibrium.
  - **Mechanism:** The parameter κ_0 directly scales the cost of vacancy creation. As shown in the model's derivation, the equilibrium labor market tightness, θ, is a decreasing function of κ_0.
  - **Identification Argument:** κ_0 is identified by matching the model's equilibrium market tightness to the data. The estimator adjusts κ_0 until the model's implied θ matches its empirical counterpart.
  - **Data Moment:** The average **vacancy-to-unemployment ratio (V/U)** for the target year, constructed from JOLTS and CPS data.
  - **Model Counterpart:** The value of θ calculated from the model's closed-form solution for a given set of parameters.

B.2.5 Summary for Implementation

This section provides a quick reference guide for the mapping between the internally estimated parameters and their primary identifying moments.

- **Parameters a_h, b_h (Skill Distribution):**
  - **Data Moment 1:** Mean of log wages (unconditional).
  - **Data Moment 2:** Variance of log wages (unconditional).
  - **Model Counterpart:** Calculate the full steady-state distribution of employed workers $n(h, \psi)$ and the conditional choice probabilities $p(\alpha \mid h, \psi)$. Simulate a large sample of (h, ψ, α) draws, compute the wage for each, and then calculate the mean and variance of the log wages.
- **Parameter c_0 (Amenity Scale):**

- **Data Moment:** Regression coefficient on an "In-Person" dummy in a Mincer regression ($\log(w)$ In-Person + Hybrid + Controls), with "Fully Remote" as the base group.
- **Model Counterpart:** Simulate a large sample of workers. Classify each into "In-Person" ($\alpha < 0.05$), "Hybrid" ($0.05 \leq \alpha \leq 0.95$), and "Fully Remote" ($\alpha > 0.95$). Run the exact same Mincer regression on the simulated data and target the coefficient on the "In-Person" dummy.

- **Parameter χ (Amenity Curvature):**
  - **Data Moment:** Share of the workforce that is "Fully Remote".
  - **Model Counterpart:** In the simulated sample, calculate the fraction of workers for whom the drawn α is greater than 0.95.
- **Parameter μ (Taste Dispersion):**
  - **Data Moment:** Share of the workforce that is "Hybrid".
  - **Model Counterpart:** In the simulated sample, calculate the fraction of workers for whom the drawn α is between 0.05 and 0.95.
- **Parameter ν (Firm-Remote Complementarity):**
  - **Data Moment:** Regression coefficient on firm remote efficiency ψ in a Mincer regression ($\log(w)$ ψ + Controls).
  - **Model Counterpart:** Simulate a large sample of workers. Run the exact same Mincer regression on the simulated data and target the coefficient on ψ.
- **Parameter ψ_0 (Remote Productivity Scale):**
  - **Data Moment:** Regression coefficient on a "High-ψ Firm" dummy in a Mincer regression ($\log(w)$ $I(\psi > \text{median})$ + Controls).
  - **Model Counterpart:** Simulate a large sample of workers. Classify firms as "High-ψ" if their ψ is above the median of the ψ distributi. on. Run the exact same Mincer regression on the simulated data and target the coefficient on the "High-ψ" dummy.
- **Parameter ϕ (Skill-Remote Complementarity):**
  - **Data Moment:** The difference in the average remote work share between high-ψ and low-ψ firms: $\mathbb{E}[\alpha \mid \psi > \text{median}] - \mathbb{E}[\alpha \mid \psi < \text{median}]$.
  - **Model Counterpart:** In the simulated sample, classify firms as "High-ψ" or "Low-ψ". Calculate the average drawn α within each group and take the difference.

- **Parameter κ_0 (Vacancy Cost Scale):**
  - **Data Moment:** The average Vacancy-to-Unemployment (V/U) ratio.
  - **Model Counterpart:** The equilibrium market tightness θ that solves the model's fixed-point problem.

B.2.6 Summary Table for the Paper

This table provides a formal summary of the internally estimated parameters and their corresponding empirical targets, suitable for inclusion in the main body of the paper.

Table X: Summary of Moments for SMM Estimation

Parameter(s)	Description	Empirical Target Moment
Skill Distribution		
a_h, b_h	Shape of the worker skill distribution	Mean of log wages (unconditional)
		Variance of log wages (unconditional)
Preferences		
c_0	Scale of in-office disutility	Compensating Wage Differential (In-Person vs. Remote)
χ	Curvature of in-office disutility	Share of Workforce in Fully Remote Arrangements
μ	Scale of idiosyncratic taste shocks	Share of Workforce in Hybrid Arrangements
Production Technology		
ψ_0	Baseline remote productivity	Wage Premium for High-ψ Firms
ν	Return to firm remote efficiency	Slope of the Wage-Efficiency Profile
ϕ	Skill-remote complementarity	Difference in Avg. Remote Share (High-ψ vs. Low-ψ Firms)

Parameter(s)	Description	Empirical Target Moment
Search Frictions		
κ_0	Scale of vacancy posting costs	Labor Market Tightness (V/U Ratio)

B.2.7 Rigorous Justification for the Wage-Efficiency Profile

This appendix formally shows that the sensitivity of the expected wage with respect to firm remote efficiency ψ is directly and monotonically related to the parameter ν, justifying the use of the wage-ψ slope as the primary identifying moment for ν.

Step 1: The Effect of ψ on the Flow Surplus $s(h, \psi)$

The flow surplus is defined by the "inclusive value" or "log-sum-exp" formula:

$$s(h, \psi) = \mu \ln \left(\int_0^1 \exp \left(\frac{V(h, \psi; \alpha)}{\mu} \right) d\alpha \right) - b(h)$$

To find the sensitivity to ψ, we differentiate with respect to ψ. The derivative of the log-sum-exp term is a standard result in random utility theory, yielding the expectation of the derivative of the inner term:

$$\frac{\partial s(h, \psi)}{\partial \psi} = \int_0^1 p(\alpha \mid h, \psi) \frac{\partial V(h, \psi; \alpha)}{\partial \psi} d\alpha = \mathbb{E}_\alpha \left[\frac{\partial V(h, \psi; \alpha)}{\partial \psi} \right]$$

The derivative of the deterministic value $V(\alpha) = Y(\alpha) - c(1 - \alpha)$ with respect to ψ is:

$$\frac{\partial V(h, \psi; \alpha)}{\partial \psi} = \frac{\partial Y(\alpha)}{\partial \psi} = A_1 h \cdot \alpha \cdot \frac{\partial g(h, \psi)}{\partial \psi}$$

Substituting the functional form $g(h, \psi) = \psi_0 \exp(\nu\psi + \phi h)$, we have $\frac{\partial g}{\partial \psi} = g(h, \psi) \cdot \nu$.

$$\frac{\partial V(h, \psi; \alpha)}{\partial \psi} = A_1 h \cdot \alpha \cdot g(h, \psi) \cdot \nu$$

Plugging this back into the expression for the derivative of the flow surplus:

$$\frac{\partial s(h, \psi)}{\partial \psi} = \int_0^1 p(\alpha \mid h, \psi) \left(A_1 h \cdot \alpha \cdot g(h, \psi) \cdot \nu \right) d\alpha$$

$$\frac{\partial s(h,\psi)}{\partial \psi} = \underbrace{(A_1 h \cdot g(h,\psi) \cdot \nu)}_{>0} \cdot \underbrace{\mathbb{E}[\alpha \mid h,\psi]}_{>0}$$

This shows that the sensitivity of the *flow surplus* to firm efficiency ψ is directly and positively proportional to ν.

Step 2: The Effect on Total Surplus $S(h,\psi)$ and the Expected Wage $\mathbb{E}[w]$

1. **From Flow to Total Surplus:** The Bellman equation for the total surplus is:

$$S(h,\psi) = \frac{s(h,\psi) - \text{Continuation Value}}{1-\beta(1-\delta)}$$

Differentiating with respect to ψ (and holding the aggregate continuation value term constant, as it depends on the expectation over all ψ'):

$$\frac{\partial S(h,\psi)}{\partial \psi} = \frac{1}{1-\beta(1-\delta)} \frac{\partial s(h,\psi)}{\partial \psi}$$

The sensitivity of the total surplus is a discounted amplification of the sensitivity of the flow surplus. Therefore, $\frac{\partial S(h,\psi)}{\partial \psi} \propto \nu$.

2. **From Total Surplus to the Expected Wage:** The wage for a chosen α is $w(\alpha) = \text{Base Wage} + c(1-\alpha)$. The Base Wage component is an increasing function of the total surplus $S(h,\psi)$. The expected wage is:

$$\mathbb{E}[w \mid h,\psi] = \text{Base Wage}(S(h,\psi)) + \mathbb{E}[c(1-\alpha) \mid h,\psi]$$

The dominant channel through which ψ affects the expected wage is via its effect on the total surplus $S(h,\psi)$. A higher ν leads to a much larger surplus $S(h,\psi)$ in high-ψ firms, and this larger surplus must be shared with the worker, leading to a higher Base Wage. While the expected compensation term also adjusts, the primary driver of the wage-ψ profile is the surplus channel.

Conclusion: The semi-elasticity of the expected wage with respect to ψ is a positive and monotonic function of ν. This provides a rigorous justification for using the slope of the wage-efficiency profile as the identifying moment for ν.

B.3 Data Appendix

- ☐ **C.1. Data Sources and Sample Construction**
  - ☐ List all datasets used with sources and links (IPUMS CPS, SWAA, JOLTS, FRED, O*NET, etc.).
  - ☐ Provide a detailed table of the sample selection criteria (age, employment status, hours worked, wage floors, etc.) and the number of observations dropped at each stage.
- ☐ **C.2. Variable Construction**
  - ☐ Detail the construction of key variables like real hourly wage, education categories, etc.
- ☐ **C.3. Construction of the Teleworkability Index (ψ)**
  - ☐ **This is a key methodological contribution and needs significant detail.**
  - ☐ **Feature Set:** List or summarize the O*NET variables used as features.
  - ☐ **Training Data:** Describe the Occupational Requirements Survey (ORS) data used for labels.
  - ☐ **Model Specification:** Detail the two-stage Random Forest model (Stage 1: Classifier for zero vs. non-zero; Stage 2: Regressor for the intensive margin).
  - ☐ **Validation:** Report the key performance metrics from your validation set (e.g., Accuracy, F1-score for the classifier; MSE, Correlation for the regressor).
  - ☐ **Final Output:** Show the final distribution of the predicted ψ index.