AI and Returns to Experience in Entrepreneurship

Ziqing Yan* Irisa Zhou†

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Abstract

This paper studies how advances in Artificial Intelligence (AI) have altered the value of skills accumulated through different types of work experience in entrepreneurship. Using employment histories from public LinkedIn profiles (2007-2019), we exploit industry-level variation in AI exposure following the diffusion of neural networks and ImageNet after 2012. We find that among U.S. LinkedIn users, the share of founders and researchers both increased, but entry gains were concentrated among more-experienced workers, especially those with research backgrounds. To understand the mechanism behind AI's impact on the labor market, we develop a directed search model with occupational choice, multi-dimensional skills, and stochastic human capital investment. The model shows that AI shocks increase the productivity premium for researchers, shifting entrepreneurship toward more experienced individuals with research expertise.

1 Introduction

Artificial Intelligence (AI) is transforming the nature of work and has profound implications for entrepreneurship. Scholars increasingly view AI as an "external enablers" of entrepreneurship, creating new business opportunities (for example, AI startups commercializing machine learning advances) even as they disrupt existing jobs (Fossen et al., 2024). At the same time, AI may also replace or augment certain skills in the labor market. This raises the question: what types of human skills and experiences become more or less valuable for entrepreneurs in the age of AI?

Classic entrepreneurship theory emphasizes the importance of a balanced skill set. In particular, Lazear's "Jack-of-all-Trades" theory argues that individuals with a broad,

*Department of Economics, Yale University. *ziqing.yan@yale.edu*

†Department of Economics, University of Toronto. *irisa.zhou@mail.utoronto.ca*

balanced set of skills are more likely to become successful entrepreneurs (Lazear, 2004). Entrepreneurs historically needed to wear many hats—combining knowledge of management, finance, technology, and more—whereas specialists tended to work for others. However, the rise of AI could fundamentally alter this dynamic. Because AI systems excel at routine cognitive tasks such as prediction and classification, they may substitute for the kinds of generalist or routine experience once useful to entrepreneurs. By contrast, skills rooted in judgment, creativity, and domain-specific expertise are less replicable by AI and may therefore become complementary to it. This potential for AI to hollow out routine work while amplifying the importance of expertise provides the key motivation for our study.

We examine this hypothesis by studying how AI exposure affects the entrepreneurial value of different types of prior work experience. We distinguish between "repetitive" experience, characterized by well-defined and repeatable tasks, and research-oriented experience, which builds industry knowledge, analytical thinking, and problem-solving skills. Our central hypothesis is that AI acts as a substitute for the former type of experience and a complement for the latter. If AI automates routine tasks, the skills gained from such tasks lose value. Conversely, if AI enhances innovation and problem-solving, workers with substantial research experience may find their skills in higher demand when founding new ventures.

To test this idea, we use résumé data from public LinkedIn profiles provided by Revelio Labs. We focus on how career patterns changed after the early 2010s, when modern AI technologies—particularly deep learning breakthroughs around 2012—began to diffuse. We categorize industries by their AI exposure (Felten et al., 2021) and trace entrepreneurial dynamics over time.

Our first finding is that research roles expanded disproportionately in high-AI industries after 2012, relative to both earlier years and low-AI industries. Founding rates were already rising pre-2012 but accelerated thereafter, consistent with evidence from new business applications showing a surge in AI-related startups beginning around 2012 and accelerating after 2016 (Dinlersoz et al., 2024).

Second, we show that founders in the AI era entered with more prior work experience: the average rose from 8 years to roughly 9. This shift resonates with evidence that entrepreneurial success often comes later in life, with the average age of high-growth founders around 45 (Azoulay et al., 2020). AI may be tilting entry further toward seasoned professionals with accumulated expertise.

Third, AI exposure shifted the profile of who becomes a founder: from younger generalists to experienced specialists. Before 2012, in high-AI industries, we show that the researchers most likely to transition into entrepreneurship tended to have less than 10 years of research experience. After 2012, this pattern flipped: those with 10–15 years of research experience became more likely to found companies, whereas more junior candidates became relatively less likely. Notably, we do not see such a shift in low-AI-exposure industries. A researcher with a decade of experience in, say, biotech or finance might now perceive greater opportunities (and face lower hurdles) to start an AI-enabled venture than they would have in the past, whereas a less-experienced worker with only a routine skill set might be less inclined or able to do so. In short, AI appears to be reweighting the type of human capital that feeds into entrepreneurship and redistributing workers with varying levels of experience across different occupations.

Fourth, to interpret these findings and to disentangle the effect of AI, we develop a directed search model with occupational and industry choices, human capital accumulation, and multidimensional skills. The model flexibly allows AI to affect labor markets through switching costs, the speed of human capital accumulation, matching efficiency, or productivity premia. This allows us to identify the specific mechanisms and their magnitudes when a special shock like AI occurs to the labor market.

Finally, we calibrate the model and use it to assess the effect of AI on entrepreneurship. Comparative statics highlight one dominant channel: AI raises the productivity premium of research-oriented human capital. When the productivity premium for researchers increases, we observe a simultaneous and modest increase in both researchers and entrepreneurs, consistent with the small but significant empirical rise. Moreover, individuals with initially higher levels of research experience are incentivized to pursue roles in research and entrepreneurship after such an increase. This leads to a non-trivial reallocation of talent in the labor market and substantially alters the distribution of experience. The model reproduces the empirical patterns we document and provides a framework to quantify the magnitude of these effects in a general equilibrium setting.

Related literature. Our work contributes to several strands of literature.

First, we build on the broad literature examining how technological change, particularly AI, is reshaping the demand for skills. A long tradition in labor economics has documented that computerization and automation tend to reduce demand for routine skills while increasing demand for non-routine cognitive and social skills (Autor et al., 2003; Autor, 2015). Recent studies show that AI extends this trend by automating some high-skill cognitive tasks and reducing demand for certain non-AI cognitive positions (Acemoglu et al., 2022; Webb, 2019), though AI can also complement complex human work and raise productivity (Babina et al., 2024; Hampole et al., 2025). We contribute to this literature by connecting this substitution–complementarity framework to entrepreneurship, showing that AI shapes not only labor demand but also the composition of new venture formation.

Second, our work is among the first to empirically analyze the impact of AI on entrepreneurship at the micro level. Fossen et al. (2024) reviews the direct and indirect effect of AI on entrepreneurship. Gofman and Jin (2024) finds that AI professors' departures from universities reduce startup founders' AI knowledge and leads the students in affected universities to establish fewer AI startups and raise less funding. We provide new micro-level evidence that AI alters the selection of who becomes an entrepreneur, shifting the margin of entry toward experienced researchers and specialists.

Third, our research contributes to the rich literature on entrepreneurs' backgrounds and the role of human capital in new venture performance, including the seminal work of Lazear (2004). A consistent finding in prior work is that founder experience matters for entrepreneurial success. Azoulay et al. (2020) find that middle-aged entrepreneurs tend to outperform younger ones, as noted earlier. We thereby contribute to the literature by identifying a specific technological force (AI) that is altering the selection into entrepreneurship along experience lines. We show a technology-driven shift over time in who becomes an entrepreneur.

Finally, our model contributes to the literature by presenting a simple directed search framework of multidimensional skill combined with stochastic human capital accumulation à la Ljungqvist and Sargent (1998). We introduce multiple channels through which AI can impact the labor market, and, through the lens of our model, we analyze which mechanism dominates and how. We directly address the potential complementarity between AI and the researcher human capital premium, and how it affects the distribution of individuals' experience.

This paper is organized as follows. Section 2 describes the data and empirical strategy. Section 3 presents the empirical findings. Section 4 introduces the model set-up. Section 5 discusses the model calibration and conducts comparative statics analysis. Section 6 concludes.

2 Data and Empirical Strategy

2.1 Data

Our primary dataset comes from Revelio Labs, which is a labor market analytics company that collects and analyzes data from public LinkedIn profiles. The workers profile data contains detailed information on individuals' work history, including job titles, employers, dates of employment, location, and industries (NAICS). Revelio Labs uses machine learning and natural language processing techniques to extract and standardize information as well as predicting certain variables such as gender, race, seniority of positions, and salaries.

For the current analysis, we use a 2% random sample of all U.S. Linkedin users. As position start and ending dates are crucial in our analysis, we only keep positions with non-missing start date and impute the end date as the current date if it is missing. We also drop positions with end date earlier than start date. After cleaning, our sample contains around 0.95 million unique users and 3.8 million unique positions.

Identifying founders and researchers. We identify founders and researchers by searching for keywords from their job titles. The keywords for founders are:

All Founder Keywords
cofounder, co-founder, founder, owner, CEO, chief executive officer, CTO, chief technology officer

and the keywords for researchers are:

All Researcher Keywords
scientist, research, researcher, r&d, r and d, engineer, engineering, technologist, technical lead, technology lead, developer, product development, data scientist, machine learning, ai researcher, ml researcher, innovation, inventor

We also exclude confounding keywords such as "research assistant" or "research intern" as we are interested in work experience after formal education.

In addition, we combine individual work history with company level data and use the founding year of the companies to further refine our classification. Some workers, especially those with long work experience, may become the CEO of an established firm instead of starting their own firm and work as the CEO. Therefore, we set "founders" to 0 if the founding year is 5 years or more before the worker's start date of that position.

Measuring experience. Work experience is not directly available in the data. We measure the experience of workers by counting the number of years they worked in each position after the end date of their highest education. If the end date of the highest education is missing, we impute it as the start year of the worker's first position observed in the data. In addition, when examining the probability of becoming a founder, we only focus on the worker's first founding event.

AI exposure. We use the industry-level AI exposure scores (AIIE) constructed by Felten, Raj, and Seamans (2021). They first identify a set of AI-related capabilities (such as image recognition, natural language processing, and prediction) and then use O*NET task descriptions to measure the extent to which each occupation relies on these capabilities. The final occupation-level AI exposure score reflects how much AI technologies could potentially augment or automate tasks within each occupation. These results in a standardized occupation-level AI exposure score (AIOE). They then construct AIIE by taking a weighted average of the AIOE using industry employment shares as weights. We further aggregate AIIE scores at the 2-digit NAICS code level before merging with our data. The resulting 2-digit NAICS AIIE scores range from -1.56 to 2.05, with higher scores indicating greater exposure to AI technologies.

We define high-exposure industries as those with an average 2-digit NAICS code AIIE score above 1 and low-exposure industries as those with an average AIIE score below 0. The identification of the effect of AI exposure on returns to experience relies on the comparison between high-exposure and low-exposure industries. We also exclude "Agriculture" (NAICS2d = 11) and "Construction" (NAICS2d = 23) from the low-exposure category as they have very different characteristics from other industries.

Under these definitions, high AI exposure industries include five 2-digit NAICS industries, such as "Information" (NAICS2d = 51) and "Professional, Scientific, and Technical Services" (NAICS2d = 54). Low AI exposure industries include ten 2-digit NAICS industries, such as "Retail Trade" (NAICS2d = 44-45) and "Manufacturing" (NAICS2d = 31-33).

2.2 AI Shocks

We exploit AI shocks as an exogenous source of variation in AI exposure across industries and over time. The first important turning point was the victory of "AlexNet" at the ImageNet Large Scale Visual Recognition Challenge in late 2012. This deep convolutional neural network achieved an error rate of 15.3%, more than 10 percentage points lower than the runner-up. This was a stunning breakthrough that demonstrated the practical power of deep learning for tasks like image recognition. It created the ecosystem for a new wave of startups built on computer vision and pattern recognition (e.g., in medical imaging, autonomous driving, and photo applications). Therefore, we choose 2012 as the first AI shock treatment year.

2.3 Difference-in-Differences

We implement a difference-in-differences (DiD) approach to estimate the impact of AI exposure on the returns to experience in entrepreneurship. The treatment group consists of individuals in high AI exposure industries, while the control group includes those in low AI exposure industries. We define the pre-treatment period as the years between 2007–2012 and the post-treatment period as the years between 2012–2019 to avoid the complication of the COVID pandemic. Our main regression specification is as follows:

$$Y_{ijt} = \alpha + \beta \text{Post}_t \cdot \text{HighAI}_{ijt} + \lambda_t + \lambda_j + \lambda_i + \epsilon_{ijt} \tag{1}$$

where Y_{ijt} is the outcome variable for individual i in industry j in year t, Post_t is a binary indicator for the post-treatment period, HighAI_{ijt} is a binary indicator for being in high AI exposure industries. The coefficient β captures the differential changes in the outcomes between the treatment and control groups. We further control for year fixed effects λ_t and industry fixed effects λ_j to account for common time trends as well as initial heterogeneity across industries. We include individual fixed effects λ_i to control for unobserved time-invariant characteristics of individuals that might affect their outcomes. ϵ_{ijt} is the i.i.d error term. Standard errors are clustered at the individual level.

To capture the dynamic effects of AI exposure on returns to experience, we also estimate an event study specification:

$$Y_{ijt} = \alpha + \sum_{k=-5, k\neq -1}^{7} \beta_k \text{Post}_{2012+k} \cdot \text{HighAI}_{ijt} + \lambda_t + \lambda_j + \lambda_i + \epsilon_{ijt} \tag{2}$$

where k is the time relative to the treatment (year 2012), and β_k captures the treatment effect at time $2012 + k$. This specification allows us to test the parallel trends assumption and observe how the impact of AI exposure evolves over time, both in the short run and the long run.

3 Empirical Findings

3.1 Probability of becoming a founder

First, we examine how AI exposure affects the probability of becoming a founder. Figure 1 presents the trends in the probability of being a founder for individuals in high AI exposure industries (AIIE score > 1), middle AI exposure industries (AIIE between 0 and 1), and low AI exposure industries (AIIE score < 0). The figure shows a clear divergence

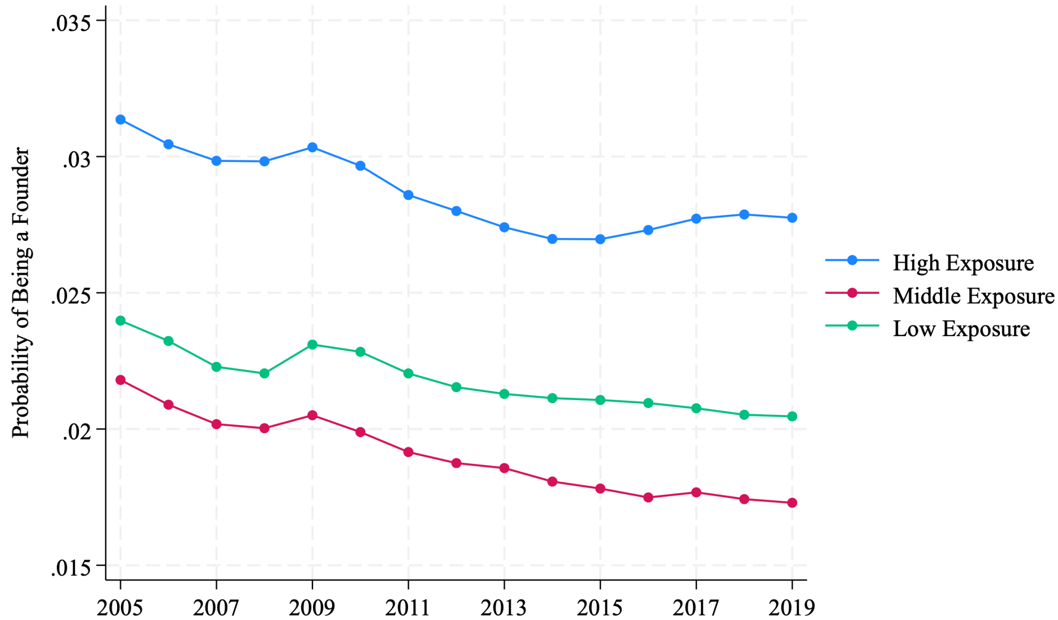


Figure 1: Probability of Becoming a Founder by AI Exposure

in trends two years after the AI shock at the end of 2012, with individuals in high AI exposure industries experiencing a noticeable increase in the probability of becoming a founder. In contrast, the probability remains relatively flat for individuals in low and middle AI exposure industries. This visual evidence suggests that AI advancements have encouraged more individuals to pursue entrepreneurial ventures in AI-intensive sectors.

Table 1 presents the results from estimating Equation (1), focusing only on high and low exposure industries for sharper comparison. We find that individuals in high AI exposure industries are significantly more likely to become founders after the AI shock in 2012 compared to those in low AI exposure industries. Specifically, the probability of becoming a founder increases by 0.13 percentage points for individuals in high AI exposure industries relative to their counterparts in low AI exposure industries. While seemingly small, this represent a 5.7% increase from the baseline probability of 2.3 percentage points among workers in low AI exposure industries in the pre-treatment period. This suggests that AI advancements have lowered barriers to entry and encouraged more individuals to pursue entrepreneurial ventures in AI-intensive sectors.

Column (2) and (3) break down the treatment effect by whether the worker has ever worked as researchers. Research experience can help build judgemental skills and deep industry understandings that are crucial for successful entrepreneurship, especially in the age of AI when many cognitive tasks could be automated.

Table 1: Probability of Becoming a Founder by AI Exposure

	Probability of Becoming a Founder		
	(1)	(2)	(3)
	All	Among Researchers	Anong Other Workers
Post * HighAI	0.0013***	0.0014*	0.0012***
	(0.0003)	(0.0008)	(0.0004)
Control Mean	0.023	0.010	0.026
Industry FE	✓	✓	✓
Year FE	✓	✓	✓
User FE	✓	✓	✓
N	3597416	702481	2894935

Notes: LinkedIn worker profiles 2007–2019. This table presents the probability of becoming a founder for individuals in high AI exposure industries compared to those in low AI exposure industries, identified from equation (1).

Among researchers, the probability of becoming a founder increases by 0.14 percentage points for individuals in high AI exposure industries relative to their counterparts in low AI exposure industries. This represents a 14% increase from the baseline probability of 1 percent in low AI exposure industries in the pre-treatment period. Non-researchers also see a positive and significant increase in the probability of becoming a founder, but the effect is smaller in magnitude (0.12 percentage points) and represents only a 4.6% increase from the baseline.

We then examine the dynamic effects of AI exposure on the probability of becoming a founder over time by estimating Equation (2). Figure 2 plots the coefficients of the interaction terms on the probability of being a researcher from year 2007–2019. The figure shows that the probability of being a researcher in high AI exposure industries relative to low exposure industries remains quite stable between 2007–2011, but starts to diverge after the AI shock in 2012, and the effect continues to grow in subsequent years. This dynamic pattern suggests that AI advancements have progressively encouraged more individuals to pursue research roles in AI-intensive sectors.

Figure 3 the coefficients for the probability of becoming a founder from year 2007–2019. Relative to low AI exposure industries, high AI-exposure industries already saw an increase in the probability of becoming a founder even before the AI shock. This might be due to industry-specific factors that made entrepreneurship more appealing in these sectors. Two years after the AI shock, the probability of becoming a founder in high AI exposure industries accelerates. This dynamic pattern suggests that AI advancements have progressively encouraged more individuals to pursue entrepreneurial ventures in

AI-intensive sectors.

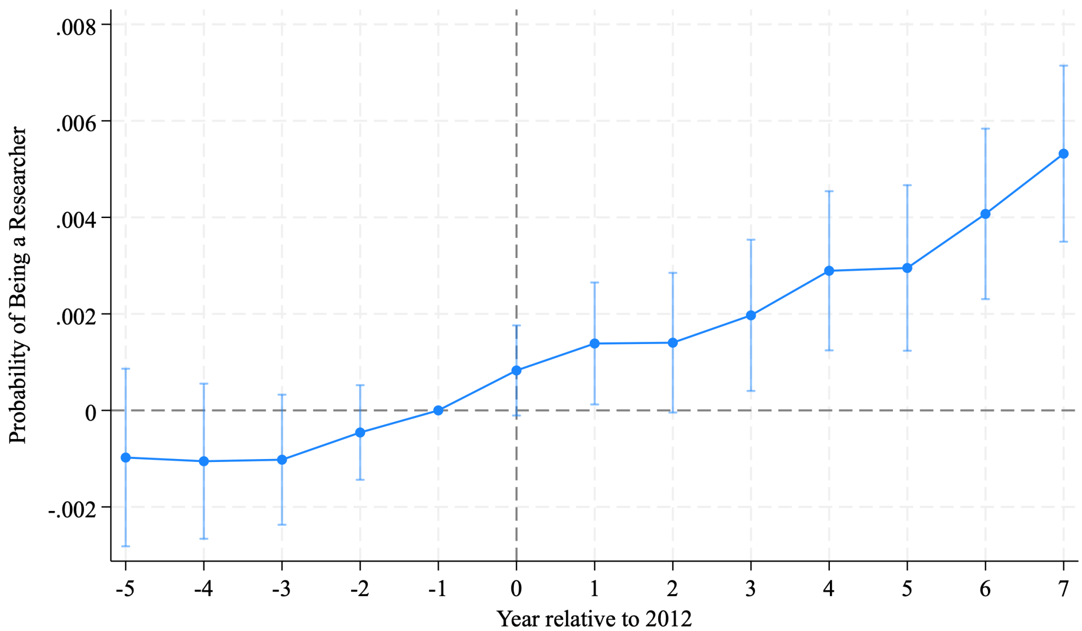


Figure 2: Probability of Being a Researcher by AI Exposure

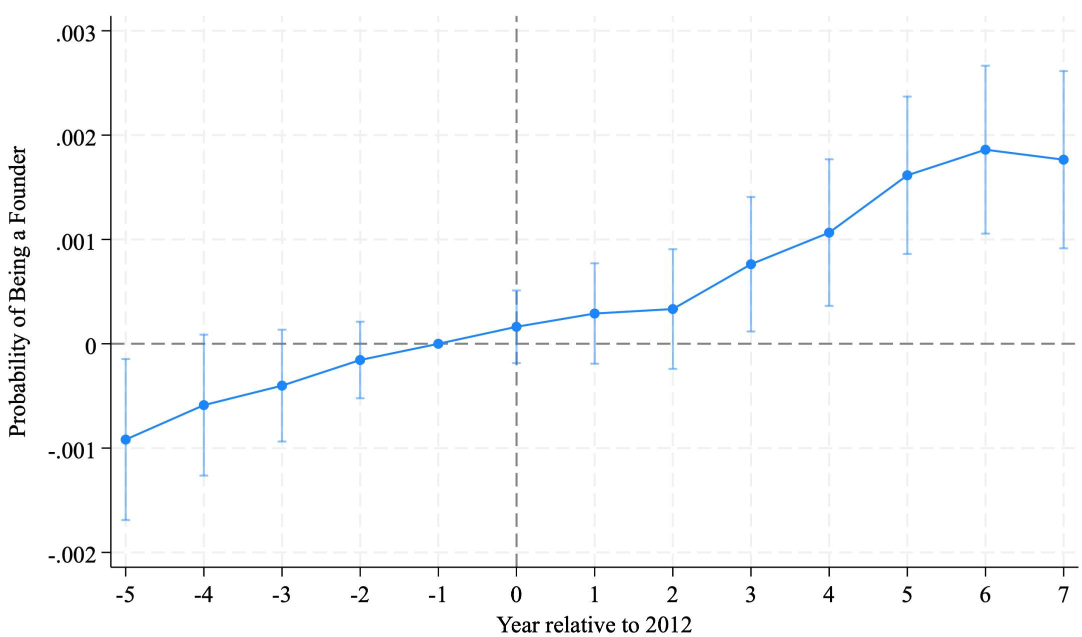


Figure 3: Probability of Becoming a Founder by AI Exposure

3.2 Total Work Experience of Founders

Prior work experience plays a significant role in shaping entrepreneurial outcomes, particularly in industries affected by technological change. Individuals with substantial work experience are more likely to acquire industry-specific knowledge, build professional networks, and develop the judgment needed to identify and exploit new opportunities. In the context of AI advancements, these advantages become even more critical, as navigating complex and rapidly evolving environments requires both expertise and adaptability. The importance of prior work experience is evident across different sectors, but is especially pronounced in AI-intensive industries, where the barriers to entry and the need for specialized skills are higher.

In this section, we compare total work experience of individuals at the time they become founders for high and low AI exposure industries. Figure 4 shows the average potential work experience of workers when they first became founders.[1] Workers in both high and low AI exposure industries exhibit increases in their work experience prior to founding a company after the AI shocks, with high exposure industries showing a more pronounced increase, suggesting that prior work experience are becoming more and more important in entrepreneurship in the age of AI.

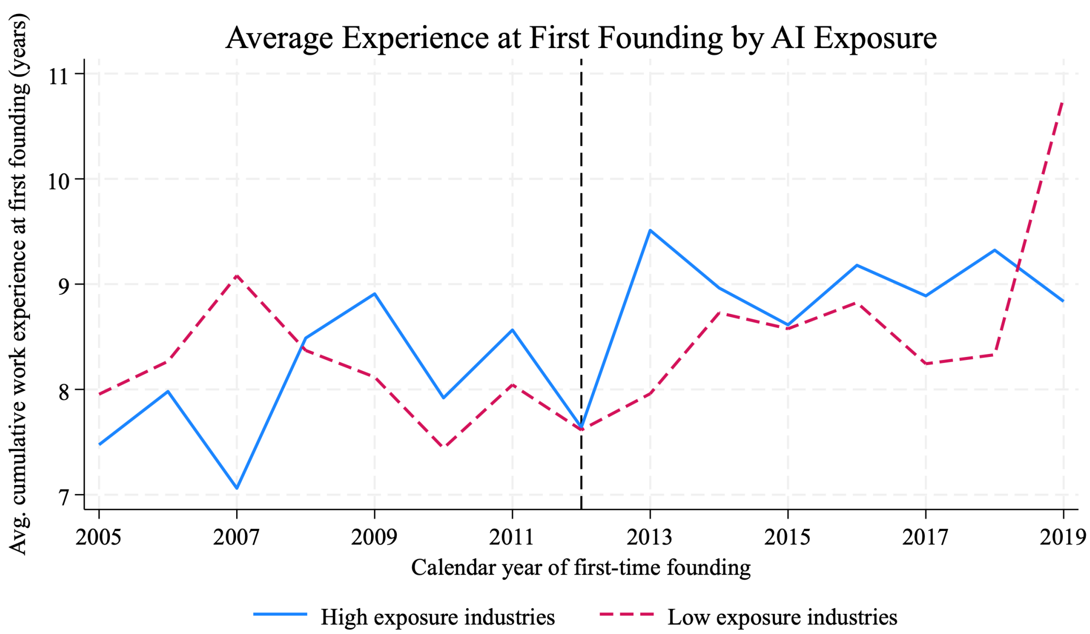


Figure 4: Work Experience of Founders by AI Exposure

[1] We impute work experience based on workers' highest education end year.

3.3 Experience as Researchers When Becoming a Founder

The types of work experience also matters in entrepreneurship. Lazear (2004) argue that individuals with diverse experiences are better equipped to identify and exploit entrepreneurial opportunities. AI advancements, which largely improves the idea generation process, could be complemented by deep industry experience. Therefore, individuals with prior research experience may have a unique advantage in founding AI-driven startups.

We analyze the role of research experience by examining the probability of becoming a founder at each experience level in the pre- and post-2012 period, separately for high and low AI exposure industries. Figure 5 presents the results for high AI exposure industries and Figure 6 shows the same probability in low AI exposure industries. Experience is restricted to 0 to 25 years to have enough observations at each level. Researchers in low exposure industries have similar probability of becoming a founder at different experience levels before and after 2012. For researchers in high exposure industries, there is a shift of the probability distribution from those with experience between 5–10 years to those with a research experience level of 10–15 years. In other words, research experience is becoming increasingly important for entrepreneurship in AI-intensive sectors. Researchers can take advantage of AI's powerful tools to automate repetitive tasks and to complement their research insights.

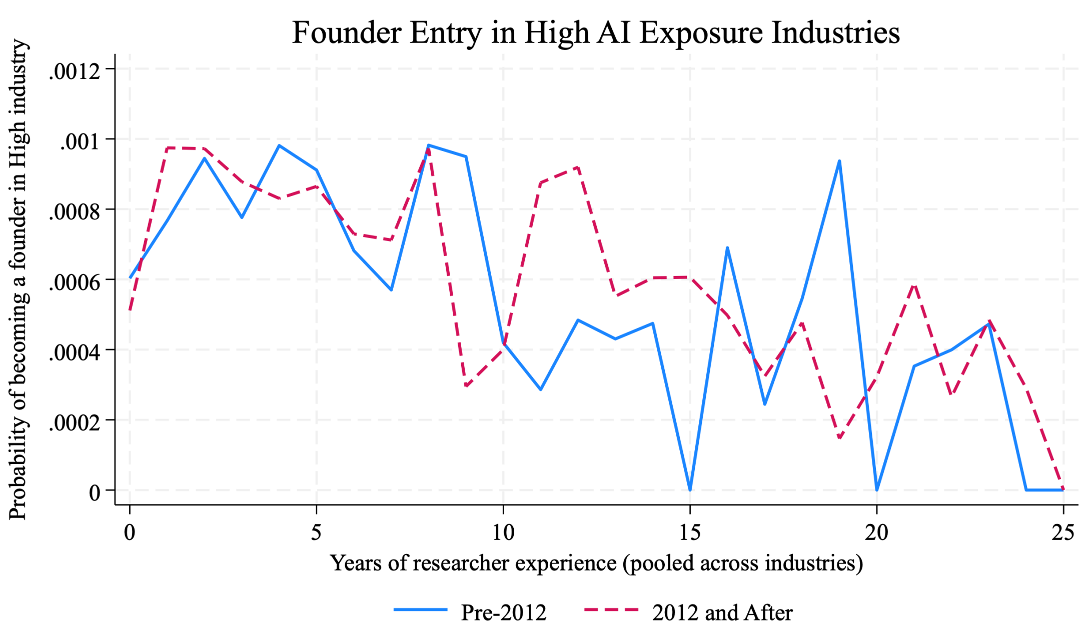


Figure 5: Probability of becoming founders by research experience – high AI exposure

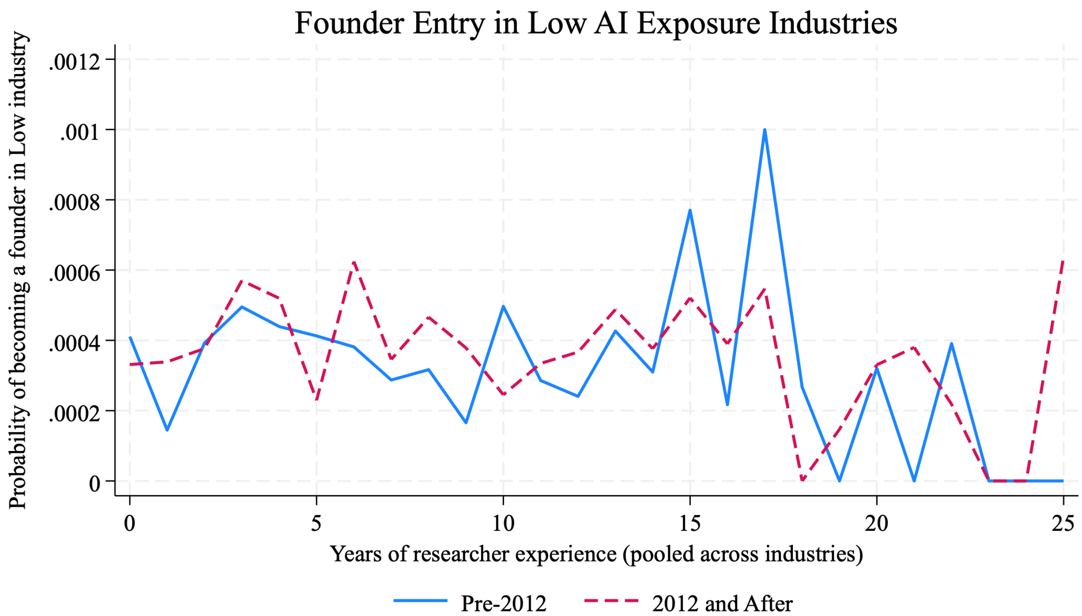


Figure 6: Probability of becoming founders by research experience – low AI exposure

4 Model

In this section, we present a model to discuss the effect of AI on the returns to experience with multiple industry and occupational choices of becoming a worker, researcher, or an entrepreneur. The setup of the model is similar to the framework in Huckfeldt (2022) with DMP style matching and a stochastic human capital accumulation similar to Ljungqvist and Sargent (1998). We particularly focus on the block recursive type equilibrium established by Menzio and Shi (2010) and Menzio and Shi (2011).

4.1 Environment

Time is discrete with a common discount rate β. The economy is populated by a continuum of agents who differ in their experiences, measured as (e_W, e_R), corresponding to a worker's experience as a worker and as a researcher. Agents follow a perpetual youth setup à la Blanchard (1985), exiting the economy at rate σ. In each time period, an equal measure of agents enters the economy as newborns, each drawing a random initial pair of experiences (e_W, e_R) from a joint distribution $F(e_W, e_R)$.

Firms post vacancies in perfectly segmented submarkets denoted by the experiences (e_W, e_R), occupation o, and industry j. In particular, there are three types of occupations: worker W, researcher R, and entrepreneur E. There are two types of industries: AI-intensive (or high exposure to AI shock) I and non-AI-intensive (or low exposure to AI shock) N. Workers search for a submarket to match with. Similar to Lazear (2004), we interpret occupations such that workers and researchers would focus more on one experience, while entrepreneur is required to have a more balanced experience pair. We assume complete contract as in Menzio and Shi (2011), such that each submarket is associated with a lifetime utility x. Given wage posting in x lifetime utility, workers direct their search into each submarket.

Workers can switch occupations and industries at a cost $c(e_W, e_R, o, j)$ both when they are unemployed and when they are employed.

4.2 Production Function

Firms in each occupation o and industry j produce output by taking only labor as input. The production function is given by a CES aggregator between the two experiences. Each occupation and industry is allowed to differ in production parameters.

$$g_{oj}(e_W, e_R) = A_{oj}(\alpha_o e_W^{\rho_{oj}} + (1-\alpha_o)e_R^{\rho_{oj}})^{\frac{1}{\rho_{oj}}} \tag{3}$$

The substitution parameter $\rho_{oj} \to \infty$ for occupations $\{W, R\}$ represents that agents in these two occupations only care about the maximum of their two experiences, while $\rho_{oj} \to 0$ for entrepreneurs, indicating that they require a more balanced pair of experiences (i.e. Cobb-Douglas production function). In our calibration, we consider large ρ_{oj} for workers and researchers and 0 for entrepreneurs, in the spirit of the key theoretical framework of Lazear (2004).

The share parameter α_o captures the relative importance of worker experience in occupation o. We assume $\alpha_W > \alpha_R$, so that worker experience is most important for workers, while researcher experience is most important for researchers.

4.3 Human Capital Accumulation

Human capital accumulation occurs stochastically while agents are employed. While employed in occupation $o\ in\{W, R\}$ and industry $j \in \{I, N\}$, with probability π_j, individuals' human capital e_o increases by Δ_e.

$$e_{o,E}^{t+1} = \begin{cases} (1-\tilde{d})\, e_{o,E}^t + \Delta_e, & \text{with probability } \pi_j \\ e_{o,E}^t, & \text{otherwise} \end{cases} \tag{4}$$

When unemployed, human capital depreciates at rate $\tilde{d_o}$ each period deterministically.

$$e_{o,U}^{t+1} = (1-\tilde{d_o})e_{o,U}^{t} \tag{5}$$

4.4 Timing of the Model

The timing of the model is illustrated as in Figure 7 and described as follows. At the beginning of each period, employed matches produce and unemployed individuals receive unemployment benfit b. After production, agents update their human capital based on their employment status and the stochastic process described earlier. Agents then experience exogenous separation shock at rate δ and are given the choice to endogenously separate to unemployment. Agents unemployed from previous time period search for new matches at the end of the period. Agents who exogenously or endogenously separate from their matches this period remain unemployed and can only search for a new match next period.

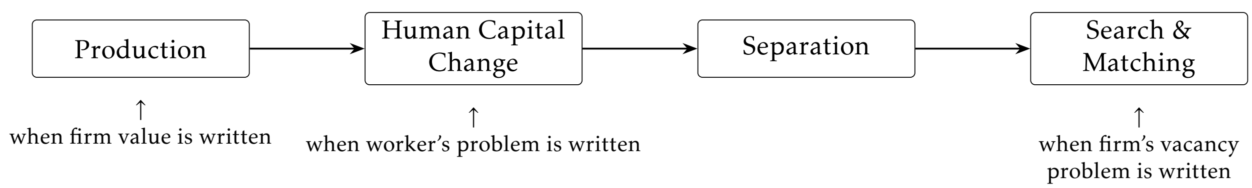


Figure 7: Timing of the Model

4.5 Value Functions

Now we are ready to write down the value functions. In particular, we will write down the match value function instead of laying out worker and firm problem separately. Let $\omega \equiv (e_W, e_R, o, j)$ denote the state of the economy.

For vacant jobs, firms post a vacancy with cost k_{oj} associated with a promised lifetime utility x.

$$V_t(\omega) = -k_{oj} + (1-\sigma)q(\theta_t(\omega))(J_t(\omega) - x) \tag{6}$$

Free-entry assumption implies:

$$q(\theta(\omega)) = \frac{k_{oj}}{J_t(\omega) - x} \tag{7}$$

For unemployed individuals conditional on not switching the industry-occupation pair, the value function is given by:

$$U_t(\omega) = b_{oj} + \max_x \left[(1-\sigma)\beta \mathbb{E}\{p(\theta_t(\omega_{t+1}))(x - U_{t+1}(\omega_{t+1})) + U_{t+1}(\omega_{t+1})\} \right] \tag{8}$$

Including endogenous switching,

$$\mathcal{U}_t(\omega) = \max_{o',j'} \{U_t(\omega) - c(\omega)\} \tag{9}$$

Finally, for employed matches, we can write down the joint value function as:

$$J_t^{\text{Act}}(\omega) = y_t(\omega) + \left[(1-\sigma)\beta \mathbb{E}\Big[\delta U_{t+1}(\omega') + (1-\delta)(J_{t+1}(\omega') + \lambda_e R(\omega'))\Big] \right] \tag{10}$$

Where $R(\omega)$ is the on-the-job search additional value:

$$R(\omega) = \max_{o,j,x} \{p(\theta(\omega))(x - J_t(\omega)) - c(\omega)\} \tag{11}$$

Considering endogenous separation, the final value function is given by:

$$J_t(\omega) = \max\{J_t^{\text{Act}}(\omega), \mathcal{U}_t(\omega)\} \tag{12}$$

Equilibrium We focus on Block Recursive Equilibrium (BRE) where the distribution of (e_W, e_R, o, j) is stationary. As long as each submarket results in the same optimal policy functions, the equilibrium can be block recursive. In particular, the optimal occupation and industry choices only depends on the agent's individual experience pairs, and does not rely on how competitive each submarket is. Market tightness is completely determined by matching efficiency and vacancy posting cost.

5 Model Calibration

In this section, we first describe our solution strategy for solving the steady state equilibrium of the model, followed by results from our calibration exercise for comparative statics.

5.1 Solution Strategy

The equilibrium is solved via standard value function iteration. The solution is obtained in the following process.

1. Precompute the flow value for each state space, and build human capital transition matrix for each state.

2. Initialize the value functions U_0 and J_0 using the separation and unemployment value

3. Given the value functions U_0 and J_0, compute net value in switching across destinations and obtain the optimal policy for both unemployed and employed individuals

4. Repeat the process in step 3 until convergence of value functions

The optimal occupation choices for any experience combination (e_W, e_R), as solved in this step, are illustrated in Figures 8a and 8b for AI-intensive and non-intensive industries, respectively. We observe that agents sort more into worker occupations; thus, as we shift from the initial distribution to the steady-state distribution of employed individuals, the concentration of experience shifts toward worker experience, while researcher experience deteriorates.

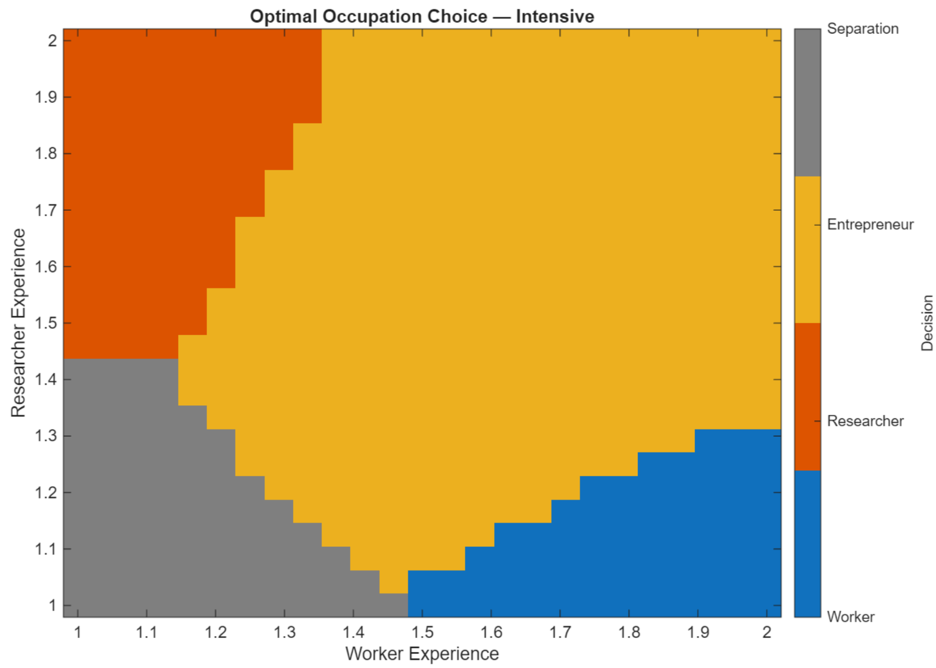
After obtaining the optimal value functions and policy functions, we build the transition matrix and invert it to obtain the steady state distributions. In particular, let μ_E and μ_U be the distributions of employed and unemployed individuals at current period, respectively. Then, the distribution of employed and unemployed individuals in the next period, denoted by μ'_E and μ'_U, can be expressed as:

$$\begin{aligned} \mu'_E &= \mu^{\text{stay}}_{E\to E} + \mu^{\text{switch}}_{E\to E} + \mu_{U\to E} \\ \mu'_U &= \mu_{U\to U} + \mu_{E\to U} + \text{NewBorn} \end{aligned} \tag{13}$$

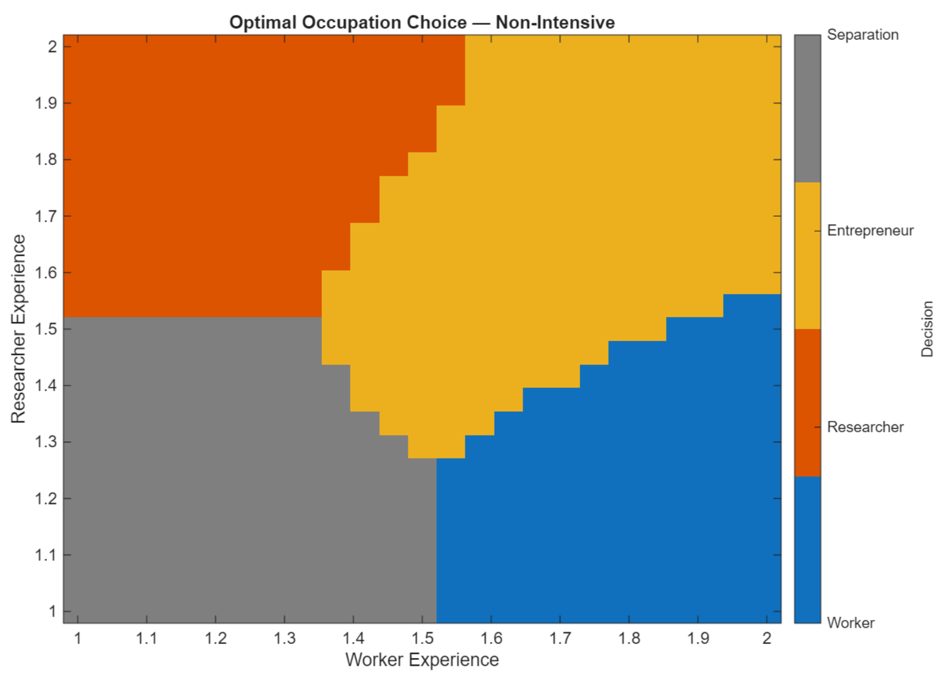
Or equivalently, we can build a transition matrix $\mathbb{TM}$ such that:

$$\begin{bmatrix} \mu'_E \\ \mu'_U \end{bmatrix} = \mathbb{TM} \begin{bmatrix} \mu_E \\ \mu_U \end{bmatrix} + \begin{bmatrix} 0 \\ \text{NewBorn} \end{bmatrix} \tag{14}$$

In our framework, the inflow of newborn individuals is set equal to the outflow of exiting individuals, ensuring a stationary population mass. Newborns are assigned to experience pairs (e_W, e_R) as unemployed, with a uniform allocation across occupations and industries. The initial experience distribution is concentrated near the lower end of the experience space, reflecting limited prior human capital. The specific distribution used is depicted in Figure 9a, where newborns are clustered at the bottom left corner of the experience pair, indicating low initial experience. Distributions are normalized to 1.

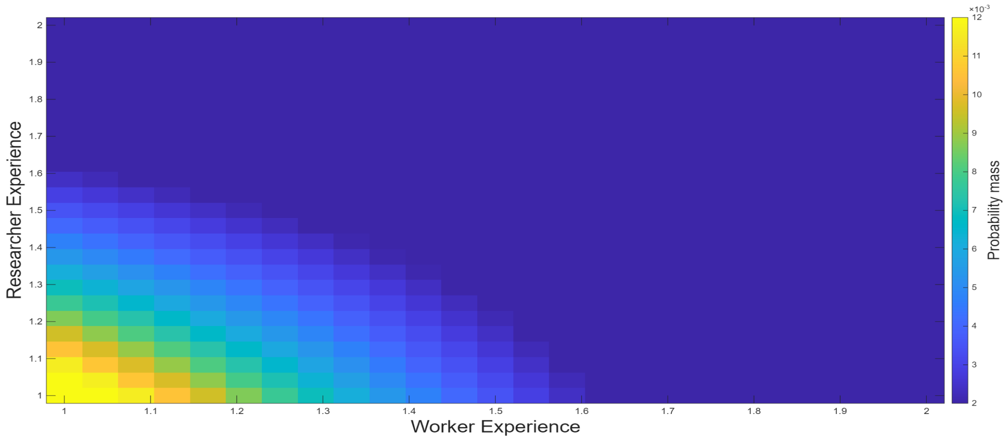


(a) AI Intensive Industries

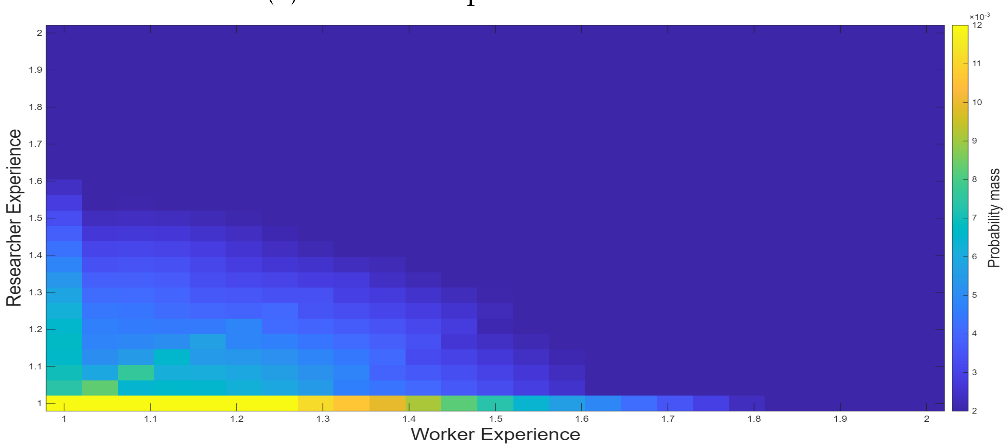


(b) AI Non-Intensive Industries

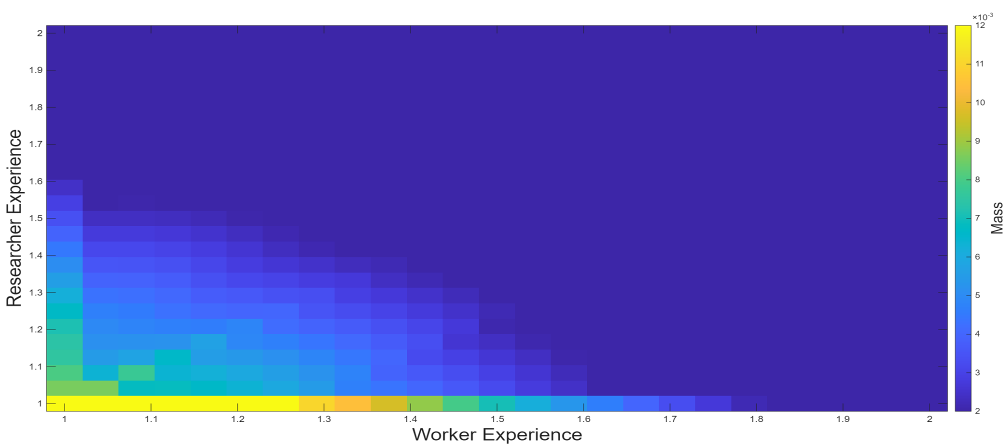
Figure 8: Optimal Occupation Choices for AI Intensive and Non-Intensive Industries



(a) Newborn Experience Distribution



(b) Employed Experience Distribution



(c) All Individuals Experience Distribution

Figure 9: Experience Distributions of (a) Newborns, (b) Employed, (c) All Individuals for the Baseline Calibration

5.2 Comparative Statics

In this section, we discuss key comparative statics. For the baseline calibration exercise, we set parameters to conventional values from the literature and focus on how changes in key parameters influence occupational shares. Proper estimation is left for future updates to this paper. As shown in Section 3, the introduction of AI leads to increases in the shares of founders and researchers, with a corresponding decrease in the share of workers. We highlight the model parameters that drive these changes.

Occupational Productivity Premium The occupational productivity premium is a key parameter influencing the distribution of workers across occupations. We simplify our productivity term by decomposing it into three components: an aggregate level $\bar{A}$, an occupation-specific premium A_o, and an industry-specific premium A_j, as shown in Equation (15).

$$A_{oj} = \bar{A} * A_o(o) * A_j(j) \tag{15}$$

For simplicity, we set $\bar{A}$ to 1 for normalization purposes. The baseline productivity is normalized so that AI-intensive industries are 10% more productive than non-intensive industries, researchers are 5% less productive than workers, and entrepreneurs are 15% more productive than workers. We vary the occupational productivity premium for workers, as illustrated in Figure 10a, and for researchers, as shown in Figure 10b, to examine how occupational shares change. The other two premia remain fixed when varying the occupational productivity premium for one occupation to observe the relative changes in occupational shares. Since our production function is continuous and smooth, the trends are monotonic even outside the range of variation demonstrated in the figures.

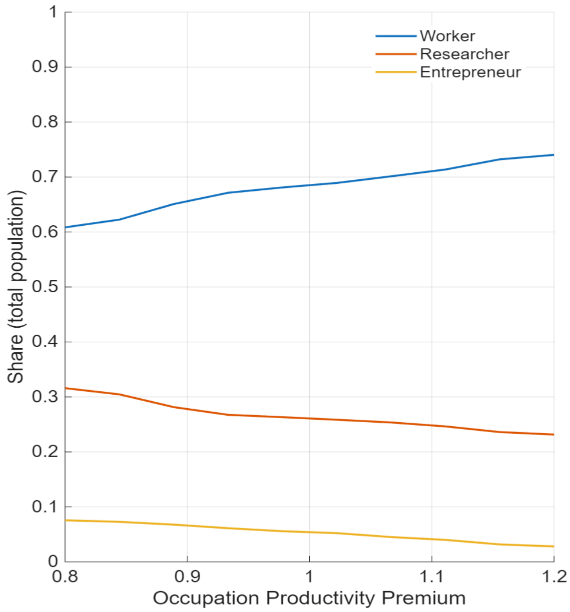
An increase in the worker productivity premium leads to more agents choosing to become workers, while fewer become entrepreneurs or researchers. In contrast, raising the researcher productivity premium increases the shares of both researchers and entrepreneurs, whereas increasing the worker productivity premium reduces both. This indicates that one way to interpret the impact of an AI shock on the labor market is through a rise in the productivity premium for researchers. This interpretation aligns well with the technological advances driven by AI that are spreading to other fields, such as Medicine, Healthcare, Finance, and etc. Therefore, these two parameters (normalize to entrepreneur productivity) are crucial in our model for estimation, which is stil ongoing.

Human Capital Accumulation Probability Since human capital accumulation is stochastic, the probability of increasing human capital is important in determining occupational choices. In our quantitative exercise, we discretize experience into grids and set researchers to have a 10% higher probability of accumulating researcher experience e_R than workers have of accumulating worker experience e_W. Therefore, we vary the worker human capital accumulation probability to observe how occupational shares change, while maintaining the 10% gap—i.e., researchers always accumulate experience faster.

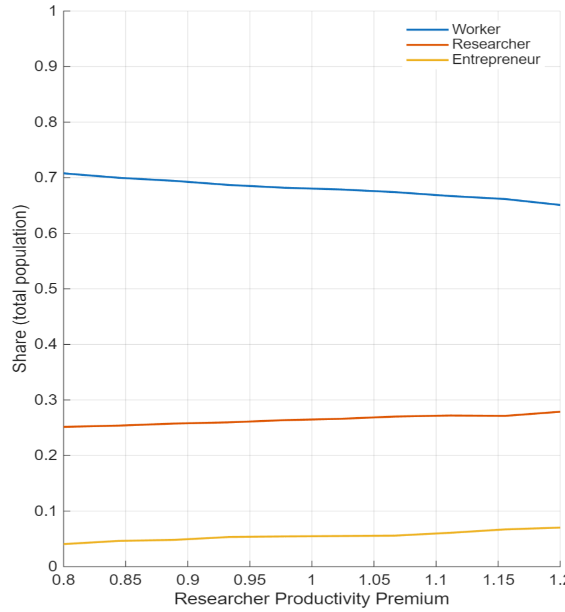
Figure 10c shows how the shares of each occupation change as the probability of human capital accumulation increases. As human capital accumulation becomes easier, the share of entrepreneurs rises, the share of workers falls, and the share of researchers first increases and then decreases. This illustrates the important mechanism of sorting agents by skill into different occupations. When it is easier to accumulate rather than lose human capital, agents are more likely to move toward the top right region of the experience space, where entrepreneurs are more likely to be found, as shown in Figure 8.

Matching Efficiency Following Menzio and Shi (2010), we choose constant elasticity of substitution contact rate functions $p(\theta) = (1+\theta^{-\gamma})^{-\frac{1}{\gamma}}$ and $q(\theta) = (1+\theta^{\gamma})^{-\frac{1}{\gamma}}$. The matching efficiency parameter γ is important in determining the tightness of the labor market. Figure 10d shows that with inefficient matching technology, most agents choose to become workers. Any small increase in matching efficiency leads to a large shift of the economy towards researchers and entrepreneurs. This is because, with more efficient matching technology, there is a higher probability of being matched with the occupation that returns higher values. Thus, more agents move into these occupations—entrepreneurs and researchers—given that they have higher productivity baselines.

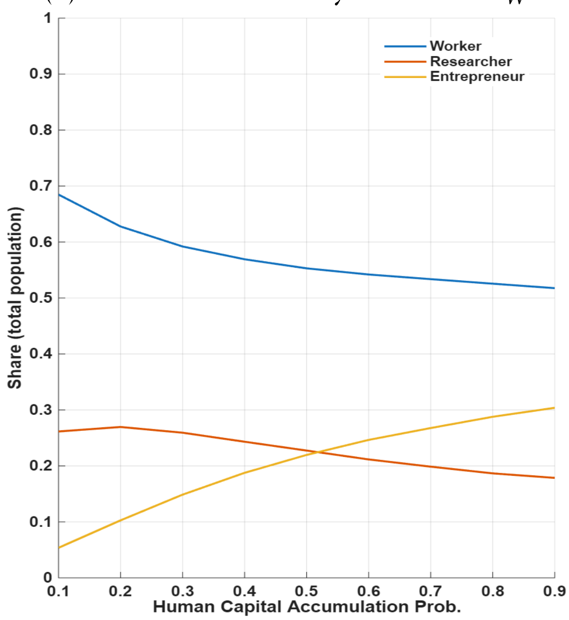
Effect of Increase in Researcher Productivity Premium on Skill Distribution From the previous discussion, we can infer that AI likely increases the researcher productivity premium. We now examine how this change affects the experience distribution of individuals. Compared with Figure 9b and 9c, Figure 11 shows a clear shift towards the upper left of the experience distribution map, making the steady-state distribution of experience more symmetric across the two experience types. Individuals with higher researcher experience are now incentivized to shift to researcher roles and entrepreneurship.



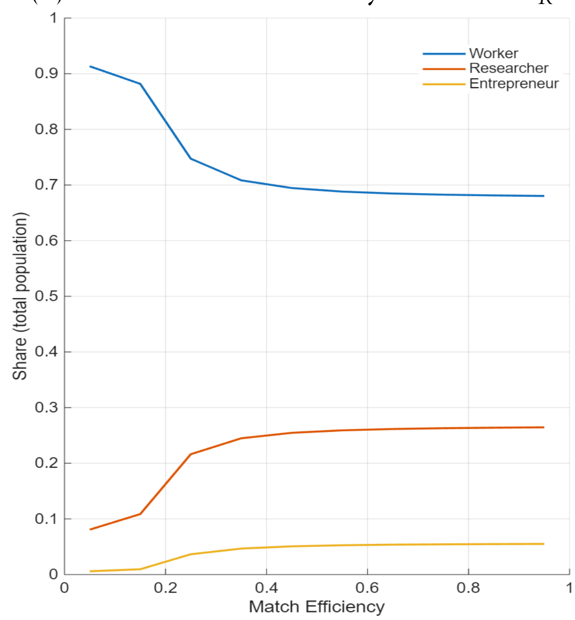
(a) Worker Productivity Premium A_W



(b) Researcher Productivity Premium A_R

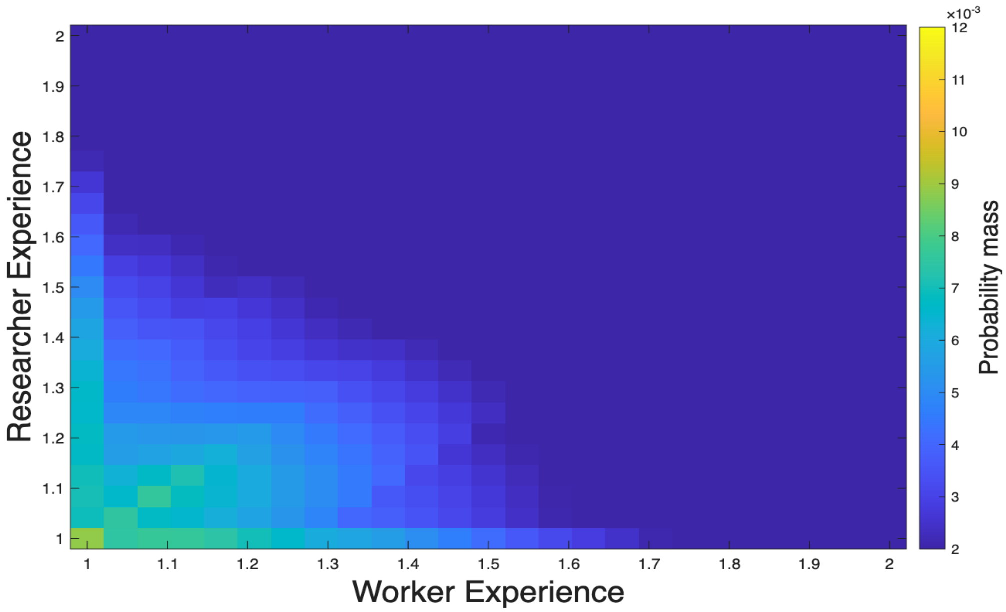


(c) Human Capital Accumulation Prob. π

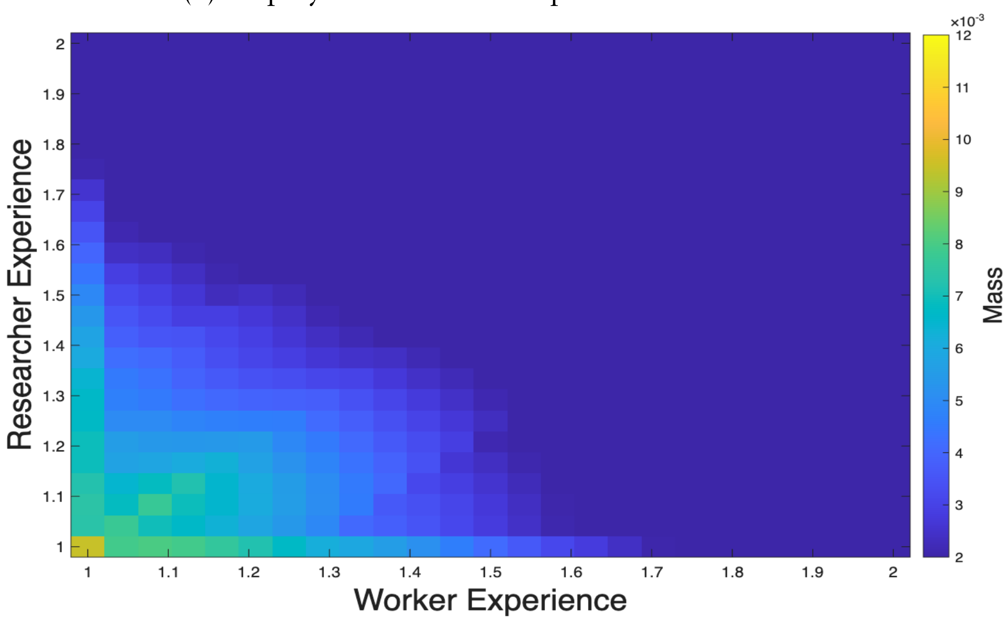


(d) Match Efficiency γ

Figure 10: Comparative Statics: Occupational Share Changes vs Key Parameter Changes



(a) Employed Individuals Experience Distribution



(b) All Individuals Experience Distribution

Figure 11: Effect of Increase in Researcher Productivity Premium on Experience Distributions for Employed Individuals and All Individuals

6 Conclusion

This paper studies the impact of Artificial Intelligence on the returns to experience in entrepreneurship. We distinguish between two main types of experience: general work experience, which is repetitive and prone to substitution by AI, and research experience, which is otherwise hard to substitute. We confirm that AI increases the rate of entrepreneurship and the share of researchers via a difference-in-differences analysis using LinkedIn data. We also find that the average work experience before becoming a founder has increased. Importantly, research experience is more valuable, and we document a shift towards more experienced researchers starting their own businesses. Through the lens of our quantitative model with multidimensional skill and human capital accumulation, we find that AI primarily increases the productivity premium for research experience, biasing the labor market towards individuals with such backgrounds. This has important implications for understanding how AI is reshaping the entrepreneurial landscape and the value of different types of experience in this context.

Our work is among the first to empirically investigate the intersection of AI and entrepreneurship through multidimensional skill frameworks. This is an active area of research, and we aim to carefully estimate the model parameters and provide quantitative results on how AI impacts entrepreneurship and the returns to experience.

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