MNE Experience Fosters Innovative Entrepreneurship: Evidence from China*

Xiaohan Yang† Xiaobo Zhang‡

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Abstract

This paper establishes a causal link between entrepreneurs' prior work experience in multinational enterprises (MNEs) and the innovation performance of their subsequent domestic ventures. Using China's FDI deregulation as a quasi-natural experiment and employing a shift-share instrumental variable design based on rich micro-level survey data, our results reveal that MNE-experienced entrepreneurs exhibit a significant "innovation premium." We unpack the "black box" of FDI knowledge spillovers through the entrepreneurial mobility channel, identifying three primary mechanisms: (i) internal technical and managerial spillovers coupled with human capital accumulation; (ii) enhanced business formalization and institutional governance; and (iii) the leveraging of external production networks to decode tacit knowledge. We find that this innovation is not merely imitative; it generates substantial improvements in product novelty, quality, and digital adoption. These advantages translate into superior business outcomes, including higher revenues, deeper integration into international trade, and higher survival rates. Our findings highlight the critical role of MNEs as "training grounds" for domestic innovative entrepreneurs and caution that "FDI flight" in an era of geopolitical decoupling may sever essential knowledge pipelines for emerging economies.

Keywords: Multinational enterprises (MNEs), FDI spillover, Entrepreneurship, Innovation, Work experience.

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†Department of Economics, The Chinese University of Hong Kong. E-mail: xiaohanyang@cuhk.edu.hk.

‡Guanghua School of Management, Peking University and International Food Policy Research Institute (IFPRI). E-mail: x.zhang@gsm.pku.edu.cn.

1 Introduction

In developing economies, the transition from Multinational Enterprises (MNEs) to high-growth startups represents a distinctive pathway to entrepreneurial success. Entrepreneurs who carry the "DNA" of global corporations often secure significant competitive advantages. For instance, Robin Li leveraged his firsthand experience at the U.S. internet firm Infoseek to found Baidu, later a dominant Chinese search engine. In Africa, Taha Jiwaji drew on the skills and strategies acquired at Capgemini to build Beem, a Pan-African cloud communications platform. Even in less technical sectors, this expertise is vital: Richard Regaspi used the operational management skills honed at a luxury health club in Dubai to scale his food and training businesses in the Philippines, his home country.[1] These narratives, spanning Asia and Africa, demonstrate that MNE experience is far more than a line on a resume; it is a powerful catalyst that equips founders with world-class standards, strategic foresight, and global networks. Consequently, understanding this "MNE-to-entrepreneur" pipeline is indispensable to analyzing modern entrepreneurial success in emerging markets.

Although these celebrated success stories are highly visible, it remains an empirical challenge to determine whether the MNE experience benefits ordinary entrepreneurs more broadly, particularly within the vast segment of small- and medium-sized enterprises (SMEs). As more workers cycle through global corporations, does this experience systematically increase the likelihood of innovative entrepreneurship? Research on how the MNE experience fosters entrepreneurship and innovation in this context remains significantly understudied, constrained by a triad of theoretical, data, and methodological challenges.

On the theoretical front, it is unclear whether MNEs promote or crowd out entrepreneurship. While MNEs offer positive spillovers (Audretsch and Feldman, 2004; Javorcik, 2004), they also provide lucrative high wage premiums that may poach local talent (Fosfuri et al., 2001; Heyman et al., 2007), discouraging high-ability individuals from taking the risks of venture creation. This perspective suggests that MNEs might inhibit knowledge diffusion by "locking in" talent, a possibility that counters the positive "spinout" narrative. Thus, the overall effect remains an open empirical question.

Another primary hurdle is the scarcity of granular, individual-level data that tracks entrepreneurs from their prior MNE employment to subsequent ventures. The data gap is

[1] Please refer to https://www.gsb.stanford.edu/insights/local-startup-pan-african-success-beem-story and https://theaseanmagazine.asean.org/article/from-migrant-worker-to-entrepreneur-a-success-story/.

particularly acute in developing countries (Angrist et al., 2021), which often lack the capacity to collect consistent, high-quality longitudinal data at the firm- and worker-levels. Though some studies utilize employer-employee matched data (e.g., Poole, 2013; Kwan et al., 2025), these sources often fail to adequately capture the earliest stages of startup activities or suffer from issues of representativeness (Hellerstein and Neumark, 2006) and selection bias.

Finally, isolating the causal effect of MNE experience is difficult. Individuals hired by MNEs are often inherently more talented, educated, and ambitious—the very traits that may correlate with entrepreneurial success. It is difficult to disentangle whether their success stems from their experience, i.e., the "imprint" effect of MNE training (Simsek et al., 2015), or their inherent personal qualities (the "selection" or "sorting" effect) as in Bai et al. (2025a).

China serves as an ideal laboratory to address these challenges for several reasons. First, following four decades of transition to an open economy, MNEs have employed millions of Chinese workers, allowing us to observe the long-run entrepreneurial behavior of this massive cohort. Second, we use the Enterprise Survey for Innovation and Entrepreneurship in China (ESIEC), which provides unique, representative micro-level data that track both entrepreneurs' career histories and their ventures' performance. By linking this with administrative data—a method known as "enriched asking" (Salganik, 2019)—we capture a holistic and objective view of business outcomes.

To address the endogeneity of MNE employment (mainly the "selection" *vs* "treatment" problem), we employ a Bartik-style instrument approach. Specifically, we leverage China's foreign direct investment (FDI) deregulation following its accession to the World Trade Organization (WTO) in 2002 as a quasi-natural experiment, as in Lu et al. (2017) and Liang et al. (2024). By interacting these sectoral policy shifts with pre-existing regional industrial compositions and migration patterns, we construct a shift-share instrumental variable (SSIV). This strategy captures plausibly exogenous variation in local exposure to MNE employment opportunities, establishing a causal identification framework.

Our results document a significant "innovation premium" for these MNE-experienced entrepreneurs. Their ventures exhibit higher rates of self-reported innovation activity and superior performance in administrative metrics such as trademark registrations. We identify three primary mechanisms: internal technology and management spillovers, firm formalization, and strategic positioning within global production networks. These findings highlight the entrepreneurial mobility channel as a vital conduit for FDI spillovers, in a spirit similar to, but distinct from, Fang et al. (2023). Beyond innovation, we also find positive effects on

firm productivity, international trade, and digitization. Moreover, supplementary analysis of a nationally representative household survey in China provides suggestive evidence that prior MNE experience also promotes entrepreneurship at the extensive margin.

While centered on the Chinese experience, these findings offer broader insights for developing economies worldwide. As the world's second-largest FDI recipient transitioning from "Made in China" to "Innovated in China," it presents a critical context for the broader implications of FDI-driven entrepreneurial development. The transition toward an open-market system and the liberalization of trade are shared trajectories across many emerging nations, where MNEs serve as critical conduits for diffusing advanced technologies and sophisticated management practices.

The experience-to-entrepreneurship pathway is likely to manifest itself in any context where institutional transformation, global integration, and nascent entrepreneurial ecosystems intersect. In these environments, the movement of MNE-trained talent into the domestic sector becomes a primary engine for structural change. Ultimately, our study suggests that for the developing world, the ability to leverage foreign presence into domestic "experiential DNA" is a cornerstone of successful economic upgrading and long-term industrial resilience. It also implies that current trends toward de-globalization and the potential retreat of foreign investment may do more than just reduce capital inflows; they may actively undermine the foundational mechanisms of entrepreneurship and innovation in developing countries. Policymakers should therefore view MNEs not merely as sources of employment or tax revenue, but as "incubators" of human capital that are vital for long-term industrial upgrading.

Our study is related to several strands of literature. First, it contributes to the extensive literature on FDI and MNE spillovers, which encompasses dimensions such as productivity (Brandt et al., 2012, 2017), spinoffs (Rizvi et al., 2025), demonstration effects (Cheung and Lin, 2004), illegal imitation (Lam, 2024), production networks (Bai et al., 2025b; Choi et al., 2025), worker mobility (Görg and Strobl, 2005; Cai et al., 2007; Balsvik, 2011), trade expansion (Aghion et al., 2023; Liang et al., 2024; Liu et al., 2024), and competition effects (Aitken and Harrison, 1999; Bao and Chen, 2018; Choi and Shim, 2024).

Within the Chinese context, the literature presents a nuanced picture. Some studies suggest that innovation spillover occurs in China through demonstration (Cheung and Lin, 2004) or competition-induced efficiency (Gong, 2023; Jiang et al., 2024; Ding et al., 2024). Conversely, others highlight a more adversarial relationship: Lu et al. (2017) document

negative horizontal spillover effects on productivity within the same industry, and find little evidence of benefits for domestic startups. Similarly, Liu et al. (2024) observes that FDI can negatively impact Chinese firms' export quality due to intensified market competition.

While existing research predominantly examines aggregate impacts or general knowledge spillovers (e.g., Burstein and Monge-Naranjo, 2009; Lin et al., 2009; Cai et al., 2022; Ma and Zhang, 2024; Cai and Xiang, 2025), it often overlooks the specific experience-to-entrepreneurship pathway. Since these effects are ultimately realized through human agency, we zoom in on the micro-impact of MNE experience on entrepreneurship and firm performance. Our work highlights the pivotal role of entrepreneurial mobility as a conduit for knowledge diffusion (Choi et al., 2025), organizational formalization (Sirén and Kohtamäki, 2016), and strategic movement along production networks (Cardoza et al., 2025). By centering the entrepreneur, we complement evidence on direct productivity benefits (Javorcik, 2004) and vertical supply-chain linkages (Setzler and Tintelnot, 2021; Alfaro-Urena et al., 2022) with a novel, person-centric channel: the transfer of operational and innovative DNA through founders.

Second, our study relates to the emerging literature on how prior experiences shape subsequent economic behavior, as documented among politicians (Chen et al., 2024; Guo et al., 2024), investors (Koudijs and Voth, 2016), scientists (Wang et al., 2019), and students (Oreopoulos et al., 2012; Huang and Dong, 2025). Previous research has documented the lasting impact of diverse backgrounds, including finance (Custódio and Metzger, 2014), military service (Benmelech and Frydman, 2015), early-life disasters (Bernile et al., 2017; O'Sullivan et al., 2021; Ru et al., 2025), aviation hobbies (Sunder et al., 2017), family environments (Cronqvist and Yu, 2017), poverty (Xu and Ma, 2022), and exposure to banking crises (Yu, 2025). However, due to a lack of effective identification strategies, the causal effects of endogenous work experiences remain under-explored, with notable exceptions focusing primarily on CEOs of public firms (Custódio and Metzger, 2013, 2014) and founders of high-tech startups (Hashai and Zahra, 2022).

While this body of literature is extensive, existing studies on entrepreneurs have focused disproportionately on publicly listed firms. This has left a critical gap in understanding how prior experience influences the decision-making of general entrepreneurs of SMEs, as opposed to that of CEOs in established, large-scale operations. We address this by investigating MNE work experience across the broader economy, leveraging China's staggered FDI liberalization as a source of quasi-experimental variation, which serves as a proxy for localized exposure

to MNE employment opportunities. Our approach overcomes identification challenges and extends evidence beyond elite samples to the general population of entrepreneurs.

Our findings offer a necessary counterpoint to existing selection-based narratives. While work such as Fang et al. (2023) suggests that firms founded by laid-off state-owned enterprise (SOE) workers perform better due to a "reluctant" selection of high-skill talent, our study identifies a different mechanism: MNE-related gains are driven by the acquisition and transfer of specific operational capabilities and networks, rather than merely the selection of inherently high-ability individuals "pushed" into entrepreneurship.

Furthermore, while our paper shares thematic ground with the literature on overseas returnees (Liu et al., 2010; Zweig and Wang, 2013; Giannetti et al., 2015), it differs in scope. Returnee literature typically focuses on an elite subset, whereas MNE employment represents a more prevalent and accessible pathway for domestic talent development in emerging economies.[2]

Third, we contribute to the relatively underdeveloped literature on MNE experience specifically. While research has explored how workers' MNE exposure influences knowledge spillovers (Balsvik, 2011) or wage premiums (Poole, 2013), studies examining how this experiential learning drives entrepreneurial decision-making and innovation remain limited.

Within the context of China, the findings on MNE experience have been largely ambiguous. For instance, Yuan and Lu (2005) observed negligible effects of MNE experience on the performance of large private firms, while Liu et al. (2014) found only a modest productivity advantage for MNE-experienced entrepreneurs. However, both studies rely on data prior to 2005—a period shortly after China's WTO accession that preceded the most significant wave of FDI inflows. By focusing on large enterprises during this early transitional era, existing literature may overlook the broader population of SMEs, where entrepreneurial dynamics and the "experiential DNA" of the founder are most critical. By utilizing recent survey data, we capture the long-term effects of FDI presence in China, moving beyond the immediate post-WTO adjustment period.

[2] Liu et al. (2010) finds that returnee entrepreneurs constitute only 3.8% of a high-tech cluster in Beijing, a figure substantially lower than the share of MNE-experienced entrepreneurs in our representative sample.

2 Data

2.1 Pattern on Foreign MNEs in China

China's FDI trajectory has undergone significant shifts since the founding of the People's Republic of China in 1949. Between 1949 and 1978, FDI was virtually nonexistent under a highly planned and closed economic regime, with only minimal inflows from its socialist allies (the *Socialist Camp*, see Hu et al., 2023) and overseas Chinese. Formal FDI was effectively suspended during this period. A pivotal turning point occurred in 1979, when China initiated trial policies and established Special Economic Zones (SEZs) to attract foreign capital, which initially arrived largely in the form of loans.

From 1992 onward, following Deng Xiaoping's southern tour and the subsequent top-down reemphasis on reform and opening up, FDI activities expanded substantially (see Appendix Figure A.1). After joining the WTO in late 2001, China entered a period of rapid economic expansion and accelerated trade liberalization, quickly becoming a leading global destination for FDI. As illustrated by the trend line, the volume of newly established foreign-invested enterprises closely mirrors aggregate FDI inflows, confirming that MNEs serve as the primary vehicle for FDI realization (narrowly defined FDI). Consequently, the economic effects of FDI are fundamentally channeled through the operations, employment, and knowledge diffusion associated with MNEs. However, in recent years, growing skepticism has emerged regarding whether FDI is now "escaping" from China, a concern underscored by a notable decline in inflows. This shift highlights both the urgency and policy relevance of examining how FDI spillovers—specifically through MNE work experience—can continue to foster domestic entrepreneurship and innovation even amid changing investment patterns.

Throughout this period, numerous overseas MNEs entered China's vast consumer and industrial markets. Although they accounted for only approximately 2-3% of all market entities in China during this time frame, they have played a disproportionately significant role in China's urban employment. As shown in Panel (a) of Figure 1, following China's WTO accession, urban employment within MNEs witnessed substantial growth. By 2014, the share of MNE employment in total urban employment peaked at nearly 8%. However, since then, this upward trajectory has reversed, with a noticeable decline in urban MNE employment.[3] By comparison, the contribution of SOEs to urban employment has declined

[3]This shift can be attributed to several factors, including intensified domestic competition, rising protectionism in major economies, and structural changes within global supply chains.

from a peak of nearly 70% in the mid-1990s to approximately 20% in 2014 and 15% in 2024, as shown in Panel (b), primarily driven by the expansion of the private sector (Lu and Feng, 2025).

2.2 Data Source

ESIEC survey data. The scarcity of representative micro-level data linking entrepreneurs' personal experiences to their business operations poses significant empirical challenges, even in the era of big data. To bridge this gap, the study primarily draws on the Enterprise Survey for Innovation and Entrepreneurship in China (ESIEC). This field survey provides high-quality data on representative private incorporated firms and self-employed individuals across 107 counties in six provinces in China: Liaoning, Shanghai, Zhejiang, Henan, Guangdong, and Gansu.

While the sampling frame was designed to be representative within each of these six provinces, benchmarking against the China Economic Census 2018 confirms that the ESIEC is nationally representative with respect to industry composition and firm-size distribution (Dai et al., 2021, see also Appendix C). A key advantage is its dual focus: the questionnaire is both entrepreneur- and business-specific. It captures a wide range of variables regarding the entrepreneur's personal characteristics, career history, and family background, alongside firm-level data on innovation activities, digitization, and financial performance. Furthermore, its compatibility with external big data sources significantly enhances its analytical potential.

Specifically, we use pooled cross-sectional data from the 2018 and 2023 waves of the ESIEC baseline surveys. To ensure data quality and align with the research design, the sample focuses exclusively on founder-entrepreneurs, who were actively involved in core business decision-making. This focus is advantageous because names listed in official business registration may suffer from delayed updates or "nominee" (proxy) arrangements. To refine the sample, we exclude professional managers who responded to surveys but were not the original founders. In addition, we exclude enterprises established after 2017 (for the 2018 wave) or 2022 (for the 2023 wave) to ensure that all included firms have a full year of performance data for the respective baseline year. These exclusions did not result in substantial sample loss or bias.[4] Notably, because the innovation module in the 2023 survey was administered

[4]A comparison of basic characteristics, e.g., industry distribution, employment size, and establishment year, between the full sample and attrited observations reveals no statistically significant differences, suggesting that sample attrition is unlikely to introduce systematic bias into the analysis.

only to incorporated private firms, our final baseline analysis consists of 5,538 valid observations: 4,742 incorporated firms from both waves and 796 self-employed individuals from the 2018 wave, as in Appendix Table B.1.

Supplementary data. Regarding innovation outcomes, we match the firm subsamples to their intellectual property (IP) statistics, specifically patents, trademarks, and copyrights. These data were obtained from administrative registration sources via *Tianyancha*, an authorized commercial data provider. We also supplement the survey data with multiple administrative records, including the universal business registration dataset from the State Administration for Market Regulation (SAMR, formerly the SAIC), Population and Economic Censuses data from the National Bureau of Statistics, and China Customs records. Additionally, the China Family Panel Studies (CFPS), a nationally representative longitudinal household survey, and an online resume dataset are also included. Each of these data sources is introduced in further detail in its respective section.

2.3 Extensive Margin

We first construct the key independent variable, $MNEJob_i$, which defines the treatment group in our study. The variable captures whether the entrepreneur i had worked in an MNE prior to founding their first business. Following standard definitions, we define an MNE as either a wholly foreign-owned enterprise or a Sino-foreign joint venture, including firms funded by capital from Hong Kong, Macao, and Taiwan (HMT regions). Notably, enterprises that originated in mainland China, including "home-grown" multinationals or domestically founded firms with current overseas ownership structures (e.g., Alibaba), are not classified as MNEs under our definition.

As presented in the summary statistics in Table 1, nearly 8.5% of surveyed entrepreneurs had prior work experience in MNEs, a proportion that remains stable across the two waves. This share is significantly higher than those reported in earlier studies (Yuan and Lu, 2005; Liu et al., 2014), which relied on data prior to 2004 — a period preceding the most rapid expansion of FDI inflows and the proliferation of foreign-invested enterprises in China (see Appendix Figure A.1).

To validate this pattern, we examine the ESIEC data alongside the supplementary data from CFPS. These two representative datasets allow us to track entrepreneurs and salaried workers, respectively, providing detailed information on birth cohorts and the timing of

MNE employment. As shown in Panels (a) and (b) of Figure 2, the proportions of both entrepreneurs and salaried workers with MNE experience exhibit a gradual upward trend across successive birth cohorts. This trajectory aligns with the expansion of FDI inflows, the rising presence of MNEs (Appendix Figure A.1), and the aggregate share of MNEs in urban employment as shown in Panel (a) of Figure 1, during the years these cohorts entered the labor market.

More importantly, the prevalence of MNE experience is substantially higher among entrepreneurs than among salaried workers. As indicated by the average (red line) and 95% confidence intervals (dashed lines) in Figure 2, only 2.7% of wage workers in the CFPS report MNE experience, a figure lower than the aggregate urban employment share, largely due to the survey's broader inclusion of rural populations. In contrast, nearly 8.5% of entrepreneurs report prior MNE work experience. A simple Bayesian framework (detailed in Appendix D.1) suggests that individuals with prior MNE experience exhibit a significantly higher propensity for entrepreneurship than the unconditional average, highlighting a robust extensive margin effect of MNE experience on entrepreneurship.

Furthermore, we utilize prior SOE experience as a comparison group. Like MNE employment, SOE positions represent formal, salaried roles within an enterprise setting and are subject to competitive selection. However, as shown in Panels (c)-(d) of Figure 2, no analogous pattern exists for SOEs. In fact, individuals with an SOE background are significantly underrepresented among entrepreneurs relative to salaried workers, as evidenced by the red and dashed lines (confidence intervals).

Overall, these descriptive findings support that MNEs serve as a training ground for domestic entrepreneurship. While acknowledging the significant extensive margin of MNE experience on entrepreneurship, our study focuses primarily on the intensive margin, specifically investigating its effects on innovation.

2.4 Variables on Innovation

Regarding the intensive margin, our baseline measure of innovation is a binary indicator capturing two primary dimensions widely recognized in the literature: process innovation and product innovation. This variable takes a value of one if the respondent reported introducing either type of innovation in the year preceding the survey. Table 1 shows that 43.2% of the entrepreneurs in our sample reported engaging in innovation. The survey further captures more detailed innovation-related information, such as marketing and environmental

innovation, as well as input-side metrics including R&D expenditure and R&D employment.

For the subsample of incorporated firms, these self-reported measures are supplemented with matched administrative data from *Tianyancha*. Specifically, we collected the number of patents, trademarks, and copyrights obtained since a firm's inception. Notably, the self-reported innovation rate (43.2%) significantly exceeds the proportion of firms holding patents (6.9%), trademarks (13.2%), or copyrights (3.0%). This discrepancy suggests that certificate-based measures may underestimate innovative activity among SMEs, which often lack the substantial research capabilities and financial resources required for formal IP registration. By integrating these measures, we advance the measurement of corporate innovation, particularly for small businesses in emerging economies (Rammer et al., 2009).

The summary statistics of primary personal characteristics and business operation indicators in Columns (1)-(2) of Table 1 are consistent with those reported in Huang et al. (2025). However, the differences between MNE-experienced and non-MNE-experienced groups, as shown in Columns (3)-(5), imply that a set of covariates must be further controlled for in our empirical specification.

To establish a more comparable control group, we refine the baseline specification by including an indicator for prior SOE work experience. This allows us to isolate the specific effect of MNE experience relative to both individuals with no prior work history and those from other organizational backgrounds, particularly SOEs. Table 1 reveals that 15.7% of entrepreneur respondents reported having SOE work experience. When comparing MNE-experienced entrepreneurs with their SOE-experienced counterparts (columns 6-7), the two groups appear largely balanced across most observable characteristics. The key exceptions are that entrepreneurs with SOE experience are more likely to be members of the Chinese Communist Party (CCP) and less likely to have engaged in export activities in the year preceding the survey.

Finally, Figure 3 presents an unconditional comparison among the groups discussed above. Panels (a) and (b) compare the self-reported innovations with patent data. We find that entrepreneurs with prior MNE work experience exhibit a significantly higher propensity to introduce process or product innovations than either the SOE-experienced group or the remaining sample. This distinction is less pronounced for patent-based measures, highlighting the importance of including self-reported innovation indicators alongside externally verified data. Notably, while the observable characteristics of the MNE-experienced and SOE-experienced groups are well balanced, their innovation performance diverges markedly.

Panels (c) and (d) show consistent patterns for input-side R&D measurements, further reinforcing the MNE-specific innovation advantage.

3 Estimation Strategy

3.1 OLS Regression

Regarding the empirical strategy, we begin by estimating the effect of prior MNE work experience on entrepreneurial innovation using an ordinary least squares (OLS) specification:

$$Y_{i,cjw} = \beta \cdot \text{MNEJob}_i + \beta_S \cdot \text{SOEJob}_i + \text{Control}_i'\gamma + \underbrace{\theta_c + \eta_j + \phi_w}_{\text{FEs}} + \epsilon_i, \tag{1}$$

where $Y_{i,cjw}$ represents the measurements for innovation (binary indicators, counts of innovation, or specific outcomes), potential channels, and other operational performance metrics for enterprise i in county c, industry j, and survey wave w.

The key independent variable $MNEJob_i$ captures the individual-level work experience in MNEs prior to the founding of the entrepreneur's first business. This retrospective construction helps mitigate concerns regarding reverse causality, as the recorded experience strictly predates the entrepreneurial venture. We address potential self-selection bias in the subsequent subsection.

The specification (1) includes $SOEJob_i$ to provide a comparable counterfactual of formal organizational experience. We further include a comprehensive set of control variables encompassing entrepreneur characteristics, such as age, gender, college education (dummy), and Communist Party membership (dummy), as well as firm attributes including total assets, registration type, and a dummy for the presence of corporate shareholders (to control for corporate spin-off). Additionally, we control for operational metrics from the year preceding the survey, including new investment (dummy), export activity (dummy), and total employment.

The regression model incorporates fixed effects for county, 1-digit industry, and survey wave. Standard errors are clustered at the level consistent with the instrumental variable introduced later in the analysis. For robustness, as the baseline dependent variable is binary, we also estimate Probit, Logit, and Poisson Pseudo Maximum Likelihood (PPML) regressions. Results remain robust in both sign and magnitude when controlling for more granular

industry fixed effects (2-digit, 3-digit, and, where available, 4-digit), as in Appendix Table B.2.

Table 2 reports the OLS estimation results. As shown in Column (1), entrepreneurs with prior MNE experience exhibit an approximately 17.5% higher probability of engaging in product or process innovation. Columns (2) through (5) decompose this effect across specific innovation types: the most substantial impact is observed in product innovation, followed by process and sales innovation, while environmental innovation remains statistically insignificant. When examining formal IP outcomes in Columns (6)–(8), the point estimates for MNE experience remain positive but become less pronounced and statistically insignificant. In contrast, prior SOE employment shows no significant relationship with overall innovation, with coefficients near zero across most specifications.

To account for local FDI spillover effects, such as agglomeration and competition effects at the county-industry level, we introduce interactive fixed effects and more disaggregated industry classifications in Panel A of Appendix Table B.2; the results remain robust. However, OLS estimates may still reflect unobserved inherent differences rather than a causal effect, raising endogeneity concerns. To address this, we employ Propensity Score Matching (PSM) using data from the 2018 wave, matching on individual characteristics and business attributes. The PSM results, presented in Appendix Table B.3, align with the baseline estimates. Nonetheless, unobservable factors may still introduce bias into our estimates. Therefore, the subsequent sections develop a more comprehensive causal identification strategy.

3.2 Identification

A key identification challenge arises from the endogeneity of prior career decisions. An individual's inherent characteristics, such as risk preference and latent ability, play a complex role in shaping migration, education, and career paths, leading to a non-random selection into MNE employment. These same traits likely influence both the decision to start a business and subsequent innovative activities. To address this, we employ a Bartik-style instrumental variable strategy that introduces plausibly exogenous variation in an entrepreneur's propensity to work in MNEs prior to founding their venture.

Our identification strategy leverages exogenous policy variation from China's Catalog for the Guidance of Foreign Investment Industries (hereafter the *Catalogue*). First introduced in 1995, the *Catalogue* is a cornerstone industrial policy that classifies sectors into four tiers:

(i) Encouraged (encouraged through incentives), (ii) Permitted (default), (iii) Restricted (subject to higher requirements), and (iv) Prohibited (complete market closure). An example is presented in Appendix Figure A.2. We coded various versions of these documents using both LLM-assisted labeling and manual checks to ensure precision.

A major revision occurred in 2002 when China implemented its WTO accession commitments, leading to substantial deregulation, particularly through the expansion of the "Permitted" category. This institutional shift triggered significant MNE entry (Lu et al., 2017) and has been widely used to examine FDI spillover effects (Lu et al., 2017; Liang et al., 2024; Liu et al., 2024). We leverage this policy shock to construct a measure of individualized MNE exposure.

We construct a shift-share instrument (Bartik-style, Bartik, 1991) that combines: (i) An industry-level policy shock from the 2002 *Catalogue* revisions (relative to the 1997 baseline), which differentially affected sectors based on their deregulation intensity, and (ii) Pre-existing industrial composition and migration patterns at the local level. The precise records of birthplace and birth year in the ESIEC allow us to match deregulation-induced MNE expansion to the specific "exposure window" when an individual was likely to enter the labor market. The identifying assumption is that local industrial composition prior to WTO accession influences post-2002 MNE job availability primarily through the policy-induced channel rather than unobserved traits, conditional on birth cohort and birthplace. This approach follows recent applications of Bartik instruments to labor mobility studies (e.g., Goldsmith-Pinkham et al., 2020; Fang et al., 2023), while innovating by focusing on individual prior experience.

We formalize our shift-share instrument for entrepreneur i born in their birthplace (county or city, depending on data availability) b in the year y as:

$$\text{Shock}_{by} = \sum_{j} \Big(\underbrace{\frac{\text{Firm}_{jb,t=1995}}{\text{Firm}_{b,t=1995}}}_{\text{share}} \times \underbrace{\text{Dereg}_{j,y+25}}_{\text{shift}} \Big), \tag{2}$$

where the *share* term represents industry j's employment share in location b in 1995 from the Economic Census Data, and $\text{Dereg}_{j,y+25}$ is a binary indicator for whether the industry j transitioned from "Restricted/Prohibited" in 1997 to "Supported/Permitted" in 2002 as the *Catalogue* was revised upon China's WTO accession, by the expected year, $y + 25$. We assume individuals enter the labor market at the age of 25 ($y+25$), a threshold based on the median age of MNE-experienced entrepreneurs at the time they start their latest job before

venturing (Appendix Table B.4), although we record their actual (possibly endogenous) age upon entry. Results are robust to alternative age thresholds.

To increase the robustness of our identification and following the logic of Bell et al. (2019), which posits that exposure to high-innovation areas matters for individual outcomes, we further account for domestic migration patterns. We construct a *nested* shift-share instrument that captures MNE job exposure that may occur outside an individual's birthplace:

$$\begin{aligned} \text{Exposure}_{by} &= \sum_{d} \Big[\underbrace{z_{b \to d, Y(y), t=2000}}_{\text{share}'} \times \underbrace{\text{Shock}_{dy}}_{\text{shift}'} \Big] \\ &= \sum_{d} \Big[\underbrace{\frac{\text{Flow}_{b \to d, Y(y), t=2000}}{\text{Pop}_{b, Y(y), t=2000}}}_{\text{share}'} \times \underbrace{\sum_{j} \Big(\frac{\text{Firm}_{jd, t=1995}}{\text{Firm}_{d, t=1995}} \times \text{Dereg}_{j, y+25} \Big)}_{\text{shift}'} \Big], \end{aligned} \tag{3}$$

where the *shift* term here follows the same spirit of specification (2) but is aggregated at the destination level d. The migration component, $z_{b \to d, Y(y), t=2000}$, measures the share of birth cohort $Y(y)$ (defined as the 5-year cohort centered on birth year y) that migrated from their birthplace b to each destination d by the year 2000. This construction explicitly includes non-migrants (where b=d). We extract these migration patterns from the 2000 Population Census, supplemented by the 2010 Census for younger cohorts. This approach provides a generalized IV that captures the birthplace-cohort exposure of MNE opportunities induced by both FDI deregulation and migration inertia.

We compare the spatial distribution of this constructed MNE exposure in 2002 in Appendix Figure A.3. The measure exhibits considerable geographic variation at the birthplace level and is not solely concentrated in coastal regions. Several inland cities demonstrate high levels of exposure, driven partly by established migration pathways to specific coastal hubs. This spatial pattern contrasts with the actual MNE entries in 2002, which were heavily clustered in eastern coastal areas.

The constructed Bartik IV is matched to each ESIEC respondent i based on their birthplace b and birth year y. It serves as an instrumental variable for $MNEJob_i$, in a two-stage

least squares (2SLS) specification as follows:

$$\text{MNEJob}_i = \alpha \cdot \text{Exposure}_{b(i)y(i)} + \beta_S \cdot \text{SOEJob}_i + \text{Control}_i'\delta + \underbrace{\mu_c + \lambda_j + \nu_w}_{\text{FEs}} + \sigma_i \tag{4}$$

$$Y_{i,cjw} = \beta \cdot \widehat{\text{MNEJob}}_i + \beta_S \cdot \text{SOEJob}_i + \text{Control}_i'\gamma + \underbrace{\theta_c + \eta_j + \phi_w}_{\text{FEs}} + \epsilon_i, \tag{5}$$

where the first-stage regression (4) generates the prediction value for the second stage. The same set of control variables and fixed effects is included in both stages, consistent with the baseline OLS specification. Standard errors in both 2SLS and OLS specifications are thus clustered at the birthplace-year level to account for correlated shocks within cohorts. For additional robustness, we also estimate a corresponding IV-Probit model to account for the binary nature of the outcome variable.

3.3 Instrument Validity

Our shift-share instrumental variable exhibits strong predictive power for entrepreneurs' prior MNE employment. As shown in Table 3, the first-stage statistics significantly exceed conventional thresholds for weak instruments across all specifications. Column (1) first presents the estimate with only fixed effects. In our baseline specification (Column 2), a one-standard-deviation increase (0.084) in the Bartik instrument is associated with a 3.6% (0.084×0.435) rise in the probability of having MNE work experience. This relationship remains robust when controlling for county-industry level spillover effects by adding fixed effects in Column (3). The binned scatter plot shows a clear linear relationship (Appendix Figure A.4).

Crucially, placebo tests in Appendix Table B.5 support the validity of the exclusion restriction. The Bartik instrument exhibits no statistically significant correlation with: (i) other non-MNE professional experiences that could independently influence innovation, including whether the individual worked outside their hometown, the number of prior jobs held, or whether they occupied managerial roles, or (ii) pre-entrepreneurship employment in other types of domestic entities, such as SOEs, government agencies, or the military. Furthermore, at the aggregated level, Appendix Figure A.5 shows that while the Bartik instrument is significantly correlated with the number of FDI firms in a city at the time a cohort entered the labor market, it is not associated with measures of local innovative capacity or performance, such as city-level patent applications, R&D expenditures, or the

density of college students.

More importantly, while the ESIEC survey is cross-sectional, our identification strategy effectively embeds a cohort-based difference-in-differences (DID) design through the construction of the instrument. The first-stage relationship (4) can be formalized as:

$$\text{MNEJob}_i = \beta \cdot \underbrace{(\text{Treat}_b \times \text{Post}_{y+25})}_{\text{Exposure}_{b(i)y(i)}} + \beta_S \cdot \text{SOEJob}_i + \text{Control}_i'\gamma + \text{TWFE} + \text{FEs} + \epsilon_i, \quad (6)$$

where the $\text{Exposure}_{b_i y_i}$ term captures the interaction between the regional treatment intensity Treat_b at the birthplace level and a binary timing indicator Post_{y+25}, which equals one if the individual turned 25 years old—a proxy for labor market entry—after the 2002 policy benchmark. This design also aligns with the "exogenous imputation" framework for shift-share instruments proposed by Borusyak et al. (2022). The exclusion restriction is satisfied provided that the effects of deregulation are proportional to the industrial composition of regions in 1995, conditional on the two-way fixed effects structure.

To validate our approach, we estimate an event study specification analogous to Equation (6). As shown in Figure 4, the deregulation significantly increased the probability of entrepreneurs taking MNE jobs after 2002, while pre-treatment trends exhibit no statistically significant differences. This fails to reject the null hypothesis of parallel trends in MNE employment propensity between more and less exposed counties prior to the reform.

Finally, we assess the external validity of our instrument using two independent employee datasets. First, we utilize the CFPS. Although birthplace information is restricted to the provincial level, we construct a corresponding cohort-province Bartik exposure measure and match it to individual workers. As shown in Panel (a) of Appendix Figure A.6, the instrument correlates positively with the share of workers in each cohort-province cell with MNE experience. Second, we use anonymized resume data from *51Job.com*, one of China's largest online recruitment platforms. Using similar methodology, we again find a statistically significant positive correlation between the Bartik instrument and the likelihood of prior MNE employment, as shown in Panel (b). These results imply that the constructed Bartik instrument possesses broad predictive power beyond the ESIEC sample, supporting its relevance as a general source of exogenous variation in MNE work experience.

4 Main Findings

4.1 Baseline Result

Following the empirical design, Table 4 presents estimations using the 2SLS specifications (4)-(5). Overall, we find robust and consistent evidence that entrepreneurs' prior MNE experience significantly increases the likelihood of their enterprises' innovation. The IV estimates reveal a local average treatment effect (LATE) for compliers, with the baseline estimate in Column (1) approximately five times larger than its OLS counterpart. This suggests a negative bias in the OLS correlation, likely because individuals who select into MNEs may differ from those who do not along unobservable dimensions that also correlate with innovation propensity. This baseline measure of innovation shows that MNE experience raises the probability of innovation by 93.4 percentage points, an economically substantial and statistically significant effect. Consistent with the OLS findings, prior SOE employment exhibits a negligible or negative association with subsequent innovation outcomes.

To rule out potential confounding from local agglomeration or competition effects spurred by FDI, we include county-by-industry fixed effects in Panel B of Appendix Table B.2. The estimated coefficients for entrepreneurs' MNE experience remain statistically significant and economically meaningful, suggesting that the results are driven by the entrepreneurial mobility channel rather than by local agglomeration or local market competition. Furthermore, results are consistent when using the alternative birthplace shock IV from specification (2) (see Appendix Table B.6).

We further explore alternative measures of innovation in Table 4. Columns (2) to (5) decompose innovation into four distinct types, revealing that MNE experience generates significant positive effects on both narrowly defined technological innovation and broader measures, such as marketing (sales) and environmental innovation. The effects on new products and marketing are particularly pronounced. In Columns (6) to (8), we shift to objective, administratively registered counts of IP. While we find significant positive effects on the number of registered trademarks and copyrights, the coefficient for patents remains statistically insignificant. Although patents are widely used in the literature as a proxy for innovation (e.g., Cheung and Lin, 2004), they may be less effective for capturing innovation in small businesses due to the high barriers to formal R&D and the specialized financial resources required for IP registration (Rammer et al., 2009).

The external IP dataset contains exact approval dates for patents and trademarks. After

merging these records with incorporated firms sampled in the ESIEC 2018 wave, we construct a panel dataset that enables us to trace the dynamic effects of MNE exposure on subsequent innovation outcomes after business entry. We apply the following event study specification:

$$Y_{it} = \sum_{k} \left[\beta_k \cdot \text{MNEJob}_i \cdot \mathbb{I}(t - t_i^{\text{entry}} = k) \right] + \underbrace{\theta_i + \eta_t}_{\text{FEs}} + \epsilon_i, \tag{7}$$

where the indicator function $\mathbb{I}(t - t_i^{\text{entry}} = k)$ denotes the years since firm establishment. The coefficient β_k captures the dynamic effects of prior MNE experience on IP approvals over time since entry. The model incorporates individual and year fixed effects, with standard errors clustered at the birthplace-by-year level. The coefficient for the establishment year ($k = 0$) is set as the baseline level.

Figure 5 presents the estimated dynamic effects of prior MNE experience on (the logarithm of) the number of total approved patents, utility model patents, and trademarks. For total patents in Panel (a), the effects remain statistically insignificant for an extended period following business entry, consistent with the static IV result reported in Column (6) of Table 4. However, we observe a clear upward trend with the dynamic effect becoming significantly positive 9 to 10 years post-entry.

This pattern suggests a learning effect: rather than innovating immediately upon entry, entrepreneurs with MNE experience appear to accumulate operational capabilities more effectively over time than their counterparts. This delayed impact also helps explain the null result in the aggregate patent regression, as young firms are highly vulnerable to exit and many do not survive the decade required to reach this significant patenting threshold. Panel (b) shows that this learning effect is more pronounced for utility model patents, which typically involve incremental, market-oriented innovations. By contrast, the dynamic effect on trademarks emerges shortly after establishment and persists as a statistically significant positive influence, confirming that MNE experience provides a long-run advantage in brand-based innovation.

Table 5 focuses on the subsample of firms engaging in production or process innovations to assess the quality of these activities. Among the 1,755 firms reporting product innovation in 2017 or 2022, we define a binary variable, *Novelty*, based on the survey question "*In what market context would you consider your product or service to be* ***new****?*." It equals one if entrepreneurs perceived their innovation as new to the national or global markets (as opposed to just the local city). The results show that businesses led by MNE-experienced

entrepreneurs exhibit a significantly higher level of product or service novelty. Furthermore, Column (2) indicates that these firms generate a significantly larger share of their total revenue from new product sales.

Similarly, for process innovation, the survey included follow-up questions regarding specific improvements resulting from these innovations. Columns (3) and (4) reveal that entrepreneurs with MNE experience achieve significantly greater quality improvements, although we find no statistically significant effect on cost reduction. These findings imply that entrepreneurs with prior MNE experience facilitate high-quality and practical applicability rather than mere imitation. In contrast, entrepreneurs with an SOE background exhibit either lower or insignificant levels of improvement in both product/service novelty and process upgrade when implementing innovation.

4.2 Robustness

We conduct a series of robustness checks to validate our empirical specification and baseline findings, as detailed in Appendix D.3. First, we demonstrate that the results are not sensitive to functional form; the Probit and IV-Probit estimation results remain consistent with our linear specification (See Appendix Table B.7). Next, we perform several placebo tests using alternative definitions of professional experience (see Appendix Table B.8). These tests help rule out the possibility that the impact of *MNEJob* is a proxy for more general professional characteristics, such as the total number of job(s) before venture, rather than the MNE experience itself.

Furthermore, we address a wide range of alternative explanations to ensure the validity of the entrepreneurial mobility channel, as detailed in Appendix D.3. To summarize, we control for individual-level factors and pre-existing entrepreneurial motivations that might drive both career paths and innovation. We examine whether our results are driven by MNEs' concentration in high-innovation industries, ensuring the effect persists even when comparing firms within the same narrow industry. We rule out the hypothesis that the effect is purely driven by an export-channel business model or by the signaling value of an MNE background for securing external financing. We account for the timing of FDI trends and other industrial policies to ensure our Bartik instrument captures the specific policy shock of the 2002 *Catalogue* revision rather than broader macroeconomic shifts.

4.3 Mechanisms and Channels

To further understand the documented pattern, we explore the potential channels underlying our baseline findings by drawing on the granular detail available in our data.

Internal technical and managerial spillovers. We begin by examining the *internal* innovative pathways through which MNE work experience may enhance innovation capacity. Following the IV regression specification reported in Table 6, we identify several key mechanisms. First, MNE-experienced entrepreneurs invest substantially more in R&D expenditures than their counterparts, as shown in Column (1). This aligns with the broader aggregate patterns among above-scale enterprises: foreign-invested enterprises exhibit the largest average scale of R&D employment, surpassing both SOEs and private domestic firms (see Appendix Figure A.7).

Second, firms led by MNE-experienced entrepreneurs also exhibit stronger internal human-capital accumulation. Specifically, they employ a significantly larger share of full-time, college-educated workers (Column 2) and a higher proportion of dedicated R&D personnel (Column 3), compared to firms whose founders lack such a background. This suggests that entrepreneurs may acquire valuable technical skills, innovation-oriented management practices, or organizational cultures during their tenure in MNEs, which they subsequently transfer to their own ventures.

Notably, we find no evidence that these firms receive more government innovation subsidies (Column 4), implying that their innovation advantage is not primarily driven by financial incentives or policy favor. In contrast, since SOEs are often perceived as having privileged access to subsidies, entrepreneurs with SOE experience appear to leverage these networks or informational advantages; they rely more on innovation subsidies than on internal human-capital accumulation. Collectively, these patterns suggest that the MNE-experience innovation premium derives primarily from transferred managerial and technological capabilities rather than policy-driven resource advantages or rent-seeking.

The 2023 wave of the ESIEC survey provides more detailed data on incorporated firms' internal innovative activities, offering further evidence for these mechanisms. As shown in Column (5) of Table 6, MNE-experienced entrepreneurs engage more in auxiliary R&D activities. Furthermore, these firms are significantly more likely to implement performance-based bonus incentives for R&D staff (Column 6), although they show no increased tendency to use equity-based incentives (Column 7). This pattern aligns with the multitask model

prediction by Hellmann and Thiele (2011), suggesting that well-designed monetary incentives effectively encourage innovation when such activities are firm-specific. The absence of equity incentives likely reflects structural constraints of small businesses, where stock options are less effective compared to those in listed firms with clear exit paths via IPO or acquisition.

Formalization. Having witnessed the formal institutional governance and business operation of MNEs firsthand, we hypothesize that founders with prior MNE experience will promote business formalization, which in turn enhances their capacity to innovate. Table 7 provides supporting evidence for this mechanism across several institutional dimensions.

First, MNE-experienced entrepreneurs are significantly more likely to establish incorporated firms rather than remain self-employed (Column 1). Because innovation typically entails high risk, the corporate structure provides a crucial institutional safeguard through limited liability, thereby encouraging more ambitious R&D projects.

Second, formalization manifests in the professionalization of the workforce. In Column (2), we find that MNE-experienced entrepreneurs provide on-the-job training at a significantly higher rate. This investment represents a critical pathway for the systematic accumulation of internal human capital.

Moreover, for the incorporated firm sample, we link our survey data with administrative annual reports containing self-reported figures on social insurance enrollment. Using this information, we construct a further measure of business formalization: the share of full-time employees covered by social insurance (Dai et al., 2025). As shown in Column (3), firms led by entrepreneurs with MNE experience pay social insurance for a significantly higher proportion of their workforce. This formal commitment helps stabilize the labor force and enhances employee motivation to engage in innovation beyond their routine duties.

Finally, MNE-experienced entrepreneurs exhibit a greater reliance on contract-based business (Column 4), suggesting that their background institutionalizes formal governance practices. This shift toward formal contracting substantially reduces the uncertainty and transaction costs often associated with collaborative innovation, while providing robust protection for intellectual outputs. In contrast, the businesses started by SOE-experienced entrepreneurs appear to be more informal on average, relying less on standardized governance and formal employee protections.

Production networks. The operation of MNEs is not isolated; they work closely with numerous domestic upstream and downstream firms. We hypothesize that prior experience with MNEs offers entrepreneurs a competitive edge in engaging in collaborative innovation through these established production networks. Table 8 presents the corresponding IV regression results, identifying the network as a critical conduit for resource acquisition and collaborative R&D. In the 2018 wave, entrepreneurs were asked to identify the primary source of their venture's first order. Response options included: *former colleagues or business partners, trade fairs/the Internet, introductions by shareholders, or other acquaintances*. As shown in Column (1), entrepreneurs with prior MNE experience are significantly more likely to obtain their first order through former colleagues or business partners from their previous employment. Interestingly, SOE-experienced entrepreneurs also show a higher propensity to leverage previous employer networks compared to those without formal organization backgrounds in SOEs or MNEs.

However, a distinct divergence emerges in the nature of these partnerships. In Columns (2) and (3), only MNE-experienced entrepreneurs exhibit a higher tendency to engage in outsourcing relationships. The outsourcing process constitutes a powerful form of "learning by doing" and "tacit-knowledge decoding," directly stimulating adaptive and secondary innovation. This aligns with the study by Cai et al. (2007) in Zhongguancun, Beijing, which noted that technical assistance associated with outsourcing from MNEs to new domestic firms—especially those founded by former MNE employees—serves as a primary learning channel. In contrast, entrepreneurs with an SOE background tend to engage less in outsourcing.

The network advantage persists asymmetrically beyond the startup stage. For MNE-experienced entrepreneurs, former colleagues and employers are more likely to serve as upstream suppliers rather than downstream customers (Columns 4 and 5). This pattern likely reflects the strategic imperatives of MNEs in the Chinese market. To adapt products and services to local consumers, MNEs require substantial downstream localization, such as localized development, wholesaling, and retailing. Former Chinese employees, who possess intimate knowledge of the MNE's technology and products alongside local market expertise, become ideal candidates to establish downstream ventures that fulfill these localization needs. In contrast, due to the stringent procurement processes typically adopted by MNEs, small independent firms, even those founded by ex-MNE employees, often face significant barriers to becoming major upstream suppliers.

When MNEs act as a supplier to these ventures, the entrepreneur's firm typically in-

corporates technologically advanced inputs into its own offerings. This integration compels them to innovate in system design and application scenarios, pushing it toward more sophisticated, adaptive innovation. This is further supported by findings from Columns (6)-(7): MNE-experienced entrepreneurs display a stronger preference for collaborating on innovation with other firms rather than with research institutions (e.g., universities). It is therefore highly probable that they engage in co-development, especially with their former MNE employers.

These findings extend the work of Cardoza et al. (2025) by demonstrating that entrepreneurs leverage prior professional connections not just for mobility, but to access outsourcing opportunities and secure initial orders from former colleagues and business partners. Overall, this external channel complements the internal mechanisms of human capital and formalization, illustrating how MNE experience fosters innovation by embedding domestic firms into a high-value global production chain.

4.4 Spillover to Business Performance and Survival

The innovation advantages induced by MNE experience translate into measurable operational and performance gains. Using our multi-source data, we examine the spillovers to business outcomes in Table 9. For the full sample, MNE-experienced entrepreneurs generated higher overall revenues (Column 1) than their non-MNE-experienced counterparts. Interestingly, this does not translate into corresponding gains in raw profit rates (Column 2), suggesting that these firms may be re-investing returns into the innovation process or R&D activities. Furthermore, these firms demonstrate higher e-commerce adoption (Column 3). As a proxy for broader digital transformation, this indicates that MNE experience fosters both technological and organizational modernization. Appendix Table B.9 confirms that these effects are robust across additional aspects of digitization in the 2023 wave. The findings also hold even when using the quarterly Online Survey of Micro-and-small Enterprises in China (OSOME), which covers more small and unregistered businesses (see Appendix D.4).

Moreover, we extend the survey data by matching it with external administrative datasets to capture broader performance spillovers. In Columns (4) and (5), we merge the 2018 wave sample with China Customs data (2000-2018). We do not extend this match to the 2023 wave because the disclosure of firm names in Customs records ceased after 2018. Over the longer term, firms with MNE-experienced founders show persistently higher engagement

in two-sided international trade, with significant involvement in both import and export activities. This pattern stands in sharp contrast to those with SOE backgrounds. This aligns with the cross-country findings of De Clercq et al. (2008) regarding FDI and export orientation, providing a micro-level foundation for how individual career paths drive firm-level internationalization.

Finally, we link the 2018 wave to official business registration records to track firm survival dynamics. Column (6) indicates that, prior to the COVID-19 pandemic, firms founded by MNE-experienced entrepreneurs maintained a significantly higher survival rate. However, this survival advantage diminished and became statistically insignificant in the post-COVID period (Column 7). This shift likely reflects the unprecedented scale of the external shock, which may have disproportionately affected trade-integrated firms.

4.5 Back-of-Envelope Analysis

To contextualize our findings, we estimate the aggregate contribution of entrepreneurs with MNE work experience to overall innovation. This analysis quantifies the macro-level implications of the individual-level "innovation premium" identified in our 2SLS results. We begin with the finding that MNE-experienced entrepreneurs exhibit an innovation premium factor of $k = 1 + 0.934$ (based on our estimated coefficient), meaning that their innovation output is approximately 93.4% higher than that of entrepreneurs without such experience. Given that these individuals constitute a proportion $p = 0.085$ (8.5%) of the entrepreneurial population, we can derive their incremental contribution analytically.

Let $i_{\text{non-MNE}}$ represent the average innovation output of an entrepreneur without MNE experience, and $i_{\text{MNE}} = k \cdot i_{\text{non-MNE}}$ be the average output of those with MNE experience. For a total of N entrepreneurs, the total innovation output is $I_{\text{total}} = pN \cdot i_{\text{MNE}} + (1-p)N \cdot i_{\text{non-MNE}} = Ni_{\text{non-MNE}}[pk + (1-p)]$. The additional innovation attributable solely to the MNE experience effect is $\Delta I = I_{\text{total}} - Ni_{\text{non-MNE}} = pN(k-1)i_{\text{non-MNE}}$. Thus, the share of total innovation explained by this premium is:

$$\frac{\Delta I}{I_{\text{total}}} = \frac{p(k-1)i_{\text{non-MNE}}}{i_{\text{non-MNE}}[pk + (1-p)]} = \frac{p(k-1)}{pk + (1-p)}. \tag{8}$$

Substituting the empirical estimates yields:

$$\frac{\Delta I}{I_{\text{total}}} = \frac{0.085 \times (1.934 - 1)}{0.085 \times 1.934 + (1 - 0.085)} = \frac{0.085 \times 0.934}{0.16439 + 0.915} = \frac{0.07939}{1.07939} \approx 0.074. \tag{9}$$

This result implies that approximately 7.4% of total entrepreneurial innovation can be attributed specifically to the additional innovation capacity gained from prior MNE work experience. This is economically significant, particularly as enterprises (across all ownership types) accounted for 73.5% of valid invention patents in China in 2024. The magnitude suggests that exposure to multinational corporate practices generates substantial knowledge spillovers that scale up to meaningfully influence aggregate innovative activity.

The calculation likely constitutes a conservative lower bound for several reasons. Regarding the extensive margin, our analysis shows that workers' MNE experience increases their propensity to enter entrepreneurship in the first place. Incorporating this higher entry rate would further amplify the aggregate impact. Moreover, it does not account for potential quality differentials in innovation. As shown in Table 5, MNE-experienced founders do not merely innovate more; they innovate better, with higher scores in novelty, sales translation, and quality upgrades. Furthermore, through the internal channel of human capital investment and on-the-job training documented earlier, these firms act as "secondary academies." When their employees eventually spin out to launch their own ventures or move to new employers, they propagate the original MNE knowledge and network advantages even further.

5 Conclusion

Our research establishes a causal link between entrepreneurs' MNE work experience and enhanced business innovation and performance, unpacking the black box of FDI knowledge spillovers through the entrepreneurial mobility channel. Using China's FDI deregulation as a quasi-natural experiment and employing a shift-share identification design based on rich micro-level survey data, we demonstrate that MNE-experienced entrepreneurs foster innovative entrepreneurship through several interconnected mechanisms: (i) internal technology and management spillovers coupled with human capital accumulation, (ii) enterprise formalization, and (iii) production-network-based knowledge transfer. Importantly, this innovation extends beyond imitation. MNE-experienced founders generate substantial novelty, higher product quality, and improved digital adoption, translating into deeper integration into international trade and superior firm survival.

While academic and policy debates have raised concerns that MNEs might strategically transfer outdated or environmentally intensive technologies to host countries (Javorcik and Wei, 2001), our findings suggest that the benefits of MNE employment are rooted in

human-capital and innovation-oriented routines. Even if a specific technology is not at the global frontier, the embedded managerial practices and quality standards still foster valuable capability building. Furthermore, recent evidence suggests that improved patent protection in China incentivizes MNEs to deploy high-quality technologies in their affiliates (Chen, 2025), and "quid pro quo" market-access policies have historically enhanced these spillovers (Bai et al., 2025b). Our finding that MNE alumni implement significant environmental innovations further alleviates these concerns.

These findings carry vital policy implications for emerging economies. First, we validate FDI deregulation not only as a capital-attracting tool, but also as a long-term engine of domestic innovation capacity. Second, our results highlight the vulnerability of emerging economies to "FDI flight" in an era of geopolitical decoupling. The exodus of MNEs does not just impact current employment; it potentially severs critical knowledge pipelines that fuel the next generation of domestic entrepreneurial firms.

As China transitions from a host country to a major FDI origin for other emerging economies, such as those in Southeast Asia and Africa, a similar cycle of "learning-by-doing" is likely to unfold globally. For instance, Chinese tech firms expanding abroad often serve as "training grounds" for local engineers who later launch their own digital startups. Overall, FDI from both developed nations and emerging leaders like China can collectively enhance global innovative and formal entrepreneurship.

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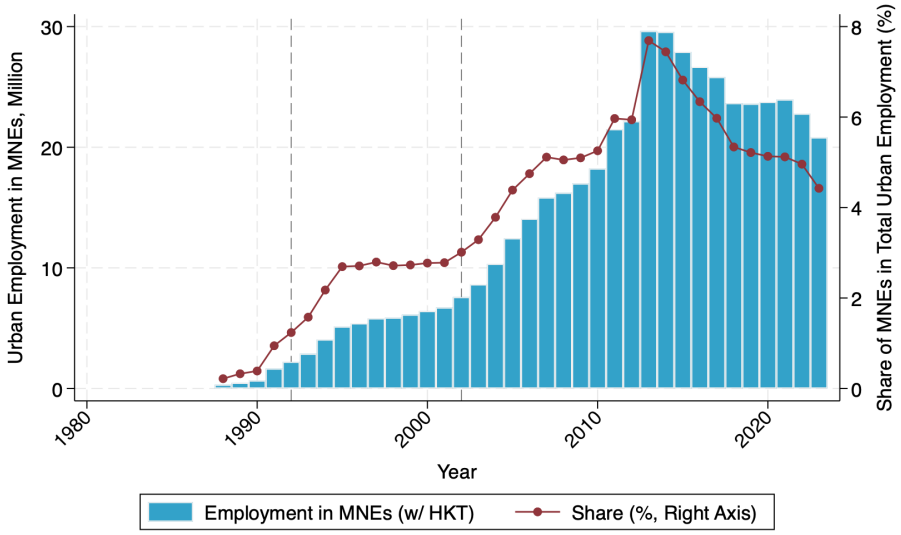
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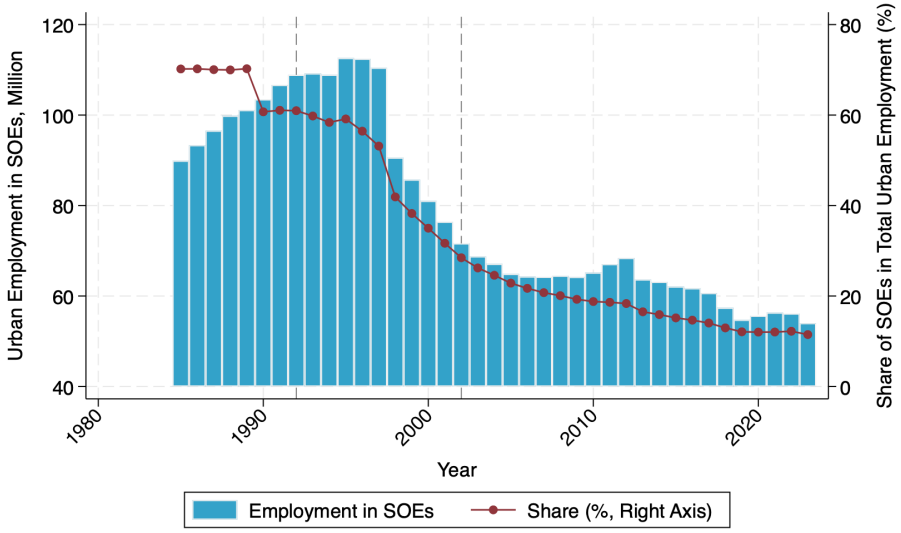
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Figures



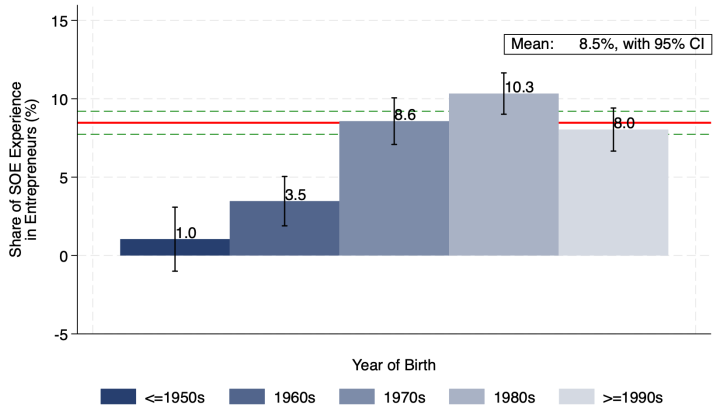
(a) Urban Employment of MNEs in China



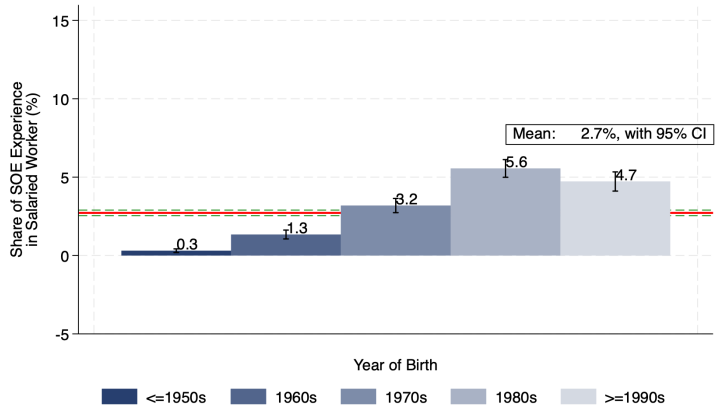
(b) Urban Employment of SOEs in China

Figure 1: Contribution of MNEs and SOEs to Urban Employment

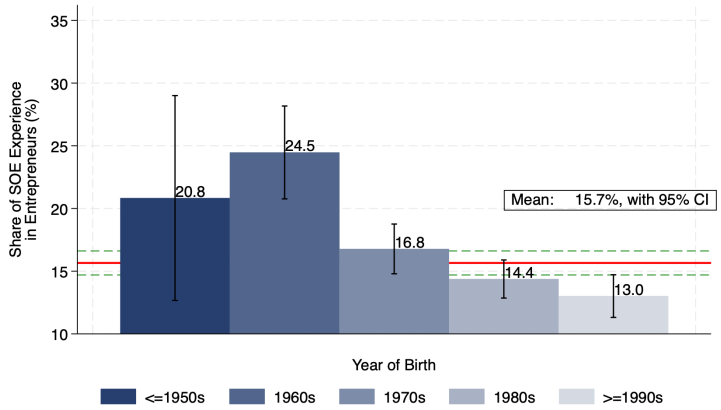
Data source: CEIC and Ministry of Human Resources and Social Security of the PRC.



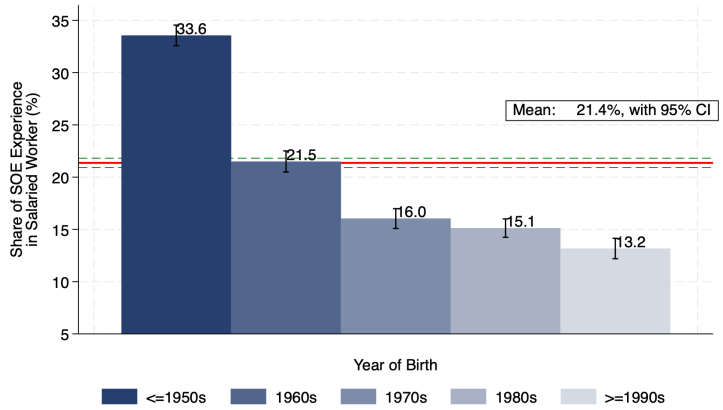
(a) MNE Experience in Entrepreneurs (ESIEC)



(b) MNE Experience in Salaried Workers (CFPS)



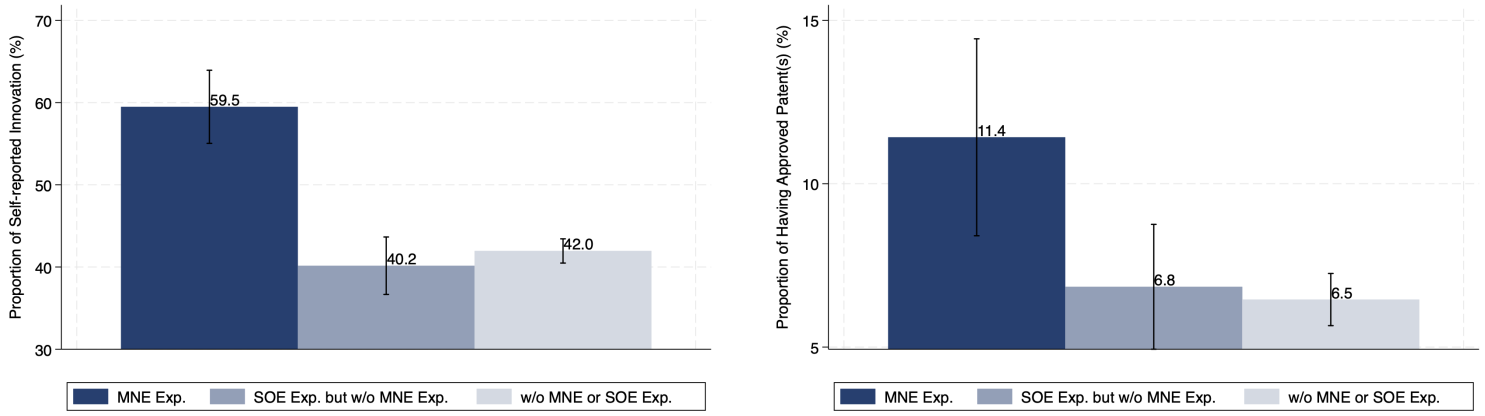
(c) SOE Experience in Entrepreneurs (ESIEC)



(d) SOE Experience in Salaried Workers (CFPS)

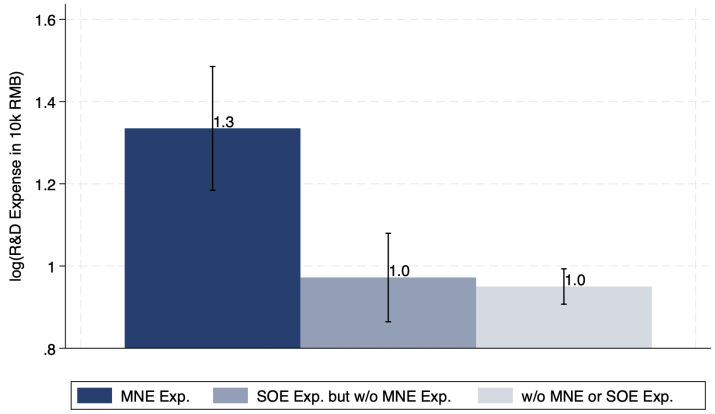
Figure 2: Share of MNE and SOE Experience in Entrepreneurs and Salaried Workers, by Birth Cohort

Data source: ESIEC 2018 & 2023 and CFPS 2010-2022. 95% confidence interval is indicated. The red line and dashed lines indicate the sample mean and 95% confidence interval.

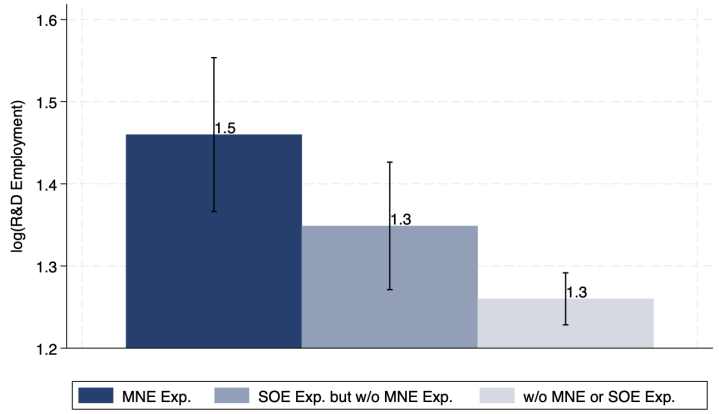


(a) Self-reported Innovation

(b) Patent



(c) R&D Expense



(d) R&D Employment

Figure 3: Comparing Innovation Variables among Groups with Different Experience

Data source: ESIEC 2018 & 2023. 95% confidence interval is indicated. The sample is partitioned into three non-overlapping groups: (1)those MNE experience; (2) those SOE experience (excluding MNE experience), and (3) those with neither, including first-time entrepreneurs without prior employment.

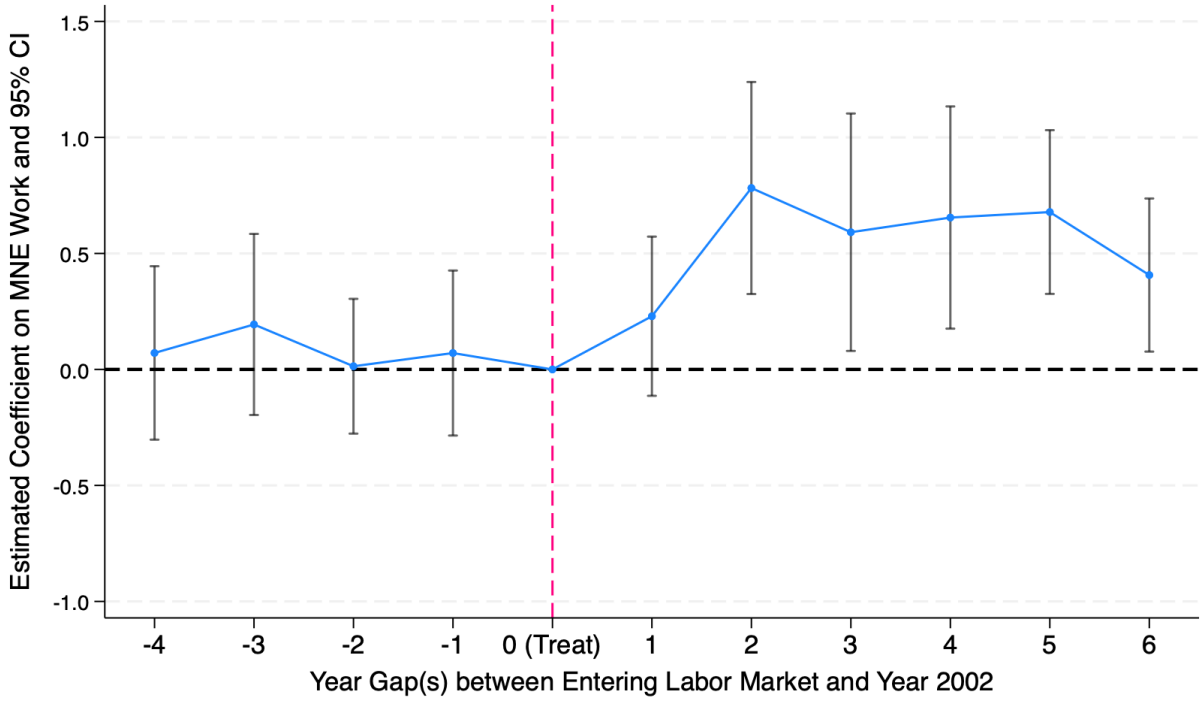
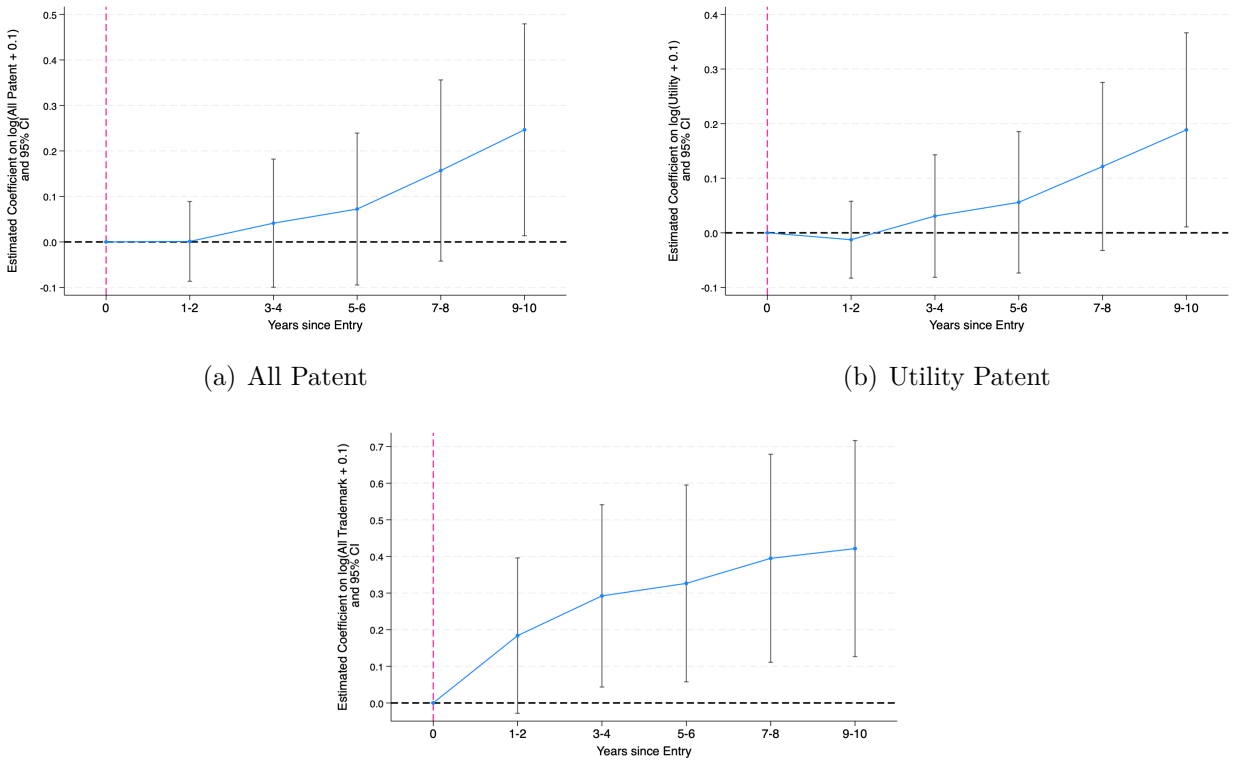


Figure 4: Event Study of MNEs Exposure (Bartik IV) on Entrepreneurs' Prior MNE Working Experience

Data source: ESIEC 2018 & 2023, Population Census, Business Registration Dataset, and the *Catalogue*. The figure displays the estimated dynamic effects of birthplace-level Bartik IV (proxying aggregate exposure to MNE employment) on the probability of an entrepreneur having prior MNE work experience. The unit of analysis is the individual. The dependent variable is a dummy variable for work experience in MNEs prior to the first venture. The key independent variables are interactions between the 2001 birthplace-level Bartik IV and the year dummies. The x-axis label represents years relative to China's WTO accession in 2002 ($t = 0$).
Regressions include individual-level controls (entrepreneur's age, gender, college education (dummy), and Communist Party membership (dummy)), and firm-level controls (total assets, the presence of corporate shareholders (dummy), registration type, new investment (dummy), export status (dummy), and total employees from the year preceding the survey).
All regressions include county, industry, and wave fixed effects. Results are robust to the inclusion of two-way fixed effects. Standard errors are clustered at the birthplace-year level. Coefficients for $\Delta t \leq -5$ and $\Delta t \geq 7$ are suppressed in the figure. The coefficient for the baseline year (2002; $t = 0$) is normalized to zero. Vertical brackets indicate 95% confidence intervals.



(a) All Patent

(b) Utility Patent

(c) Trademark

Figure 5: Dynamic Effects of MNE Experience on Patent and Trademark Registration Post-Entry

Data source: ESIEC 2018 and *Tianyancha*. The sample includes incorporated firms from the ESIEC 2018 wave, matched with administrative intellectual property (IP) records. The y-axis displays the estimated dynamic coefficients for the interaction term between an entrepreneur's prior MNE experience (*MNEJob*) and firm age cohorts. The x-axis label represents years since establishment. The dependent variables are the log-transformed number of registered patents (Subfigures a and b) and trademarks (Subfigure c). The coefficient for the year of establishment ($t = 0$) is normalized to zero as the baseline. All specifications control for individual and year fixed effects. Standard errors are clustered at the birthplace-year level. Vertical brackets indicate 95% confidence intervals.

Tables

Table 1: Summary Statistics and Mean Difference Tests (ESIEC 2018 and 2023

Variable	(1) Mean	(2) S.D.	(3) Mean by: w/ MNE Job	(4) Mean by: w/o MNE Job	(5) Mean Diff. (t-test)	(6) Mean by: w/ SOE Job but w/o MNE Job	(7) Mean Diff. (t-test)
MNE Job	0.085	0.278	n.a.	n.a.	n.a.	n.a.	n.a.
SOE Job	0.157	0.363	0.235	0.149	0.085***	n.a.	n.a.
IV	0.139	0.084	0.175	0.136	0.038***	0.124	0.050***
Innovation Dummy	0.432	0.495	0.595	0.417	0.178***	0.402	0.193***
Age $\geq$ 35	0.653	0.476	0.699	0.649	0.051*	0.705	-0.006
Female	0.243	0.429	0.247	0.243	0.005	0.222	0.025
College educated	0.328	0.469	0.448	0.316	0.131***	0.470	-0.008
CCP member	0.156	0.363	0.126	0.158	-0.033**	0.217	-0.091***
log(asset)	4.435	2.062	4.676	4.412	0.263***	4.580	0.095
Corporate Shareholder	0.066	0.248	0.070	0.065	0.005	0.069	0.002
Register as firm	0.856	0.351	0.915	0.851	0.064***	0.888	0.027
New asset	0.465	0.499	0.463	0.465	-0.002	0.487	-0.025
Export	0.037	0.190	0.062	0.035	0.027**	0.032	0.030**
log(employee)	1.401	1.223	1.453	1.396	0.056	1.372	0.081
Observations	5,538		469	5,069		757	

Data source: ESIEC 2018 & 2023. Columns (1)-(2) present the full sample statistics. Columns (3) and (4) compare the subsamples with and without MNE experience, respectively. Column (5) reports the corresponding t-test for the mean difference t-test between Columns (3) and (4). Column (6) focuses on the subsample with prior SOEs work experience but no MNE experience, ensuring this group is mutually exclusive with Column (3). Column (7) presents the t-test for mean difference between the MNE-experienced groups (Column 3) and the SOE-only group (Column 6). Significance level: *p <0.1 **p <0.05 ***p <0.01.

Table 2: OLS Regressions of MNE Work Experience on Innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS Estimation							
	Self-reported Innovation:					Approved IP Number:		
	Innovation	Product	Process	Sales	Environ.	Patent	Trademark	Copyright
MNE Job	0.175***	0.146***	0.095***	0.064*	0.023	0.060	0.045	0.095
	(0.040)	(0.033)	(0.035)	(0.036)	(0.023)	(0.166)	(0.090)	(0.065)
SOE Job	-0.027	0.006	-0.012	0.038	0.007	0.006	-0.027	0.011
	(0.023)	(0.024)	(0.022)	(0.025)	(0.016)	(0.131)	(0.061)	(0.039)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	0.144	0.143	0.096	0.115	0.193	0.095	0.056	0.045
Observations	5,538					4,742 (firms)		

Data source: ESIEC 2018 & 2023, the Population Census, the Business Registration Dataset, the *Catalogue*, and *Tianyancha*. Columns (1)–(5) use the full sample, while Columns (6)-(8) are restricted to incorporated firms across both waves. All models are estimated using OLS regressions. Regressions include entrepreneur-level controls (age, gender, college education (dummy), and Communist Party membership (dummy)) and firm-level controls (total assets, the presence of corporate shareholders (dummy), registration type, new investment (dummy), export activity (dummy), and total employment from the year preceding the survey). The subsequent tables with control variables use the same set of covariates, unless otherwise specified. County, industry, and wave fixed effects are controlled in all regressions. Standard errors are clustered at the birthplace-year level. Significance level: $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$.

Table 3: First-Stage OLS Regression of Instrument on Prior MNE Work Experience

	(1)	(2)	(3)
		MNEJob	
Bartik IV	0.403***	0.435***	0.473***
	(0.083)	(0.085)	(0.118)
SOE Job		0.042***	0.029
		(0.016)	(0.020)
Weak IV F Statistic	23.565	26.150	16.026
Control	No	Yes	Yes
FEs	Yes	Yes	Yes
County × Ind FE	No	No	Yes
Adj. R-sq	0.097	0.112	0.144
Observations		5,538	

Data source: ESIEC 2018 & 2023, the Population Census, the Business Registration Dataset, and the *Catalogue*. All models are estimated using OLS regressions. All specifications include a comprehensive set of control variables, along with county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. Significance level: *p <0.1 **p <0.05 ***p <0.01.

Table 4: 2SLS Regressions of Prior MNE Work Experience on Innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2SLS Estimation							
	Self-reported Innovation:					Approved IP Number:		
	Innovation	Product	Process	Sales	Environ.	Patent	Trademark	Copyright
MNE Job	0.934***	0.781**	0.556*	1.011**	0.482*	0.756	2.242*	1.248**
	(0.351)	(0.307)	(0.317)	(0.392)	(0.254)	(2.412)	(1.214)	(0.489)
SOE Job	-0.055*	-0.017	-0.028	0.003	-0.010	-0.021	-0.112	-0.034
	(0.028)	(0.027)	(0.025)	(0.037)	(0.019)	(0.189)	(0.089)	(0.042)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	-0.149	-0.133	-0.057	-0.264	-0.129	0.016	-0.145	-0.184
Observations	5,538					4,742 (firms)		

Data source: ESIEC 2018 & 2023, the Population Census, the Business Registration Dataset, the *Catalogue*, and *Tianyancha*. Columns (1)–(5) use the full sample, while Columns (6)-(8) are restricted to incorporated firms in both waves. All models are estimated using 2SLS regressions. All specifications include a comprehensive set of control variables, along with county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. Significance level: $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$.

Table 5: 2SLS Regressions on Innovation Performance

	(1)	(2)	(3)	(4)
	Prod. Innovation:		Proc. Innovation:	
	Novelty	% Sale	Quality ↑	Cost ↓
MNEJob	0.989*	5.297*	0.767*	-0.245
	(0.516)	(3.014)	(0.451)	(0.669)
SOE Job	-0.097	-0.622**	-0.054	-0.000
	(0.064)	(0.315)	(0.050)	(0.079)
Control	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
Adj. R-sq	-0.525	-0.160	-0.287	-0.102
Observations	1,755 (w/ Prod. Innovation)		1,743 (w/ Proc. Innovation)	

Data source: ESIEC 2018 & 2023, the Population Census, the Business Registration Dataset, and the *Catalogue*. Columns (1)-(2) are restricted to the subsample of reporting product innovation, while Columns (3)-(4) are restricted to the subsample reporting process innovation. All results are estimated using 2SLS regressions. All specifications include a comprehensive set of control variables, along with county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level.
Novelty is a binary variable equal to one if the respondent reports that the product/service innovation is new to the national or global market (rather than only to the local city).
%Sale measures the share of total firm revenue generated from sales of new products.
Quality ↑ captures whether process innovation leads to improvements in product quality.
Cost ↓ captures whether process innovation results in cost reductions, as reported in the same follow-up questions.
Statistical significance is indicated by $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$.

Table 6: 2SLS Regressions on Channels: Internal Spillovers

	(1) R&D Expense (log)	(2) College-Edu. Employees (log)	(3) R&D Employees (log)	(4) Gov. Subsidies for Innovation	(5) R&D Related Activities	(6) Dummy for Incentives: Bonus	(7) Dummy for Incentives: Equity
MNE Job	1.902**	1.960***	1.235**	-0.052	1.115**	1.142*	0.102
	(0.807)	(0.746)	(0.528)	(0.127)	(0.548)	(0.666)	(0.253)
SOE Job	-0.089	-0.052	-0.033	0.013	-0.041	-0.038	-0.016
	(0.062)	(0.061)	(0.041)	(0.011)	(0.040)	(0.039)	(0.015)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	-0.067	0.350	0.100	-0.019	-0.260	-0.320	-0.032
Observations	5,538				2,535 (firms in ESIEC 2023)		

Data source: ESIEC 2018 & 2023, the Population Census, the Business Registration Dataset, and the *Catalogue*. Columns (1)–(4) utilize the full sample, while Columns (5)-(7) are restricted to the subsample of incorporated firms in the 2023 wave. All results are estimated using 2SLS regressions. All specifications include a comprehensive set of control variables, along with county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. Statistical significance is indicated by $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$.

Table 7: 2SLS Regressions on Potential Channels: Formalization

	(1) Register as Firm	(2) On-Job Training	(3) % Social Insurance	(4) Rely on Contract
MNEJob	0.473**	1.060***	0.566**	0.658**
	(0.233)	(0.342)	(0.246)	(0.266)
SOE Job	0.011	-0.051*	-0.044**	-0.023
	(0.017)	(0.028)	(0.019)	(0.028)
Control	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
Adj. R-sq	0.018	-0.225	-0.126	-0.115
Observations	5,538		4,742 (firms)	

Data source: ESIEC 2018 & 2023, the Population Census, the Business Registration Dataset, the *Catalogue*, and Business Annual Report from *Tianyancha*. Columns (3)-(4) include only the sample of incorporated firms across both waves. All results are estimated using 2SLS regressions. All specifications include a comprehensive set of control variables, along with county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. Statistical significance is indicated by $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$.

Table 8: 2SLS Regressions on Potential Channels: Production Network

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First Order Helped by Previous *Colleagues*	Order Outsourcing:		Previous *Colleagues* as:		R&D Collaborate w/ :	
		Receive	Send	Upstream	Downstream	Other Firms	Institutions
MNEJob	0.392**	0.872***	0.792***	0.429***	0.180	0.462*	-0.105
	(0.159)	(0.296)	(0.289)	(0.109)	(0.264)	(0.241)	(0.286)
SOE Job	0.038**	-0.053**	-0.032	-0.011	-0.019	-0.035**	0.031*
	(0.017)	(0.025)	(0.026)	(0.010)	(0.020)	(0.017)	(0.017)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	0.369	-0.230	-0.152	0.343	-0.022	-0.355	-0.057
Observations	3,003 (ESIEC 2018)	5,538				2,535 (firms in ESIEC 2023)	

Data source: ESIEC 2018 & 2023, the Population Census, the Business Registration Dataset, and the *Catalogue*. Column (1) uses only the 2018 wave sample, while Columns (6)-(7) are restricted to the subsample of incorporated firms in the 2023 wave. All results are estimated using 2SLS regressions. All specifications include a comprehensive set of control variables, along with county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. Statistical significance is indicated by $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$.

Table 9: 2SLS Regressions on Spillover to Performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Revenue (log)	Profit Rate	Ever Import	Ever Export	Exit: before 2019	Exit: before 2025
MNEJob	3.327***	1.214	0.317**	0.302*	-0.542*	-0.299
	(1.017)	(1.999)	(0.147)	(0.155)	(0.278)	(0.435)
SOE Job	-0.039	0.018	-0.051**	-0.043*	0.033	0.016
	(0.079)	(0.182)	(0.026)	(0.026)	(0.024)	(0.034)
Control	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	-0.170	-0.033	-0.455	-0.307	-0.435	-0.100
Observations	5,538		2,207 (firms in ESIEC 2018)			

Data source: ESIEC 2018 & 2023, the Population Census, the Business Registration Dataset, Custom Records, and the *Catalogue*. Columns (1)–(2) utilize the full sample, while Columns (3)-(6) are restricted to the subsample of incorporated firms in the 2018 wave. All results are estimated using 2SLS regressions. All specifications include a comprehensive set of control variables, along with county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. Statistical significance is indicated by $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$.

Appendix A Appendix Figures

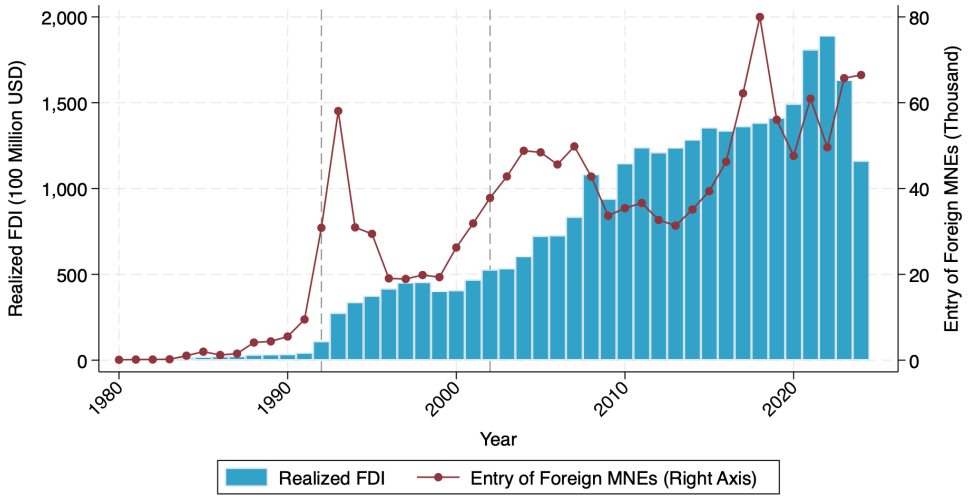


Figure A.1: Realized Foreign Direct Investment and MNEs Entry in China

Data source: CEIC, Ministry of Commerce of the PRC, and the Business Registration Dataset.

中华人民共和国国家发展计划委员会
中华人民共和国国家经济贸易委员会
中华人民共和国对外贸易经济合作部
令
第 21 号

新的《外商投资产业指导目录》及附件业经国务院2002年3月4日批准，现予以发布，自2002年4月1日起施行。1997年12月29日国务院批准，1997年12月31日国家计委、国家经贸委和外经贸部发布的《外商投资产业指导目录》同时废止。

国家发展计划委员会主任：曾培炎

国家经济贸易委员会主任：李荣融

对外贸易经济合作部部长：石广生

二〇〇二年三月十一日

外商投资产业指导目录

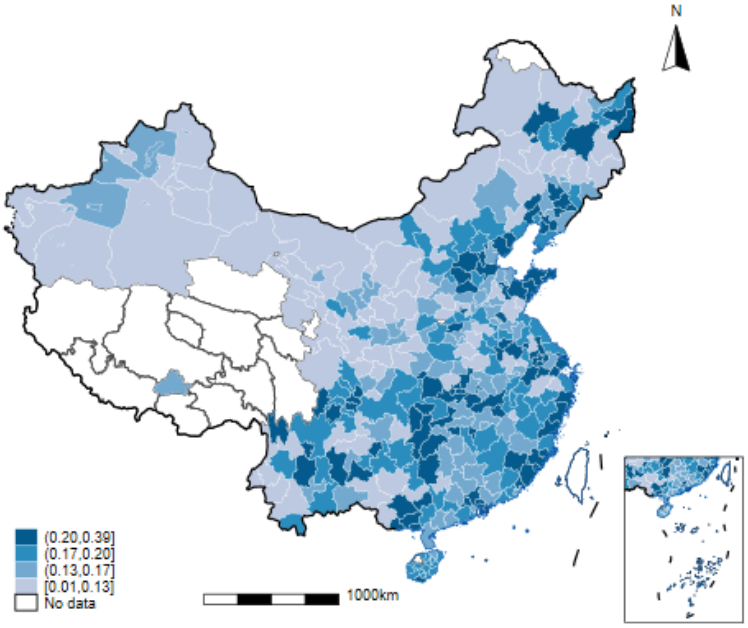
鼓励外商投资产业目录

一、农、林、牧、渔业

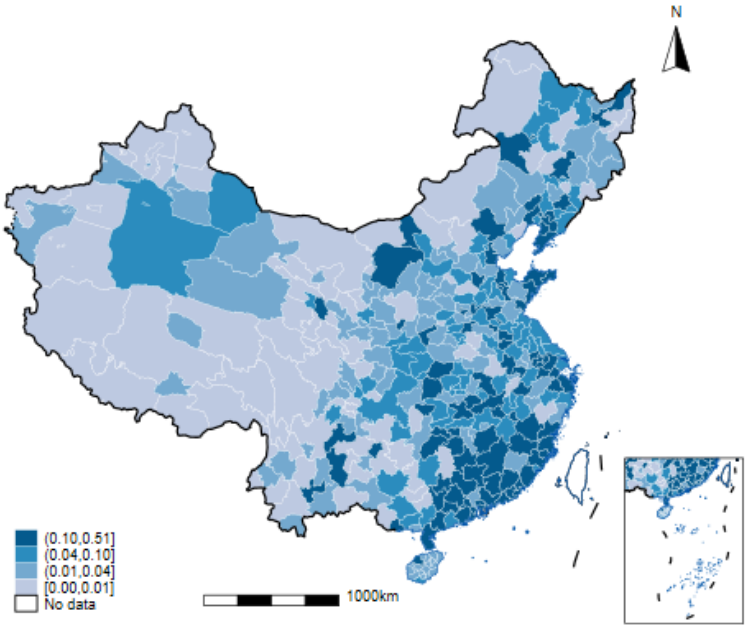
1. 中低产农田改造
2. 蔬菜（含食用菌、西甜瓜）、水果、茶叶无公害栽培技术及产品系列化开发、生产
3. 糖料、果树、花卉、牧草等农作物优质高产新技术、新品种（转基因品种除外）开发、生产
4. 花卉生产与苗圃基地的建设、经营
5. 农作物秸秆还田及综合利用、有机肥料资源的开发生产
6. 中药材种植、养殖（限于合资、合作）
7. 林木（竹）营造及良种培育
8. 天然橡胶、剑麻、咖啡种植
9. 优良种畜种禽、水产苗种繁育（不含我国特有的珍贵优良品种）
10. 名特优水产品养殖、深水网箱养殖
11. 防治荒漠化及水土流失的植树种草等生态环境保护工程建设、经营

二、采掘业

Figure A.2: An Example of the *Catalogue*



(a) Bartik IV in 2002



(b) MNEs Entry in 2002

Figure A.3: Spatial Distribution of the Bartik IV and MNE Entry in 2002

Data source: the Population Census, Business Registration Dataset, and the *Catalogue*.

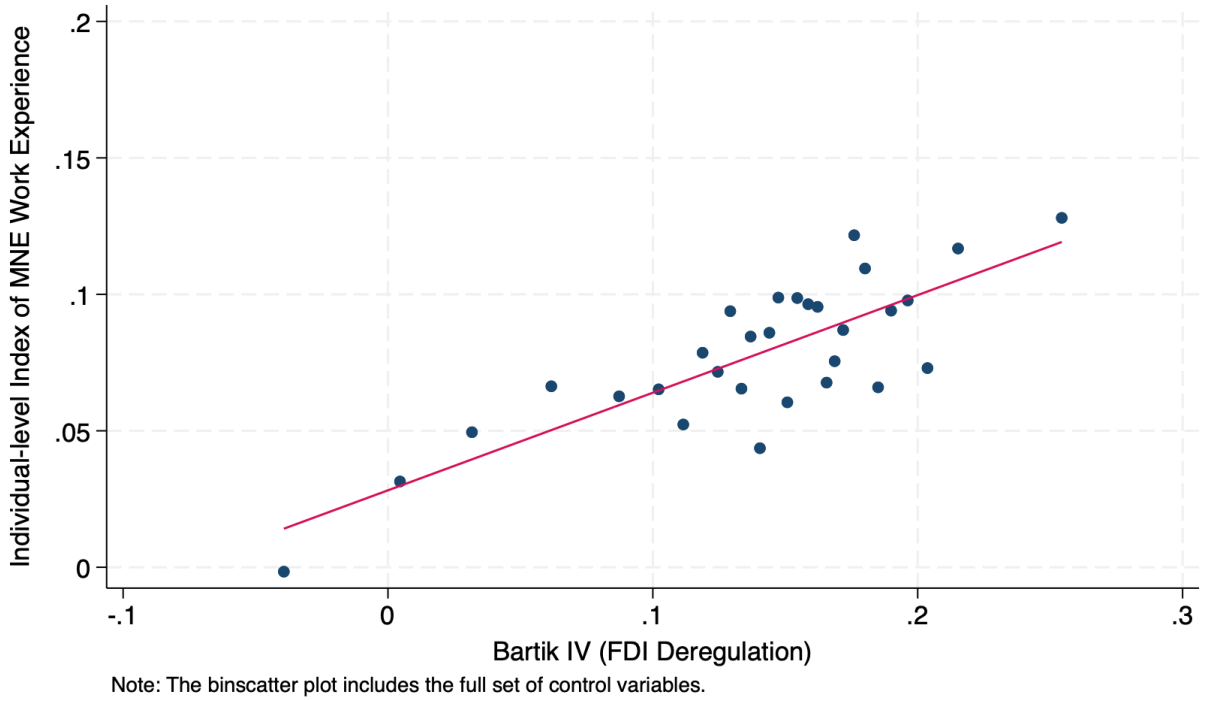
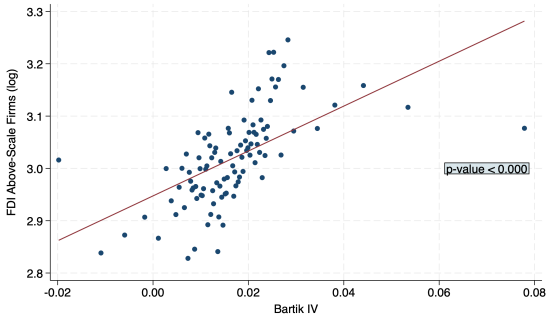
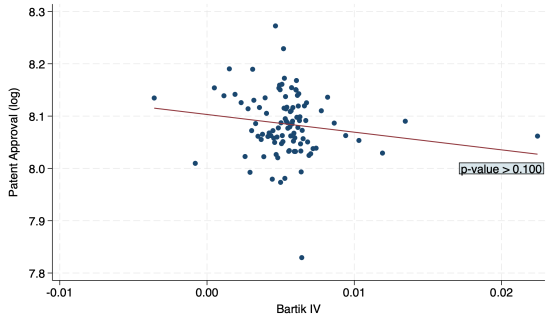


Figure A.4: Binned Scatter of Bartik IV (MNE Exposure) on Entrepreneurs' MNE Work Experience

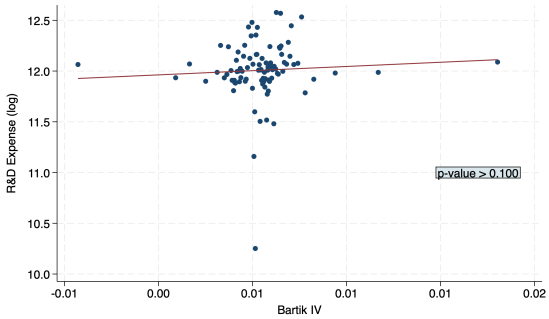
Data source: ESIEC 2018 & 2023, the Population Census, Business Registration Dataset, and the *Catalogue*. The plot controls for entrepreneur characteristics (age, gender, college education (dummy), and Communist Party membership (dummy) and firm characteristics (total assets, the presence of corporate shareholders (dummy), registration type, new investment (dummy), export activity (dummy), and total employees from the year preceding the survey). Unless otherwise noted, subsequent figures utilize this same set of covariates. All specifications include county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. A binned scatter plot is presented.



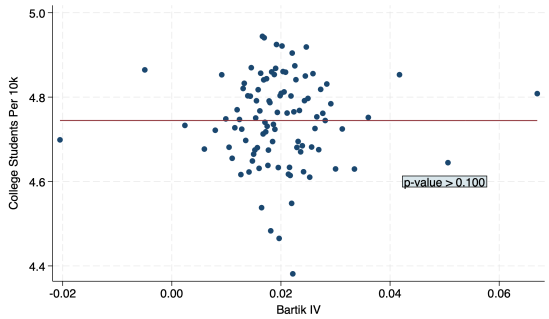
(a) FDI Above-Scale Firms



(b) Patent Application



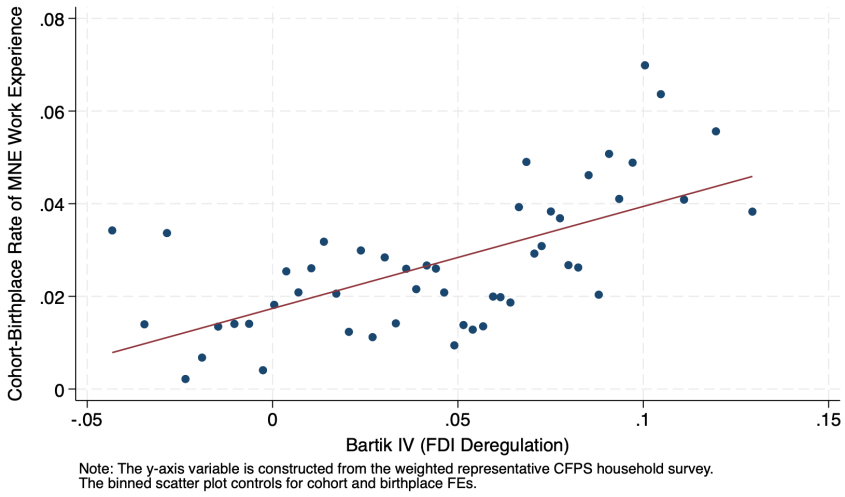
(c) R&D Expense



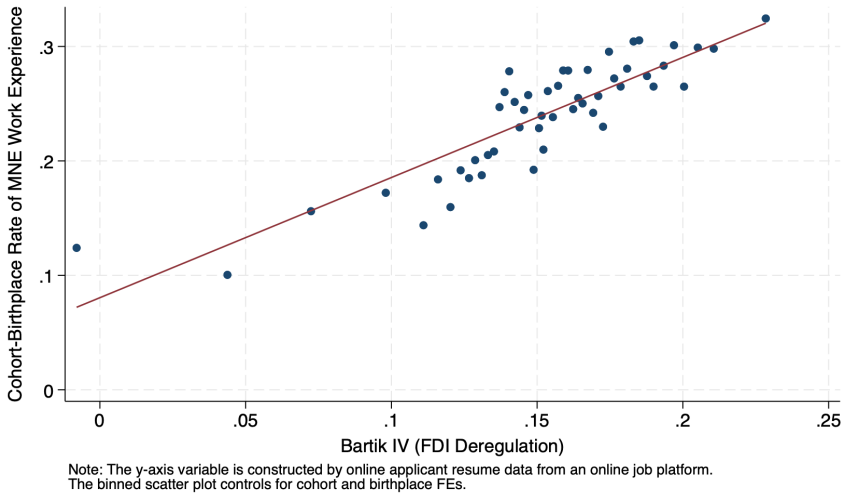
(d) College Student Intensity

Figure A.5: City-level Correlation between Bartik IV and Innovation Characteristics

Data source: China City Statistical Yearbook, the Population Census, Business Registration dataset, and the *Catalogue*. The figures present binned scatter plots, controlling for birth cohort and birthplace fixed effects.



(a) Household Survey: CFPS



(b) Online Resume: 51Job

Figure A.6: Binned Scatter of Bartik IV (MNE Exposure) on MNE Working Experiences in External Data

Data source: CFPS 2010-2022, Online Resume Data from `51job.com`, the Population Census, Business Registration Dataset, and the *Catalogue*. The figures present binned scatter plots, controlling for birth cohort and birthplace fixed effects. The average share of MNE experience in Panel (a) is consistent with that in Figure 2. The higher rate observed in Panel (b) reflects the composition of the 51Job CV sample, which primarily comprises active job market participants. As indicated in Appendix Figure A.13, workers with prior MNE experience exhibit higher turnover rates, contributing to their over-representation in current-job (resume) samples.

$$\text{Avg.} = \frac{\text{Total R\&D Employment}}{\text{Number of Above-Scale Firms}}$$

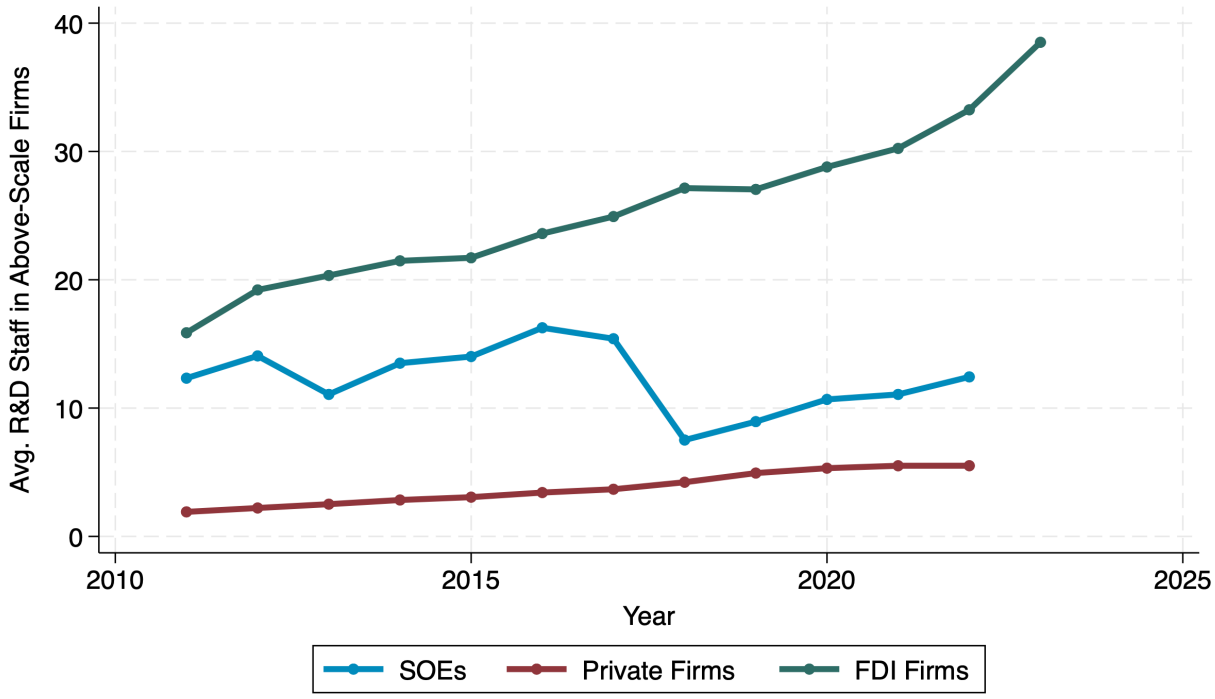
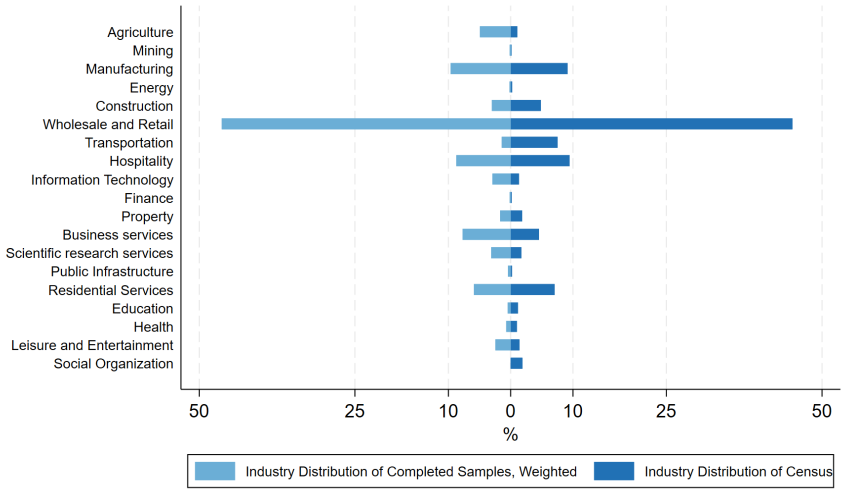
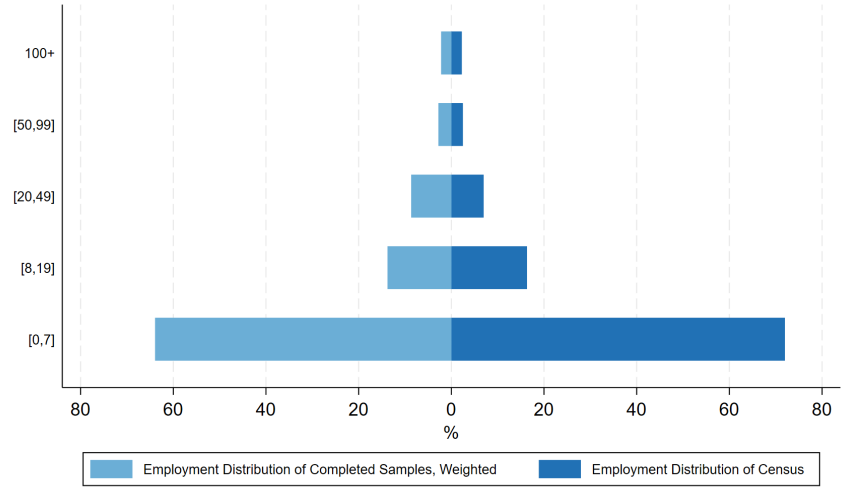


Figure A.7: Average R&D Employment Scale in Above-Scale Firms

Data source: CEIC and National Bureau of Statistics of the PRC.



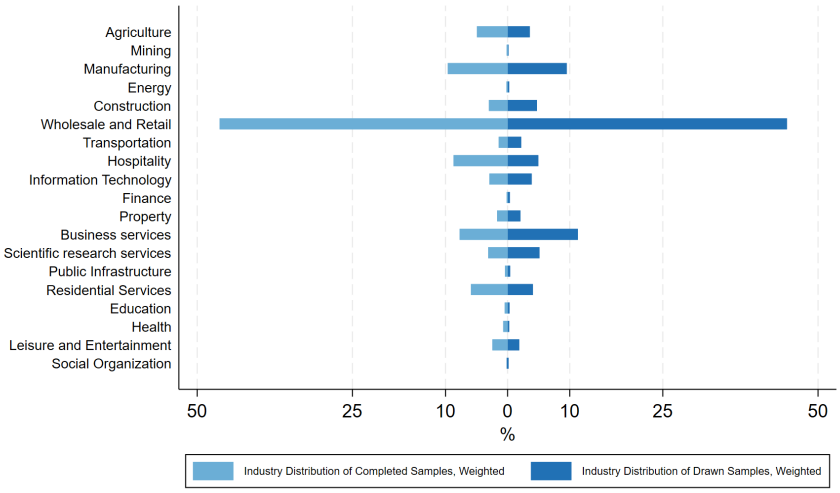
(a) Industry Distribution



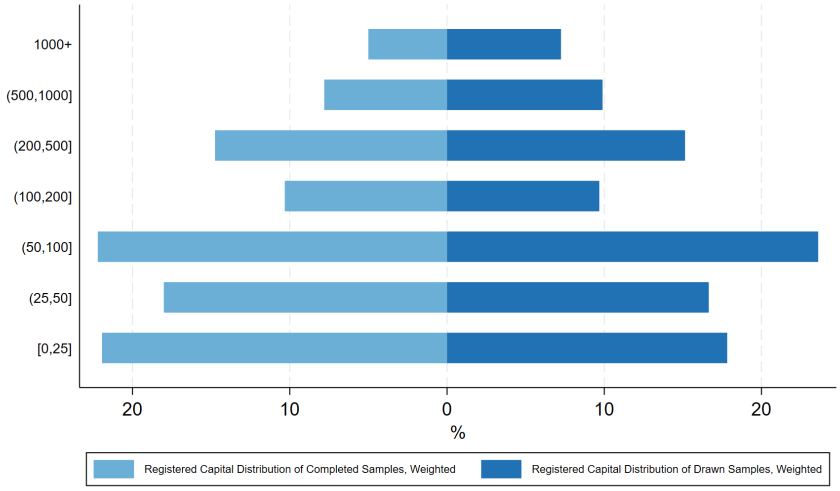
(b) Employment Distribution

Figure A.8: Industry and Size Distribution of the ESIEC Sample (Weighted) *vs* the 2018 Economic Census

Panel (a) displays the distribution across 19 industries at the SIC one-digit level. Panel (b) displays firm size intervals based on total employment. The horizontal axis represents the fraction of firms within each category for both the ESIEC survey in 2018 (weighted) and in the 2018 China Economic Census. In the ESIEC sampling design, the wholesale and retail industry was undersampled at one-quarter of its actual population density due to firm homogeneity. To ensure comparability with the census data, the ESIEC fractions for this industry have been adjusted by a factor of four while maintaining the relative weights of all other categories.
Data source: ESIEC 2018 and the China Economic Census 2018.



(a) Industry Distribution



(b) Registered Capital Distribution

Figure A.9: Industry and Size Distribution of the Completed *vs* Drawn ESIEC Samples (Both Weighted)

Panel (a) presents the distribution across 19 industries at the SIC one-digit level, while Panel (b) displays firm size intervals based on registered capital. The horizontal axis depicts the fraction of firms in each category for both the completed samples (respondents who finished the survey) and the total drawn samples for ESIEC 2018. Both samples are weighted. Due to the homogeneity of firms in the wholesale and retail industry, the sampling design assigned them a probability of one-quarter of their actual population fraction. To ensure comparability, we adjust the weights for this industry by a factor of four while maintaining the relative weights of other categories.
Data source: ESIEC 2018 and the Business Registration Dataset.

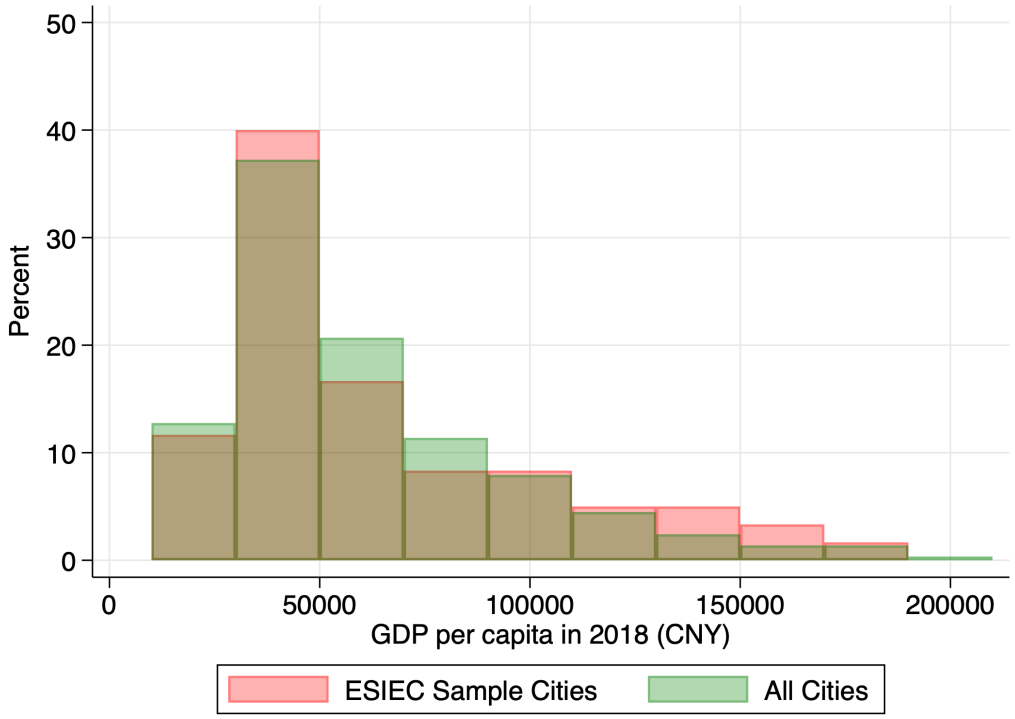


Figure A.10: GDP per capita Distribution of the ESIEC Cities and All Cities in 2018

Data source: ESIEC 2018 and the China City Statistical Yearbook.

$$(\text{Non-FDI Entry})_{ct} = \sum_{k=-3}^{4} \Big[\beta_k \cdot \text{Exposure}_c \cdot \mathbb{I}(t = k)\Big] + \text{TWFE} + \epsilon_i.$$

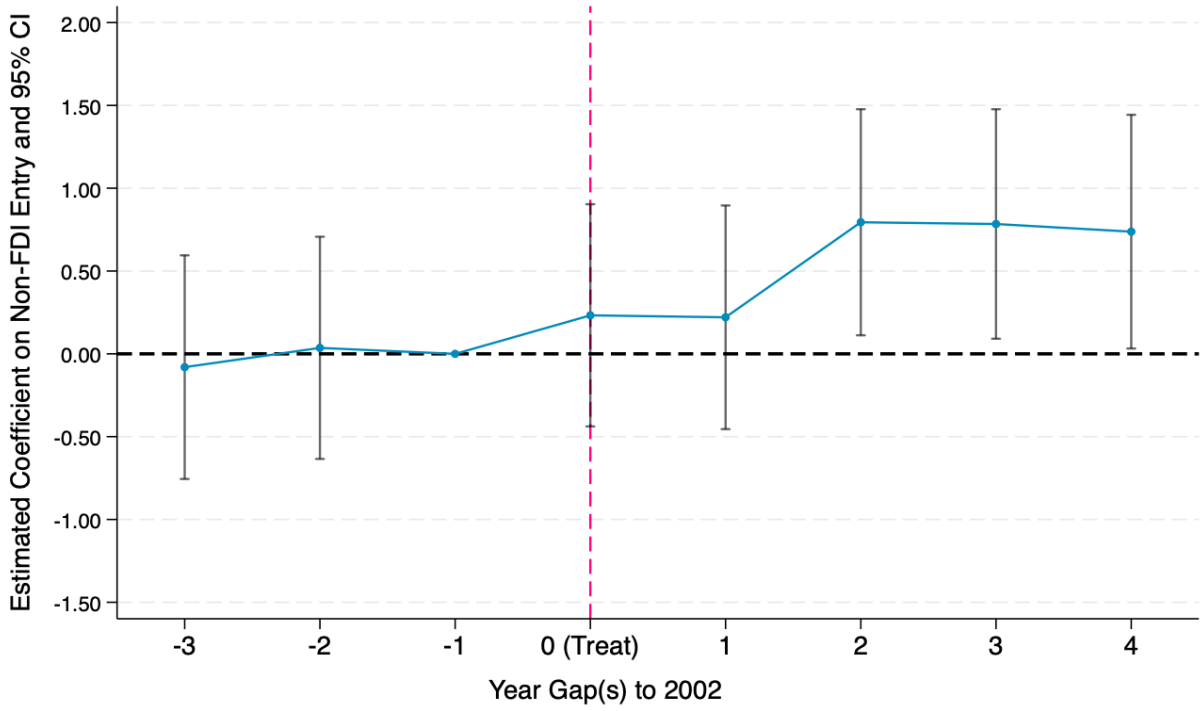


Figure A.11: Event Study of Bartik IV (MNE Exposure) on Entry at Birthplace

Data source: Population Census, Business Registration Dataset, and the *Catalogue*. The figure presents the dynamic effects of county-level Bartik IV (proxying aggregate exposure to MNE employment) on the entry of domestic (non-FDI) firms. The unit of observation is at the county-year level. The dependent variable is the logarithm of the number of newly registered non-FDI firms plus one. The $Exposure_c$ term represents the Bartik IV calculated for the year 2001. The x-axis indicates years relative to China's accession to the WTO (t=0 corresponds to 2002). All specifications include county and year fixed effects. Standard errors are clustered at the county level. The coefficient for the year 2001 (t = -1) is set as the default baseline. Coefficients for periods $\Delta t \leq -4$ and $\Delta t \geq 5$ are estimated but omitted from the visualization. Vertical brackets indicate 95% confidence intervals.

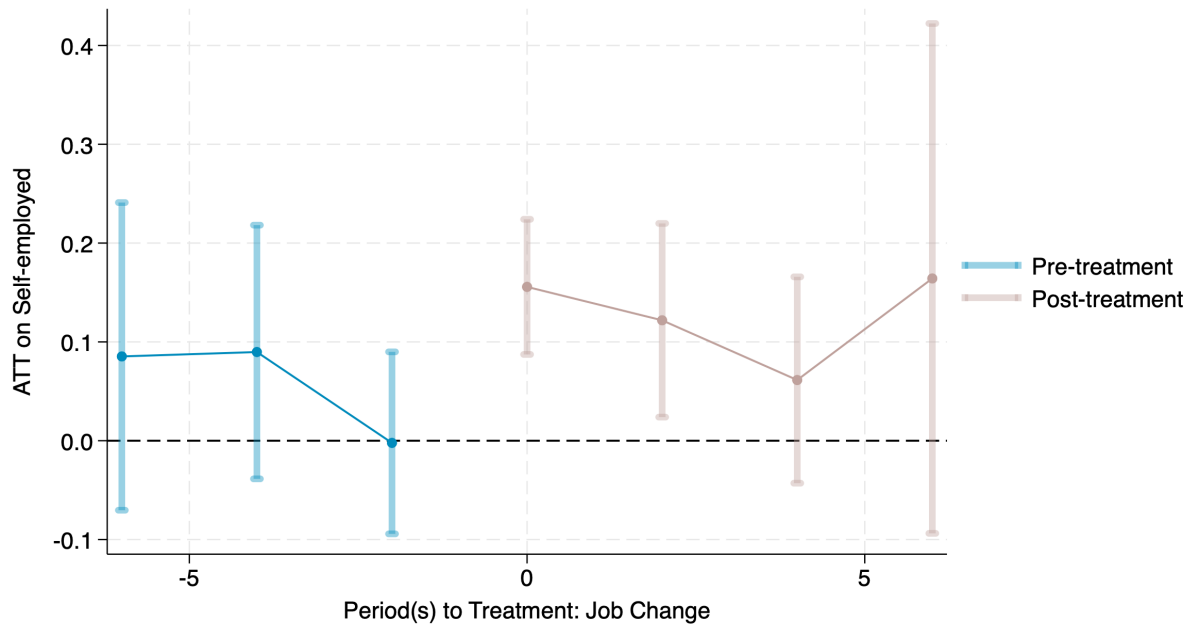


Figure A.12: Event Study of Adults' Entrepreneurship Following Job Changes

Data source: CFPS 2010-2022. This figure illustrates the dynamic effects of prior MNE experience on the propensity of salaried workers to enter self-employment following a job change. The sample is restricted to individuals observed as salaried workers in the initial periods. The x-axis represents the number of survey waves (years) relative to the first observed job change during the tracking period. The y-axis displays the corresponding regression coefficients using Callaway and Sant'Anna (2021) doubly robust difference-in-differences estimator. Vertical brackets indicate 95% confidence intervals.

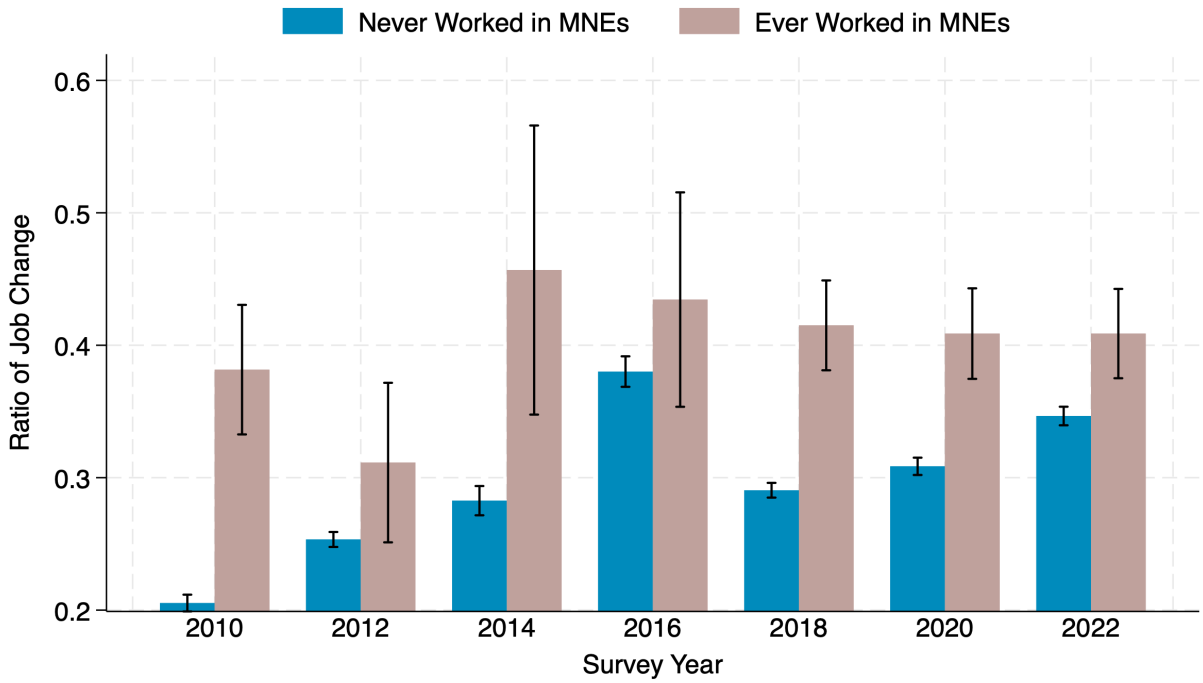


Figure A.13: Turnover Rates for Salaried Workers from CFPS data

Data source: CFPS 2010-2022. Vertical brackets indicate 95% confidence intervals.



Figure A.14: Self-reported Motivations for Entrepreneurship in ESIEC 2023

Data source: ESIEC 2023. The figure displays the distribution of self-reported primary motivations for starting a business among respondents in the ESIEC 2023 wave. Vertical brackets indicate 95% confidence intervals.

Appendix B Appendix Tables

Table B.1: Valid Entrepreneur Sample Size

Wave	Self-Employed	Incorporated Firm	*Count*
2018	796	2,207	3,003
2023	1,143	2,535	3,678
Count	1,939	4,742	6,681

Data source: ESIEC 2018 & 2023. The sample is restricted to entrepreneur respondents.

$$\text{Baseline Sample Size } 5,538 = (796 + 2,207) + 2,535$$

Table B.2: Robust OLS and 2SLS Regressions of MNE Work Experience on Innovation

	(1)	(2)	(3)	(4)	(5)
			Innovation		
Panel A: OLS Estimates					
MNE Job	0.199***	0.175***	0.160***	0.167***	0.148***
	(0.047)	(0.039)	(0.053)	(0.038)	(0.042)
SOE Job	-0.026	-0.033	0.007	-0.029	-0.052**
	(0.028)	(0.021)	(0.033)	(0.021)	(0.024)
Control	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes
Ind FE Level	1-digit	2-digit	2-digit	3-digit	4-digit
County × Ind FE	Yes	No	Yes	No	No
Adj. R-sq	0.211	0.168	0.255	0.183	0.195
Observations	5,538				4,533
Panel B: IV Estimates					
MNE Job	0.757**	0.902***	0.864**	0.840**	0.784
	(0.359)	(0.349)	(0.340)	(0.360)	(0.492)
SOE Job	-0.038	-0.065**	-0.051*	-0.059**	-0.080**
	(0.028)	(0.027)	(0.026)	(0.028)	(0.035)
Control	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes
Ind FE Level	1-digit	2-digit	2-digit	3-digit	4-digit
County × Ind FE	Yes	No	Yes	No	No
Weak IV F Statistic	16.026	38.974	35.586	34.880	18.330
Adj. R-sq	-0.350	-0.150	-0.202	-0.183	-0.275
Observations	5,538				4,533

Data source: ESIEC 2018 & 2023, Population Census, Business Registration Dataset, and the *Catalogue*. OLS regressions are reported in Panel A, and 2SLS using the Bartik IV are presented in Panel B. All specifications control for entrepreneur characteristics (age, gender, college education (dummy), and Communist Party membership (dummy)) and firm characteristics (total assets, the presence of corporate shareholders (dummy), registration type, new investment (dummy), export activity (dummy), and total employees) from the year preceding the survey. Unless otherwise noted, subsequent tables utilize this same set of covariates. County, industry, and wave fixed effects are controlled. Standard errors are clustered at the birthplace-year level. The "`Ind FE Level`" row specifies the granularity of industry fixed effects (1-digit to 4-digit). Columns(1) and (3) control for the interactive county-by-industry FEs. Significance level: *p <0.1 **p <0.05 ***p <0.01.

Table B.3: PSM Treatment Effect Estimation Using ESIEC 2018

	(1)	(2)	(3)
	Innovation, by Matching Methods:		
	Nearest Neighbor	Kernel	Radius
Treatment Effect (ATT)	0.146***	0.123***	0.158**
	(0.043)	(0.037)	(0.088)
Matched Sample Size		2,212	

Data source: ESIEC 2018. The table reports Propensity Score Matching (PSM) estimates of entrepreneurs' MNE experience on firm innovation. The propensity score and common support are estimated using entrepreneur characteristics (age, gender, college education (dummy), and Communist Party membership (dummy)) and business attributes (total assets, the presence of corporate shareholders (dummy), registration type, and export status). Standard errors are calculated using Bootstrap with 50 repetitions. Significance level: $^{*}p < 0.1$ $^{**}p < 0.05$ $^{***}p < 0.01$.

Table B.4: Age Distribution of Entrepreneurs at Career or Business Entry

Subsample	Age when starting the:	Mean	p10	p50	p90
w/ MNE working experience	latest job	26.1	20.0	25.0	33.0
	first business	31.0	23.0	31.0	40.0
w/o MNE working experience	latest job	24.2	18.0	23.0	32.0
	first business	30.9	22.0	29.0	42.0
w/o working experience	latest job	-	-	-	-
	first business	29.7	20.0	27.0	42.0

Data source: ESIEC 2018 & 2023. The sample is restricted to newly established businesses.

Table B.5: Placebo Test of First-stage Regression Using Alternative Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Job(s) before Starting Business:					Military
	Outside Hometown	Number of Job(s)	in SOEs	in Gov.	as Managers	
Bartik IV	-0.110	0.269	-0.042	0.021	0.079	0.066
	(0.075)	(0.519)	(0.097)	(0.070)	(0.093)	(0.048)
Control	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	0.184	0.051	0.024	0.054	0.043	0.069
Observations	5,538					

Data source: ESIEC 2018 & 2023, Population Census, Business Registration Dataset, and the *Catalogue*. This table reports OLS estimates for the placebo tests. All specifications include the baseline set of entrepreneur and firm-level control variables, as well as county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. Significance level: $^{*}p < 0.1$ $^{**}p < 0.05$ $^{***}p < 0.01$.

Table B.6: 2SLS Regressions of MNE Work Experience on Innovation Using Alternative IV Construction

	(1)	(2)	(3)
	Innovation		
	2SLS: Birthplace Shock as IV		
MNEJob	1.595***	1.136***	0.922**
	(0.452)	(0.373)	(0.378)
SOEJob		-0.062**	-0.042
		(0.030)	(0.029)
Control	No	Yes	Yes
FEs	Yes	Yes	Yes
County × Ind FE	No	No	Yes
Week IV F Statistic	20.022	22.225	12.835
Adj. R-sq	-0.676	-0.261	-0.439
Observations		5,538	

Data source: ESIEC 2018 & 2023, Business Registration Dataset, and the *Catalogue*. This table reports 2SLS estimates using an alternative instrumental variable construction. All specifications include the baseline set of entrepreneur- and firm-level control variables, as well as county, industry, and wave fixed effects. Significance level: *p <0.1 **p <0.05 ***p <0.01.

Table B.7: Probit and IVProbit Regressions on Innovation

	(1)	(2)	(3)	(4)	(5)	(6)
	Innovation					
	Probit			IVProbit		
MNEJob	0.142***	0.146***	0.155***	0.946***	0.789***	0.744***
	(0.036)	(0.035)	(0.034)	(0.121)	(0.149)	(0.163)
SOEJob		-0.012	-0.011		-0.036**	-0.035*
		(0.019)	(0.019)		(0.018)	(0.017)
Control	No	Yes	Yes	No	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes
County × Ind FE	No	No	Yes	No	No	Yes
pseudo R-sq	0.077	0.115	0.149	0.061	0.106	0.122
Observations	5,538					

Data source: ESIEC 2018 & 2023, Population Census, Business Registration Dataset, and the *Catalogue*. This table reports marginal effects from Probit and IV-Probit regressions. All specifications include the baseline set of entrepreneur- and firm-level control variables, as well as county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. Significance level: $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$.

Table B.8: Regression Using Alternative Specification of Work Experience

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Innovation			
	OLS	2SLS	OLS	OLS	OLS	OLS	OLS
MNEJob	0.161***	0.979**					
	(0.042)	(0.380)					
Number of Job(s)	0.004	-0.013					
	(0.004)	(0.009)					
Most Recent Job in MNEs			0.137***				
			(0.047)				
Family's Job in MNEs				0.119			
				(0.073)			
SOEJob (Job(s) in SOEs)					-0.021		
					(0.023)		
Job(s) in Gov.						0.009	
						(0.035)	
Job outside Hometown							0.022
							(0.022)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	0.136	-0.169	0.130	0.129	0.128	0.128	0.128
Observations	5,538						

Data source: ESIEC 2018 & 2023, Population Census, Business Registration Dataset, and the *Catalogue*. This table reports results using alternative measures or specifications of the primary work experience variable. All models include the baseline set of entrepreneur- and firm-level control variables, as well as county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. Significance level: *p <0.1 **p <0.05 ***p <0.01.

Table B.9: Regressions on Digital Adoption Using ESIEC 2023 Data

	(1)	(2)	(3)	(4)	(5)	(6)
	App Adoption		Digital Device		AI Knowledge	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
MNEJob	0.105***	1.383**	0.077**	1.808***	0.176***	1.422**
	(0.034)	(0.673)	(0.037)	(0.592)	(0.036)	(0.586)
SOEJob	-0.026	-0.055*	-0.046**	-0.086**	0.022	-0.006
	(0.023)	(0.029)	(0.022)	(0.038)	(0.023)	(0.026)
Control	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	0.114	-0.486	0.264	-0.840	0.163	-0.427
Weak IV F Stat.	20.032 (for 2SLS only)					
Observations	3,678 (ESIEC 2023)					

Data source: ESIEC 2023, Population Census, Business Registration Dataset, and the *Catalogue*. This table reports regression results examining the relationship between MNE work experience and various measures of digital adoption. All specifications include the baseline set of entrepreneur- and firm-level control variables, as well as county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. Significance level: *p <0.1 **p <0.05 ***p <0.01.

Table B.10: Impact of MNE Experience on Adult Entrepreneurship Following Job Changes

	(1)	(2)	(3)	(4)	(5)
	Outcome: Start Self-Employed upon Job Change				
	OLS		Staggered DID Method		
	Full Sample	Subsample w/ Job Change	Full Sample	Not-yet-treated As Control	Subsample w/ Job Change
ATT	0.145***	0.151***	0.126***	0.126***	0.132***
	(0.028)	(0.030)	(0.034)	(0.034)	(0.034)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	0.566	0.494	-	-	-
Observations	150,039	86,635	150,039	150,039	86,635

Data source: CFPS 2010-2022. This table examines the propensity of individuals to enter entrepreneurship upon changing jobs. Columns (3)-(5) are estimated using the Callaway and Sant'Anna (2021) doubly robust difference-in-differences estimator to account for staggered treatment timing. All specifications include individual and year fixed effects. Standard errors are clustered at the individual level. Significance level: *p <0.1 **p <0.05 ***p <0.01.

Table B.11: 2SLS Regressions on Entrepreneurial Entry Histories

	(1) Firm	(2) Serial	(3) Gov. Network	(4) Joint	(5) Borrow or Credit	(6) Subsidy	(7) Same Ind.
MNEJob	0.473**	-0.070	-0.426**	0.974***	-0.213	-0.229	0.753***
	(0.233)	(0.284)	(0.195)	(0.259)	(0.268)	(0.158)	(0.258)
SOEJob	0.011	0.035*	0.050***	-0.004	0.026	0.020	-0.070***
	(0.017)	(0.021)	(0.017)	(0.023)	(0.022)	(0.016)	(0.021)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	0.018	-0.006	-0.175	-0.214	-0.028	-0.071	-0.246
Observations	5,538						4,063 ($\geq$ 1 Job(s))

Data source: ESIEC 2018 & 2023, Population Census, Business Registration Dataset, and the *Catalogue*. Column (7) only includes entrepreneurs with at least one job before venturing. This table reports 2SLS estimates on entrepreneurial entry using the Bartik IV. All specifications include the baseline set of control variables, alongside county, industry, and wave fixed effects. Standard errors are clustered at the birthplace-year level. Significance level: *p <0.1 **p <0.05 ***p <0.01.

Table B.12: OLS Suggestive Evidence Based on the OSOME Data

	(1) Online Operation	(2) Online Sales	(3) Remote Work	(4) Electric System
MNE Job	0.014**	0.016***	0.013***	0.264***
	(0.006)	(0.006)	(0.003)	(0.020)
SOE Job	-0.012**	-0.018***	0.006**	0.209***
	(0.005)	(0.005)	(0.003)	(0.018)
IT Job	0.158***	0.149***	0.052***	0.405***
	(0.007)	(0.007)	(0.004)	(0.023)
Control	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
Adj. R-sq	0.095	0.103	0.031	0.163
Observations	49,264		33,333	

Data source: OSOME (2020Q4 - 2021Q2). OLS regressions are reported. Controls include the entrepreneurial characteristics (age, education, gender, years of work experience) and business attributes (reported impact of COVID-19, total employment, registered type, and revenue). All specifications include city, industry, and wave fixed effects. Standard errors are clustered at the city level. Significance level: *p <0.1 **p <0.05 ***p <0.01.

Appendix C ESEIC Survey Representativeness

We provide suggestive evidence regarding the representativeness of the ESIEC survey data through several comparisons. First, we compare the industrial distributions of the ESIEC sample with the 2018 China Economic Census. In the ESIEC sampling design, the wholesale and retail industry was intentionally undersampled at a rate of one-quarter of its actual population fraction due to the high degree of firm homogeneity in that sector. To ensure comparability with census data, we reweighted the ESIEC wholesale and retail fraction by a factor of four. As shown in Appendix Figure 8(a) below, the distribution of firms at the SIC-1 (1-digit Standard Industrial Classification code) level closely resembles the national distribution. Furthermore, as shown in Appendix Figure 8(b), while the 2018 China Economic Census contains a slightly higher proportion of enterprises with fewer than seven employees than ESIEC, these differences are not statistically significant on average.

Second, we compare the distributions between the respondent sample (those who completed the questionnaires) and the total sampled frame in 2018. Appendix Figure 9(a) illustrates that the industrial composition at the SIC-1 level is nearly identical for both groups. Similarly, Appendix Figure 9(b) presents the distribution of registered capital across seven intervals, showing no significant difference either.

Given that regional variation in China is often more pronounced at the city level than at the province level, we also compare city-level GDP per capita in 2018 between the cities included in our sample and all cities nationwide. Appendix Figure A.10 shows that the city-level distribution in our sample largely reflects that of the general Chinese urban landscape. To further account for regional heterogeneity, we control for county-level fixed effects in our baseline regressions.

A comparison with macro-level employment data further supports the representativeness of the ESIEC sample. Among the enterprises in ESIEC, 21.53% are self-employed enterprises that do not employ additional staff. Enterprises with seven or fewer full-time employees account for 70.5%, while those with 8-19 employees account for 14.8%, those with 20-99 employees account for 12.4%, and those with over 100 employees account for 2.4%.

Extrapolating from these figures, if there are approximately 20 million registered active enterprises nationwide (based on the operational rate of 24.19% among the 80 million entities registered by the end of 2017), they would provide nearly 300 million jobs (assuming an average of 15 employees per enterprise). Furthermore, according to the China Statistical Yearbook 2018, the total employed population was 776 million. In 2017, the number of registered self-employed individuals nationwide was 336 million. Together, small businesses and registered self-employed entities provide approximately 636 million jobs, accounting for

77% of the total employment [(300 + 336) / 776]. This calculation aligns closely with the 2018 Report on Financial Services for Chinese Small and Micro Enterprises by the People's Bank of China, which highlights that small businesses contribute 80% of national employment.[5]

[5]Please refer to https://www.pbc.gov.cn/goutongjiaoliu/113456/113469/3848271/2019071514262262632.pdf.

Appendix D Supplementary Evidence

D.1 Bayesian Derivation of the Entrepreneurial Likelihood Given MNE Experience

This section provides a formal Bayesian derivation to support the proposition that prior MNE work experience is positively associated with the propensity for entrepreneurship.

Let E denote the event of being an entrepreneur, MNE represents the event of having MNE work experience, and $\overline{E}$ denotes being a non-entrepreneur (a member of the broader labor force excluding entrepreneurs). The empirical observation in Figure 2 indicates that the proportion of entrepreneurs with MNE experience exceeds the corresponding proportion among non-entrepreneurs. Formally, this can be written as:

$$P(\text{MNE} \mid E) > P(\text{MNE} \mid \overline{E}).$$

We aim to show that this inequality implies $P(E \mid \text{MNE}) > P(E)$.

First, note that the overall probability of having MNE experience in the labor force is:

$$P(\text{MNE}) = P(\text{MNE} \mid E)P(E) + P(\text{MNE} \mid \overline{E})P(\overline{E}).$$

Given $P(\text{MNE} \mid E) > P(\text{MNE} \mid \overline{E})$, and noting that $P(\text{MNE})$ is a weighted average of these two conditional probabilities with weights $P(E)$ and $P(\overline{E}) = 1 - P(E)$, it follows that:

$$P(\text{MNE} \mid \overline{E}) < P(\text{MNE}) < P(\text{MNE} \mid E),$$

assuming $0 < P(E) < 1$. Specifically, we establish that:

$$P(\text{MNE} \mid E) > P(\text{MNE}).$$

Now, by Bayes' theorem, the posterior probability of entrepreneurship given MNE experience is:

$$P(E \mid \text{MNE}) = \frac{P(\text{MNE} \mid E)\, P(E)}{P(\text{MNE})}.$$

Rearranging the terms to compare the posterior to the prior probability $P(E)$:

$$\frac{P(E \mid \text{MNE})}{P(E)} = \frac{P(\text{MNE} \mid E)}{P(\text{MNE})}.$$

Given $P(\text{MNE} \mid E) > P(\text{MNE})$, the right-hand side exceeds one, implying:

$$\frac{P(E \mid \text{MNE})}{P(E)} > 1 \quad \Longrightarrow \quad P(E \mid \text{MNE}) > P(E).$$

Thus, the empirical condition $P(\text{MNE} \mid E) > P(\text{MNE} \mid \overline{E})$, i.e., a higher prevalence of MNE experience among entrepreneurs relative to non-entrepreneurs, leads to the conclusion that MNE-experienced individuals are more likely to be entrepreneurs than a randomly selected individual from the labor force.

D.2 Extensive Margin

While our analysis has mainly focused on the intensive margin—namely, innovation outcomes and their spillover effects on business performance, this section provides suggestive evidence regarding the extensive margin: whether the prior MNE work experience increases the overall propensity for entrepreneurship. At the aggregated level, we employ an event study approach to show that the constructed exposure to MNEs (proxied by the Bartik IV in 2001) is associated with a slight increase in new non-FDI firm entries within an entrepreneur's birth city, as illustrated in Appendix Figure A.11.

To examine this at the micro level, we use the longitudinal CFPS survey data to track salaried workers over time. The CFPS provides detailed work history, allowing us to track the timing of MNE work experience. We define the variable $MNEJob_{it}$ as a binary indicator equal to one starting from the year when a worker began his or her first job at an MNE. We further identify in each wave of the survey whether a person changed his/her job for the first time during the observation period, as a $Post_{it}^{Job\ Change}$ indicator. These form a DID framework to examine whether individuals transition into self-employment (including business ownership) upon changing jobs, specified as follows:

$$\text{SelfEmp}_{it} = \beta \cdot (\text{MNEJob}_{it} \times \text{Post}_{it}^{\text{Job Change}}) + \alpha_i + \gamma_t + \epsilon_{it}, \tag{D.1}$$

where the dependent variable is a time-varying dummy for the respondent's self-employed status. In the panel data regression, individual and year fixed effects are controlled. Standard errors are clustered at the individual level.

These estimates provide suggestive evidence, as the decision to change jobs and its timing may be endogenous. An event study using the Callaway and Sant'Anna (2021) approach (Appendix Figure A.12) reveals that workers with MNE experience are significantly more likely to enter self-employment following a job change than their peers. Appendix Table

B.10 presents both the OLS regression and staggered DID results. Despite the potential endogeneity of job changes, we find no evidence to reject the parallel trends assumption in the pre-treatment period. On average, the increased probability of entering self-employment persists for approximately two survey waves (three to four years). Moreover, the CFPS data indicate that turnover rates are higher among employees with MNE experience, particularly after 2014—a period coinciding with the reported trend of MNEs "starting to escape China" (see Appendix Figure A.13).

Finally, we return to the ESIEC survey to examine the entrepreneurial entry history. As previously discussed in the main text, entrepreneurs with MNE experience often secure their first business orders through outsourcing relationships with former employers, providing a distinct entry advantage. To explore other mechanisms, we regress various aspects of business establishment on MNE experience using the same IV specifications outlined in Eq.(4) and (5).

As shown in Column (1) of Appendix Table B.11, former MNE employees are more likely to establish incorporated firms rather than unincorporated self-employed ventures. This is consistent with our earlier findings of business formalization, proxied by social insurance enrollment and on-the-job training. While these individuals were not overrepresented among serial entrepreneurs (Column 2), their ventures typically involved more founding partners (Column 4). Moreover, these businesses rely significantly less on government connections or personal acquaintances for their launch (Column 3) and are less dependent on informal credit or government subsidies (Columns 5 and 6). Additionally, they are more likely to venture into the same industry as their previous MNE employment.[6]

Overall, these extensive-margin patterns further support the entrepreneurial mobility channel: skills, networks, and resources acquired in MNEs facilitate the creation of more structured, formally organized, and market-oriented ventures.

D.3 Robustness Check

We first check whether the baseline results are consistent across alternative econometric specifications. We find that results from the Probit and IV-Probit estimation are consistent with our linear baseline models, as shown in Appendix Table B.7, confirming that the choice

[6]The 2023 wave included a question on entrepreneurs' primary motivation for starting their business. As shown in Appendix Figure A.14, compared to those without any job experience or without MNE experience, entrepreneurs with an MNE background were significantly more likely to report "self-actualization" as their main reason and less likely to cite "income" as their primary driver. This suggests that prior exposure to MNEs may shape entrepreneurial intentions toward more intrinsic, non-pecuniary goals. Although it could also be driven by self-selection, we find no direct evidence in our data that pre-venture "passion for innovation" motivation systematically differs between those with and without MNE experience.

of functional forms does not drive the results.

To further validate the measurement of MNE experience, we conduct a series of placebo tests using alternative definitions and aspects of work experience, as reported in Appendix Table B.8. These tests help rule out the possibility that the effect of *MNEJob* is merely a proxy for other confounding factors, such as general work experience.

Columns (1) and (2) control for the total number of prior jobs held by the entrepreneur. The estimated effect of MNE experience remains robust and statistically significant, indicating that our findings are not merely capturing general labor market exposure. Notably, when we redefine the treatment variable to include only the most recent pre-entrepreneurship job in an MNE, the estimated effect remains unchanged. This suggests that more recent MNE exposure may have a particularly strong influence on subsequent innovation performance.

Moreover, we examine whether having family members (parents or spouses) with MNE work experience affects entrepreneurial innovation. The results show no significant effect, reinforcing that the mobility channel is individual-specific rather than a social network effect. Finally, we test alternative types of work experience, such as employment in SOEs, the government, or the public sector, as well as jobs taken outside the entrepreneur's hometown. None of them presents significant effects. This aligns with the previous finding that none of these alternative experience measures is correlated with the Bartik instrument, supporting both the exogeneity of our IV and the specificity of the MNE exposure effect (Appendix Table B.5). Together, these placebo tests bolster the measurement of our main results.

We also conduct extensive robustness tests to address alternative explanations for our findings.[7] First, beyond our IV approach, we account for potential self-selection by controlling for entrepreneurs' education levels, risk attitudes, pre-venture innovative tendencies (proxied by subjective entrepreneurial motivation being "*passion for innovation*" in the 2023 wave), and their interaction terms with *MNEJob*. We find that these factors do not explain our results. In fact, we observe a negative interaction between education and MNE experience, contradicting the alternative hypothesis that MNEs merely select high-ability individuals who would have innovated regardless.

Second, to ensure our results are not driven by MNEs' concentration in highly innovative industries, we include more detailed industry fixed effects and the prior-venture job industry fixed effects. The estimates remain unchanged.

Third, we evaluate whether the observed innovation effects are driven by exposure to international markets. For instance, entrepreneurs with MNE backgrounds are more familiar with global markets and export procedures, and may therefore engage in innovation aimed

[7] While tables are omitted for brevity, they are available upon request.

at international standards and competition. To test this export-oriented hypothesis, we analyze heterogeneity across export status and within Economic Development Zones, some of which were explicitly designed to promote exports. The results show no disproportionately larger effects, suggesting that the observed effect is not primarily mediated by export market exposure.

Fourth, we address potential concerns regarding coincidental timing between growing FDI inflows and broader innovation trends. This issue has been substantially mitigated in our empirical design by accounting for spatial variation in MNE exposure and including comprehensive fixed effects. Moreover, Figure 2 shows that the time trend of entrepreneurs with MNE experience does not follow a monotonic pattern, further alleviating this concern. Regression controlling for interaction terms with birth cohort dummies also remains robust.

Fifth, to distinguish between novel innovation and mere imitation, we examine the self-reported novelty of their innovations in domestic and international markets in Table 5. Entrepreneurs with prior MNE experience exhibit significantly higher levels of innovation novelty.

Sixth, we rule out a signaling-based financing channel by showing that MNE experience neither improves access to external bank credit at entry nor is associated with higher self-reported social class.

Seventh, we control for industrial policy effects through county-industry fixed effects (Appendix Table B.2) and government subsidies, finding no significant difference. We also explicitly control for agglomeration and competition by incorporating the industrial clustering index, as developed by Ruan and Zhang (2025), which captures the strength of agglomeration within local industrial clusters in the survey year, and the Herfindahl–Hirschman Index (HHI) measured at the county-industry level, which serves as an inverse indicator of local market competition intensity. The inclusion of these proxies and their interaction terms with *MNEJob*) does not alter our baseline findings.

Overall, our results remain consistent and robust across all tests, strongly supporting the entrepreneurial mobility mechanism—where knowledge diffusion occurs via MNE work experience—over alternative explanations.

D.4 Micro Business

The above analyses have primarily focused on formally registered businesses, as our sample was drawn from official business registration records. However, a substantial number of self-employed individuals and small businesses in China operate without formal registration. As noted by Cong et al. (2024), approximately 38.7% of such entities were unregistered,

highlighting the importance of considering informality in understanding the entrepreneurial landscape.

To this end, we utilize the quarterly Online Survey of Micro-and-small Enterprises in China (OSOME), an online small business survey conducted on the most widely used e-payment platform, Alipay (Kong et al., 2022), by Peking University and Ant Group. One key difference lies in its inclusion of unregistered self-employed businesses, covering a larger share of active unregistered self-employed businesses for the first time.[8] From the fourth quarter of 2020 to the second quarter of 2021, additional questions were introduced regarding business owners' prior work experience, which we use to construct our key independent variables. We also control for a set of basic firm and entrepreneur characteristics, including employment size, age, education level, gender, total years of work experience, registration type, quarterly revenues, and COVID-19 lockdown status, given that the survey was conducted during the pandemic. Since we didn't observe the birthplace in the OSOME data, we report the OLS regression to have some suggestive evidence in Appendix Table B.12. On the one hand, we find that prior working experience, in MNEs and in the Internet or information technology (IT) sectors, matters for their digitization, particularly in terms of online operations and sales, as well as the adoption of remote work and electric systems. On the other hand, consistent with the baseline finding, though the IT job experience substantially motivates their digitization, the impact of MNE experience is still significantly positive after controlling for it.

[8] Active small businesses on the Alipay platform are defined as those that had transactions in at least three months, more than 90 transactions, and a total volume of more than 2,000 yuan RMB (nearly 270 US dollars) in the past twelve months. Alipay reached 1.2 billion monthly users in 2019 and is the primary payment method for 90% of people in China, along with WeChat Pay (Klein, 2020).