The Welfare Effects of Place-Based Talent Incentives

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March 24, 2026

Abstract

Local governments increasingly compete for skilled workers through place-based subsidies, yet their welfare effects remain uncertain. We study China's Talent Incentive Programs (TIPs), which offer subsidies to attract high-skill workers across cities. Combining staggered difference-in-differences with a quantitative spatial model featuring endogenous occupational choice, we find that subsidies attract high-skill workers to treated cities but raise the economy-wide opportunity cost of entrepreneurship, crowding skilled workers out of firm creation. This occupational reallocation compresses skill-based inequality by 29 percent. Aggregate welfare gains are modest because spatial sorting gains are largely offset by the entrepreneurship distortion. The occupational choice margin raises welfare by 11 percent relative to a model without firm dynamics, as low-skill workers buffer by entering entrepreneurship. The distributional and aggregate effects of place-based talent policies depend critically on this endogenous occupational margin.

Keywords: High-Skill Migration, Occupational Choice, Dynamic Spatial Equilibrium
JEL codes: R23, R12, J24, L26, H71

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1 Introduction

Place-based policies increasingly target workers rather than firms, offering relocation grants, housing subsidies, and tax breaks to attract skilled individuals.[1] More than 70% of Chinese cities now operate talent subsidy schemes, providing variation in policy timing, generosity, and eligibility that allows study of aggregate effects at scale. Yet whether these subsidies improve aggregate welfare remains theoretically ambiguous. Local gains may be purely redistributive, and existing frameworks often treat the set of firms as given, leaving unexamined whether subsidies alter occupational choices, particularly entrepreneurship, not just where workers locate.

This paper studies the aggregate and distributional effects of talent subsidies using China's Talent Incentive Programs (TIPs), a nationwide set of place-based policies in which local governments offer housing subsidies, living stipends, and relocation grants to attract skilled workers. Cities adopted TIPs at different times between 2000 and 2019 across 283 cities, with sharp educational eligibility thresholds and large internal migration flows that make aggregate and distributional effects potentially important. To evaluate both the local and aggregate welfare effects of these policies, we combine staggered difference-in-differences estimation with a dynamic spatial equilibrium model featuring migration, occupational choice, and endogenous public services.

The key insight is that talent subsidies reduce the cost of relocating, raising the expected value from moving and thereby increasing the opportunity cost of entrepreneurship for high-skilled workers. Workers can move to exploit better opportunities elsewhere, while entrepreneurs remain tied to local markets through their firms. The subsidy therefore pulls potential firm-creators into wage work, and whether this response raises or lowers welfare depends on whether the spatial efficiency gain from better worker sorting outweighs the loss of productive capacity from reduced entrepreneurship. In standard quantitative spatial models (Caliendo et al., 2019; Fajgelbaum and Gaubert, 2020), better spatial sorting generates welfare gains with no occupational cost because the set of firms is taken as given. Our framework shows that high-skill exit from entrepreneurship partially offsets the spatial sorting gain, but the compensating entry of low-skill entrepreneurs provides a buffer that raises aggregate welfare above what a model with fixed firm sets would predict.

The reduced-form evidence confirms large local effects. High-skill immigration into treated cities increases by 17%, firm entry rises substantially in skill-intensive sectors, and low-skill workers show effectively zero migration response, consistent with eligibility restrictions. The model counterfactual reveals modest aggregate welfare gains of 0.17%, comparable in magnitude to estimates from rural-urban migration subsidies (Lagakos et al., 2023) but operating through spatial sorting

[1] Examples include Tulsa Remote offering $10,000 relocation packages to remote workers in the US, with evidence showing positive local welfare effects when housing vacancy absorbs inflows (Yoo, 2025); China's Thousand Talents Plan targeting overseas scholars; Italy's tax breaks for return migrants with elasticities near 0.9 (Ippedico and Bassetto, 2024); and broader visa programs for attracting foreign talent (Kerr et al., 2016). Unlike place-based policies that subsidize firm relocation or capital investment (e.g., enterprise zones, Special Economic Zones), these programs directly target individuals based on personal characteristics rather than firm attributes.

offset by occupational distortion. Endogenous occupational adjustment adds 11% to aggregate welfare through the low-skill buffer channel, as low-skill workers enter entrepreneurship to fill gaps left by exiting high-skill entrepreneurs. Distributional effects are large and skill-biased, with high-skill workers gaining 1.46% in welfare versus 0.04% for low-skill workers.

Our empirical strategy exploits staggered TIPs adoption using difference-in-differences designs. We assemble novel datasets combining city-pair migration flows, firm registration records, city-level economic outcomes, and hand-collected municipal policy documents. TIPs offer two main components, including living stipends or relocation grants providing direct income transfers (the dominant component adopted by nearly all participating cities) and housing subsidies. These benefits function as direct transfers to eligible migrants, reducing both the pecuniary cost (housing, moving expenses) and institutional cost (hukou access) of relocating to treated cities. We focus on housing and living subsidy adoption as our main treatment variables, since housing and living costs represent the binding constraints deterring high-skill workers from moving across space (Diamond and Suarez Serrato, 2025). These instruments offer observable variation in policy intensity and, unlike China-specific institutional features such as hukou reform, correspond to policy tools available in other countries, making the results broadly applicable.

The reduced-form evidence confirms the local effects previewed above and reveals additional detail. Firm entry rises substantially following policy adoption, with growth concentrated in skill-intensive sectors. High-skill entrepreneurship increases by 18%, suggesting that TIPs affects occupational choice through two channels. High-skill migrants may start their own firms after relocating, or local skilled workers may become entrepreneurs in response to the influx of potential employees. On the fiscal side, subsidy expenditure rises by 3.25%, but there is no evidence that revenue per capita declines, suggesting that the program does not drain local government capacity. The skill premium widens, consistent with demand for high-skill labor outpacing the supply response. These findings align with recent evidence that return migration boosts local productivity in China (Du et al., 2025), and confirm that financial incentives substantially affect high-skill mobility (Ippedico and Bassetto, 2024).

These reduced-form results establish that TIPs generates large local gains in migration, entrepreneurship, and output. However, they cannot resolve three critical questions. First, are these gains real or redistributive? Local treatment effects may reflect talent reallocation from control cities rather than aggregate productivity increases. Second, how do general-equilibrium adjustments in wages, land prices, and entrepreneurial returns affect inequality across skill groups and regions? Third, what are the spatial spillovers to non-TIPs cities? To address these questions, we develop a dynamic spatial equilibrium model with skill heterogeneity, endogenous migration, and endogenous entrepreneurship. The model builds on Huỳnh (2025) by introducing two types of workers (high-skill and low-skill)[2] and allowing entrepreneurship to respond endogenously to local factor

[2]In China, college admission is determined by a highly competitive national entrance examination (gaokao) with strict annual quotas. This creates a sharp, largely permanent skill distinction. Cross-group mobility is limited because acquiring college credentials as an adult is institutionally difficult and rare, justifying our treatment of skills as fixed

supplies and policy regimes. The model captures general-equilibrium feedbacks through labor and land markets, inter-city trade linkages, and occupational choice, with TIPs subsidies modeled as reductions in migration costs.

A key model insight is that whether firm dynamics are net positive or negative for aggregate welfare depends on the government budget constraint. When subsidy costs reduce public goods provision, low-skill workers, who receive no subsidy but bear the fiscal burden, need an alternative source of income. The exit of high-skill entrepreneurs opens profitable niches, and low-skill workers fill them, shifting their welfare from negative to positive.

We calibrate the model and conduct counterfactual experiments to quantify the allocative and welfare effects of TIPs. Despite large local employment effects (high-skill labor in treated cities increases by 5.0%), the aggregate welfare gain is modest because spatial sorting gains are partially offset by occupational distortion. Steady-state dynamics reveal a nuanced pattern. High-skill entrepreneurs exit economy-wide as employment returns rise, but low-skill workers enter entrepreneurship to fill the gap, eventually restoring total firm counts. Even in treated cities, high-skill entrepreneurship declines in absolute terms despite the eventual recovery in total firms.

Distributional effects are large and skill-biased. Entrepreneurship dynamics play a critical role in both efficiency and equity. When we shut down occupational choice (holding firm entry/exit fixed), high-skill workers gain even more (1.98%), since eliminating the occupational distortion raises high-skill wages further. However, low-skill workers are hurt under this scenario (-0.03%), losing the margin of adjustment into entrepreneurship when wage employment becomes less attractive. With endogenous firm dynamics, low-skill workers enter entrepreneurship as a buffer, shifting their welfare from negative to positive. The occupational buffer raises aggregate welfare while compressing skill-based inequality by 29%.

This paper contributes to the literature on place-based policies and spatial equilibrium (see Neumark and Simpson, 2015, for a survey). Quantitative spatial models emphasize that welfare effects depend on worker mobility, sorting, and agglomeration spillovers (Caliendo et al., 2019; Fajgelbaum and Gaubert, 2020). Empirical evidence shows place-based policies generate large local gains, but aggregate effects depend on whether these are offset elsewhere through general equilibrium (Busso et al., 2013; Kline and Moretti, 2014; Alder et al., 2016). Fajgelbaum and Gaubert (2020) derive optimal spatial policies when productivity and amenity spillovers create inefficient sorting, showing that welfare-improving subsidies often target low-productivity locations to correct spatial misallocation. Gaubert et al. (2025) extend this framework to study place-based redistribution, showing that welfare gains depend on the structure of sorting and spillovers. Most place-based programs target firms through tax incentives or direct subsidies, with welfare gains from subsidy competition that are often modest (Slattery, 2025). Our contribution differs in focus and mechanism. We study policies targeting high-skill individuals rather than firms and incorporate an occupational margin absent from models with fixed production capacity. This approach introduces a novel

types rather than endogenous human capital accumulation.

tradeoff where policies can improve spatial sorting while simultaneously distorting occupational choice.

Our contribution to the migration subsidies literature addresses how existing findings on migration and productivity, which appear to conflict, in fact measure different objects. Bryan et al. (2014) find large private income gains for individual movers, while Lagakos et al. (2023) find modest aggregate welfare effects of around 0.5%. These studies estimate different quantities, private returns versus aggregate welfare, and our paper quantifies both within a unified framework. Similarly, high-skill agglomeration raises productivity through human capital spillovers (Moretti, 2004), yet large-scale migration can reduce manufacturing productivity by inducing labor-intensive technology adoption (Imbert et al., 2022). Our mechanism shows the sign depends on occupational composition, not just skill composition. By restricting eligibility to college-educated workers, TIPs activates high-skill spillovers while the occupational margin determines whether firm creation rises or falls. While the return migration literature emphasizes entrepreneurship-led productivity gains,[3] our reduced-form estimates show entrepreneurship rising in treated cities (local relative effects) while GE counterfactuals show high-skill entrepreneurship declining economy-wide (absolute effects). Recent evidence that high-growth startups themselves migrate toward favorable locations (Bryan and Guzman, 2026) underscores the importance of modeling firm dynamics jointly with worker mobility, as we do here.

The remainder of this paper proceeds as follows. Section 2 describes the institutional background of TIPs and our data construction. Section 3 presents the empirical strategy and reduced-form evidence on migration, entrepreneurship, and local economic outcomes. Section 4 develops the dynamic spatial equilibrium model. Section 5 describes the calibration strategy. Section 6 presents quantitative results, including aggregate welfare effects, distributional consequences, and decompositions isolating the spatial sorting and occupational distortion channels. Section 7 concludes and discusses implications for talent-attraction policies more broadly.

2 Institutional Background and Data

2.1 China's Talent Incentive Programs (TIPs)

Over the past two decades, municipal governments in China have increasingly leveraged Talent Incentive Programs (TIPs) as a core development strategy. A major turning point was the 2010 issuance of the National Medium- and Long-Term Talent Development Plan Outline (2010–2020), which elevated talent development to a national strategic priority and helped trigger a

[3] A substantial body of work documents that return migrants start firms and generate productivity spillovers (McCormick and Wahba, 2001; Démurger and Xu, 2011; Wahba and Zenou, 2012; Du et al., 2025; Prato, 2025). Chen et al. (2020) study forced talent inflows under China's sent-down program, finding inequality reductions in less-developed counties.

sustained "war for talent" across cities.[4] While the central government sets broad innovation and human-capital goals, local governments retain substantial discretion over the design, magnitude, and timing of these initiatives. This decentralization has intensified inter-city competition for high-skilled labor, particularly college graduates, and has facilitated frequent, policy-driven experimentation in both incentives and implementation mechanisms.

Unlike traditional place-based policies that subsidize firms or infrastructure, TIPs directly target human capital. Local officials emphasize that skilled workers generate productivity, innovation, and entrepreneurial spillovers, thereby easing constraints on firm entry and local growth. In practice, TIPs are often implemented through responsibility-style targets that push recruitment and retention objectives down to local public institutions and enterprises. The resulting policy emphasis is especially pronounced in cities seeking industrial upgrading, where attracting and retaining skilled workers is viewed as a prerequisite for moving into higher value-added activities.

The TIPs analyzed in this paper typify this broader policy environment. Participating cities offer a menu of benefits to eligible high-skill individuals, including housing subsidies, relocation and living allowances, preferential access to public services (e.g., schooling and healthcare), and, in some cases, research funding, and career advancement support. Policy orientation varies: some programs focus on attracting "high-level" talent tied to strategic sectors or key projects, while others explicitly support firms as the primary channel for talent recruitment. Eligibility criteria are typically defined using sharp thresholds based on education, age, occupation, or prior employment experience. Crucially, cities adopt TIPs at different times, driven primarily by local fiscal capacity, development objectives, and regional competition rather than transient economic shocks. While program details differ across locations, the core structure—subsidizing high-skill migration rather than firms—remains common.

TIPs provide a particularly informative setting for studying local competition for talent. First, staggered adoption across cities supports a difference-in-differences research design. Second, eligibility thresholds generate sharp treatment definitions. Third, internal migration in China is large and responsive to policy-induced changes in real costs of living and access to local services, allowing TIPs to generate meaningful reallocation effects. Finally, rich administrative and survey data enable us to track migration, firm dynamics, and local economic outcomes over time. Together, these features make TIPs well-suited for studying both local treatment effects and broader general-equilibrium spillovers induced by policy-driven competition for talent.

2.2 Data

We assemble a comprehensive database combining four distinct panels to study the interplay between talent incentives, migration, entrepreneurship, and local economic development.

[4] In 2010, the Central Committee of the Communist Party of China and the State Council issued the *National Medium- and Long-Term Talent Development Plan Outline (2010–2020)*. Based on searches of the PKULaw (Beida Fabao) database, governments at central and local levels issued 810 talent-related policy documents since 2000, including about 700 local policies since 2010.

Figure 1—TIPs Policy Adoption and Subsidy Intensity



(a) Share of Cities with Any TIPS (b) Policy Co-occurrence (c) Subsidy Intensity

Notes: Panel (a) plots the yearly share of cities with any talent incentive policy (TIP). Panel (b) shows the co-occurrence of policy types among TIPs cities; each cell reports the share of TIPS cities that ever adopted both policies (upper triangle shown, diagonal is the share for each policy). Panel (c) plots the distribution of normalized subsidy amounts (including life and housing support) for selected years (2010 and 2015).

Talent Incentive Policy Data We construct a novel city-year panel of these policies between 2000 and 2019 by manually collecting information from official municipal government documents, policy announcements, and archived web sources. We classify these incentives into five broad categories: housing subsidies (e.g., purchase subsidies, rental allowances), living and family stipends (e.g., cost-of-living or salary supplements, spousal employment, children's education), residency (*hukou*) privileges, job and career advancement support (e.g., recruitment bonuses), and research funding (e.g., grants, startup fund). For each city, we record the year of program adoption and code the generosity of housing and life subsidies offered to eligible individuals.[5] Appendix A provides detailed documentation of data sources, coding procedures, and validation checks.

Panel (a) of Figure 1 illustrates the expansion of TIPs from 2000 to 2019, revealing a clear diffusion pattern. Policy adoption began with a decade of localized experimentation (2000–2009), where the share of treated cities rose gradually from near zero (2.5%) to approximately 20%. This initial phase was driven by pioneer cities piloting initiatives based on idiosyncratic local needs rather than a coordinated national mandate. A structural break appears around 2010, marking the onset of rapid acceleration and widespread adoption. By 2019, the policy landscape approached saturation, with over 70% of cities having implemented talent incentives. This trajectory confirms that TIPs have evolved from novel, isolated interventions into a ubiquitous instrument of regional development policy in China.

Panel (b) decomposes the internal structure of TIPs, revealing that housing support serves as

[5]To quantify the intensity of housing and life subsidies, for each policy, we calculate the total present value of monetary benefits—comprising both lump-sum grants and recurring monthly allowances for housing and living expenses. Recurring payments are annualized and discounted over a ten-year service horizon using a 2.5% discount rate (proxied by the one-year fixed deposit rate), yielding a cumulative capitalization factor of 8.75. To facilitate cross-city comparison and account for purchasing power parity, we normalize this total subsidy value by the local median residential housing price per square meter. The resulting metric thus represents the subsidy's real value measured in equivalent square meters of local housing.

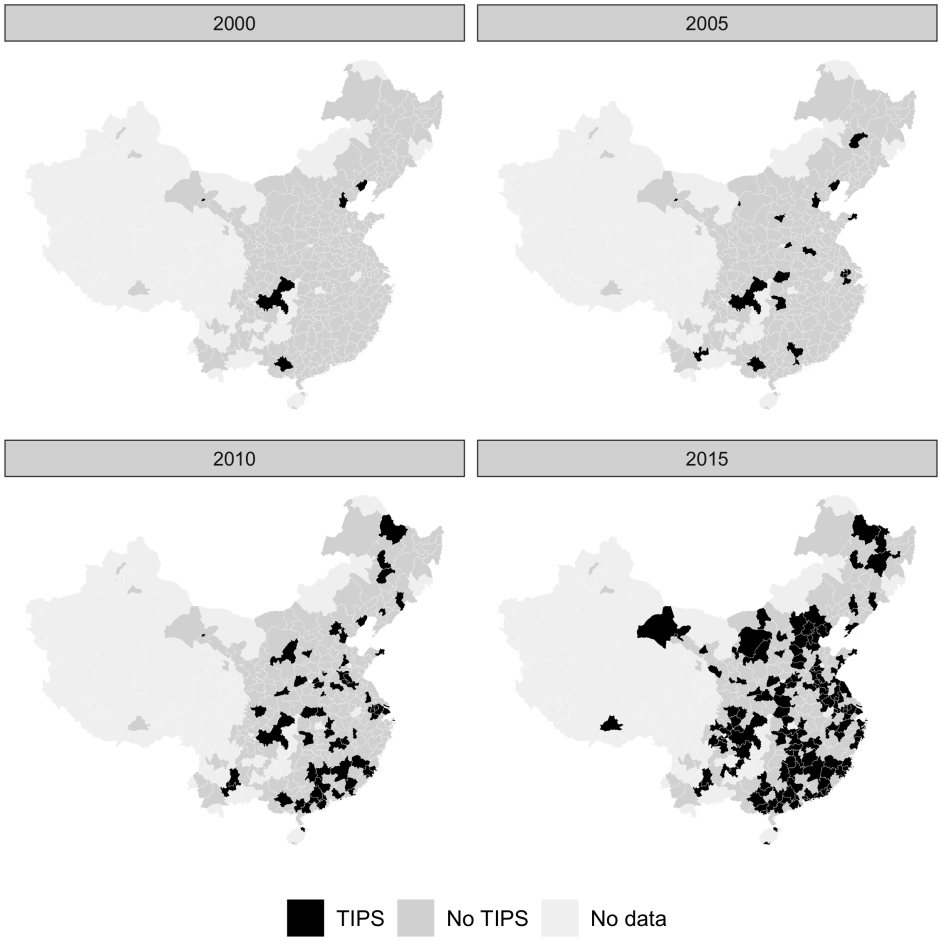
the cornerstone of local talent strategies. The dark diagonal cells indicate that housing subsidies are the most prevalent component, adopted by nearly all TIP-active cities. The high off-diagonal correlation between housing and life/family subsidies points to a dominant policy bundle designed to alleviate pecuniary cost-of-living and migration frictions. Hukou/residency facilitation also appears prominently and tends to co-occur with housing support, indicating that cities target both financial and administrative barriers to mobility. In practice, hukou policies lower institutional migration costs—access to public services, schooling, and social insurance—which complements housing subsidies in raising the effective (real) wage. In contrast, non-monetary incentives such as research funding or promotion support appear less frequently and are typically offered only in conjunction with core housing benefits. This pattern suggests that municipal governments view high living costs—and hukou-related access constraints—as primary binding frictions on skilled labor mobility, prioritizing real wage subsidies and residency reforms over purely amenity-based or career-oriented incentives.

Panel (c) documents the intensification of this competition over time. By plotting the distribution of subsidy generosity (normalized by local median housing costs) for 2010 and 2015, the figure illustrates a clear rightward shift. While the extensive margin of policy adoption expanded rapidly during this period (as shown in panel a), panel (c) confirms a simultaneous expansion on the intensive margin. In 2015, a significantly larger mass of cities offered subsidies exceeding the median housing cost benchmark compared to 2010. The widening dispersion in the 2015 distribution further highlights the heterogeneity in local fiscal aggression. This variation is crucial for our identification strategy, as it indicates that cities are distinguishing themselves not merely by having a policy, but by the magnitude of the incentive package offered to prospective migrants.

Figure 2 illustrates the spatiotemporal evolution of these programs across Chinese prefectural-level cities from 2000 to 2019. The panels reveal a distinct staggered adoption pattern, transitioning from isolated local experimentation to widespread regional diffusion. In 2000 (panel a), adoption was sparse and geographically fragmented, limited to a few pioneer cities. This distribution suggests that the policy began as a series of localized pilots rather than a coordinated national mandate. Between 2005 and 2010 (panels b and c), clustering began to emerge, particularly in the economically active Yangtze River Delta and central provinces, indicating that neighboring or commercially competitive jurisdictions emulated successful strategies to compete for talent (Zhou, 2004; Li and Zhou, 2005; Zhou, 2007; Fang et al., 2022).

By 2015 (panel d), the majority of cities in Eastern and Central China had activated talent incentives, though Western regions largely lagged. However, by 2019 (panel e), the policy landscape approached saturation, with adoption extending deep into Western and inland provinces. This final stage signals the transition of TIPs from a regional competitive tool to a nationwide development standard. Crucially, the variation shown across these two decades is neither monotonic nor strictly region-specific. The heterogeneous timing and geographic placement of adoption—spanning from early coastal adopters to late inland followers—provide the necessary variation for a staggered

Figure 2—The Staggered Rollout of Talent Incentive Programs across Chinese Cities, 2000-2015



Notes: This figure displays the geographic distribution of cities that adopted talent incentive programs across five cross-sections: 2000, 2005, 2010, and 2015. Shaded areas indicate prefectural-level cities with an active policy in the given year. The data are manually collected from municipal government websites and official policy documents.

difference-in-differences framework, ensuring the persistence of distinct treatment and control groups throughout the sample period.

City-Pair Migration Data Our analysis relies on a city-pair-year panel that tracks bilateral migration flows between origin and destination cities. Migration counts are constructed from the 2000 and 2010 Population Censuses and the 2005 1% Population Sample Survey (Mini-census). We decompose migration flows into subgroups by skill level (high-skilled vs. low-skilled) and *hukou* status (urban vs. rural).[6] To capture transportation costs and market integration, we include variables such as high-speed rail (HSR) connectivity, travel time, and bilateral trade volume.

[6]We define high-skilled individuals as those possessing a college degree or higher.

Firm and Entrepreneurship Data We utilize a city-sector-year panel to measure local business dynamism. Data are obtained from annual firm registration records in the registry database of the State Administration for Industry and Commerce (SAIC), which is the official agency for firm registration in China. This dataset tracks the universe of firm registrations and exits, disaggregated by industrial code. Key outcomes include the count of newly registered firms, broken down into parent companies and subsidiary/self-employment entities to distinguish between corporate expansion and grassroots entrepreneurship. We also observe the stock of incumbent firms, exit counts, and firm survival rates over three- and five-year horizons. Innovation activity is measured by the annual count of patents granted at the city-sector level.

Policy and Local Economic Outcomes We construct a novel city-year panel covering the period 2000–2019 by manually collecting information from official municipal government documents, policy announcements, and archived web sources. Our key independent variable is a binary indicator, $TIPS_{it}$, which equals one if a city has an active talent incentive program in a given year. We further classify these policies into five broad categories: housing subsidies, life and family stipends, residency (*hukou*) privileges, promotion and advancement support, and research funding. Beyond the binary adoption status, we also code the generosity of housing and life subsidies to capture the intensive margin of policy competition.

We match these policy variables with city-level economic indicators from statistical yearbooks. These include GDP, fiscal revenue (decomposed into VAT, corporate income tax, and individual income tax), fixed capital investment, and foreign direct investment (FDI). We also measure local amenities and infrastructure using data on road area, green space, and transportation volume (passenger and freight). Labor market conditions are captured by employment stocks disaggregated by education level and average annual wages for high- and low-skilled workers.[7]

Individual Employment Dynamics To examine micro-level employment responses to talent policies, we employ individual-level survey data tracking employment status transitions. This panel records each individual's city of residence, education level (college vs. non-college), and employment type (worker, self-employed, entrepreneur, or non-working). We construct cross-employment-type transition indicators to identify whether talent incentives facilitate occupational climbing or entry into entrepreneurship.

Summary Statistics Our empirical analysis uses a comprehensive panel of 283 prefectural-level cities from 2000 to 2019. Summary statistics reported in Appendix Table A2 reveal that cities adopting TIPs are systematically more developed than non-adopters, exhibiting significantly higher GDP, high-skill wages, and innovation output. These baseline disparities necessitate our identification strategy: rather than relying on cross-sectional comparisons, we employ a staggered

[7] We supplement the city-level wage series with skill-specific wage data from the 2005 1% Population Sample Survey (Mini-census).

difference-in-differences design that isolates causal effects by exploiting the differential timing of policy rollout among a dynamic pool of not-yet-treated controls.

Granular microdata further validate the mechanisms through which talent incentives operate. As documented in Appendix Table A3, high-skill intensive sectors constitute a more dynamic portion of the economy, characterized by higher rates of firm creation compared to traditional manufacturing. This suggests these industries exhibit greater sensitivity to human capital supply. Complementing this preliminary evidence, Appendix Figure A1 demonstrates that high-skilled labor exhibits a flatter distance decay in migration flows, confirming a higher responsiveness to spatial incentives over longer distances.

Finally, Appendix Table A4 highlights a distinct occupational sorting pattern: high-skilled workers in treated cities exhibit a transition rate from employment to entrepreneurship (1.19%) nearly double that of control cities. However, discerning whether this reflects a net stimulation of entrepreneurship or merely the spatial reallocation of entrepreneurial talent requires a general equilibrium framework capable of accounting for how migration subsidies alter the relative returns between wage employment and entrepreneurship.

3 Reduced-Form Evidence

We estimate the causal effects of TIPS using a staggered difference-in-differences design that exploits variation in policy adoption across cities and over time.

3.1 Empirical Strategy

We exploit quasi-experimental variation from the staggered adoption of TIPs across cities using an event-study framework. Treatment is defined as the adoption of either housing or living subsidies for high-skill workers, which are typically bundled together as documented in Section 2. We aim to estimate the dynamic evolution of outcomes using the following specification:

$$Y_{gt} = \alpha_g + \lambda_t + \sum_{k \neq -1} \delta_k \mathbf{1}\{t - T_g = k\} + \varepsilon_{gt}, \tag{1}$$

where g indexes units (cities for GDP, firm entry, and wages; city pairs for migration flows), α_g denotes unit fixed effects, λ_t denotes year fixed effects, and T_g is the adoption year of either housing or living subsidies. The coefficients δ_k capture the treatment effect k periods relative to the adoption year ($k = -1$).

Recent advances in the econometric literature highlight that standard two-way fixed effects (TWFE) estimators can be biased in staggered adoption designs with heterogeneous treatment effects (De Chaisemartin and D'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). In such settings, TWFE may implicitly assign negative weights to certain group-time comparisons, potentially distorting the average treatment effect. To

address these identification challenges, we employ the dynamic difference-in-differences estimator developed by De Chaisemartin and d'Haultfoeuille (2024). This estimator ensures that group-time average treatment effects are aggregated using non-negative, economically meaningful weights and is particularly well-suited to our setting as it explicitly accounts for treatment reversals, instances where cities pause or retract subsidy programs due to policy expiration or leadership changes.

3.2 Results

Effects on Migration and Entrepreneurship Figure 3 presents event-study estimates organized by skill level. The top row shows effects on high-skill outcomes, the bottom row shows effects on the corresponding low-skill outcomes. The contrast between rows is the central finding of the reduced-form analysis.

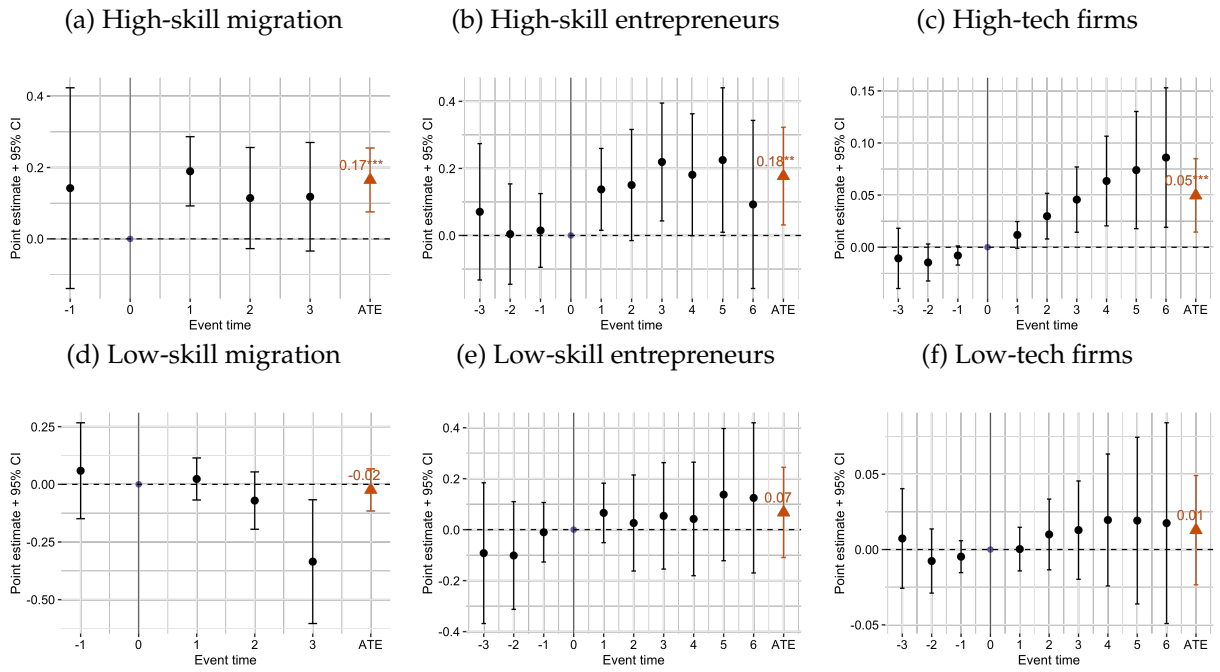
We estimate the causal effect of TIP adoption on talent mobility using city-pair migration flows from the 2000, 2005, 2010, and 2015 censuses. All specifications include city-pair fixed effects to absorb time-invariant gravity forces (e.g., distance, cultural proximity) and year fixed effects to control for aggregate mobility shocks. Panel (a) reveals a sharp and immediate response among high-skilled workers: immigration jumps by approximately 19% in the first period post-adoption and stabilizes between 12–16% in subsequent periods. The aggregated ATE indicates a statistically significant 17% increase in high-skill inflows, representing a substantial reallocation of college-educated labor toward incentive-offering cities. Importantly, the coefficients prior to adoption cluster near zero, supporting the parallel trends assumption and ruling out anticipatory migration. In contrast, panel (d) shows that the policy has no discernible impact on low-skilled migration. Point estimates fluctuate around zero, and the ATE is statistically insignificant. This null result confirms that the observed high-skill inflows are driven by the specific eligibility criteria of TIPs rather than generic local demand shocks that would affect all workers.

Panel (b) shows that high-skill entrepreneurship expands significantly following policy adoption, with the ATE indicating a robust 18% increase. Panel (c) corroborates this pattern using the universe of firm registration records: firm entry increases substantially in high-tech sectors. The bottom row again provides the placebo contrast. Low-skill entrepreneurship (panel e) and low-tech firm entry (panel f) show no significant response, confirming that TIPs reshapes the skill composition of local entrepreneurial activity rather than stimulating aggregate firm formation. Pre-trends in all panels are flat and statistically insignificant, ruling out the possibility that cities adopted TIPs in response to pre-existing business opportunities or sector-specific shocks.

Local Economic Consequences Figure 4 examines three dimensions of local economic adjustment: fiscal costs, revenue responses, and labor market consequences. Understanding the fiscal channel is important because TIPs subsidies are financed from city budgets, creating a direct tradeoff between talent attraction and public goods provision.

Panel (a) shows that TIPs increase subsidy expenditure by 3.25% on average, confirming the

Figure 3—Reduced-Form Effects on Migration, Entrepreneurship, and Firm Entry by Skill Level



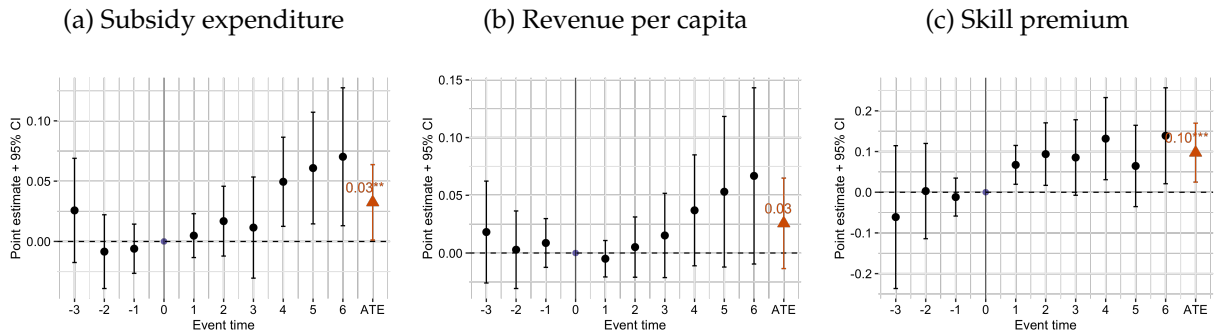
Notes: Event-study estimates using De Chaisemartin and d'Haultfoeuille (2024). Each panel plots treatment effects by years relative to policy adoption. Black dots show period-by-period dynamic effects; the colored triangle shows the average treatment effect (ATE). Error bars are 95% confidence intervals (standard errors clustered at the city level). Top row: high-skill outcomes. Bottom row: corresponding low-skill outcomes. Panels (a, d): migration flows (city-pair-year observations, 2000–2019). Panels (b, e): entrepreneur counts by skill from census/survey microdata. Panels (c, f): total registered firms by technology intensity (high-tech includes IT, advanced manufacturing, biotech, R&D-intensive industries per OECD classifications; low-tech includes traditional manufacturing, services, resource extraction).

fiscal cost channel. Panel (b) shows that revenue per capita is not statistically distinguishable from zero, providing no evidence that TIPs reduces local government revenue. The point estimates are positive but imprecise, suggesting that the fiscal cost of subsidies does not crowd out local revenue capacity. These fiscal patterns directly discipline the model's government budget constraint in Section 5.

Panel (c) documents a concurrent rise in the skill premium, which grows by approximately 7–9% in the medium run and 10–14% in the long run. The widening wage gap, occurring despite the positive labor supply shock from high-skill immigration, implies that talent incentives stimulate a demand response that outpaces supply. This pattern is consistent with the skill-biased firm entry documented in panel (c) of Figure 3, where complementarity between high-skill labor and new firms raises the skill premium. Real GDP expands gradually following policy adoption, accruing gains of approximately 3.5% after four years and 5.3% after six years (Appendix Figure A2).

Implications for Structural Analysis The reduced-form evidence establishes three key patterns. First, TIPS successfully attracts high-skill migrants (17% ATE) and stimulates high-skill entrepreneurship (18% ATE) in treated cities. Second, effects are skill-selective, with null results

Figure 4—Local Economic Consequences



Notes: See Figure 3 notes for estimation details. Panel (a): log real subsidy expenditure. Panel (b): log real revenue per capita. Panel (c): skill premium $= \log(w_H) - \log(w_L)$, where wages are average annual earnings by skill from census/survey data.

for low-skill migration and entrepreneurship serving as placebo tests. Third, TIPs generates measurable fiscal costs (3.25% increase in subsidy expenditure) with no evidence of declining local revenue, while widening the skill premium.

However, several critical questions remain beyond the reach of reduced-form analysis. Difference-in-differences estimates identify *relative* effects, the advantage of treated cities compared to control cities, but cannot reveal *absolute* effects on entrepreneurship or aggregate outcomes. The 18% increase in high-skill entrepreneurship in treated cities could reflect new firm creation, or it could simply reallocate entrepreneurs from control cities with no net national change. Similarly, we observe effects only in treated cities but learn nothing about spillovers to control cities. If TIPS drains talent from non-adopting cities, those cities may experience declining entrepreneurship and firm exit that are invisible in the DiD design. The mechanisms linking migration to entrepreneurship also remain unclear. Does talent inflow stimulate entrepreneurship through labor supply, occupational choice, or agglomeration channels? Finally, we cannot measure welfare, which depends on whether workers move to more productive locations (spatial efficiency gains) or whether subsidies distort occupational choices (occupational inefficiency).

The rising skill premium and fiscal costs foreshadow a central tension that the structural model will formalize. TIPs improves spatial sorting by moving high-skill workers toward subsidizing cities, but the fiscal drain from subsidies reduces public goods provision, and the widening skill premium suggests distributional consequences that reduced-form analysis cannot quantify. To address these limitations, we develop a quantitative dynamic spatial equilibrium model with endogenous migration, occupational choice, and government budgets. The model allows us to simulate counterfactual economies with and without TIPS, decompose mechanisms by shutting down firm dynamics or the fiscal channel, and compute welfare using compensating variation that accounts for equilibrium price adjustments.

4 A Dynamic Spatial Model

The model captures three interconnected margins. Workers choose locations based on wages, amenities, and migration costs; high-skill subsidies reduce those costs in treated cities. Workers also choose between employment and entrepreneurship, with entry decisions tied to expected profits. Trade links cities through goods markets, so productivity gains in one place change prices and wages everywhere. The framework extends Huỳnh (2025) by incorporating skill heterogeneity and entrepreneurship, allowing us to trace how policies targeting high-skill workers affect low-skill wages, firm entry across the skill distribution, and the spatial allocation of activity.

4.1 Environment

The economy consists of $\mathcal{N}$ locations indexed by i over discrete time periods t. Each location has population $\mathcal{L}_{it} = L_{it} + N_{it}$, comprising L_{it} workers and N_{it} entrepreneurs. Workers are differentiated by skill type $s \in \{\text{low}, \text{high}\}$.

Locations differ in fundamentals $\mathcal{F}_t = \{d_{int}, A_{it}, m_{int}\}_{i,n}$—trade costs, productivity, and baseline migration costs—and policies $\mathcal{P}_t$ that subsidize high-skill migration into targeted destinations. Local governments provide public services G_{it} that enter utility on a per-capita basis $(G_{it}/\mathcal{L}_{it})$, capturing congestion effects.

4.2 Workers

Workers face a fundamental trade-off each period: exploit current opportunities or invest in future options. A worker earns her wage, enjoys local amenities, and then chooses between three paths: stay and continue working, migrate elsewhere as an employee, or become an entrepreneur. Each path offers different expected payoffs, and idiosyncratic tastes ensure that workers with similar fundamentals may choose differently.

The utility function embeds this structure. The first term captures today's consumption—real wages adjusted for local public services. The second term is the maximum of two continuation values: the option to migrate elsewhere as a worker (which itself embeds optimal future location choice), or the option to become an entrepreneur. Taste shocks smooth these choices, generating transition probabilities rather than corner solutions. Formally, indirect utility is

$$u^w_{s,it} = \log(C_{s,it}) + \max\left\{\Xi_{s,it} + \chi\varepsilon^0_{s,it}, \beta V_{s,it+1} + \chi\varepsilon_{s,it}\right\} \tag{2}$$

where $\beta \in (0,1)$ is the discount factor.

Worker consumption combines private real wages and local public services:

$$C^w_{s,it} = \left(\frac{G_{it}}{\mathcal{L}_{it}}\right)^{\gamma} \left(\frac{w_{s,it}}{P_{it}}\right)^{1-\gamma} \tag{3}$$

where $w_{s,it}$ is the nominal wage for skill-s workers in city i at time t, $G_{it}/\mathcal{L}_{it}$ is per-capita public goods provision, and γ governs the expenditure share on public goods. When $\gamma = 0$, consumption reduces to real wages. The price index aggregates varieties from all locations:

$$P_{it} = \left(\sum_{n=1}^{\mathcal{N}} N_{nt} (p_{nit})^{1-\sigma} \right)^{1/(1-\sigma)} \tag{4}$$

where σ is the elasticity of substitution and p_{nit} is the price of goods from n sold in i.

4.2.1 Occupational Choice

Workers draw idiosyncratic taste shocks across occupations from a Type-I Extreme Value distribution with dispersion $\chi > 0$. Those with high entrepreneurial draws transition to firm ownership. The probability of becoming an entrepreneur is:

$$\psi_{s,it} = \frac{\exp(\beta V_{s,it+1}/\chi)}{\exp(\Xi_{s,it}/\chi) + \exp(\beta V_{s,it+1}/\chi)} \tag{5}$$

where $V_{s,it+1}$ is the expected value of entrepreneurship and $\Xi_{s,it}$ is the option value of remaining a worker (which embeds future migration opportunities). The probability of remaining a worker is:

$$\psi^0_{s,it} = \frac{\exp(\Xi_{s,it}/\chi)}{\exp(\Xi_{s,it}/\chi) + \exp(\beta V_{s,it+1}/\chi)}. \tag{6}$$

Higher χ implies greater taste heterogeneity and lower aggregate responsiveness to policy changes.

4.2.2 Migration

Workers who remain employees draw location-specific preference shocks $\epsilon_t = \{\epsilon_{nt}\}_{n=1}^{\mathcal{N}}$ and choose their destination based on expected lifetime utility net of migration costs.

TIPs policies offer housing subsidies, purchase discounts, and relocation allowances to high-skill migrants. I model these as migration cost reductions rather than income transfers because the subsidies are conditional on moving, typically one-time or front-loaded (paid upon arrival rather than as ongoing income), and target the decision to migrate rather than post-migration consumption.

Migration costs decompose into bilateral frictions and destination-specific housing costs. Bilateral friction $\bar{m}_{s,in}$ captures distance, cultural barriers, and information costs between origin i and destination n. Housing costs $h_{n,t}$ represent the upfront expense of purchasing residence in destination n, which is necessary given China's high home-ownership rates among internal migrants. TIP subsidies $T_{s,n,t}$ offset a fraction $\theta_{s,n,t} \equiv T_{s,n,t}/h_{n,t}$ of housing costs for skill-s workers moving to city n. For high-skill workers in treated cities, $\theta_{h,n,t} > 0$; for low-skill workers, $\theta_{l,n,t} = 0$.

Total migration cost combines these components:

$$m_{s,in,t} = \bar{m}_{s,in} + \log h_{n,t} - \log\left(1 + \theta_{s,n,t}\right), \tag{7}$$

where $\bar{m}_{s,ii} = 0$ (no cost to stay) and $\bar{m}_{s,in} > 0$ for $n \neq i$. Housing costs enter logarithmically, consistent with log utility: paying h yuan for housing reduces consumption, yielding disutility $\log h$. The subsidy enters as $-\log(1 + \theta_{s,n,t})$, which captures diminishing returns and remains well-defined even when $\theta > 1$.

Workers draw idiosyncratic location preferences ϵ_{nt} and choose their destination to maximize $\beta U_{s,nt+1} - m_{s,in,t} + \nu\epsilon_{nt}$. The option value of migration $\Xi_{s,it}$ represents the expected maximum utility over all possible destinations:

$$\Xi_{s,it} = \mathbb{E}\max_{n}\left\{\beta U_{s,nt+1} - m_{s,in,t} + \nu\epsilon_{nt}\right\} = \nu\log\left[\sum_{k=1}^{\mathcal{N}}\exp\left(\nu^{-1}\left[\beta U_{s,kt+1} - m_{s,ik,t}\right]\right)\right]. \tag{8}$$

The migration share $\mu_{s,in,t}$, representing the probability that a worker in i moves to n, follows from the logit structure:

$$\mu_{s,in,t} = \frac{\exp\left(\nu^{-1}\left[\beta U_{s,n,t+1} - m_{s,in,t}\right]\right)}{\sum_{k=1}^{\mathcal{N}}\exp\left(\nu^{-1}\left[\beta U_{s,k,t+1} - m_{s,ik,t}\right]\right)}. \tag{9}$$

Combining this equation and the migration cost decomposition (7) reveals three channels: higher expected utility $U_{s,n,t+1}$ increases migration, higher housing prices $h_{n,t}$ reduce migration with elasticity $1/\nu$, and higher subsidy shares $\theta_{s,n,t}$ increase migration with the same elasticity. Notably, housing costs and subsidies enter symmetrically because they represent one-time costs incurred at the moment of moving, unlike future utility flows which are discounted by β.

4.3 Entrepreneurs

Entrepreneurs are the engines of local productivity. Unlike workers, they are rooted in place—operating differentiated firms that hire local labor, occupy local land, and sell to consumers everywhere. Their decisions to enter, continue, or exit shape the number of varieties available in each city, which in turn affects prices, real wages, and the attractiveness of locations to workers.

4.3.1 Production

The production technology allows for skill complementarity—a parameter that matters greatly for policy incidence. When high-skill and low-skill workers are complements ($\rho < 1$), attracting talent raises low-skill wages: more engineers make production workers more productive. When they are substitutes ($\rho > 1$), the effect reverses.

The production function nests CES labor aggregation within Cobb-Douglas combination with

land:

$$q_{it} = A_{it}\left(\sum_{s=h,l}\phi_{s,it}^{\frac{1}{\rho}}L_{s,it}^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho\xi}{\rho-1}}(H_{it})^{1-\xi} \tag{10}$$

where A_{it} is total factor productivity, ξ is the labor share, $\phi_{s,it}$ captures skill intensity, and land H_{it} is fixed at $\bar{H}_i$. Cost minimization yields a unit cost bundle:

$$x_{it} = B\left(\sum_{s}\phi_{s,it}w_{s,it}^{1-\rho}\right)^{\frac{\xi}{1-\rho}}(r_{it})^{1-\xi} \tag{11}$$

where $B = \xi^{-\xi}(1-\xi)^{-(1-\xi)}$ is a constant. Land market clearing pins down the rental rate:

$$r_{it}H_{it} = \frac{1-\xi}{\xi}\sum_{s=\{h,l\}}w_{s,it}L_{s,it}. \tag{12}$$

Local government expenditure is financed by land rental revenue net of TIP subsidy costs:

$$P_{it}G_{it} = r_{it}H_i - \text{TIP}_{it} \tag{13}$$

where TIP_{it} is the total subsidy bill for city i at time t, defined in Section 4.4. For cities without active TIPs, $\text{TIP}_{it} = 0$ and the budget reduces to $P_{it}G_{it} = r_{it}H_i$.

Entrepreneurs ship goods across locations at iceberg trade cost d_{int}, setting prices as a constant markup over delivered unit cost:

$$p_{int} = \frac{\sigma}{\sigma-1}\frac{d_{int}x_{it}}{A_{it}}. \tag{14}$$

Summing sales across destinations yields profits:

$$\pi_{it} = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(\frac{A_{it}}{x_{it}}\right)^{\sigma-1}\sum_{n=1}^{\mathcal{N}}(d_{int})^{1-\sigma}X_{nt}(P_{nt})^{\sigma-1} \tag{15}$$

where X_{nt} is total expenditure in location n. Profits rise with productivity A_{it}, fall with input costs x_{it}, and depend on market access through trade costs d_{int}.

4.3.2 Dynamic Decisions

After consuming profits, entrepreneurs choose whether to continue operating or exit to the labor market. Each option carries an idiosyncratic taste shock ε, drawn from a Type-I Extreme Value distribution with dispersion χ. The realized value is:

$$v_{s,it} = \log(C_{it}^{e}) + \max\{\beta V_{s,it+1} + \chi\varepsilon_{s,it}^{0},\ \beta U_{s,it+1} + \chi\varepsilon_{s,it}^{1}\} \tag{16}$$

where entrepreneurs consume real profits:

$$C_{it}^{e} = \frac{\pi_{it}}{P_{it}}.$$

Integrating over the taste shocks yields the expected value:

$$V_{s,it} = \log(C_{it}^{e}) + \chi \log\left[\exp\left(\beta V_{s,it+1}/\chi\right) + \exp\left(\beta U_{s,it+1}/\chi\right)\right]. \tag{17}$$

The continuation probability follows from the logit structure:

$$\varsigma_{s,it} = \frac{\exp(\beta V_{s,it+1}/\chi)}{\exp(\beta V_{s,it+1}/\chi) + \exp(\beta U_{s,it+1}/\chi)}. \tag{18}$$

When profits are high, $\varsigma_{s,it}$ rises and more entrepreneurs continue. This endogenous exit margin amplifies talent-attraction policies: high-skill inflows raise local demand, boosting profits and firm survival.

4.4 TIP Subsidies

TIPs offer monetary incentives to high-skill migrants, with subsidy value $T_{h,n,t}$ per migrant in city n at time t. The subsidy share $\theta_{h,n,t} \equiv T_{h,n,t}/h_{n,t}$ measures the subsidy relative to local housing prices, with $\theta_{h,n,t} > 0$ only in cities with active TIPs. Low-skill workers receive no subsidies: $\theta_{l,n,t} = 0$ for all cities and periods. As specified in equation (7), these subsidies reduce migration costs through the term $-\log(1 + \theta_{s,n,t})$, making destination cities more attractive to high-skill workers.

TIPs operate through two channels. The first is the migration channel. Subsidies reduce the effective cost of moving to treated cities, attracting more high-skill workers. The second is the fiscal channel. Subsidizing migrants requires expenditure, which crowds out public goods provision. The total subsidy bill for city n at time t equals the per-migrant subsidy times the number of high-skill workers who migrate in:

$$\text{TIP}_{nt} = T_{h,n,t} \sum_{i \neq n} \mu_{h,in,t}\, \psi_{h,i,t}^{0}\, L_{h,i,t} \tag{19}$$

where $\mu_{h,in,t}$ is the share of high-skill workers in city i who migrate to n, $\psi_{h,i,t}^{0}$ is the share who remain workers (rather than becoming entrepreneurs), and $L_{h,i,t}$ is the high-skill labor force in city i. The fiscal cost is endogenous. Cities that attract more migrants face larger subsidy bills, which reduce public goods provision through the government budget (13), making the city less attractive and dampening further inflows.

4.5 Equilibrium

Trade shares follow the gravity structure from monopolistic competition:

$$\lambda_{int} = N_{it} \left(\frac{p_{int}}{P_{nt}} \right)^{1-\sigma}. \tag{20}$$

Cities with more firms (N_{it}) and lower prices capture larger market shares. Total income combines government spending, profits, and wages:

$$\Pi_{it} = P_{it} G_{it} + \pi_{it} N_{it} + \sum_{s} w_{s,it} L_{s,it}. \tag{21}$$

Labor market clearing equates the wage bill to labor's share of sales revenue:

$$w_{s,it} L_{s,it} = \xi \frac{\sigma - 1}{\sigma} \kappa_{s,it} \sum_{n=1}^{\mathcal{N}} \lambda_{int} \Pi_{nt} \tag{22}$$

where $\kappa_{s,it} = \phi_{s,it} w_{s,it}^{1-\rho} / (\phi_{h,it} w_{h,it}^{1-\rho} + \phi_{l,it} w_{l,it}^{1-\rho})$ is skill s's share of labor payments.

Population dynamics link periods. Entrepreneurs of skill s in location i next period consist of continuing incumbents plus new entrants from the labor force:

$$N_{s,it+1} = \varsigma_{s,it} N_{s,it} + \psi_{s,it} L_{s,it}. \tag{23}$$

Workers arrive from two sources: exiting entrepreneurs and migrants who chose to remain employees:

$$L_{s,it+1} = (1 - \varsigma_{s,it}) N_{s,it} + \sum_{n=1}^{\mathcal{N}} \mu_{s,ni,t} \psi^{0}_{s,nt} L_{s,nt}. \tag{24}$$

Equilibrium requires prices to clear markets and agents to optimize. I define it in two layers: a static equilibrium within each period, and a sequential equilibrium governing the evolution of state variables over time.

Definition 1 (Static equilibrium)**.** Given fundamentals $\mathcal{F}_t \equiv \{A_{it}, d_{int}, m_{in}\}_{i,n}$, policies $\mathcal{P}_t$, and state variables $\mathcal{S}_t \equiv \{L_{s,it}, N_{it}\}_{s,i}$, a *static equilibrium* is a set of prices $\{w_{s,it}, r_{it}, P_{it}\}_{s,i}$ and allocations satisfying monopolistic pricing (14) and CES price aggregation (4); cost minimization (11) and factor market clearing (12)–(22); and income accounting (21); and gravity trade shares (20).

The static equilibrium determines within-period prices and allocations. Given these, agents make forward-looking decisions that determine next period's state variables.

Definition 2 (Sequential competitive equilibrium)**.** Given initial state $\mathcal{S}_0$ and sequences $\{\mathcal{F}_t, \mathcal{P}_t\}_{t \geq 0}$, a *sequential competitive equilibrium* is a path $\{L_{s,t}, N_t, w_{s,t}, r_t, P_t, \mu_{s,t}, \varsigma_{s,t}, \psi_{s,t}, V_{s,t}, U_{s,t}\}_{t \geq 0}$ such that workers solve their dynamic problem (2)–(9); entrepreneurs solve their continuation problem

(16)–(18); population evolves via (24) and (23); and the static equilibrium conditions of Definition 1 hold at each t.

4.6 Solving the Model with Policy Changes

Quantifying general equilibrium effects requires solving for counterfactual allocations without talent policies. The challenge is that a growing economy with 285 cities and staggered policy rollout would require estimating fundamentals—productivities, amenities, trade costs—separately for each location and period, which is infeasible. I address this using the dynamic hat algebra of Caliendo et al. (2021), extended to incorporate entrepreneurship and occupational choice. This approach solves for equilibria using only growth rates and policy changes, without requiring levels of unobserved fundamentals.

The solution proceeds in two steps. First, I construct the baseline economy using observed data from 2010 to 2015. I assume fundamentals and policies stabilize after 2015 and solve forward to a steady state. Proposition 1 formalizes that given allocations at t, the sequential equilibrium can be solved in growth rates $\dot{y}_{t+1} \equiv y_{t+1}/y_t$ without knowing fundamental levels (proof in Appendix D).

Proposition 1. *Fix period t and suppose $\{\mathcal{F}_{t'}, \mathcal{P}_{t'}\}_{t'>t}$ are constant from t onward. Given the allocation at t, $(\mathcal{S}_t, \mu_{t-1}, \varsigma_{t-1}, \psi_{t-1}, \lambda_t)$, the sequential equilibrium in gross growth form, $\{\dot{y}_{t+1} \equiv y_{t+1}/y_t\}$ for all endogenous y, can be computed without the levels of fundamentals or policies at t.*

Second, I solve for the counterfactual by removing talent policies while holding all other fundamentals at their baseline paths. Using hat notation $\hat{x}_{t+1} = \dot{x}'_{t+1}/\dot{x}_{t+1}$, where primes denote counterfactual values, Proposition 2 shows the counterfactual equilibrium can be computed using only observed allocations and policy changes.

Proposition 2 (Dynamic Hat Algebra)**.** *Given baseline allocations $\{\mathcal{S}_t, \mu_{t-1}, \varsigma_{t-1}, \psi_{t-1}, \lambda_t\}_{t=0}^{\infty}$ and policy changes $\{\hat{\mathcal{P}}_t\}_{t=1}^{\infty}$ relative to baseline, the counterfactual equilibrium $\{\mathcal{S}'_t, \mu'_{t-1}, \varsigma'_{t-1}, \psi'_{t-1}, \lambda'_t\}_{t=1}^{\infty}$ can be determined without information on fundamental levels.*

I assume agents do not anticipate the counterfactual at $t = 0$ but learn about policy changes from $t = 1$ onward. This isolates the causal effect of talent policies by answering how would China's economy have evolved if cities had not competed for high-skill workers, holding constant all other drivers of growth and structural change?

Welfare effects are measured using compensating variation. For workers initially in location i, the welfare change is

$$\hat{W}_i = \sum_{t=1}^{\infty} \beta^t \log \frac{\hat{w}_{it}/\hat{P}_{it}}{(\hat{\mu}_{iit})^{\nu}(\hat{\psi}_{it}^0)^{\chi}}, \tag{25}$$

which captures changes in real wages and the value of migration and occupational choice options.

5 Calibration and Quantitative Implementation

I discipline the model through calibration to observed allocations rather than formal structural estimation. The objective is to build a factual baseline that reproduces the 2010 economy and its transition through 2015, so that counterfactuals isolate the role of TIPs rather than confounding policy effects with mismeasured fundamentals. The calibration uses trade and migration shares as sufficient statistics for unobserved costs and amenities.

The data pipeline harmonizes city-year and city-pair information into a consistent city set and exports matrices. The harmonization takes the intersection of cities observed in migration flows, trade flows, labor by skill, wage-bill shares, GDP, and firm data, producing a single set of 280 cities and annual matrices for 2010–2015. From 2016 onward, fundamentals are held constant and the economy converges to a steady state. TIPs enters as a destination-level migration-cost shifter for high-skill workers, constructed from the city-year policy intensity matrix.

The choice of 2010 as the baseline year reflects migration data constraints. Chinese census microdata provide migration flows only at five-year intervals (2000, 2005, 2010, 2015). I use 2010–2015 flows because this period provides complete coverage of skill-differentiated wages, entrepreneur counts, and firm dynamics needed to discipline the model's occupational choice and entry margins. Earlier census periods lack systematic wage and entrepreneurship data by skill. Trade flows are interpolated annually from four-year periods spanning 2007–2017. This data structure means the counterfactual isolates TIPs policies adopted or intensified during 2010–2015. Any talent programs that existed before 2010 at constant intensity are embedded in the baseline migration cost structure $\bar{m}_{s,in}$ and hence held fixed across scenarios.

Structural parameters are taken from the literature and held fixed in all experiments. The annual discount factor is $\beta = 0.95$. The elasticity of substitution is $\sigma = 6$. The migration elasticity is $\nu = 1.6$, and the skill-substitution elasticity is $\rho = 4.0$, following Caliendo et al. (2021). The occupational-choice dispersion is $\chi = 0.86$ as in Huỳnh (2025). The labor share is $\xi = 0.7$, a standard value for China. The public goods expenditure share γ is calibrated as the mean ratio of total fiscal expenditure to GDP across cities during 2010–2015, yielding $\gamma = 0.185$.

The per-migrant subsidy $T_{h,n,t} = \theta_{h,n,t} \cdot h_{n,t}$ in (19) is the product of the subsidy share from Section 4.4 and local housing prices. Since the dot algebra operates in growth rates without price levels, I express the fiscal drain as a share of government revenue:

$$\phi_{nt} \equiv \frac{\text{TIP}_{nt}}{r_{nt} H_n} = \frac{\theta_{h,n,t}\, h_{n,t}\, \text{Inflow}_{h,nt}}{r_{nt}\, H_n} \tag{26}$$

where $\text{Inflow}_{h,nt} = \sum_{i \neq n} \mu_{h,in,t}\, \psi^0_{h,i,t}\, L_{h,i,t}$ is the endogenous high-skill inflow from the model's migration matrix. The government budget (13) then becomes $P_{nt} G_{nt} = r_{nt} H_n (1 - \phi_{nt})$.

The reduced-form evidence directly disciplines the fiscal cost. Figure 4 in Section 3.2 shows that TIPs increase subsidy expenditure by 3.25% on average, confirming the fiscal cost channel.

Revenue per capita increases by approximately 5%, driven by higher rents as treated cities attract more workers and economic activity. These patterns motivate the model's fiscal channel. TIPs generate a fiscal drain that is partially self-financing through the general equilibrium rent response.

I use the DiD estimate to calibrate the fiscal drain directly. The cross-city variation in ϕ comes from two observable forces: subsidy generosity $\theta_{h,n,t}$ (from data) and migrant attraction $\text{Inflow}_{h,nt}$ (endogenous from the model). Housing prices and rents co-move strongly across cities, since both reflect local land scarcity and demand pressure, so their ratio $h_{n,t}/(r_{nt}H_n)$ in (26) is approximately constant. I absorb this ratio into a scalar α and express the fiscal drain as

$$\phi_{nt} = \alpha \cdot \theta_{h,n,t} \cdot \frac{\text{Inflow}_{h,nt}}{\overline{\text{Inflow}}_h} \tag{27}$$

where $\overline{\text{Inflow}}_h$ is the mean high-skill inflow across treated city-years, normalizing the inflow term to have mean one. I choose α so that the average ϕ across treated city-years matches the DiD moment: $\bar{\phi} = 0.0325 \times 0.114 = 0.0037$, where 3.25% is the subsidy expenditure effect and 11.4% is the share of subsidy expenditure in the total government budget. With the normalization, $\alpha \approx \bar{\phi}/\bar{\theta}$. The revenue side is left to the model's general equilibrium, where the endogenous rent response determines whether the fiscal drain translates into lower public goods provision.

6 Counterfactual Analysis

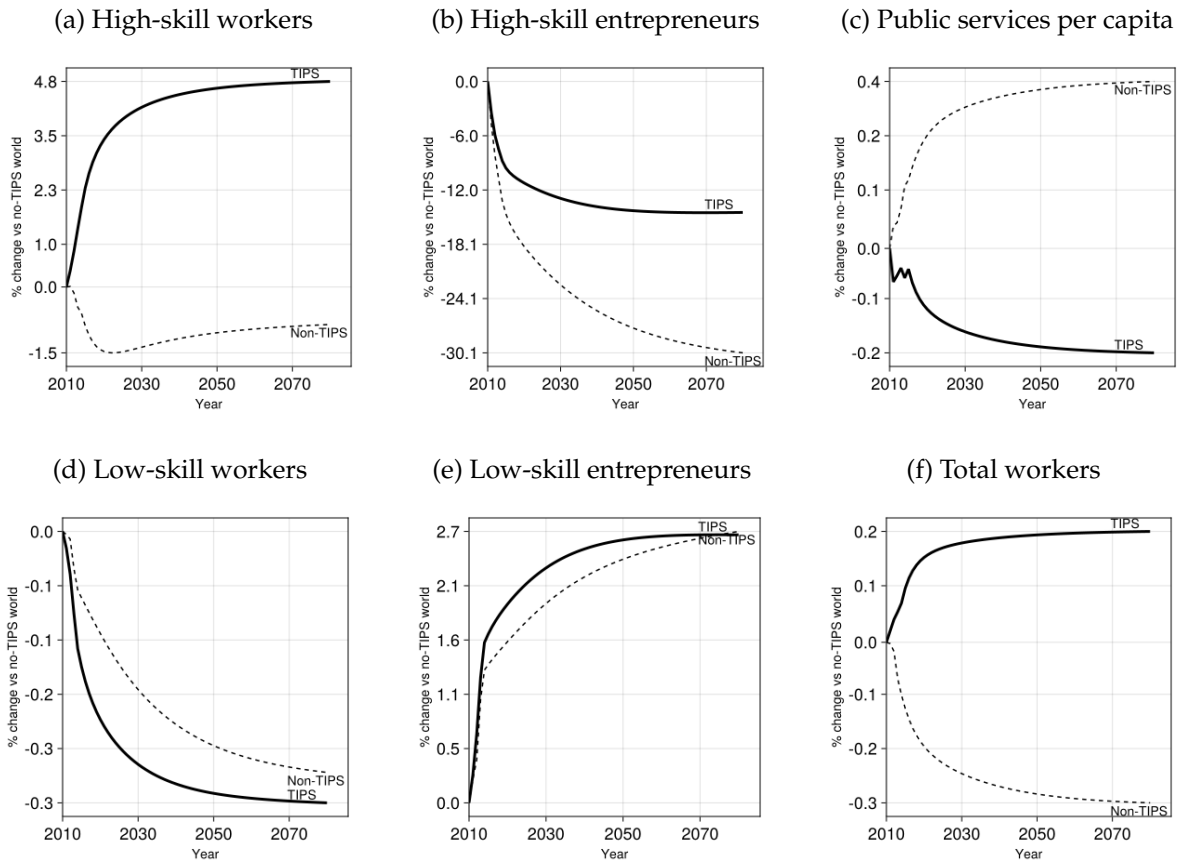
The counterfactual removes TIP subsidies from 2010 onward while holding all other fundamentals at their baseline paths. I solve for the no-policy equilibrium using the dynamic hat-algebra system described above, with the baseline economy (observed TIPs) as the reference. Agents do not anticipate the counterfactual at $t = 0$ but update beliefs from $t = 1$ forward.

TIPs cities are defined as locations that either introduced new talent programs in 2010 or increased subsidy generosity between 2010 and 2015, as measured by housing subsidy amounts in administrative records. Cities with pre-existing subsidies at constant levels before 2010 are classified as controls. This identification aligns with the reduced-form difference-in-differences strategy. Both the DiD and the model counterfactual measure effects of new or expanded TIPs during the 2010–2015 rollout, relative to a world where these specific policy changes did not occur.

6.1 Effects on Workers and Firms

Figure 5 compares labor and entrepreneurship outcomes between the baseline economy (with TIPs) and the counterfactual economy (without TIPs). Each panel plots the percentage change under TIPs relative to the no-TIPs counterfactual, separately for TIPs cities (solid line) and non-TIPs cities (dashed line). The top row shows high-skill allocation effects and fiscal costs, paralleling the reduced-form evidence in Figure 3. The bottom row shows low-skill general equilibrium spillovers and total migration.

Figure 5—Effects of TIPs on Workers and Firms



Notes: Percentage change in outcomes under TIPs relative to the no-TIPs counterfactual. Solid lines show TIPs cities (policy intensity > 0 during 2010–2015), dashed lines show non-TIPs cities. Row 1 shows high-skill allocation effects and fiscal costs. Row 2 shows low-skill spillovers and total migration. Total entrepreneurs appear in Appendix Figure A3.

Panel (a) shows the migration effect. TIPs attracts high-skill workers to treated cities, with employment rising approximately 2.31% above the no-TIPs counterfactual by 2015 and 5.01% in steady state. Non-TIPs cities lose high-skill workers (approximately 0.8% below counterfactual by 2015), confirming that the spatial reallocation is partly zero-sum. The imperfect offset reflects occupational reallocation. High-skill entrepreneurs switching to employment increases total high-skill employment even with fixed population. Low-skill workers (panel d) experience modest declines everywhere, but less severe in TIPs cities (-0.16%) than in non-TIPs cities. Skill substitutability in production means high-skill inflows reduce low-skill marginal product, but non-TIPs cities suffer worse because high-skill outflows trigger firm exit and broader labor demand collapse.

Panel (b) reveals the occupational distortion. High-skill entrepreneurship falls everywhere, declining approximately 8% in TIPs cities and 10% in non-TIPs cities by 2015, reaching 14% and 28% respectively at steady state. The subsidy reduces migration friction for high-skill workers. Since only workers migrate while entrepreneurs are rooted in place, the subsidy raises the option value of the employment path, which preserves mobility, relative to entrepreneurship, which

requires location commitment. This pulls high-skill workers out of firm ownership economy-wide. Panel (e) shows the occupational buffer. Low-skill entrepreneurship rises modestly everywhere (1–2.7%). The exit of high-skill entrepreneurs reduces product market competition, raising expected profits for remaining and entering firms. Low-skill workers, whose mobility is unaffected by the skill-targeted subsidy ($\theta_l = 0$), fill the entrepreneurial gap.

This result reconciles an apparent puzzle from the reduced-form evidence. Section 3 documents an 18% relative increase in high-skill entrepreneurship in treated cities, yet panel (b) shows declining high-skill entrepreneurship everywhere in absolute terms. The resolution lies in distinguishing relative from absolute effects. The DiD compares treated to control cities, identifying that treated cities perform better (smaller declines). The structural counterfactual compares the world with TIPs to a world without, revealing that TIPs reduces high-skill entrepreneurship everywhere through general equilibrium effects on occupational returns.

Panel (f) shows that total worker migration to TIPs cities is positive but modest, reflecting the net of high-skill inflows and low-skill declines. The net effect on total entrepreneurship, shown in Appendix Figure A3, displays a non-monotonic pattern. Total entrepreneurs in TIPs cities dip to approximately -0.3% around 2015 before recovering to $+0.2\%$ at steady state. Non-TIPs cities experience a sustained decline, reaching approximately -0.5% at steady state, because high-skill entrepreneur exit dominates low-skill entry without the compensating demand effects that TIPs-induced migration creates in treated cities. The pattern reflects two forces operating at different speeds. High-skill entrepreneur exit is fast, responding immediately to subsidies. Low-skill entrepreneur entry is slow, accumulating gradually as reduced competition raises expected profits. The recovery in TIPs cities reflects the eventual accumulation of low-skill entrants offsetting the high-skill decline.

Firm dynamics amplify migration responses substantially. Without firm dynamics, the high-skill stock increase in treated cities is only 1.00% in 2015 and 1.59% in steady state, compared to 2.31% and 5.01% in the Benchmark (Appendix Table A5). Roughly two-thirds of the long-run high-skill inflow operates through occupational choice and firm survival responses rather than direct migration alone. Initial worker inflows create local demand, which improves firm survival in TIPs cities. These retained firms attract additional workers beyond those responding directly to the subsidy, creating a general equilibrium multiplier.

6.2 Welfare Effects and Mechanism Decomposition

Whether these reallocations improve aggregate welfare depends on whether spatial sorting gains offset occupational distortions and fiscal costs. Table 1 presents the central decomposition, reporting welfare effects (compensating variation, %) across four model specifications that vary along two dimensions: whether firm dynamics are active (Benchmark vs. No FD) and whether government expenditure adjusts endogenously to subsidy costs (Exogenous vs. Endogenous G). The Endogenous G Benchmark is the main specification, the model that most completely represents

Table 1—Welfare Decomposition. Firm Dynamics and Government Budget Channels

	Exogenous G		Endogenous G	
	Benchmark	No FD	Benchmark	No FD
Skilled	1.458	2.083	1.460	1.981
[5th–95th pctl.]	[0.55–2.19]	[1.06–2.83]	[0.59–2.25]	[1.07–2.75]
Unskilled	0.027	−0.004	0.041	−0.030
[5th–95th pctl.]	[0.01–0.05]	[−0.02–0.01]	[0.00–0.07]	[−0.07–0.00]
National Average	0.161	0.191	0.174	0.157
FD effect on national welfare	−16%		+11%	

Notes: Population-weighted mean welfare changes (compensating variation, %) under four model specifications. "Exogenous G" holds government expenditure fixed regardless of subsidy costs. "Endogenous G" allows subsidy costs to reduce city budgets and public goods provision. "Benchmark" includes endogenous firm entry, exit, and occupational choice. "No FD" (No Firm Dynamics) fixes firm counts and occupational allocations at 2010 levels. The FD effect row reports the percentage change in national welfare when moving from No FD to Benchmark within each G specification.

the economic forces at work.

The main specification (Endogenous G, Benchmark) yields a national welfare gain of 0.174%, comparable in magnitude to the welfare effects of migration subsidies in Lagakos et al. (2023), but operating through a different mechanism. Gains are concentrated among high-skill workers (1.460%), with an order-of-magnitude smaller gain for low-skill workers (0.041%). The 5th–95th percentile ranges reveal substantial spatial heterogeneity. High-skill welfare ranges from 0.59% to 2.25% across cities, while low-skill welfare ranges from 0.00% to 0.07%.

The table's columns decompose this result along two dimensions. Reading across rows within each G regime isolates the role of firm dynamics. Reading across G regimes within each firm dynamics specification isolates the fiscal channel. The sign reversal in the bottom row is the headline finding. With exogenous G, firm dynamics reduce national welfare by 16%. With endogenous G, firm dynamics raise national welfare by 11%. The direction of the firm dynamics effect on aggregate welfare depends on whether government budgets adjust to subsidy costs.

The mechanism behind this sign reversal operates through low-skill welfare. Consider first the Exogenous G columns. Without firm dynamics, TIPs generates large high-skill gains (2.083%) because subsidies overcome migration frictions, enabling workers to access more productive cities. Low-skill welfare is near zero (−0.004%) because high-skill migration reduces their marginal product through skill substitution, with no compensating gains. Activating firm dynamics introduces occupational distortion. The subsidy raises the option value of employment by enhancing mobility, since workers can migrate to subsidized cities while entrepreneurs, rooted in place, cannot. This pulls high-skill workers out of entrepreneurship, reducing high-skill welfare to 1.458%. The oc-

cupational buffer raises low-skill welfare to $+0.027\%$, but this improvement does not offset the high-skill loss in population-weighted terms. The net effect is negative: firm dynamics reduce aggregate welfare by 16%.

Now consider the Endogenous G columns. Without firm dynamics, the fiscal drain from subsidies reduces public goods with no escape valve for low-skill workers, who receive no subsidy but bear the same reduction in public goods. Low-skill welfare turns sharply negative (-0.030%). Activating firm dynamics provides the escape valve. The exit of high-skill entrepreneurs reduces product market competition, raising expected profits for any entering firm. Low-skill workers fill the entrepreneurial gap because the skill-targeted subsidy does not enhance their mobility ($\theta_l = 0$), leaving them without the pull toward employment that high-skill workers face. Low-skill entrepreneurship expands, and low-skill welfare turns positive ($+0.041\%$). Because low-skill workers constitute the majority of the population, this welfare improvement dominates the high-skill loss in population-weighted terms. The net effect reverses: firm dynamics raise aggregate welfare by 11%.

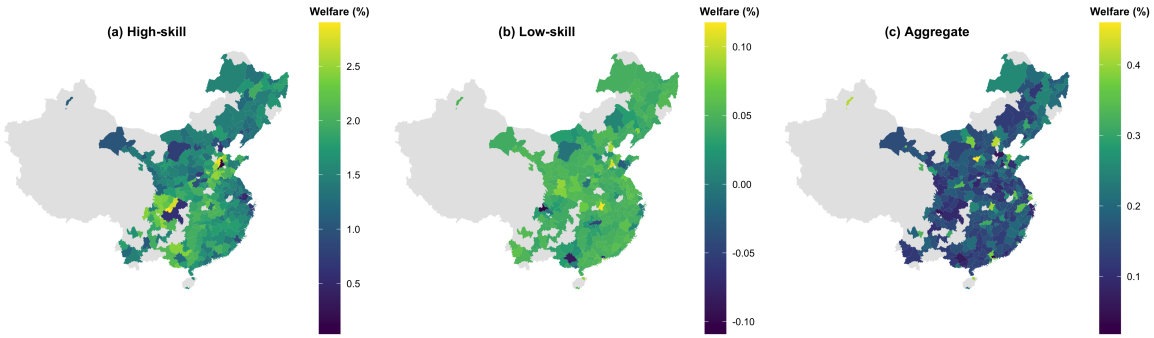
The sign reversal reveals a discriminating prediction of the model. In the standard spatial equilibrium framework without firm dynamics, talent subsidies generate a spatial-sorting gain that is modestly offset by fiscal costs. The occupational margin, absent in canonical models, simultaneously dampens high-skill welfare (through distortion) and raises aggregate welfare (through the low-skill buffer). Whether the occupational margin is net positive or negative for aggregate welfare depends on the severity of fiscal costs. When fiscal costs are zero (Exogenous G), the occupational buffer is too small to offset the distortion. When fiscal costs are realistic (Endogenous G), the buffer becomes the primary channel through which low-skill workers achieve positive welfare. Entrepreneurial income from entering vacated niches partially offsets the fiscal cost that low-skill workers bear from reduced public goods.

The high-skill/low-skill welfare gap falls from 2.01 percentage points without firm dynamics to 1.42 points with them, a 29% reduction in inequality. This distributional compression does not come at an efficiency cost. Firm dynamics raise national welfare by 11% relative to the No FD counterfactual. The entrepreneurship margin thus delivers both distributional benefits, shifting low-skill welfare from negative to positive, and aggregate efficiency gains.

Figure 6 maps these welfare effects across space.

High-skill welfare gains range from near-zero in major provincial capitals like Jinan (0.04%) to peaks exceeding 2.9% in cities across Shandong and Sichuan provinces. Aggregate welfare gains remain positive everywhere, averaging 0.174% nationally but varying from 0.02% to 0.46% across cities. Low-skill welfare shows a tighter spatial distribution, with modest positive gains in most locations but turning slightly negative in ten cities, including Chengdu (-0.11%) and Changsha (-0.04%). These negative low-skill outcomes appear in cities experiencing particularly severe high-skill out-migration to TIPs cities, where skill substitutability in production and firm exit overwhelm the occupational buffer.

Figure 6—Welfare Effects Across Space



Notes: Geographic distribution of welfare changes (compensating variation, %) across 280 Chinese cities under TIPs relative to the no-TIPs counterfactual. Panel (a) shows high-skill welfare, panel (b) shows low-skill welfare, and panel (c) shows aggregate welfare (population-weighted average of high- and low-skill within each city). Each panel uses its own color scale to reveal within-group spatial variation. Gray areas indicate cities outside the estimation sample.

Panel (c) of Figure 5 illustrates the fiscal cost channel directly. TIPs cities experience persistently lower per-capita public goods, reaching approximately -0.2% at steady state, as subsidy costs (ϕ) drain city revenue. Non-TIPs cities experience rising per-capita public goods ($+0.35\%$ at steady state) because they lose population without bearing subsidy costs, spreading their unchanged budgets over fewer residents. The fiscal asymmetry falls entirely on low-skill workers. The subsidy reduces migration costs for high-skill workers, raising the effective value of relocating to treated cities. High-skill welfare remains positive because spatial sorting gains from reduced migration friction more than compensate for the reduction in public goods. Low-skill workers receive no subsidy but bear the same reduction in G, making the fiscal channel a source of regressive welfare effects that the occupational buffer partially offsets.

7 Concluding Remarks

This paper studies the welfare effects of place-based talent subsidies, using China's Talent Introduction and Promotion Schemes (TIPS) as a laboratory. Reduced-form evidence shows that talent subsidies attract high-skill migrants (17% ATE) and stimulate high-skill entrepreneurship in treated cities (18% ATE). A dynamic spatial equilibrium model with endogenous migration, occupational choice, firm dynamics, and government budgets then reveals the general equilibrium forces that reduced-form evidence cannot capture.

The central finding is a spatial-sorting versus occupational-distortion tradeoff. TIPS improves the geographic distribution of talent, generating a 0.17% aggregate welfare gain comparable to the migration subsidy effects in Lagakos et al. (2023). Subsidies simultaneously distort occupational choice, pulling high-skill workers out of entrepreneurship everywhere, reconciling the 18% relative increase in high-skill entrepreneurs (from the DiD) with an 8–14% absolute decline (from the

counterfactual). The occupational margin dampens high-skill welfare gains (from 1.98% to 1.46%) while providing a buffer for low-skill workers, whose welfare shifts from -0.03% to $+0.04\%$ as reduced product market competition raises expected profits for entering firms.

Whether firm dynamics are net positive or net negative for aggregate welfare depends on the government budget constraint. With exogenous government spending, occupational distortion dominates and firm dynamics reduce welfare by 16%. With endogenous spending, the occupational buffer raises welfare by 11% and reduces welfare inequality by 29% without sacrificing aggregate efficiency, a rare instance where distributional and efficiency objectives are aligned.

These results carry implications for place-based policy design beyond China. Evaluating talent-attraction programs solely on treated-city outcomes misses the general equilibrium occupational effects that ultimately determine welfare. More broadly, any place-based subsidy that enhances worker mobility will tilt occupational choice toward employment, since workers can exploit the mobility gain while entrepreneurs, rooted in place, cannot. Policies that preserve entrepreneurial incentives, for example through subsidies conditional on business creation, could amplify welfare gains by reducing occupational distortion while maintaining the spatial-sorting benefit.

The model treats productivity as exogenous, omitting human capital externalities. It assumes fixed skill types, abstracting from human capital accumulation decisions that talent subsidies may distort. The government budget is calibrated to a static expenditure share rather than a dynamic fiscal rule. Each of these extensions would enrich the mechanism decomposition without altering the fundamental tradeoff between spatial sorting and occupational distortion that drives the results.

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A Construction of Talent Incentive Program Measures

This appendix details the construction, quantification, and validation of the Talent Incentive Programs (TIPs) dataset. To ensure transparency and replicability, we employed a rigorous three-step protocol to transform qualitative policy text into standardized quantitative indicators.

A.1 Data Collection

We constructed a comprehensive database of talent policies for 283 prefecture-level cities from 2000 to 2019. The data collection proceeded in three stages:

Step 1: Keyword Search and Retrieval. We performed a systematic search of official municipal government websites (including Organization Departments and the Ministry of Human Resources and Social Security) and policy compendia. We utilized a dictionary of keywords such as "Talent Introduction" (*rencai yinjin*), "High-level Talent" (*gaocengci rencai*), "Housing Subsidy" (*goufang butie*), and "Settlement Allowance" (*anjiafei*), among others.

Step 2: Verification and Filtering. We cross-referenced retrieved documents with *China City Statistical Yearbooks* and local government gazettes to verify implementation dates. We restricted our sample to policies that: (i) explicitly target newly introduced talent (migrants) rather than incumbent workers; and (ii) offer material benefits to high-skill individuals defined by education (e.g., PhD, Master's) or professional credentials. Policies exclusively targeting recent undergraduates (without high-skill distinction), low-skill labor, or short-term visitors were excluded.

Step 3: Digitization and Coding. We manually extracted key policy parameters into a structured dataset, recording the policy document number, implementation date, validity period, target audience tiers (e.g., Chinese Academy of Sciences (CAS) and the Chinese Academy of Engineering (CAE) Academicians vs. recent graduates), and specific incentive amounts. Table A1 provides a selected list of key policy documents for major cities.

A.2 Variable Construction and Quantification

A major challenge in coding TIPs is the heterogeneity in target talents. Policies often list tiers ranging from Academicians to Master's graduates. To ensure comparability across cities and capture the incentives relevant to the marginal mobile researcher, we calculate the average subsidy amount across all specified talent tiers listed in the policy document. This approach provides a representative measure of the city's fiscal commitment to attracting high-skill labor.

We construct a continuous measure of policy intensity for city i in year t, denoted as Sub_{it}, which aggregates the total monetary value of housing and living benefits relative to local housing costs. The construction proceeds in three steps, with values prior to 2007 imputed using 2007 data to address missing information on subsidy amounts:

First, we calculate the net present value (NPV) of housing ($Sub_{it}^{Housing}$) and living (Sub_{it}^{Living}) subsidies. For each component, the total value is defined as the sum of one-time lump-sum grants

Table A1—Selected List of Talent Incentive Policies and Quantification Examples (2000–2019)

City	Year	Policy Document Title	English Translation (Excerpt)	Quantification (PhD Tier)
Beijing	2009	Opinions on Implementing the "Project for Overseas High-Level Talents"	**Settlement Subsidy**: Match employer subsidy... up to **1 million RMB**.	**Housing (H_{it})**: 100.0 (Overseas tier) (Note: Early policies often targeted only top-tier overseas talent).
Shanghai	2010	Provisions on Implementing the Plan for Introducing Overseas High-Level Talents	**Housing**: Provide housing of at least 150 sqm... or a one-time settlement grant of **1 million RMB**.	**Housing (H_{it})**: 100.0 (Overseas tier) **Living (L_{it})**: 0
Daqing	2013	Regulations on Several Talent Preferential Policies	**Settlement Fee**: 2 million for Academicians... **100,000 RMB for 985 PhDs**, 50,000 for Masters...	**Housing (H_{it})**: 10.0 (Lump sum) **Living (L_{it})**: 0
Guiyang	2014	Measures for Introducing High-Level Talents	**Housing**: 1M for Type 1... **150k RMB for Type 4 [PhD]**... **Living**: Monthly... **800 RMB for Type 4**.	**Housing (H_{it})**: 15.0 **Living (L_{it})**: $0.08 \times 12 \times 8.75 = 8.4$
Hangzhou	2015	Opinions on Talent Development System Reform	**Rental Subsidy**: ... Type E (Senior/PhD) talent provided rental housing or **1,200 RMB/month**.	**Housing (H_{it})**: $0.12 \times 12 \times 8.75 = 12.6$
Hengyang	2015	Measures for High-Level Talent Introduction	**Housing**: ...**1,000 RMB/month for Type 5 [PhD]**. **Living**: ...**1,000 RMB/month for Type 5**.	**Housing (H_{it})**: 10.5 **Living (L_{it})**: 10.5
Shenzhen	2016	Measures for Promoting Talent Priority Development	**Rent & Living Subsidy**: ... 25,000 RMB for Masters, **30,000 RMB for PhDs**.	**Housing (H_{it})**: 0 **Living (L_{it})**: 3.0 (Lump sum)
Chengdu	2017	Implementation Plan for the "Rongpiao" Project	**Hukou**: Full-time university graduates (Bachelor+) can apply for Hukou with just a graduation certificate.	**Policy ($TIPS_{it}$)**: 1 (Quantification based on Hukou liberalization value).
Wuhan	2017	Measures for Supporting University Graduates	**Housing**: ...Talent apartments... Purchase subsidy... National-level industry leaders can apply for **500,000 RMB**.	**Housing (H_{it})**: 50.0 (Leader tier) (Specific PhD cash value not listed in this excerpt).
Nanjing	2018	Implementation Measures for Strengthening Talent Housing	**Rental Subsidy**: ... Type D 3600... **Type E (Doctorate) 2,400 RMB/month**.	**Housing (H_{it})**: $0.24 \times 12 \times 8.75 = 25.2$
Handan	2019	Opinions on Supporting Talent Innovation	**Purchase Subsidy**: One-time subsidy of **80,000 RMB for PhDs**, 50,000 for Masters...	**Housing (H_{it})**: 8.0 (Primary benefit coded)

Notes: This table lists representative policy documents and illustrates the variable construction process. Original Chinese policy text is available from the authors upon request. Financial values are expressed in 10,000 RMB (2010 constant prices). For recurring monthly payments, we calculate the Net Present Value (NPV) using a capitalization factor of 8.75 (reflecting a 10-year horizon at a 2.5% discount rate).

and the annualized NPV of recurring monthly allowances. Consistent with the ten-year service horizon typically offered by talent incentives, we apply a cumulative capitalization factor of 8.75, which corresponds to a 10-year annuity discounted at a 2.5% annual rate (proxied by the one-year fixed deposit rate). The calculation formulas are:

$$Sub_{it}^{Housing} = \text{LumpSum}_{it}^{H} + \left(\text{Monthly}_{it}^{H} \times 12 \times 8.75\right) \tag{A.1}$$

$$Sub_{it}^{Living} = \text{LumpSum}_{it}^{L} + \left(\text{Monthly}_{it}^{L} \times 12 \times 8.75\right) \tag{A.2}$$

Second, to facilitate cross-city comparison and account for purchasing power parity, we normalize the total subsidy value by the local median residential housing price per square meter (P_{it}). The resulting metric represents the subsidy's real value measured in equivalent square meters of local housing:

$$Sub_{it} = \frac{Sub_{it}^{Housing} + Sub_{it}^{Living}}{P_{it}} \tag{A.3}$$

Third, to address data quality issues, we apply a hierarchical imputation strategy for missing subsidy values in years where a policy is known to be active ($TIPS_{it} = 1$). Missing values are filled sequentially using: (1) the city's mean subsidy value over the sample period; (2) the province-year mean; (3) the province-wide mean; and (4) the national annual mean. Finally, to mitigate the influence of outliers, the continuous intensity variable is winsorized at the 2nd and 98th percentiles.

For the binary adoption indicator, if a policy document specifies an expiry date (e.g., "valid for 3 years"), the variable turns to 0 after that period unless a superseding policy is issued. If no expiry is listed, we assume the policy remains active until explicitly repealed or replaced.

B Summary Statistics

B.1 City-Level Characteristics and Policy Targeting

Our analysis draws on a panel of 283 prefectural-level cities from 2000 to 2019. Table A2 presents summary statistics for key city-level economic fundamentals and innovation metrics. Consistent with the strategic targeting of TIPs, treated cities are systematically more developed than control cities. As shown in panel A, treated cities exhibit significantly higher average GDP (187.3 billion RMB vs. 69.4 billion RMB) and average wages for high-skilled workers (38,065 RMB vs. 31,505 RMB). Panel B further highlights the innovation gap: treated cities account for the vast majority of R&D expenditure and patent applications. These baseline disparities underscore the necessity of our staggered difference-in-differences strategy. Our key identifying assumption is parallel trends: conditional on controls and fixed effects, outcomes in treated and control cities would have followed similar trajectories in the absence of the policy. The credibility of this assumption is

significantly strengthened by the staggered nature of the rollout. Because the control group consists of a dynamic pool of not-yet-treated cities, rather than relying solely on a fixed set of never-treated units that may be intrinsically different, we can identify the causal effect from differential timing rather than static cross-sectional differences.

Table A2—Summary Statistics and Balance of City Characteristics (2000–2019)

	(1)	(2)	(3)	(4)
	Full Sample	**Treated Cities**	**Control Cities**	**Diff (2)-(3)**
	Mean (SD)	Mean (SD)	Mean (SD)	Difference
Panel A: Economic Fundamentals				
GDP (100 million RMB)	1,587.75	1,873.11	694.04	1,179.07***
	(2,678.16)	(3,000.37)	(624.65)	
Housing Price (RMB/sqm)	4,121.67	4,486.82	3,000.49	1,486.33***
	(3,430.43)	(3,789.16)	(1,467.45)	
Avg. Wage High-Skill (RMB)	36,693.05	38,064.72	31,505.34	6,559.39***
	(22,024.44)	(22,568.27)	(18,983.65)	
Panel B: Innovation Capacity				
R&D Expenditure (10k RMB)	66,840.34	84,015.02	14,058.54	69,956.48***
	(275,596.53)	(315,136.25)	(22,324.25)	
Patent Applications	22,191.99	28,238.94	3,619.21	24,619.73***
	(75,455.10)	(85,938.29)	(6,391.17)	
Observations (City-Year)	5,700	4,332	1,368	-
Number of Cities	283	216	67	-

Notes: This table reports city-level summary statistics for the period 2000–2019. The "Treated Cities" group includes cities that adopted a Talent Incentive Program (TIPS) at any point during the sample period (ever-adopters), while "Control Cities" never adopted such policies. Standard deviations are reported in parentheses. Column 4 reports the difference in means between the treated and control groups, with stars indicating significance levels from a two-sided t-test: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

B.2 Sectoral Heterogeneity and Firm Dynamism

To understand how talent incentives affect industrial structure, we exploit granular firm-level registration data. Table A3 documents the variation in firm dynamics across sectors, distinguishing between high-skill intensive industries (e.g., ICT, pharmaceuticals) and low-skill intensive industries (e.g., traditional manufacturing). High-skill sectors exhibit greater dynamism, characterized

by a higher new firm entry rate (22.63%) compared to low-skill sectors (20.15%). We also observe distinct patterns in survival and exit: high-skill industries show a slightly lower exit rate (10.87% vs. 11.66%) and a comparable three-year survival rate (94%). The distinctively higher rate of firm creation suggests that high-skill industries are more sensitive to changes in the supply of human capital. Consequently, we expect the relaxation of migration constraints via TIPs to have a more pronounced impact on firm entry in these technology-intensive sectors.

Table A3—Firm Dynamics and Innovation by Sector Type

	High-Skill Sectors		**Low-Skill Sectors**	
Variable	Mean	SD	Mean	SD
New Firm Entry Rate (%)	22.63	18.02	20.15	18.74
Exit Rate (%)	10.87	65.14	11.66	54.76
3-Year Survival Rate (Ratio)	0.94	0.12	0.94	0.12
Observations (City-Sector-Year)	22,400		33,600	

Notes: his table reports summary statistics of firm dynamics and innovation output at the city-sector-year level. "High-Skill Sectors" are defined as technology-intensive industries following the classification by Lu and Dang (2014), which includes pharmaceutical manufacturing, high-end equipment manufacturing (e.g., aerospace, electronics, instrumentation), and modern services (e.g., information technology, scientific R&D, and technical services). "Low-Skill Sectors" comprise traditional manufacturing and retail industries not included in the technology-intensive category. Entry and Exit rates are calculated relative to the stock of incumbent firms. Patent applications refer to the raw count of applications filed.

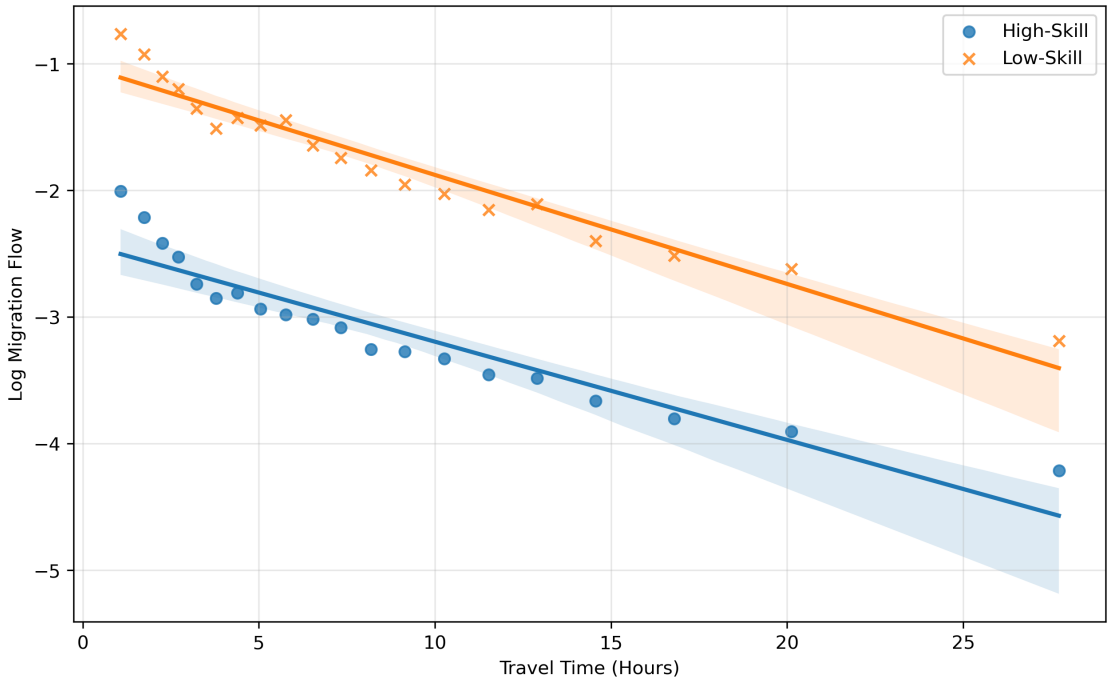
B.3 Migration Gravity and Talent Mobility

A prerequisite for TIPs to succeed is the responsiveness of high-skilled labor to place-based incentives. Figure A1 illustrates the distance decay of migration flows against travel time between origin and destination cities using census data. The visualization confirms standard trade and migration theory: flows decline significantly as travel time increases. Crucially, however, the slope of the distance decay is flatter for high-skilled migrants (blue line) compared to low-skilled migrants (orange line). This stylized fact indicates that high-skilled talent is relatively less sensitive to geographic friction and more willing to relocate over longer distances for better opportunities, validating the premise that local policy incentives can effectively attract non-local talent.

B.4 Micro-Evidence on Occupational Choice

Finally, we use individual-level survey data to examine the occupational composition of the workforce. Table A4 reports annual occupational transition probabilities. Panel A reveals a distinct sorting pattern for high-skilled workers: in treated cities, the probability of transitioning from paid

Figure A1—Migration Gravity by Skill Level



Notes: This figure plots the relationship between the natural logarithm of migration flows and travel time (in hours) between origin and destination cities. The data is binned into 20 quantiles of travel time. The blue circles (and blue line) represent high-skilled migrants (college degree or above), while the orange crosses (and orange line) represent low-skilled migrants. Shaded areas indicate 95% confidence intervals. The figure demonstrates that while all migration declines with distance, high-skilled talent is relatively more mobile (exhibiting a flatter slope), indicating lower sensitivity to geographic friction compared to low-skilled labor.

employment to entrepreneurship is 1.19%, nearly double the 0.67% rate observed in control cities. In contrast, panel B shows that for low-skilled workers, the entrepreneurship transition rates are comparable between treated (1.26%) and control (1.10%) cities. This concentration of high-skilled entrepreneurial transitions in treated cities establishes a key stylized fact. However, discerning whether this reflects a net stimulation of entrepreneurship or simply the spatial reallocation of entrepreneurial talent requires a general equilibrium framework that accounts for how migration subsidies alter the relative returns between wage employment and entrepreneurship.

C Additional Empirical Results

D Theory Appendix

D.1 Welfare measure

This subsection derives the welfare expression used in the main text.

Table A4—Occupational Transition Matrix: Treated vs. Control Cities

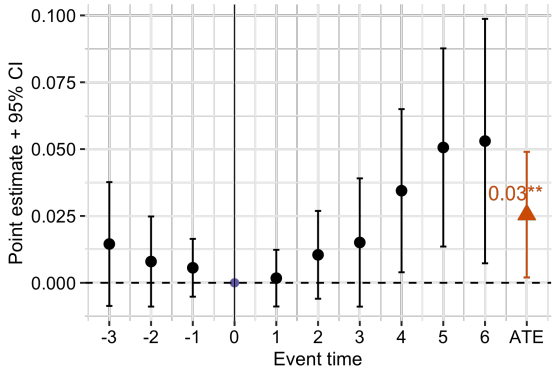
	Treated Cities		Control Cities	
Transition (Origin → Destination)	**Share (%)**	**Obs.**	**Share (%)**	**Obs.**
Panel A: High-Skilled Workers (College+)				
Retention (Stayers)				
Non-employed → Non-employed	1.55	26	1.92	20
Employed → Employed	44.89	755	18.67	194
Self-employed → Self-employed	0.95	16	1.25	13
Entrepreneur → Entrepreneur	1.31	22	1.35	14
Transitions from Non-Employed				
Non-employed → Employed	16.71	281	18.58	193
Non-employed → Self/Entre	0.42	7	0.57	6
Transitions from Employed				
Employed → Non-employed	16.77	282	23.77	247
Employed → Self-employed	0.77	13	0.19	2
Employed → Entrepreneur	**1.19**	**20**	**0.67**	**7**
Other Transitions (Aggregated)				
From Self-employed (to Non/Emp/Entre)	1.55	26	0.86	9
From Entrepreneur (to Non/Emp/Self)	1.67	28	1.16	12
Total (High-Skill)	**100.00**	**1,682**	**100.00**	**1,039**
Panel B: Low-Skilled Workers (Non-College)				
Retention (Stayers)				
Non-employed → Non-employed	10.62	825	7.14	343
Employed → Employed	26.85	2,087	9.65	464
Self-employed → Self-employed	5.76	448	6.43	309
Entrepreneur → Entrepreneur	2.33	181	2.50	120
Transitions from Employed				
Employed → Non-employed	15.77	1,226	18.51	890
Employed → Self-employed	0.97	75	0.64	31
Employed → Entrepreneur	**1.26**	**98**	**1.10**	**53**
Other Transitions (Aggregated)				
Transitions from Non-Employed	15.20	1,181	12.09	581
Transitions from Self-employed	4.08	317	4.85	233
Transitions from Entrepreneur	4.58	356	4.76	229
Total (Low-Skill)	**100.00**	**7,772**	**100.00**	**4,807**

Notes: This table reports the one-year occupational transition probabilities. Panel A reports results for high-skilled workers (college degree or above), while Panel B reports results for low-skilled workers. "Treated Cities" had an active Talent Incentive Program (TIP) in the survey year. The bolded row highlights the transition from paid employment to entrepreneurship. Some less critical transition categories (e.g., from self-employment) are aggregated to conserve space.

Step 1: Log-sum identities. Recall the worker stay share

$$\psi^0_{s,it} \equiv \frac{e^{\Xi_{s,it}/\chi}}{e^{\Xi_{s,it}/\chi} + e^{\beta V_{s,it+1}/\chi}}. \tag{D.1}$$

Figure A2—Real GDP Effects



Notes: See Figure 3 notes for estimation details. Outcome is log real GDP at the city-year level.

Table A5—TIPs. Changes in the Stock of Labor in Treated Cities

	Total Labor		Low-Skill		High-Skill	
	Benchmark	No Firm Dynamics	Benchmark	No Firm Dynamics	Benchmark	No Firm Dynamics
2010	0.00	0.00	0.00	0.00	0.00	0.00
2015	0.11	0.06	-0.16	-0.06	2.31	1.00
2025	0.19	0.09	-0.26	-0.10	3.92	1.54
Steady State	0.23	0.07	-0.34	-0.13	5.01	1.59

Notes: Percentage changes in labor stocks within treated cities at key horizons, comparing the baseline economy (with TIPs) to the counterfactual (without TIPs). "Benchmark" includes endogenous firm dynamics and occupational choice. "No Firm Dynamics" fixes firm counts and occupational allocations at 2010 levels. Workers can migrate but cannot switch between employment and entrepreneurship.

Then

$$\chi \log\left[e^{\Xi_{s,it}/\chi} + e^{\beta V_{s,it+1}/\chi}\right] = \Xi_{s,it} + \chi \log\left(\frac{1}{\psi^0_{s,it}}\right). \tag{D.2}$$

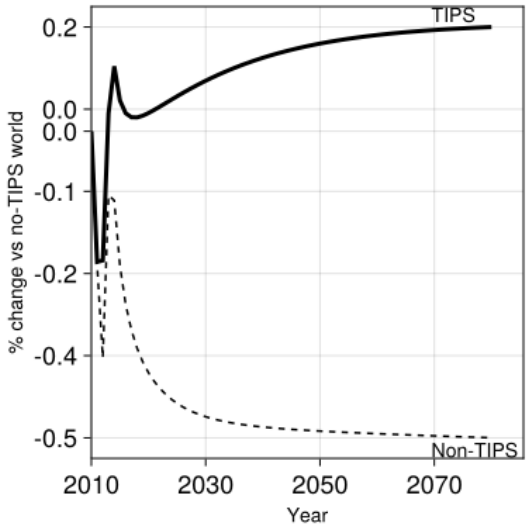
Substituting (D.2) into (2) yields

$$U_{s,it} = \log\left(\frac{w_{s,it}}{P_{it}}\right) + \Xi_{s,it} + \chi \log\left(\frac{1}{\psi^0_{s,it}}\right). \tag{D.3}$$

Step 2: Migration logit identity. From the migration logit (9), choosing $n = i$ and using $m_{s,ii,t} = 0$ implies

$$\Xi_{s,it} = \beta U_{s,it+1} + \nu \log\left(\frac{1}{\mu_{s,ii,t}}\right). \tag{D.4}$$

Figure A3—Effects of TIPs on Total Entrepreneurs



Notes: Percentage change in total entrepreneurs under TIPs relative to the no-TIPs counterfactual. Solid line shows TIPs cities, dashed line shows non-TIPs cities. The non-monotonic pattern in TIPs cities reflects fast high-skill entrepreneur exit followed by gradual low-skill entrepreneur entry.

Combining (D.3) and (D.4) gives the one-step recursion

$$U_{s,it} = \log\left(\frac{w_{s,it}}{P_{it}}\right) + \beta U_{s,it+1} + \nu \log\left(\frac{1}{\mu_{s,ii,t}}\right) + \chi \log\left(\frac{1}{\psi^0_{s,it}}\right). \tag{D.5}$$

Iterating forward yields

$$U_{s,i0} = \sum_{t=0}^{\infty} \beta^t \log\left(\frac{w_{s,it}/P_{it}}{(\mu_{s,ii,t})^{\nu}(\psi^0_{s,it})^{\chi}}\right). \tag{D.6}$$

Step 3: Compensating variation. Define $\bar{c}_{s,i}$ so that $U'_{s,i0} - U_{s,i0} = \sum_{t=0}^{\infty} \beta^t \log(\bar{c}_{s,i})$. Using (D.6) and expressing counterfactuals in hats,

$$\log(\bar{c}_{s,i}) = \sum_{t=1}^{\infty} \beta^t \log\left(\frac{\frac{\hat{w}_{s,it}}{\hat{P}_{it}}}{(\hat{\mu}_{s,ii,t})^{\nu}\,(\hat{\psi}^0_{s,it})^{\chi}}\right), \tag{D.7}$$

which is equation (25) in the main text.

D.2 Proof of Proposition 1

Notation. For any variable y_{it}, let $\dot{y}_{it+1} \equiv y_{it+1}/y_{it}$ denote the gross growth rate from period t to $t+1$. We use the convention that the subscript indicates the "new" period. Define the composite factor price $\tilde{\omega}_{s,it} \equiv w_{s,it}\, r_{it}^{\frac{1-\xi}{\xi}}$ with growth $\dot{\tilde{\omega}}_{s,it+1} = \tilde{\omega}_{s,it+1}/\tilde{\omega}_{s,it}$, and the within-labor share $\kappa_{s,it}$.

Step 1: Temporary equilibrium in dots. Using the static block of Definition 1, the identities for $\tilde{\omega}$ and κ, and constant $\{A_{it}, d_{int}\}$ from t onward, the $t \to t+1$ growth system reduces to:

$$\dot{P}_{it+1} = \left(\sum_n \lambda_{nit} \dot{N}_{nt+1} \left(\dot{p}_{nit+1} \right)^{1-\sigma} \right)^{1/(1-\sigma)} \tag{D.8}$$

$$\dot{p}_{int+1} = \dot{x}_{it+1} = \left(\sum_{s \in \{h,l\}} \kappa_{s,it} \, \dot{\phi}_{s,it+1} \left(\dot{\tilde{\omega}}_{s,it+1} \right)^{1-\rho} \right)^{\frac{\xi}{1-\rho}} \tag{D.9}$$

$$\dot{\lambda}_{int+1} = \dot{N}_{it+1} \left(\frac{\dot{p}_{int+1}}{\dot{P}_{nt+1}} \right)^{1-\sigma} \tag{D.10}$$

$$\dot{\pi}_{it+1} = \frac{1}{\sigma} \sum_{n=1}^{\mathcal{N}} (\dot{x}_{it+1})^{1-\sigma} (\dot{P}_{nt+1})^{\sigma-1} \frac{\lambda_{int}}{N_{it}} \frac{\Pi_{nt+1}}{\pi_{it}} \tag{D.11}$$

$$\Pi_{it+1} = \underbrace{\dot{r}_{it+1} \frac{1-\xi}{\xi} \sum_s w_{s,it} L_{s,it}}_{\text{land rent}} + \underbrace{\sum_{s=h,l} \dot{w}_{s,it+1} \dot{L}_{s,it+1} \cdot w_{s,it} L_{s,it}}_{\text{wage income}} + \underbrace{\dot{\pi}_{it+1} \dot{N}_{it+1} \cdot \pi_{it} N_{it}}_{\text{aggregate profits}} \tag{D.12}$$

$$\dot{w}_{s,it+1} = \frac{\sigma - 1}{\sigma} \frac{\xi \kappa_{s,it+1}}{\dot{L}_{s,it+1} w_{s,it} L_{s,it}} \sum_{n=1}^{\mathcal{N}} \dot{\lambda}_{int+1} \lambda_{int} \Pi_{nt+1} \tag{D.13}$$

$$\kappa_{s,it+1} = \kappa_{s,it} \frac{\dot{\phi}_{s,it+1} (\dot{\tilde{\omega}}_{s,it+1})^{1-\rho}}{(\dot{x}_{it+1})^{\frac{1-\rho}{\xi}}} \tag{D.14}$$

Finally, land/rent growth follows from $r_{it} H_i = \frac{1-\xi}{\xi} \sum_s w_{s,it} L_{s,it}$:

$$\dot{r}_{it+1} = \left(\frac{\dot{\tilde{\omega}}_{h,it+1} \, \dot{L}_{h,it+1}}{\dot{\kappa}_{h,it+1}} \right)^{\xi} = \left(\frac{\dot{\tilde{\omega}}_{l,it+1} \, \dot{L}_{l,it+1}}{\dot{\kappa}_{l,it+1}} \right)^{\xi}. \tag{D.15}$$

The equality follows from cost minimization: the Cobb-Douglas structure ensures that either skill type can serve as the reference for computing land rent growth. Equations (D.8)–(D.15) form the *temporary equilibrium in dots*.

To derive (D.8), first recall from the model the sectoral price index in location i and period t as:

$$P_{it} = \left(\sum_{n=1}^{\mathcal{N}} N_{nt} (p_{nit})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

Taking the ratio of the next-period and current-period price indices yields

$$\dot{P}_{it+1} = \frac{P_{it+1}}{P_{it}} = \left(\frac{\sum_{n=1}^{\mathcal{N}} N_{nt+1} \, (p_{nit+1})^{1-\sigma}}{\sum_{n=1}^{\mathcal{N}} N_{nt} \, (p_{nit})^{1-\sigma}} \right)^{\frac{1}{1-\sigma}}.$$

I can rewrite the numerator as

$$\sum_{n=1}^{\mathcal{N}} N_{nt+1} \left(p_{nit+1}\right)^{1-\sigma} = \sum_{n=1}^{\mathcal{N}} \sum_{s} \left[N_{nt} \left(p_{nit}\right)^{1-\sigma}\right] \dot{N}_{nt+1} \left(\dot{p}_{nit+1}\right)^{1-\sigma}.$$

Recall the trade share λ_{nit}:

$$\lambda_{nit} = \frac{N_{nt} \left(p_{nit}\right)^{1-\sigma}}{\sum_{n'=1}^{\mathcal{N}} N_{n't} \left(p_{n'it}\right)^{1-\sigma}}. = \lambda_{int} = N_{it} \left(\frac{p_{int}}{P_{nt}}\right)^{1-\sigma}$$

Then,

$$\frac{\sum_n N_{nt+1} \left(p_{nit+1}\right)^{1-\sigma}}{\sum_n N_{nt} \left(p_{nit}\right)^{1-\sigma}} = \sum_{n=1}^{\mathcal{N}} \lambda_{nit} \dot{N}_{nt+1} \left(\dot{p}_{nit+1}\right)^{1-\sigma}.$$

Putting all pieces together gives (D.8).

We now turn to the unit cost bundle x_{it}. From the cost minimization problem, the unit cost is given by

$$x_{it} = \left(\frac{P_{it}^L}{\xi}\right)^{\xi} \left(\frac{r_{it}}{1-\xi}\right)^{1-\xi}, \tag{D.16}$$

where P_{it}^L is the CES labor price index,

$$P_{it}^L = \left(\sum_{s \in \{h,l\}} \phi_{s,it} \, w_{s,it}^{1-\rho}\right)^{\frac{1}{1-\rho}}. \tag{D.17}$$

We assume A_i is constant over time. Define the gross growth of a variable z_{it} by

$$\dot{z}_{it} \equiv \frac{z_{it}}{z_{i,t-1}}. \tag{D.18}$$

In particular, $\dot{x}_{it} = x_{it} / x_{i,t-1}$.

Next, define the composite factor price

$$\widetilde{\omega}_{s,it} \equiv w_{s,it} \, r_{it}^{\frac{1-\xi}{\xi}}, \qquad \dot{\widetilde{\omega}}_{s,it} = \frac{w_{s,it}}{w_{s,i,t-1}} \left(\frac{r_{it}}{r_{i,t-1}}\right)^{\frac{1-\xi}{\xi}}. \tag{D.19}$$

Let the share of skill s in total labor payments (wage bill) in period $t-1$ be

$$\kappa_{s,i,t-1} \equiv \phi_{s,i,t-1} \left(\frac{w_{s,i,t-1}}{P_{i,t-1}^L}\right)^{1-\rho}, \qquad \sum_s \kappa_{s,i,t-1} = 1, \tag{D.20}$$

and denote the relative change in labor efficiency parameters by

$$\dot{\phi}_{s,it} \equiv \frac{\phi_{s,it}}{\phi_{s,i,t-1}}. \tag{D.21}$$

From equations (D.16)–(D.21), one can derive that the gross growth of unit costs is

$$\dot{x}_{it} = \left(\sum_{s \in \{h,l\}} \kappa_{s,i,t-1} \, \dot{\phi}_{s,it} \left(\dot{\tilde{\omega}}_{s,it} \right)^{1-\rho} \right)^{\frac{\xi}{1-\rho}}. \tag{D.22}$$

In particular, from (D.16) with A_i constant over time, take the gross growth between $t-1$ and t:

$$\dot{x}_{it} \equiv \frac{x_{it}}{x_{i,t-1}} = \left(\frac{P^L_{it}}{P^L_{i,t-1}} \right)^{\xi} \left(\frac{r_{it}}{r_{i,t-1}} \right)^{1-\xi} = \left(\dot{P}^L_{it} \right)^{\xi} \left(\dot{r}_{it} \right)^{1-\xi}. \tag{D.23}$$

From (D.17), divide by the same expression at $t-1$ and use the within-labor share definition (D.20),

$$\begin{aligned} \left(\dot{P}^L_{it} \right)^{1-\rho} &= \frac{\sum_s \phi_{s,it} \, w_{s,it}^{1-\rho}}{\sum_s \phi_{s,i,t-1} \, w_{s,i,t-1}^{1-\rho}} = \sum_s \underbrace{\frac{\phi_{s,i,t-1} \, w_{s,i,t-1}^{1-\rho}}{\sum_{s'} \phi_{s',i,t-1} \, w_{s',i,t-1}^{1-\rho}}}_{= \kappa_{s,i,t-1}} \frac{\phi_{s,it}}{\phi_{s,i,t-1}} \left(\frac{w_{s,it}}{w_{s,i,t-1}} \right)^{1-\rho} \\ &= \sum_s \kappa_{s,i,t-1} \, \dot{\phi}_{s,it} \left(\frac{w_{s,it}}{w_{s,i,t-1}} \right)^{1-\rho}. \end{aligned} \tag{D.24}$$

By definition (D.19),

$$\dot{\tilde{\omega}}_{s,it} = \frac{w_{s,it}}{w_{s,i,t-1}} \left(\frac{r_{it}}{r_{i,t-1}} \right)^{\frac{1-\xi}{\xi}} \quad \Rightarrow \quad \frac{w_{s,it}}{w_{s,i,t-1}} = \dot{\tilde{\omega}}_{s,it} \left(\dot{r}_{it} \right)^{-\frac{1-\xi}{\xi}}.$$

Plug this into (D.35):

$$\begin{aligned} \left(\dot{P}^L_{it} \right)^{1-\rho} &= \sum_s \kappa_{s,i,t-1} \, \dot{\phi}_{s,it} \left[\dot{\tilde{\omega}}_{s,it} \left(\dot{r}_{it} \right)^{-\frac{1-\xi}{\xi}} \right]^{1-\rho} \\ &= \left(\dot{r}_{it} \right)^{-\frac{(1-\xi)(1-\rho)}{\xi}} \sum_s \kappa_{s,i,t-1} \, \dot{\phi}_{s,it} \left(\dot{\tilde{\omega}}_{s,it} \right)^{1-\rho}. \end{aligned} \tag{D.25}$$

Raise both sides of (D.36) to the power $1/(1-\rho)$:

$$\dot{P}^L_{it} = \left(\dot{r}_{it} \right)^{-\frac{1-\xi}{\xi}} \left(\sum_s \kappa_{s,i,t-1} \, \dot{\phi}_{s,it} \left(\dot{\tilde{\omega}}_{s,it} \right)^{1-\rho} \right)^{\frac{1}{1-\rho}}. \tag{D.26}$$

Insert (D.26) into (D.34) yields

$$\begin{aligned}\dot{x}_{it} &= \left[\left(\dot{r}_{it}\right)^{-\frac{1-\xi}{\xi}}\left(\sum_{s}\kappa_{s,i,t-1}\,\dot{\phi}_{s,it}\left(\dot{\tilde{\omega}}_{s,it}\right)^{1-\rho}\right)^{\frac{1}{1-\rho}}\right]^{\xi}\left(\dot{r}_{it}\right)^{1-\xi}\\ &= \left(\dot{r}_{it}\right)^{-(1-\xi)}\left(\dot{r}_{it}\right)^{1-\xi}\left(\sum_{s}\kappa_{s,i,t-1}\,\dot{\phi}_{s,it}\left(\dot{\tilde{\omega}}_{s,it}\right)^{1-\rho}\right)^{\frac{\xi}{1-\rho}}\\ &= \left(\sum_{s\in\{h,l\}}\kappa_{s,i,t-1}\,\dot{\phi}_{s,it}\left(\dot{\tilde{\omega}}_{s,it}\right)^{1-\rho}\right)^{\frac{\xi}{1-\rho}}, \end{aligned} \tag{D.27}$$

which is exactly equation (D.22).

I now turn to the rental cost of land. Recall the market clearing condition for land market,

$$r_{it}\,H_i \;=\; \frac{1-\xi}{\xi}\frac{w_{h,it}\,L_{h,it}}{\kappa_{h,it}},$$

Because the outer aggregator is Cobb-Douglas with labor share ξ, cost minimization implies

$$r_{it}H_{it} \;=\; \frac{1-\xi}{\xi}\sum_{s\in\{h,l\}} w_{s,it}L_{s,it}. \tag{D.28}$$

Define the within-labor CES cost share for skill h at (i,t) by

$$\kappa_{h,it} \;\equiv\; \frac{w_{h,it}L_{h,it}}{\sum_{s\in\{h,l\}} w_{s,it}L_{s,it}} \quad\Longrightarrow\quad \sum_{s} w_{s,it}L_{s,it} \;=\; \frac{w_{h,it}L_{h,it}}{\kappa_{h,it}}. \tag{D.29}$$

Substituting (D.29) into (D.28) yields

$$r_{it}H_{it} \;=\; \frac{1-\xi}{\xi}\,\frac{w_{h,it}L_{h,it}}{\kappa_{h,it}}. \tag{D.30}$$

Taking ratios over time yields

$$\dot{r}_{it+1} = \frac{r_{it+1}}{r_{it}} = \frac{\dot{w}_{h,it}\dot{L}_{h,it}}{\dot{\kappa}_{h,it}}$$

Starting from the definition of the composite price for skilled labor h,

$$\tilde{\omega}_{h,it} \;\equiv\; w_{h,it}\,r_{it}^{\frac{1-\xi}{\xi}}, \tag{D.31}$$

its gross growth between $t-1$ and t is

$$\dot{\tilde{\omega}}_{h,it} \;\equiv\; \frac{\tilde{\omega}_{h,it}}{\tilde{\omega}_{h,i,t-1}} \;=\; \frac{w_{h,it}}{w_{h,i,t-1}}\left(\frac{r_{it}}{r_{i,t-1}}\right)^{\frac{1-\xi}{\xi}} \;=\; \dot{w}_{h,it}\left(\dot{r}_{it}\right)^{\frac{1-\xi}{\xi}}. \tag{D.32}$$

Solving (D.32) for $\dot{r}_{it}$ gives

$$\dot{r}_{it} = \left(\frac{\dot{\tilde{\omega}}_{h,it} \dot{L}_{h,it}}{\dot{\kappa}_{h,it}} \right)^{\xi}. \tag{D.33}$$

Next, I want to show that the bilateral trade share

$$\dot{\lambda}_{int+1} = \dot{N}_{it+1} \left(\frac{\dot{p}_{int+1}}{\dot{P}_{nt+1}} \right)^{1-\sigma}.$$

Recall the definition of the sectoral trade share

$$\lambda_{int} = \frac{N_{it} \left(p_{int} \right)^{1-\sigma}}{\sum_{o=1}^{\mathcal{N}} N_{ot} \left(p_{ont} \right)^{1-\sigma}},$$

Then,

$$\dot{\lambda}_{int+1} = \frac{\lambda_{int+1}}{\lambda_{int}} = \frac{\frac{N_{it+1} \left(p_{int+1} \right)^{1-\sigma}}{\sum_{o=1}^{\mathcal{N}} N_{ot+1} \left(p_{ont+1} \right)^{1-\sigma}}}{\frac{N_{it} \left(p_{int} \right)^{1-\sigma}}{\sum_{o=1}^{\mathcal{N}} N_{ot} \left(p_{ont} \right)^{1-\sigma}}}.$$

Observe that

$$\sum_{o=1}^{\mathcal{N}} N_{ot+1} \left(p_{ont+1} \right)^{1-\sigma} = \sum_{o=1}^{\mathcal{N}} \left[N_{ot} \left(p_{ont} \right)^{1-\sigma} \right] \dot{N}_{ot+1} \left(\dot{p}_{ont+1} \right)^{1-\sigma}.$$

Recall the dot definition of P_{nt+1}.

$$\left(\dot{P}_{nt+1} \right)^{1-\sigma} = \frac{\sum_{o=1}^{\mathcal{N}} N_{ot+1} \left(p_{ont+1} \right)^{1-\sigma}}{\sum_{o=1}^{\mathcal{N}} N_{ot} \left(p_{ont} \right)^{1-\sigma}}.$$

Therefore,

$$\dot{\lambda}_{int+1} = \frac{N_{it+1} \left(p_{int+1} \right)^{1-\sigma}}{N_{it} \left(p_{int} \right)^{1-\sigma}} \frac{\sum_{o=1}^{\mathcal{N}} N_{ot} \left(p_{ont} \right)^{1-\sigma}}{\sum_{o=1}^{\mathcal{N}} N_{ot+1} \left(p_{ont+1} \right)^{1-\sigma}} = \dot{N}_{it+1} \left(\dot{p}_{int+1} \right)^{1-\sigma} \frac{1}{\left(\dot{P}_{nt+1} \right)^{1-\sigma}}.$$

This completes the dot derivation for trade share (D.10).

Next, I want to show the profit equation (D.11). Recall the level definition of profits:

$$\pi_{it} = \left(\tfrac{\sigma-1}{\sigma} \right)^{\sigma} \left(\tfrac{A_{it}}{x_{it}} \right)^{\sigma-1} \sum_{n=1}^{\mathcal{N}} \left(d_{in} \right)^{1-\sigma} X_{nt} \left(P_{nt} \right)^{\sigma-1},$$

or

$$\pi_{it+1} = \sum_{n} \dot{\pi}_{int+1} \pi_{int}$$

where π_{int} is the profit of selling from i to n which is given by

$$\pi_{int} = \frac{p_{int} y_{int}}{\sigma} = \frac{\lambda_{int} X_{nt}}{\sigma N_{it}}$$

Also, I can write

$$\dot{\pi}_{int+1} = \frac{\pi_{int+1}}{\pi_{int}} = \frac{(p_{int+1})^{1-\sigma}(P_{nt+1})^{\sigma-1} X_{nt+1}}{(p_{int})^{1-\sigma}(P_{nt})^{\sigma-1} X_{nt}} = (\dot{x}_{it+1})^{1-\sigma}(\dot{P}_{nt+1})^{\sigma-1}\dot{X}_{nt+1}$$

Hence, we obtain

$$\pi_{it+1} \;=\; \frac{1}{\sigma}\sum_{n=1}^{\mathcal{N}} (\dot{x}_{it+1})^{1-\sigma}\left(\dot{P}_{nt+1}\right)^{\sigma-1}\frac{\lambda_{int}}{N_{it}}\, X_{nt+1}.$$

Local government expenditure from (13), substituting $r_{it} = \dot{r}_{it} r_{it-1}$:

$$P_{it}G_{it} = \dot{r}_{it} r_{it-1} H_i - \text{TIP}_{it} = \dot{r}_{it}\frac{1-\xi}{\xi}\sum_{s=\{h,l\}} w_{s,it-1}L_{s,it-1} - \text{TIP}_{it}$$

where TIP_{it} is the fiscal cost from (19). When $\text{TIP}_{it} = 0$ (untreated cities or periods before TIPs), government expenditure equals rent revenue as before.

Turning to local income, recall from (21) that $\Pi_{it} = P_{it}G_{it} + \pi_{it}N_{it} + \sum_s w_{s,it}L_{s,it}$. Expressing in dot notation and substituting the government budget:

$$\begin{aligned}\Pi_{it+1} &= P_{it+1}G_{it+1} + \pi_{it+1}N_{it+1} + \sum_{s=h,l}\dot{w}_{s,it+1}\dot{L}_{s,it+1}w_{s,it}L_{s,it} \\ &= \dot{r}_{it+1}\frac{1-\xi}{\xi}\sum_s w_{s,it}L_{s,it} - \text{TIP}_{it+1} + \pi_{it+1}N_{it+1} \\ &\quad + \sum_{s=h,l}\left(\dot{\tilde{\omega}}_{s,it+1}\right)^{\xi}\left(\dot{\kappa}_{s,it+1}\right)^{1-\xi}\left(\dot{L}_{s,it+1}\right)^{\xi} w_{s,it}L_{s,it}\end{aligned}$$

Finally, from the market-clearing condition (22):

$$\dot{w}^{\xi}_{s,it+1} = \frac{\sigma-1}{\sigma}\frac{\xi\kappa_{s,it+1}}{\dot{L}^{\xi}_{s,it+1}(\dot{\kappa}_{s,it+1})^{1-\xi}w_{s,it}L_{s,it}}\sum_{n=1}^{\mathcal{N}}\dot{\lambda}_{int+1}\lambda_{int}\Pi_{nt+1}.$$

where

$$\kappa_{s,it} = \kappa_{s,it-1}\frac{\dot{\phi}_{s,it}(\dot{\tilde{\omega}}_{s,it})^{1-\rho}}{(\dot{x}_{it})^{\frac{1-\rho}{\xi}}}$$

To get this equation, recall the definition of $\kappa_{s,it}$,

$$\frac{\kappa_{s,it}}{\kappa_{s,i,t-1}} = \frac{\phi_{s,it}}{\phi_{s,i,t-1}}\left(\frac{w_{s,it}/P^L_{it}}{w_{s,i,t-1}/P^L_{i,t-1}}\right)^{1-\rho} = \dot{\phi}_{s,it}\frac{(\dot{w}_{s,it})^{1-\rho}}{(\dot{P}^L_{it})^{1-\rho}}. \tag{D.34}$$

and the unit cost index is

$$x_{it} = \left(\frac{P_{it}^L}{\xi}\right)^{\xi} \left(\frac{r_{it}}{1-\xi}\right)^{1-\xi} \;\Rightarrow\; \dot{x}_{it} = (\dot{P}_{it}^L)^{\xi} (\dot{r}_{it})^{1-\xi}.$$

Thus,

$$(\dot{P}_{it}^L)^{1-\rho} = \left(\frac{\dot{x}_{it}}{(\dot{r}_{it})^{1-\xi}}\right)^{\frac{1-\rho}{\xi}} = (\dot{x}_{it})^{\frac{1-\rho}{\xi}} \; (\dot{r}_{it})^{-\frac{(1-\xi)(1-\rho)}{\xi}}. \tag{D.35}$$

We also have

$$(\dot{w}_{s,it})^{1-\rho} = \left(\dot{\tilde{\omega}}_{s,it}\right)^{1-\rho} \; (\dot{r}_{it})^{-\frac{(1-\xi)(1-\rho)}{\xi}}. \tag{D.36}$$

Substituting (D.35) and (D.36) into (D.34) gives

$$\frac{\kappa_{s,it}}{\kappa_{s,i,t-1}} = \dot{\phi}_{s,it} \, \frac{\left(\dot{\tilde{\omega}}_{s,it}\right)^{1-\rho} (\dot{r}_{it})^{-\frac{(1-\xi)(1-\rho)}{\xi}}}{(\dot{x}_{it})^{\frac{1-\rho}{\xi}} \; (\dot{r}_{it})^{-\frac{(1-\xi)(1-\rho)}{\xi}}} = \dot{\phi}_{s,it} \, \frac{\left(\dot{\tilde{\omega}}_{s,it}\right)^{1-\rho}}{(\dot{x}_{it})^{\frac{1-\rho}{\xi}}}.$$

Multiplying both sides by $\kappa_{s,i,t-1}$ yields (D.14)

$$\kappa_{s,it} = \kappa_{s,i,t-1} \, \frac{\dot{\phi}_{s,it} \left(\dot{\tilde{\omega}}_{s,it}\right)^{1-\rho}}{(\dot{x}_{it})^{\frac{1-\rho}{\xi}}}$$

Step 2: Value and share recursions in dots.

Lemma 1 (Normalization Lemma)**.** *Fix a finite index set $\mathcal{K}$. For each $k \in \mathcal{K}$ and time t, let $z_{k,t} \in \mathbb{R}$ and define*

$$S_t(\theta) \;\equiv\; \sum_{k \in \mathcal{K}} \exp\big(\theta \, z_{k,t}\big), \qquad \theta > 0.$$

Let the period-$(t-1)$ softmax weights be

$$s_{k,t-1}(\theta) \;\equiv\; \frac{\exp(\theta z_{k,t-1})}{S_{t-1}(\theta)}.$$

Then

$$\frac{S_t(\theta)}{S_{t-1}(\theta)} \;=\; \sum_{k \in \mathcal{K}} s_{k,t-1}(\theta) \, \exp\big(\theta[z_{k,t} - z_{k,t-1}]\big).$$

Consequently,

$$\exp\Big(\tfrac{1}{\theta}\left[\log S_t(\theta) - \log S_{t-1}(\theta)\right]\Big) \;=\; \left(\sum_{k \in \mathcal{K}} s_{k,t-1}(\theta) \, \exp\big(\theta[z_{k,t} - z_{k,t-1}]\big)\right)^{1/\theta}.$$

Proof. *Divide $S_t(\theta)$ by $S_{t-1}(\theta)$, multiply and divide each term by $\exp(\theta z_{k,t-1})$, and recognize the weights*

$s_{k,t-1}(\theta)$. *Write*

$$\frac{S_t(\theta)}{S_{t-1}(\theta)} = \frac{\sum_k \exp(\theta z_{k,t})}{\sum_c \exp(\theta z_{c,t-1})} = \sum_k \frac{\exp(\theta z_{k,t-1})}{S_{t-1}(\theta)} \frac{\exp(\theta z_{k,t})}{\exp(\theta z_{k,t-1})} = \sum_k s_{k,t-1}(\theta)\ \exp\big(\theta[z_{k,t} - z_{k,t-1}]\big).$$

Taking $\frac{1}{\theta}$ times logs and exponentiating yields the second display. □

Notation. Define consumption growth for entrepreneurs:

$$\dot{c}^e_{s,it+1} \equiv \frac{\dot{\pi}_{it+1}}{\dot{P}_{it+1}} \tag{D.37}$$

and for workers:

$$\dot{c}^w_{s,it+1} \equiv \frac{\dot{w}_{s,it+1}}{\dot{P}_{it+1}}. \tag{D.38}$$

For migration costs that include housing prices $h_{n,t}$ and subsidy shares $\theta_{s,n,t} = T_{s,n,t}/h_{n,t}$, define the housing-subsidy shifter:

$$\tau_{s,n,t+1} \equiv \left(\frac{h_{n,t}}{h_{n,t+1}}\right)^{1/\nu} \left(\frac{1+\theta_{s,n,t+1}}{1+\theta_{s,n,t}}\right)^{1/\nu}. \tag{D.39}$$

This captures changes in migration attractiveness due to housing market dynamics and policy adjustments.

Applying Lemma 1 to the log-sum-exp terms in the value functions gives:

$$\dot{v}_{s,it+1} = \dot{c}^e_{s,it+1} \left[\varsigma_{s,it} \left(\dot{v}_{s,it+2}\right)^{\frac{\beta}{\chi}} + (1-\varsigma_{s,it}) \left(\dot{u}_{s,it+2}\right)^{\frac{\beta}{\chi}}\right]^{\chi} \tag{D.40}$$

$$\dot{u}_{s,it+1} = \frac{\dot{w}_{s,it+1}}{\dot{P}_{it+1}} \left[\psi^0_{s,it}(\dot{\Xi}_{s,it+1})^{1/\chi} + \psi_{s,it}(\dot{v}_{s,it+2})^{\beta/\chi}\right]^{\chi} \tag{D.41}$$

$$\dot{\Xi}_{s,it+1} = \left(\sum_n \mu_{s,in,t}(\dot{u}_{s,n,it+2})^{\beta/\nu} \tau_{s,n,t+1}\right)^{\nu} \tag{D.42}$$

Similarly, applying Lemma 1 to the multinomial logit probabilities yields:

$$\psi_{s,it} = \frac{\psi_{s,i,t-1}(\dot{v}_{s,it+1})^{\beta/\chi}}{\psi^0_{s,i,t-1}(\dot{\Xi}_{s,it})^{1/\chi} + \psi_{s,i,t-1}(\dot{v}_{s,it+1})^{\beta/\chi}}, \tag{D.43}$$

$$\psi^0_{s,it} = \frac{\psi^0_{s,i,t-1}(\dot{\Xi}_{s,it})^{1/\chi}}{\psi^0_{s,i,t-1}(\dot{\Xi}_{s,it})^{1/\chi} + \psi_{s,i,t-1}(\dot{v}_{s,it+1})^{\beta/\chi}}, \tag{D.44}$$

$$\varsigma_{s,it} = \frac{\varsigma_{s,i,t-1}(\dot{v}_{s,it+1})^{\beta/\chi}}{\varsigma_{s,i,t-1}(\dot{v}_{s,it+1})^{\beta/\chi} + (1-\varsigma_{s,i,t-1})(\dot{u}_{s,it+1})^{\beta/\chi}}. \tag{D.45}$$

$$\mu_{s,in,t+1} = \frac{\mu_{s,in,t}(\dot{u}_{s,n,it+2})^{\beta/\nu}\tau_{s,n,t+1}}{\sum_c \mu_{s,ic,t}(\dot{u}_{s,c,it+2})^{\beta/\nu}\tau_{s,c,t+1}}. \tag{D.46}$$

We now sketch the derivations for the share update equations.

Entry share (D.43)**.** From (5):

$$\psi_{s,it+1} = \frac{\exp(\beta V_{s,it+2}/\chi)}{\exp(\Xi_{s,it+1}/\chi) + \exp(\beta V_{s,it+2}/\chi)}.$$

Divide numerator and denominator by the period-t normalizer $\exp(\Xi_{s,it}/\chi) + \exp(\beta V_{s,it+1}/\chi)$ and recognize $\psi_{s,it}$ and $\psi^0_{s,it}$ as weights. Applying Lemma 1 with $\theta = 1/\chi$ yields (D.43).

Migration share (D.46)**.** The derivation for migration shares requires care when migration costs include housing prices and subsidies. From (9), the migration share at time t is

$$\mu_{s,in,t} = \frac{\exp\left(\frac{\beta U_{s,n,t+1} - m_{s,in,t}}{\nu}\right)}{\sum_{k=1}^{\mathcal{N}} \exp\left(\frac{\beta U_{s,k,t+1} - m_{s,ik,t}}{\nu}\right)} = \frac{\exp\left(\frac{\beta U_{s,n,t+1} - m_{s,in,t}}{\nu}\right)}{S_t}$$

where $S_t \equiv \sum_k \exp\left(\frac{\beta U_{s,k,t+1} - m_{s,ik,t}}{\nu}\right)$ is the normalizer. Substituting the cost decomposition $m_{s,in,t} = \bar{m}_{s,in} + \log(h_{n,t}) - \log(1 + \theta_{s,n,t})$ gives

$$\begin{aligned} m_{s,in,t+1} - m_{s,in,t} &= \log(h_{n,t+1}) - \log(h_{n,t}) - \log(1 + \theta_{s,n,t+1}) + \log(1 + \theta_{s,n,t}) \\ &= \log\left(\frac{h_{n,t+1}}{h_{n,t}}\right) + \log\left(\frac{1 + \theta_{s,n,t}}{1 + \theta_{s,n,t+1}}\right). \end{aligned}$$

Note that $\bar{m}_{s,in}$ cancels because it is constant over time. The exponential ratio in the numerator becomes

$$\begin{aligned} \frac{\exp\left(\frac{\beta U_{s,n,t+2} - m_{s,in,t+1}}{\nu}\right)}{\exp\left(\frac{\beta U_{s,n,t+1} - m_{s,in,t}}{\nu}\right)} &= \exp\left(\frac{\beta(U_{s,n,t+2} - U_{s,n,t+1})}{\nu}\right) \cdot \exp\left(\frac{m_{s,in,t} - m_{s,in,t+1}}{\nu}\right) \\ &= \left(\frac{\exp(U_{s,n,t+2})}{\exp(U_{s,n,t+1})}\right)^{\beta/\nu} \cdot \left(\frac{h_{n,t}}{h_{n,t+1}}\right)^{1/\nu} \cdot \left(\frac{1 + \theta_{s,n,t+1}}{1 + \theta_{s,n,t}}\right)^{1/\nu}. \end{aligned}$$

Define $\dot{u}_{s,n,t+2} \equiv \exp(U_{s,n,t+2})/\exp(U_{s,n,t+1})$ and the housing-subsidy shifter

$$\tau_{s,n,t+1} \equiv \left(\frac{h_{n,t}}{h_{n,t+1}}\right)^{1/\nu} \left(\frac{1 + \theta_{s,n,t+1}}{1 + \theta_{s,n,t}}\right)^{1/\nu}.$$

Applying Lemma 1 with $\theta = 1/\nu$ to the ratio S_{t+1}/S_t gives

$$\frac{S_{t+1}}{S_t} = \sum_c \mu_{s,ic,t} \cdot (\dot{u}_{s,c,t+2})^{\beta/\nu} \cdot \tau_{s,c,t+1}.$$

Thus the migration share update is

$$\mu_{s,in,t+1} = \frac{\mu_{s,in,t} \cdot (\dot{u}_{s,n,t+2})^{\beta/\nu} \cdot \tau_{s,n,t+1}}{\sum_c \mu_{s,ic,t} \cdot (\dot{u}_{s,c,t+2})^{\beta/\nu} \cdot \tau_{s,c,t+1}}. \tag{D.47}$$

The housing-subsidy shifter τ enters with exponent $1/\nu$ rather than β/ν because housing costs and subsidies represent one-time establishment costs incurred at the moment of moving, not discounted future utility flows. The utility term $\dot{u}$ appears with exponent β/ν because $U_{s,n,t}$ represents the present discounted value of all future flows. This distinction is critical: conflating these exponents would misstate the migration elasticity with respect to subsidies.

Continuation probability (D.45)**.** We start from (18),

$$\varsigma_{s,it} = \frac{\exp(\beta V_{s,it+1}/\chi)}{\exp(\beta V_{s,it+1}/\chi) + \exp(\beta U_{s,it+1}/\chi)}.$$

Divide the numerator and denominator by $\exp(\beta V_{s,i,t}/\chi) + \exp(\beta U_{s,i,t}/\chi)$, use

$$\varsigma_{s,i,t-1} = \frac{\exp(\beta V_{s,i,t}/\chi)}{\exp(\beta V_{s,i,t}/\chi) + \exp(\beta U_{s,i,t}/\chi)}, \qquad 1 - \varsigma_{s,i,t-1} = \frac{\exp(\beta U_{s,i,t}/\chi)}{\exp(\beta V_{s,i,t}/\chi) + \exp(\beta U_{s,i,t}/\chi)},$$

and recognize $\dot{v}_{s,it+1} \equiv \exp(V_{s,it+1})/\exp(V_{s,i,t})$ and $\dot{u}_{s,it+1} \equiv \exp(U_{s,it+1})/\exp(U_{s,i,t})$. Then,

$$\varsigma_{s,it} = \frac{\varsigma_{s,i,t-1} \left(\dot{v}_{s,it+1}\right)^{\beta/\chi}}{\varsigma_{s,i,t-1} \left(\dot{v}_{s,it+1}\right)^{\beta/\chi} + \left(1 - \varsigma_{s,i,t-1}\right) \left(\dot{u}_{s,it+1}\right)^{\beta/\chi}},$$

which is (D.45). □

Step 3: Law of motion. Recall the laws of motion for entrepreneurs and workers from (23)–(24). The only nontrivial terms are the shares which we have just derived in Step 2. This closes the system in dot form. No levels of fundamentals/policies at t are required, proving the claim. □

D.3 Computational Algorithm

The baseline economy is computed using nested iteration. Given structural parameters $(\beta, \chi, \nu, \sigma, \rho, \xi)$ and initial conditions at the last data period t_0, the algorithm proceeds in two loops:

Outer loop: Value functions. Starting from initial guesses $\dot{u}^{(0)}_{s,it} = \dot{v}^{(0)}_{s,it} = 1$, iterate on worker and entrepreneur value functions $\{\dot{u}_{s,it+1}, \dot{v}_{s,it+1}\}$ using equations (D.41)–(D.40). Each outer iteration updates migration shares $\mu_{s,in,t}$, entry shares $\psi_{s,it}$, and continuation shares $\varsigma_{s,it}$ via the logit structure in (D.46)–(D.45), then evolves population stocks forward. Convergence occurs when $\max_{i,s,t} |\dot{u}^{(k+1)}_{s,it} - \dot{u}^{(k)}_{s,it}|$ is small enough.

Inner loop: Temporary equilibrium. For each period t, given population growth rates $\{\dot{L}_{s,it+1}, \dot{N}_{it+1}\}$, solve for factor prices $\{\dot{w}_{s,it+1}, \dot{r}_{it+1}\}$ and trade shares $\dot{\lambda}_{int+1}$ using the static equilibrium system (D.8)–(D.15). The inner loop iterates on composite factor prices $\dot{\tilde{\omega}}_{s,it+1}$ with dampening until the price vector converges.

D.4 Proof of Proposition 2

For any variable y, let $\dot{y}_{t+1} \equiv y_{t+1}/y_t$ (baseline) and $\hat{y}_{t+1} \equiv \dot{y}'_{t+1}/\dot{y}_{t+1}$ (counterfactual-to-baseline ratio). Agents do not anticipate policy at $t = 0$; the policy sequence is learned at $t = 1$. Define the consumption hat $\hat{c}_{s,it} \equiv \frac{\hat{w}_{s,it}}{\hat{P}_{it}}$.

For migration costs with housing subsidies, the hat for the housing-subsidy shifter is

$$\hat{\tau}_{s,n,t} = \frac{\tau'_{s,n,t}}{\tau_{s,n,t}} = \left(\frac{h'_{n,t-1}/h'_{n,t}}{h_{n,t-1}/h_{n,t}}\right)^{1/\nu} \left(\frac{(1+\theta'_{s,n,t})(1+\theta_{s,n,t-1})}{(1+\theta'_{s,n,t-1})(1+\theta_{s,n,t})}\right)^{1/\nu}. \tag{D.48}$$

When housing prices are exogenous (identical in baseline and counterfactual, $h'_{n,t} = h_{n,t}$ for all n, t), the first term equals one and

$$\hat{\tau}_{s,n,t} = \left(\frac{(1+\theta'_{s,n,t})(1+\theta_{s,n,t-1})}{(1+\theta'_{s,n,t-1})(1+\theta_{s,n,t})}\right)^{1/\nu}. \tag{D.49}$$

To see why this formula emerges, recall the migration cost specification $m_{s,in,t} = \bar{m}_{s,in} + \log(h_{n,t}) - \log(1+\theta_{s,n,t})$. The bilateral friction $\bar{m}_{s,in}$ is identical across scenarios and cancels in hats. With exogenous housing, the cost difference between scenarios is $m'_{s,in,t} - m_{s,in,t} = \log(1+\theta_{s,n,t}) - \log(1+\theta'_{s,n,t})$. In the dot system, migration shares depend on $\tau_{s,n,t+1} = [(1+\theta_{s,n,t+1})/(1+\theta_{s,n,t})]^{1/\nu}$, the growth rate of subsidy attractiveness. The hat compares counterfactual and baseline growth rates: $\hat{\tau}_{s,n,t} = \tau'_{s,n,t}/\tau_{s,n,t}$, which simplifies to (D.49). This captures the differential effect of TIPs policies across scenarios. In the no-policy counterfactual where $\theta'_{s,n,t} = 0$ for all treated cities while $\theta_{s,n,t} > 0$ in baseline, we have $\hat{\tau}_{s,n,t} = \left[(1+\theta_{s,n,t-1})/(1+\theta_{s,n,t})\right]^{1/\nu}$, reflecting that removing subsidies increases migration costs. The formula (D.49) shows that policy effects enter through relative subsidy generosity across periods. If baseline subsidies increase from $t-1$ to t (i.e., $\theta_{s,n,t} > \theta_{s,n,t-1}$) while counterfactual subsidies remain zero, then $\hat{\tau}_{s,n,t} < 1$, indicating that the counterfactual has relatively higher migration costs to city n, reducing inflows compared to baseline.

Value functions for $t > 1$. From the dot recursions in §D.2, form counterfactual dots and divide:

$$\hat{u}_{s,it} = \hat{c}_{s,it} \left[\psi'^{0}_{s,i,t-1} \dot{\psi}^{0}_{s,it} \left(\hat{\Xi}_{s,it}\right)^{1/\chi} + \psi'_{s,i,t-1} \dot{\psi}_{s,it} \left(\hat{v}_{s,it+1}\right)^{\beta/\chi} \right]^{\chi}, \tag{D.50}$$

$$\hat{\Xi}_{s,it} = \left(\sum_{n} \mu'_{s,in,t-1} \dot{\mu}_{s,in,t} \left(\hat{u}_{s,n,it+1}\right)^{\beta/\nu} \hat{\tau}_{s,n,t} \right)^{\nu}, \tag{D.51}$$

$$\varsigma'_{s,it} = \frac{\varsigma'_{s,i,t-1} \dot{\varsigma}_{s,it} \left(\hat{v}_{s,it+1}\right)^{\beta/\chi}}{\varsigma'_{s,i,t-1} \dot{\varsigma}_{s,it} \left(\hat{v}_{s,it+1}\right)^{\beta/\chi} + \left(1 - \varsigma'_{s,i,t-1}\right) \left(1 - \dot{\varsigma}_{s,it}\right) \left(\hat{u}_{s,it+1}\right)^{\beta/\chi}}, \tag{D.52}$$

$$\psi'_{s,it} = \frac{\psi'_{s,i,t-1} \dot{\psi}_{s,it} \left(\hat{v}_{s,it+1}\right)^{\beta/\chi}}{\psi'^{0}_{s,i,t-1} \dot{\psi}^{0}_{s,it} \left(\hat{\Xi}_{s,it}\right)^{1/\chi} + \psi'_{s,i,t-1} \dot{\psi}_{s,it} \left(\hat{v}_{s,it+1}\right)^{\beta/\chi}}, \tag{D.53}$$

$$\mu'_{s,in,t} = \frac{\mu'_{s,in,t-1} \dot{\mu}_{s,in,t} \left(\hat{u}_{s,n,it+1}\right)^{\beta/\nu} \hat{\tau}_{s,n,t}}{\sum_{c} \mu'_{s,ic,t-1} \dot{\mu}_{s,ic,t} \left(\hat{u}_{s,c,it+1}\right)^{\beta/\nu} \hat{\tau}_{s,c,t}}. \tag{D.54}$$

At $t = 1$. Because there is no policy difference at $t = 0$, continuation terms load on both $t = 1$ and $t = 2$ and weights are the *baseline* shares at $t = 1$:

$$\hat{u}_{s,i1} = \hat{c}_{s,i1} \left[\psi^{0}_{s,i1} \left(\hat{\Xi}_{s,i1}\right)^{1/\chi} + \psi_{s,i1} \left(\hat{v}_{s,i1}\right)^{\beta/\chi} \left(\hat{v}_{s,i2}\right)^{\beta/\chi} \right]^{\chi}, \tag{D.55}$$

$$\hat{\Xi}_{s,i1} = \left(\sum_{n} \mu_{s,in,1} \left(\hat{u}_{s,n,1}\right)^{\beta/\nu} \left(\hat{u}_{s,n,2}\right)^{\beta/\nu} \hat{\tau}_{s,n,1} \right)^{\nu}, \tag{D.56}$$

$$\varsigma'_{s,i1} = \frac{\varsigma_{s,i1} \left(\hat{v}_{s,i1}\right)^{\beta/\chi} \left(\hat{v}_{s,i2}\right)^{\beta/\chi}}{\varsigma_{s,i1} \left(\hat{v}_{s,i1}\right)^{\beta/\chi} \left(\hat{v}_{s,i2}\right)^{\beta/\chi} + \left(1 - \varsigma_{s,i1}\right) \left(\hat{u}_{s,i1}\right)^{\beta/\chi} \left(\hat{u}_{s,i2}\right)^{\beta/\chi}}, \tag{D.57}$$

$$\psi'_{s,i1} = \frac{\psi_{s,i1} \left(\hat{v}_{s,i1}\right)^{\beta/\chi} \left(\hat{v}_{s,i2}\right)^{\beta/\chi}}{\psi^{0}_{s,i1} \left(\hat{\Xi}_{s,i1}\right)^{1/\chi} + \psi_{s,i1} \left(\hat{v}_{s,i1}\right)^{\beta/\chi} \left(\hat{v}_{s,i2}\right)^{\beta/\chi}}, \tag{D.58}$$

$$\mu'_{s,in,1} = \frac{\mu_{s,in,1} \left(\hat{u}_{s,n,1}\right)^{\beta/\nu} \left(\hat{u}_{s,n,2}\right)^{\beta/\nu} \hat{\tau}_{s,n,1}}{\sum_{c} \mu_{s,ic,1} \left(\hat{u}_{s,c,1}\right)^{\beta/\nu} \left(\hat{u}_{s,c,2}\right)^{\beta/\nu} \hat{\tau}_{s,c,1}}. \tag{D.59}$$

Temporary block, all $t \geq 1$ Take counterfactual and baseline dot systems from §D.2 and divide:

$$\hat{P}_{it+1} = \Big(\sum_n \lambda'_{nit}\, \dot{\lambda}_{nit+1}\, \hat{N}_{nt+1}\, (\hat{x}_{nt+1})^{1-\sigma} \Big)^{\frac{1}{1-\sigma}}, \tag{D.60}$$

$$\hat{p}_{int+1} = \hat{x}_{it+1} = (\hat{w}_{h,it+1})^{\xi}\, (\hat{r}_{it+1})^{1-\xi} = \Big(\sum_s \kappa_{s,it}\, \hat{\phi}_{s,it+1}\, (\widehat{\widetilde{\omega}}_{s,it+1})^{1-\rho} \Big)^{\frac{\xi}{1-\rho}}, \tag{D.61}$$

$$\lambda'_{int+1} = \lambda'_{int}\, \dot{\lambda}_{int+1}\, \hat{N}_{it+1}\, (\hat{x}_{it+1})^{1-\sigma}\, (\hat{P}_{nt+1})^{\sigma-1}, \tag{D.62}$$

$$\pi'_{it+1} = \frac{1}{\sigma} \sum_{n=1}^{\mathcal{N}} (\dot{x}'_{it+1})^{1-\sigma}\, (\dot{P}'_{nt+1})^{\sigma-1}\, \frac{\lambda'_{int}}{N'_{it}}\, X'_{nt+1}. \tag{D.63}$$

$$\Pi'_{it+1} = P'_{it+1} G'_{it+1} + \sum_{s \in \{h,l\}} w'_{s,it+1} L'_{s,it+1} + \pi'_{it+1} N'_{it+1}. \tag{D.64}$$

$$\hat{w}^{\xi}_{s,it+1} = \frac{\sigma - 1}{\sigma}\, \frac{\xi\, \hat{\kappa}_{s,it+1}}{\hat{L}^{\xi}_{s,it+1}}\, \frac{\sum_n \lambda'_{int+1} X'_{nt+1}}{\sum_n \lambda_{int+1} X_{nt+1}}, \tag{D.65}$$

$$\hat{\kappa}_{s,it+1} = \frac{\kappa_{s,it+1}}{\kappa_{s,it}}\, \frac{\hat{\phi}_{s,it+1}\, (\widehat{\widetilde{\omega}}_{s,it+1})^{1-\rho}}{(\hat{x}_{it+1})^{\frac{1-\rho}{\xi}}}. \tag{D.66}$$

Here $\widehat{\widetilde{\omega}}_{s,it+1}$ is the composite factor price hat defined as in §D.2.

Representative derivations. We sketch one key line per block; the rest follow by the same steps.

Value function: $\dot{\Xi}_{s,it}$ for $t > 1$. From (D.42) in the baseline,

$$\dot{\Xi}_{s,it} = \Big(\sum_n \mu_{s,in,t-1} (\dot{u}_{s,n,it+1})^{\beta/\nu} (\dot{m}_{s,in,t})^{-1/\nu} \Big)^{\nu}.$$

Write the counterfactual analogue, divide, and substitute $\dot{u}' = \dot{u} \cdot \hat{u}$ and $\dot{m}' = \dot{m} \cdot \hat{m}$:

$$\hat{\dot{\Xi}}_{s,it} = \left(\frac{\sum_n \mu'_{s,in,t-1} (\dot{u}_{s,n,it+1})^{\beta/\nu} (\hat{u}_{s,n,it+1})^{\beta/\nu} (\dot{m}_{s,in,t})^{-1/\nu} (\hat{m}_{s,in,t})^{-1/\nu}}{\sum_n \mu_{s,in,t-1} (\dot{u}_{s,n,it+1})^{\beta/\nu} (\dot{m}_{s,in,t})^{-1/\nu}} \right)^{\nu}.$$

Using the dot definition of $\mu_{s,in,t}$ (eq. (D.46)), the denominator is a normalizer, yielding (D.51).

Value function $\hat{u}_{s,it}$ for $t > 1$. From (D.41), take the CF-to-baseline ratio and group consumption into $\hat{c}_{s,it}$:

$$\hat{u}_{s,it} = \hat{c}_{s,it} \left[\frac{\psi'^{0}_{s,i,t-1} (\dot{\Xi}'_{s,it})^{1/\chi} + \psi'_{s,i,t-1} (\dot{v}'_{s,it+1})^{\beta/\chi}}{\psi^{0}_{s,i,t-1} (\dot{\Xi}_{s,it})^{1/\chi} + \psi_{s,i,t-1} (\dot{v}_{s,it+1})^{\beta/\chi}} \right]^{\chi}.$$

Apply Lemma 1 to the two-term softmax (parameter $\theta = 1/\chi$) with period-$(t-1)$ weights, and substitute $\dot{\Xi}' = \dot{\Xi} \cdot \hat{\dot{\Xi}}$ and $\dot{v}' = \dot{v} \cdot \hat{v}$, giving (D.50).

Static: $\hat{P}_{it+1}$. From (D.8), $\dot{P}_{it+1} = \big(\sum_n \lambda_{nit}\, \dot{N}_{nt+1} (\dot{p}_{nit+1})^{1-\sigma} \big)^{1/(1-\sigma)}$, and analogously for CF. Divide CF by baseline, use $\dot{p}' = \dot{p} \cdot \hat{p}$, $\dot{N}' = \dot{N} \cdot \hat{N}$, and express the denominator via $\dot{\lambda}_{nit+1} = \dot{N}_{it+1} (\dot{p}_{nit+1} / \dot{P}_{nt+1})^{1-\sigma}$; this yields (D.60). Markup implies $\hat{p}_{int+1} = \hat{x}_{it+1}$.

Combining systems (D.50)–(D.54), (D.55)–(D.59), (D.60)–(D.66), and the laws of motion closes the counterfactual equilibrium entirely in hats, without levels of fundamentals or policies, which

proves the proposition. □

D.5 Counterfactual Algorithm

Counterfactuals are solved using hat notation $\hat{y} \equiv y'/y$ (counterfactual relative to baseline). Given the baseline equilibrium and policy shocks $\{\hat{\tau}_{s,in,t}\}$ (e.g., removing TIP subsidies), the algorithm iterates on value function hats $\{\hat{u}_{s,it}, \hat{v}_{s,it}\}$ until convergence using the same criteria as the baseline algorithm.

The outer loop updates counterfactual migration shares $\mu'_{s,in,t}$, entry shares $\psi'_{s,it}$, and continuation shares $\varsigma'_{s,it}$ using the hat equations (D.50)–(D.54), then evolves counterfactual populations forward. The inner loop solves for counterfactual factor prices and trade shares using hat versions of the static equilibrium system (D.60)–(D.66). This approach requires only ratios relative to baseline, avoiding the need to recover level fundamentals.