Preferential Credit Policy with Sectoral Markup Heterogeneity *

Kaiji Chen† Yuxuan Huang‡ Xuewen Liu § Zhikun Lu¶
Yong Wang‖

February 17, 2026

Abstract

Many emerging economies employ preferential credit policies that target selected sectors. This paper quantifies the implications of such policies for aggregate productivity and welfare. Using Chinese firm-level data from 2009–2020, we first document that sectors with higher markups receive larger credit subsidies and exhibit higher revenue-based productivity. Motivated by these facts, we develop a multi-sector quantitative model with endogenously determined markups and calibrate it to match the distribution of sales both within and across sectors. We find that preferential credit subsidies raise aggregate productivity and welfare by reallocating market shares toward high-markup sectors. These gains persist in an extended framework with endogenous firm entry.

JEL classification: F39, E23, L52, O11

*We are indebted to Editor Yan Bai and two anonymous referees for their comments for improving the paper; Qianqian Tang for capable research assistance; Daniel Yi Xu for sharing the matlab code of his paper "How Costly are Markups?", published in 2023 JPE. Our thanks for helpful discussions and comments also go to Joel David, Helu Jiang, Pete Klenow, Ernest Liu, Yongseok Shin, Kjetil Storesletten, Shang-Jin Wei, Daniel Yi Xu, Mu-Jeung Yang, Xiaodong Zhu and participants of 2023 CES North American Conference, 1st annual Conference on China and the Global Economy, and 2023 International Conference on New Structural Economy for helpful discussions.

†Emory University

‡University of International Business and Economics

§HKU Business School, The University of Hong Kong

¶New York University, Shanghai

‖Institute of New Structural Economics, Peking University

1 Introduction

Many emerging and advanced economies employ preferential credit policies as a form of industrial policy targeted at selected sectors and firms. From the standard perspective on resource misallocation, the widespread use of such policies is puzzling: by distorting the allocation of credit across sectors, they may exacerbate inefficiencies and allow low-productivity firms to enter or remain in the market. This raises several fundamental questions. What are the economic rationales for preferential credit policies? How do these interventions affect aggregate productive efficiency? Addressing these questions is essential not only for understanding the role of industrial policy in emerging economies, but also for assessing the extent to which policymakers should intervene to support specific industries.

This paper addresses these issues using China as a laboratory. China has devoted substantially more resources to supporting favored industries through subsidized credit than other major economies. According to Dipippo, Mazzocco and Kennedy (2022), China's industrial policy spending reached at least 1.73 percent of GDP in 2019, with below-market-rate bank credit accounting for the largest component (0.52 percent of GDP)—more than twice the scale of Japan, the second-largest spender (0.22 percent of GDP). Moreover, China's preferential credit policies have covered a wide range of industries, from photovoltaics and LCD panels in the early 2000s to electric vehicles in more recent years.

A distinctive feature of China's post-2010 industrial policy framework is that sector selection is systematic rather than ad hoc. Government documents explicitly prioritize industries expected to generate high value-added and strong economic returns, frequently emphasizing their positions in high-profit segments of the value chain and their roles as engines of long-run growth. This institutional background is central to understanding China's pattern of credit allocation. Preferential credit is not merely intended to relax financing constraints for disadvantaged firms; instead, it is designed to reallocate resources toward the targeted sectors. A prominent example is the electric vehicle (EV) industry. Designated as a "strategic emerging industry" in 2009, the sector subsequently received extensive policy support. After a decade, China's EV sales accounted for nearly 60 percent of global EV purchases, and in 2023 China surpassed Japan as the world's largest exporter, with BYD overtaking Tesla as the top EV seller in 2023Q4.[1] These interventions generate systematic differences in financing costs across sectors and shape market outcomes in ways that may have first-order aggregate consequences.

This paper studies how China's sector-specific preferential credit policies affect aggregate

[1] Another example is the LCD panel industry. By 2021, China accounted for roughly half of global TFT-LCD panel production, whereas at the beginning of the 2000s it relied entirely on imports for LCD TV manufacturing.

productive efficiency, combining empirical analysis with a quantitative model. Empirically, we establish causal relationships between sectoral markups, credit subsidies, and firm-level selection outcomes. Using firm-level data from the National Tax Survey Database (NTSD), we estimate firm-level markups and effective credit subsidies. We then quantify the elasticity of credit subsidies with respect to markups. To address concerns about reverse causality, we construct Bartik instruments based on provincial–sectoral variation in markups.

We document three key facts. First, sectors with higher markups exhibit higher revenue-based productivity, consistent with under-allocation of resources to high-markup sectors and the presence of cross-sector distortions. Second, sectors with higher markups receive larger credit subsidies. Third, sectors receiving larger credit subsidies display higher zombie ratios. These facts show that preferential credit in China is tilted toward high-markup, high-revenue-productivity sectors, though it might incur less efficient firm-level selection.

Motivated by these empirical findings, we develop a multi-sector quantitative framework in which preferential credit is explicitly linked to sectoral markups.[2] The benchmark model features imperfect competition with endogenous markups, generating dispersion in sectoral markups and corresponding wedges in revenue productivity. High-markup sectors—those with higher profit margins—are inefficiently small relative to the first best, leading to cross-sector misallocation. Preferential credit, modeled as a reduction in the effective user cost of capital, reallocates activity toward high-markup sectors and compresses cross-sector wedges. To capture the empirical correlation between markups and subsidies, we parameterize the subsidy schedule as an increasing function of sectoral markups.

We discipline the model using two moments from the NTSD data that are central for aggregate outcomes: (i) the elasticity of substitution across sectors and (ii) the elasticity of credit subsidies with respect to sectoral markups. The elasticity of substitution is identified by matching the cross-sector relationship between markups and market shares, while the subsidy elasticity is pinned down by matching the distribution of market shares across sectors. The calibrated model reproduces the observed dispersion in sectoral markups and the positive correlation between markups and revenue productivity. Quantitatively, introducing preferential credit reduces aggregate TFP losses by roughly one half and generates sizable gains in aggregate welfare relative to a laissez-faire case.

We examine the robustness of these results in an extended model with endogenous firm entry. In this framework, sectoral TFP depends on the endogenous productivity cutoff for firm entry and exit, which in turn responds to credit subsidies. Preferential credit thus in-

[2]The focus of our paper is on sectoral patterns in credit allocation that arise from industrial policy, rather than on firm-level credit discrimination within sectors. Accordingly, our empirical and theoretical analyses abstract from within-sector subsidy heterogeneity and instead emphasize how average credit conditions vary across sectors.

troduces an additional trade-off: it can raise sectoral productivity through an idea-discovery channel by encouraging entry, but it also weakens selection by lowering entry and exit thresholds and increasing the zombie ratio. Despite this trade-off, we find that the positive effects of preferential credit on aggregate productivity and welfare remain substantial, as the quantitative importance of the reallocation and entry-driven productivity channels dominates the negative selection effect due to inefficient entry.

Our paper contributes to the growing literature on industrial policy in emerging economies (e.g., Liu (2019); Kim, Lee and Shin (2021)). The seminal work of Liu (2019) shows that when downstream sectors are subject to market imperfections—such as financial constraints—these distortions propagate upstream by reducing demand for intermediate inputs below the first-best level. This mechanism provides a second-best rationale for subsidizing upstream sectors, as observed in the industrial policies of Korea and China. Our paper complements Liu (2019) along two key dimensions. First, rather than emphasizing distortions in intermediate-input demand arising from downstream frictions, we highlight distortions on the supply side of intermediate inputs that stem from sectoral markup heterogeneity, and show how these distortions motivate preferential credit policies. Second, whereas Liu (2019) models market imperfections as reduced-form wedges, our empirical evidence and theoretical framework identify endogenous variation in sectoral markups as a central friction shaping policy intervention.

Second, our paper is related to the literature that studies markup dispersion as a source of resource misallocation. This literature emphasizes that dispersion in market power can generate aggregate inefficiencies. Edmond, Midrigan and Xu (2015) show that increased competition through international trade reduces markup dispersion and raises aggregate productivity, while Peters (2020) develops a dynamic model in which firms invest to increase markups but are endogenously replaced by more productive competitors. Edmond, Midrigan and Xu (2023) analyze the welfare costs of markups in a dynamic model with heterogeneous firms and show that efficient allocation can be implemented through a nonlinear subsidy scheme that combines a uniform component eliminating the aggregate markup with a size-dependent component correcting misallocation.[3] Building on this work, we quantify the aggregate implications of preferential credit subsidies—an instrument widely used in emerging economies—and examine how such policies interact with endogenous markup dispersion to affect resource allocation and welfare.

Finally, our paper contributes to the extensive literature on resource misallocation, par-

[3]Rather than focusing on product-market markups, Berger, Herkenhoff and Mongey (2022) studies labor market power in a general equilibrium model of oligopsony.

ticularly in the context of China.[4] Using a structural model with reduced-form wedges, the seminal work of Hsieh and Klenow (2009) documents large potential aggregate TFP gains from eliminating misallocation. Subsequent work has explored how financial frictions and policy distortions affect aggregate productivity through both intensive and extensive margins. For example, Midrigan and Xu (2014) argue that financial frictions in China generate relatively modest TFP losses through misallocation, with larger effects operating through inefficient technology adoption and barriers to entry. Bai, Lu and Tian (2018), using a heterogeneous-firm model with default risk and loan issuance costs, find that financial frictions account for a substantial share of dispersion in the marginal product of capital within manufacturing. David and Venkateswaran (2019) emphasize the role of size-dependent policies and financial imperfections in driving capital misallocation in China.

Most of this literature treats different sources of distortions—market imperfections and policy distortions—as independent. More recent work relaxes this assumption. For instance, Bai, Jin and Lu (2024) shows in a Melitz-style model that export subsidies can induce endogenous selection of less productive firms into exporting, potentially offsetting conventional welfare gains from trade liberalization.[5] In contrast to the view that the first-best policy is the complete removal of policy distortions or financial frictions, we argue that, in the presence of pervasive market imperfections—a common feature of emerging economies—industrial policies such as preferential credit, though distortive in nature, can partially offset underlying misallocation and improve aggregate efficiency.

The remainder of the paper is organized as follows. Sections 2 and 3 provide institutional background on China's preferential credit policies and establish the empirical relationships among sectoral markups, credit subsidies, and zombie firms. Sections 4 and 5 develop a quantitative model with endogenous markups and calibrate it to assess the effects of preferential credit subsidies on aggregate productivity and welfare. Section 6 examines the robustness of the results in an extended framework with endogenous firm entry. Section 7 concludes.

2 Institutional Background

China's system of sectorally targeted credit subsidies has developed within a broader industrial policy framework that prioritizes directing financial resources toward industries characterized by high value-added, strong technological potential, and strong economic returns. Since 2010, successive State Council decisions, Five-Year Plans, and ministerial implementa-

[4] See Restuccia and Rogerson (2017) for a comprehensive review.

[5] A related literature has long emphasized that idiosyncratic distortions may be correlated with firm-level productivity; see, for example, Guner, Ventura and Xu (2008) and Restuccia and Rogerson (2008).

tion documents have formalized this approach by identifying "strategic emerging industries" and "advanced manufacturing clusters" using criteria closely tied to expected profitability and long-run growth potential.

This section summarizes key features of China's industrial policy since 2010 by discussing a set of major government documents. Our objective is twofold. First, we document that official policy guidance has tended to prioritize sectors that are high value-added, high-margin/high-return, and technologically intensive. Second, we show that preferential credit and related financial instruments constitute core policy tools for supporting these sectors. Together, these institutional features provide the rationale for both the empirical patterns analyzed in Section 3 and the modeling choice in which sectoral credit subsidies increase with sectoral markups. Table 1 summarizes the key policy documents discussed in this section.

2.1 Targeted Sectors in the Post-2010 Industrial Policy Framework

China's modern industrial policy framework was formally established with the State Council's 2010 *Decision on Accelerating the Fostering and Development of Strategic Emerging Industries* (State Council Document No. 32 [2010]). This official definition is particularly informative for understanding the government's selection criteria. SEIs are characterized not only by technological intensity but also *strong comprehensive economic returns*. These characteristics align closely with higher expected markups and profit margins relative to traditional manufacturing.

Beyond the SEI framework, policy documents during the 2010s consistently emphasize "advanced manufacturing" as the focal point of industrial upgrading. An influential 2018 article in *Qiushi*—the Party's central theory journal—describes advanced manufacturing as those segments of manufacturing that lie in the *high-profit, high value-added* segments of the value chain. The policy objective is therefore not merely to support technologically advanced sectors; it is to support *industries with high profitability and strong market potential*.

Recent policy documents on "new-quality productive forces" by the National Development and Reform Commission (NDRC) and the State-Owned Assets Supervision and Administration Commission (SASAC) reinforce this emphasis, describing strategic emerging industries as *strong economic returns, high value-added*, and a high degree of knowledge and technological intensity. In short, high profitability is an important feature of the sectors prioritized in China's industrial policy, not an accidental byproduct.

As a result, China's industrial policies have concentrated on a relatively stable set of sectors, including semiconductors and integrated circuits, energy vehicles (EVs) and power batteries, upstream solar photovoltaics, high-speed rail and advanced equipment manufacturing, telecommunications equipment and digital infrastructure, and biopharmaceuticals. These sectors are technologically sophisticated and capital intensive, with high current or future profitability and high value-added in the production chain.[6]

2.2 Credit Subsidies as Core Instruments of Industrial Policy

Within this policy framework, preferential credit constitutes a central instrument for supporting prioritized sectors. The 2010 State Council decision explicitly calls for increasing financial support for strategic emerging industries and guiding financial institutions to expand credit provision. Subsequent Five-Year Plans and sector-specific programs follow the same pattern: low-interest loans, dedicated credit windows, policy bank lending, and credit guarantees are directed toward sectors that meet SEI-style criteria. In many strategic sectors—including EVs, advanced electronics, renewable energy technologies, advanced materials, and high-end equipment manufacturing—credit subsidies represent the dominant form of government support, exceeding direct budgetary transfers.

This financial orientation is reinforced by coordinated guidance issued by the People's Bank of China (PBOC), the National Development and Reform Commission (NDRC), and the Ministry of Industry and Information Technology (MIIT), which explicitly instruct financial institutions to expand medium- and long-term lending to advanced manufacturing, strategic emerging industries, and key technological bottlenecks, while improving loan pricing, maturity structure, and risk-sharing mechanisms for qualified firms.[7]

In practice, preferential credit operates by reducing the effective cost of capital through subsidized or guided interest rates, extended loan maturities for fixed investment and R&D, and coordinated fiscal–financial instruments that channel medium- and long-term funding into designated sectors. Recent multi-agency guidelines issued in 2025 explicitly urge financial institutions to expand medium- and long-term financing for key sectors such as integrated circuits, advanced materials, medical equipment, and other advanced manufacturing segments—effectively aligning bank credit with supply-side industrial objectives.

In sum, China's post-2010 industrial policy framework consistently prioritizes sectors characterized by high current or expected profit margins and substantial value-added potential. While official documents do not frame these objectives in terms of sectoral markups, the targeted characteristics map naturally into sectors with high current or future profitabil-

[6]State Council (2012), "Strategic Emerging Industries Development Plan"; see also the 14th Five-Year Plan outline at gov.cn.

[7]PBOC (2020), "Guiding Opinions on Strengthening Financial Support for Manufacturing"; NDRC (2020), "Notice on Supporting the Development of Strategic Emerging Industries"; MIIT (2021), "Guiding Opinions on High-Quality Development of Manufacturing".

ity. Preferential credit emerges as a central policy instrument for supporting these sectors. These institutional features motivate the paper's empirical focus on the relationship between sectoral markups and credit subsidies and provide a disciplined foundation for modeling preferential credit as increasing in sectoral markups.

3 Empirical linkage between sectoral markup, credit subsidy, and zombie ratio

This section provides empirical evidence that disciplines our theoretical framework in the following sections. Specifically, we establish the causal effect of sector-level markups on the average credit subsidy that the sector receives and the relationship between credit subsidy and zombie ratio at the sectoral level. Section 3.1 describes the construction of the firm- and sector-level variables used in the analysis. Section 3.2 presents the empirical relationship between markups, revenue productivity, and credit subsidies, while Section 3.3 studies the link between credit subsidies and sectoral zombie ratios.

3.1 Data construction

Our empirical analysis is based on firm-level data from the National Tax Survey Database (NTSD) over the period 2009–2020, supplemented by aggregate variables from the National Bureau of Statistics of China. The NTSD is jointly administered by the Ministry of Finance and the State Taxation Administration and employs a stratified random sampling design to ensure representativeness. The survey covers firms of heterogeneous sizes across all sectors and reports more than 400 financial and operational indicators. We restrict the sample to manufacturing firms in two-digit industries 13–43, yielding a balanced coverage of 887 four-digit manufacturing sectors. The sample consists of approximately 80% key monitoring enterprises and 20% firms drawn from stratified random sampling.[8] Appendix Table A1 reports the summary statistics for variables constructed in this section and later used in our empirical regressions.

Following the existing literature, we measure the firm-level markups as the output elasticity of intermediate inputs divided by their cost share.[9] The cost share of intermediate inputs is directly observed in the data as the ratio of expenditures on intermediate mate-

[8] While the NTSD covers the period 2009–2020, the regression analysis in this section uses data from 2009–2016 due to the availability of regional and sectoral controls required for identification.

[9] See De Loecker and Warzynski (2012). For recent applications of this approach, see De Loecker, Eeckhout and Unger (2020) for the U.S. economy, and Lu and Yu (2015) and Liu and Mao (2019) for Chinese firms.

rials to sales revenue. To obtain the output elasticity, we estimate production functions at the industry level and apply the approach of De Loecker and Warzynski (2012) to obtain consistent estimates. Appendix A provides detailed information on the production function estimation and markup construction.

As is well recognized in the literature, estimating markups from firm-level revenue data involves important measurement challenges.[10] Bils, Klenow and Ruane (2021), for example, find that estimated markups may reflect not only market power but also other factors, including financial frictions, measurement error, and the misclassification of fixed costs as variable inputs. Ideally, isolating "true" markups would require product-level price and quantity data as well as a clear separation of fixed and variable inputs, which are unavailable in our setting. Accordingly, our markup estimates should be interpreted as imperfect but informative measures of firm-level markups that capture the wedges relevant for pricing decisions and resource allocation.

Let $\mu_{i,t}$ denote the markup of firm i in year t. We aggregate firm-level markups to the four-digit sector level using a sales-weighted harmonic mean, consistent with the aggregation implied by our model in Section 4. Denoting firm sales by $\omega_{i,t}$, sector-level markups are defined as

$$\mu_{s,t} = \left(\sum_{i \in s} \frac{\omega_{i,t}}{\sum_{j \in s} \omega_{j,t}} \frac{1}{\mu_{i,t}} \right)^{-1}. \tag{1}$$

We next construct firm-level credit subsidies. Although the NTSD does not directly report subsidy amounts, they can be inferred from the gap between the minimum required interest rate implied by benchmark lending rates and the firm's effective borrowing rate. Following Caballero, Hoshi and Kashyap (2008), the minimum required interest rate faced by firm i in year t is computed as a weighted average of short-term and medium-to-long-term benchmark lending rates:

$$R_t^i = rs_{t-1} \frac{BS_{t-1}^i}{B_{t-1}^i} + \left(\frac{1}{5} \sum_{j=1}^{5} rl_{t-j} \right) \frac{BL_{t-1}^i}{B_{t-1}^i},$$

where BS_{t-1}^i and BL_{t-1}^i denote short-term and medium-to-long-term bank loans held by firm i at $t-1$, respectively, rs_t and rl_t are benchmark short- and long-term lending rates, and $B_t^i = BS_{t-1}^i + BL_{t-1}^i$ denotes total bank liabilities.[11] [12]

[10]See, for example, Bils, Klenow and Ruane (2021) and Bond et al. (2021).

[11]Due to data limitations, we exclude bond financing from the calculation of R_t^i, in contrast to Caballero, Hoshi and Kashyap (2008). Bond financing represents a negligible share of liabilities for Chinese manufacturing firms in our sample period. This omission biases the required interest rate downward, making our identification of interest subsidies conservative.

[12]In the calculation of the benchmark lending rate, we explore specifications using different combinations

The effective interest rate is defined as

$$EIR_t^i = \frac{IntExp_t^i}{B_t^i},$$

where $IntExp_t^i$ is the firm's reported interest expenditure, conditional on positive interest payments (Liu, 2019). The firm-level credit subsidy is then given by

$$\tau_t^i = 1 - \frac{EIR_t^i}{R_t^i}. \tag{2}$$

Finally, we construct sectoral zombie ratios using an identification strategy that combines the FN–CHK approach (Caballero, Hoshi and Kashyap, 2008; Fukuda and Nakamura, 2011) with additional solvency and persistence criteria (Nie et al., 2016). A firm is classified as a zombie if it satisfies three conditions simultaneously: (i) its effective interest rate falls below the required benchmark rate; (ii) its earnings before interest and taxes are insufficient to cover the hypothetical minimum interest expense; and (iii) its debt-to-asset ratio exceeds 50%. The profitability criterion ensures that efficient firms receiving preferential credit are not misclassified as zombies. To capture persistent financial distress rather than transitory shocks, we additionally require that a firm be identified as a zombie in both year t and year $t-1$. Appendix B details the implementation of this procedure. Sectoral zombie ratios are computed as the fraction of zombie firms among all firms in each four-digit manufacturing sector.

3.2 Linkage between markups, revenue productivity, and credit subsidies

This subsection investigates the empirical relationships associated with sectoral markups. We proceed in two steps. First, we document the relationship between sectoral markups and firm-level revenue productivity (TFPR) as a diagnostic for allocative inefficiency. Second, we estimate the effect of sector-level markups on the credit subsidies received by firms operating in those sectors.

As a preliminary check on the nature of distortions in the data, we examine the correlation between firm-level TFPR and sectoral markups. Canonical models of misallocation, such as Hsieh and Klenow (2009), imply that in the absence of distortions, TFPR should be equalized across firms. A positive association between markups and TFPR therefore signals allocative

of official bank lending rates corresponding to different loan maturities. In the Appendix B, we provide a detailed discussion on the construction of these measures and present robustness checks regarding the choice of short- versus long-term interest rate combinations.

inefficiency: firms in high-markup sectors face frictions that prevent them from expanding, keeping marginal revenue products elevated relative to the economy-wide benchmark.

We estimate the following specification:

$$\log(TFPR^i_{s,t}) = \gamma_0 + \gamma_1\mu_{s,t} + \gamma_2 X_{s,t} + \alpha_s + \alpha_t + \epsilon_{i,s,t}, \tag{3}$$

where $TFPR_{i,s,t}$ denotes the revenue productivity of firm i in sector s at year t, and $\mu_{s,t}$ is the sectoral markup.

Table 2 reports the estimation results. Column (1) uses TFPR in levels, while Column (2) uses log TFPR. Both specifications reveal a positive and statistically significant relationship between sectoral markups and firm-level TFPR, with a coefficient of 2.108 in the log specification. This finding indicates that resources are under-allocated to high-markup sectors, where marginal returns remain elevated.

Having established that high-markup sectors exhibit higher TFPR, we turn to our central hypothesis: firms operating in these sectors receive greater credit subsidies. This hypothesis is consistent with the institutional background discussed in Section 2, which shows that Chinese government tend to target sectors with high profitability and expected economic returns and support them with preferential credit subsidies.

To test this hypothesis, we estimate:

$$\log(1 - \tau^i_{s,t}) = \beta_0 + \beta_1\mu_{s,t} + \beta_2 X_{s,t} + \alpha_s + \alpha_t + \epsilon^i_{s,t}, \tag{4}$$

where $\tau^i_{s,t}$ denotes the credit subsidy rate of firm i in sector s at time t, and $\mu_{s,t}$ is the (log) four-digit sectoral markup. The vector $X_{s,t}$ includes sector-level export shares and SOE shares, which capture firms' differential credit access related to ownership and trade exposure. Sector and year fixed effects are included to absorb time-invariant heterogeneity and aggregate shocks. The coefficient of interest, β_1, captures the average elasticity of firms' credit subsidy with respect to sectoral markups.

A key empirical challenge is the potential endogeneity of markups. Credit subsidies and markups may be jointly determined: firms with stronger profitability may obtain preferential financing, which in turn reinforces their market power. To address this concern, we adopt two complementary strategies. First, we exploit variation in markups at the sector level while measuring credit subsidies at the firm level, which limits direct reverse causality. Second, we employ a Bartik (shift-share) instrumental variable strategy to further mitigate endogeneity concerns.

We begin by decomposing sectoral markups as:

$$\mu_{s,t} \equiv \sum_c \omega_{s,c,t} \times \mu_{s,c,t},$$

where $\omega_{s,c,t}$ denotes the revenue share of county c in sector s, and $\mu_{s,c,t}$ is the sector–county-level markup. This accounting identity motivates the construction of a Bartik instrument using predetermined county revenue shares in a sector and time-varying county-level markup shocks. Specifically, the instrument is defined as

$$z^{BI}_{s,t} = \sum_c \omega_{s,c,0} \times \mu_{c,t},$$

where $\omega_{s,c,0}$ denotes the revenue share in the base year and $\mu_{c,t}$ is the county-level markup in year t. Following standard practice (Goldsmith-Pinkham, Sorkin and Swift, 2020), we choose 2011 as the base year for constructing the initial shares.[13] The identifying variation arises from differential exposure of sectors to county-level markup shocks, while holding fixed initial sectoral composition.

Recent advances by Borusyak, Hull and Jaravel (2022) emphasize that the validity of shift-share instruments hinges on the exogeneity of the underlying shocks. We therefore conduct balance tests at the county–year level and find that markup shocks are correlated with baseline SOE and export shares. To address this concern, we include "Bartik controls" that flexibly control for sectoral exposure to baseline (2011) county-level SOE and export shares.[14]

We estimate equation (4) using two-stage least squares, clustering standard errors at the county level. The first-stage regression is given by

$$\mu_{s,t} = \beta^F_0 + \beta^F_1 z^{BI}_{s,t} + \beta^F_2 X_{s,t} + \Gamma Z^{Ctrl}_s + \alpha_s + \alpha_t + \epsilon_{s,t},$$

where Z^{Ctrl}_s denotes the Bartik controls. The second-stage regression replaces $\mu_{s,t}$ with its fitted value:

$$\log(1 - \tau^i_{s,t}) = \beta^S_0 + \beta^S_1 \hat{\mu}_{s,t} + \beta^S_2 X_{s,t} + \Gamma Z^{Ctrl}_s + \alpha_s + \alpha_t + \epsilon^i_{s,t}. \tag{5}$$

[13]We exclude earlier years to avoid distortions associated with the Global Financial Crisis and China's large-scale stimulus during 2009–2010, which generated substantial transitory variation in regional industrial activity.

[14]Results are robust to including interactions of these Bartik controls with year fixed effects.

We also report the reduced-form specification:

$$\log(1-\tau^i_{s,t}) = \beta^R_0 + \beta^R_1 z^{BI}_{s,t} + \beta^R_2 X_{s,t} + \Gamma Z^{Ctrl}_s + \alpha_s + \alpha_t + \epsilon^i_{s,t}. \tag{6}$$

The elasticity of credit subsidy to markups (β^S_1) can then be calculated using the reduced-form coefficient (β^R_1) divided by the estimated coefficient (β^F_1) in 2SLS estimation, i.e., $\beta^S_1 = \beta^R_1/\beta^F_1$.

Table 3 presents the results. Under OLS, the estimated coefficient on sectoral markups is negative but statistically insignificant. In contrast, the first-stage estimate in Column (3) is positive and statistically significant ($\beta^F_1 = 0.080$), confirming instrument relevance. The implied 2SLS elasticity, computed as $\beta^R_1/\beta^F_1 = -0.582/0.080 = -7.275$, closely matches the directly estimated second-stage coefficient of -7.238 reported in Column (4). Taken together, these results indicate that sectors with higher markups receive larger credit subsidies. This empirical linkage provides direct support for the mechanism emphasized in our theoretical framework.

3.3 Linkage between credit subsidies and zombie firms

We now examine the empirical relationship between credit subsidies and the prevalence of zombie firms at the sectoral level. Our hypothesis is that higher credit subsidies to a sector increase the share of zombie firms. Because subsidized credit lowers financing costs for all firms within a sector—including low-productivity ones—it may encourage those unproductive firms to stay, rather than exiting the market.

To test this hypothesis, we estimate sector-level regressions of zombie ratios on measures of credit subsidies, controlling for sectoral SOE and export shares. A key empirical concern is reverse causality: sectors with a high prevalence of zombies may induce banks or local governments to extend subsidized credit to prevent firm failures. To address this concern, we instrument credit subsidies using variation in official benchmark lending rates. In addition, we exploit the predicted component of firm-level subsidies obtained from the markup-based IV specification in equation (5), which isolates variation in credit subsidies driven by sectoral markups rather than contemporaneous financial distress.

Table 4 reports the estimated effects of credit subsidies on sectoral zombie ratios. Columns (1) and (2) use the credit subsidy measure τ constructed directly from NTSD data. In both specifications, the estimated coefficients are positive, and the estimate in Column (1) is statistically significant, with a point estimate of 6.078. This implies that sectors receiving larger interest rate subsidies exhibit significantly higher shares of zombie firms.

Columns (3) and (4) replace the observed subsidy with the predicted subsidy from Table 3, capturing the component of credit subsidies driven by sectoral markup variation. The estimated coefficients remain positive and statistically significant at the 1 percent level. The point estimate in Column (3) implies that a one–percentage-point increase in the credit subsidy rate raises the sectoral zombie ratio by approximately 4.3 percentage points.

Taken together, these results establish a linkage between preferential credit allocation and the persistence of zombie firms. Combined with the evidence in Section 3.2, they indicate a chain of relationships in which high-markup sectors receive greater credit subsidies, which in turn sustain a higher share of zombie firms. These empirical patterns motivate our linkage of preferential credit subsidy to sectoral markups in the theoretical framework and our discussion of the role of preferential credit policy in inefficiency entry and exit later on.

4 A Model with Endogenous Markups

Building on the empirical evidence documented above, we develop a multi-sector model with heterogeneous intermediate-good producers operating within sectors. Competition within each sector is oligopolistic, and firms differ in productivity. Heterogeneity in market shares arises both within and across sectors, generating endogenous variation in markups.

The economy is populated by a representative household endowed with K units of capital, which it supplies inelastically to intermediate-good producers. The household consumes final goods and owns all firms in the economy. The government finances credit subsidies through lump-sum taxes levied on the representative household.

The representative household chooses consumption of the final good, C, to maximize utility $u(C)$ subject to the budget constraint

$$PC \leq RK + \Pi - T,$$

where P is the price of the final good, R is the rental rate of capital, $\Pi = \int_0^1 \sum_{i=1}^{N(s)} \pi_i(s)\, ds$ denotes aggregate firm profits, and T is a lump-sum tax (negative if transfers).

4.1 Final-good producers

A representative final-good producer aggregates differentiated sectoral outputs using a CES technology across sectors:

$$Y = \left(\int_0^1 y(s)^{\frac{\eta-1}{\eta}}\, ds \right)^{\frac{\eta}{\eta-1}}, \tag{7}$$

where $\eta > 1$ is the elasticity of substitution across sectors $s \in [0, 1]$. Each sector consists of a finite number of potential intermediate-good producers. Within a sector s, output is a

CES aggregate of $N(s)$ intermediate goods,

$$y(s) = \left(\sum_{i=1}^{N(s)} y_i(s)^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}}, \tag{8}$$

where $\gamma > \eta$ is the elasticity of substitution across firms within a sector.

As in Atkeson and Burstein (2008), Edmond, Midrigan and Xu (2015), and Berger, Herkenhoff and Mongey (2022), we assume in the benchmark economy that the number of potential producers $N(s)$ is exogenous. Firms decide whether to operate, but entry costs and endogenous entry decisions are abstracted from. This assumption allows us to isolate the role of preferential credit subsidies in shaping aggregate productivity through their impact on sectoral markup dispersion. In Section 6, we relax this assumption and examine the robustness of our main results with endogenous firm entry.

The representative household purchases the final good at price P. Profit Maximization by final-good producers yields standard CES demand functions:

$$y(s) = \left(\frac{p(s)}{P} \right)^{-\eta} Y, \tag{9}$$

$$y_i(s) = \left(\frac{p_i(s)}{p(s)} \right)^{-\gamma} \left(\frac{p(s)}{P} \right)^{-\eta} Y, \tag{10}$$

where $p(s)$ and $p_i(s)$ denote sectoral and firm-level prices, respectively.

The corresponding aggregate and sectoral price indices are given by

$$P = \left(\int_0^1 p(s)^{1-\eta} \, ds \right)^{\frac{1}{1-\eta}}, \tag{11}$$

and

$$p(s) = \left(\sum_{i=1}^{N(s)} p_i(s)^{1-\gamma} \right)^{\frac{1}{1-\gamma}}. \tag{12}$$

4.2 Intermediate-good producers

Intermediate-good producer i in sector s produces output using capital according to

$$y_i(s) = a_i(s) k_i(s), \tag{13}$$

where $a_i(s)$ denotes firm-level productivity, drawn from a distribution described in Section 5.1. Capital is financed at gross rate R and receives a sector-specific credit subsidy $\tau(s)$, so that the effective user cost of capital is $R\,(1-\tau(s))$. In addition to variable input costs, operating production requires a fixed cost $\bar{k}$, denominated in units of capital. Firms may choose not to operate in order to avoid paying this fixed cost.[15]

Credit subsidies are modeled at the sectoral, rather than firm, level. Firm-level targeting is not the focus of this paper for two reasons. First, our empirical analysis shows that subsidy rates vary primarily across sectors rather than across firms within a sector. Second, our objective is to quantify the role of credit subsidies as an instrument of industrial policy, rather than to characterize optimal government policy.

Intermediate-good producers face the demand system given by equations (10)–(12) and compete à la Cournot within each sector. Taking the interest rate as given, firm i in sector s chooses price and output to solve

$$\pi_i(s) = \max_{p_i(s),\, y_i(s)} \left[p_i(s) - \frac{R\,(1-\tau(s))}{a_i(s)} \right] y_i(s) - R\,(1-\tau(s))\,\bar{k}, \tag{14}$$

subject to the demand system above. Producing $y_i(s)$ entails a fixed cost $\bar{k}$ as well as variable costs, such that the total capital required is $\kappa_i\,(s) = k_i\,(s) + \bar{k}$. This implies that operation is profitable only if

$$\left(p_i(s) - \frac{R\,(1-\tau(s))}{a_i(s)} \right) y_i(s) \geq R\,(1-\tau(s))\,\bar{k}. \tag{15}$$

Conditional on operating, the optimal price is a markup over marginal cost:

$$p_i(s) = \mu_i(s) \frac{R\,(1-\tau(s))}{a_i(s)}, \tag{16}$$

where $\mu_i(s)$ denotes the firm-level markup,

$$\mu_i(s) \equiv \frac{\varepsilon_i(s)}{\varepsilon_i(s)-1}. \tag{17}$$

The demand elasticity faced by firm i is a harmonic average of the across-sector and within-sector elasticities, η and γ:

$$\varepsilon_i(s) = \left(\frac{\omega_i(s)}{\eta} + \frac{1-\omega_i(s)}{\gamma} \right)^{-1}, \tag{18}$$

[15] The presence of fixed operating costs in an oligopolistic environment generates the possibility of multiple equilibria within a sector. Following Edmond, Midrigan and Xu (2015), we order firms by productivity and focus on equilibria in which firms sequentially decide whether to operate, with more productive firms deciding first.

where $\omega_i(s) \in [0,1]$ is firm i's revenue share within sector s,

$$\omega_i(s) = \frac{p_i(s)y_i(s)}{\sum_{j=1}^{N(s)} p_j(s)y_j(s)} = \left(\frac{p_i(s)}{p(s)}\right)^{1-\gamma}. \tag{19}$$

Equation (18) implies that firms face heterogeneous demand elasticities depending on their market shares. Firms with small revenue shares primarily compete with other firms within the same sector and therefore face demand elasticity close to γ. In contrast, firms with large market shares internalize substitution toward goods produced in other sectors and face lower demand elasticities. In the limit as $\omega_i(s) \to 0$, $\varepsilon_i(s) \to \gamma$, which corresponds to the monopolistic competition case.

Combining equations (17) and (18) yields a linear relationship between a firm's inverse markup and its market share:

$$\frac{1}{\mu_i(s)} = \frac{\gamma - 1}{\gamma} - \left(\frac{1}{\eta} - \frac{1}{\gamma}\right)\omega_i(s). \tag{20}$$

Since $\eta < \gamma$, the coefficient on $\omega_i(s)$ is negative: within a sector, firms with larger market shares face lower demand elasticities and charge higher markups. Equation (20) further implies that the markup is an increasing and convex function of a firm's market share.

Substituting equation (16) into (19) yields

$$\omega_i(s) = \frac{\mu_i(s)^{1-\gamma} a_i(s)^{\gamma-1}}{\sum_{j=1}^{N(s)} \mu_j(s)^{1-\gamma} a_j(s)^{\gamma-1}}. \tag{21}$$

Equations (20) and (21) jointly determine firm-level markups and market shares. Higher productivity lowers marginal cost, allowing a firm to expand its revenue share. Because demand elasticity depends on market share, higher productivity indirectly raises markups by reducing the elasticity faced by the firm.

Finally, equations (20) and (21) imply that the sectoral credit subsidy $\tau(s)$ does not affect firm-level markups or market shares except through the extensive margin. In this oligopolistic framework, the extensive margin plays a limited role: highly productive firms always operate, while sufficiently unproductive firms never do. As a result, subsidies primarily affect marginal firms with negligible market shares and have little direct impact on within-sector allocations.

The capital market clearing condition is

$$\int_0^1 \sum_{i=1}^{N(s)} \left(k_i(s) + \bar{k}\right) ds = K, \tag{22}$$

and final-good market clearing implies $C = Y$. The government budget constraint requires

$$T = R \int_0^1 \tau(s) \sum_{i=1}^{N(s)} \left(k_i(s) + \bar{k}\right) ds. \tag{23}$$

4.3 Sectoral productivity and markups

Let $\mu(s)$ denote the sector-level markup, defined as the harmonic mean of firm-level markups weighted by revenue shares:

$$\mu(s) = \left(\sum_{i=1}^{N(s)} \frac{\omega_i(s)}{\mu_i(s)} \right)^{-1}. \tag{24}$$

Equation (24) implies that preferential credit subsidies do not affect sectoral markups except through the extensive margin. As discussed above, sector-specific credit subsidies do not alter inframarginal firms' market shares or markups. While subsidies may induce marginal firms to operate, thereby reducing sectoral markups along the extensive margin, this effect is quantitatively small in our simulations because marginal firms have negligible market shares.

Define sectoral physical productivity as

$$a(s) \equiv \frac{y(s)}{\sum_{i=1}^{N(s)} k_i(s)}.$$

It can be shown that $a(s)$ satisfies

$$a(s) = \left(\sum_{i=1}^{N(s)} \left(\frac{\mu_i(s)}{\mu(s)} \right)^{-\gamma} a_i(s)^{\gamma-1} \right)^{\frac{1}{\gamma-1}}. \tag{25}$$

Equation (25) expresses sectoral productivity as a CES aggregate of firm-level productivities, where weights depend inversely on relative markups. Holding firm-level productivity fixed, higher firm-level markups reduce a firm's contribution to sectoral productivity by distorting relative prices and lowering output below the efficient level. Because more productive firms tend to command larger market shares and thus charge higher markups, endogenous markup dispersion in the model reduces sectoral productivity relative to an environment with homogeneous within-sector markups.

We next characterize the sectoral price index.

Lemma 1 *The price index of sector s is given by*

$$p(s) = \frac{\mu(s)\,(1 - \tau(s))\,R}{a(s)}. \tag{26}$$

Proof. See Appendix D.

Lemma 1 implies that sectors with higher markups charge higher prices and, as a result, produce less output. Preferential credit subsidies targeted toward high-markup sectors reduce their effective prices, reallocating production toward sectors that are inefficiently small in the absence of intervention.

Let $\omega(s) \equiv \frac{p(s)y(s)}{PY}$ denote the sectoral revenue share. Substituting equation (26) into this definition yields

$$\omega(s) = \left(\frac{\mu(s)\,(1-\tau(s))\,R}{a(s)P} \right)^{1-\eta}. \tag{27}$$

Equation (27) shows that preferential credit subsidies increase a sector's market share by lowering its effective price.

We now turn to revenue productivity. Because it is not feasible to separately observe variable inputs and fixed operating costs in the data, we define firm-level revenue productivity (TFPR) as the ratio of total revenue to total capital input:

$$TFPR_i(s) \equiv \frac{p_i(s)y_i(s)}{\kappa_i(s)}, \qquad \kappa_i(s) = k_i(s) + \bar{k}.$$

Up to proportionality constants, TFPR satisfies

$$\frac{py}{\kappa} \propto \mu(1-\tau)\left(1 - \frac{\bar{k}}{\kappa(a,\mu,\tau)}\right).$$

In the absence of fixed costs, as in Hsieh and Klenow (2009), TFPR directly measures the firm-level wedge $\mu(1-\tau)$. With fixed operating costs, TFPR depends on both markups and physical productivity. Higher markups raise TFPR by depressing output relative to the efficient benchmark, while higher physical productivity increases TFPR by expanding variable input demand. As a result, unlike in Hsieh and Klenow (2009), TFPR and physical productivity a are positively correlated in our model even in the absence of idiosyncratic distortions.

Aggregating to the sectoral level, revenue productivity of sector s is given by

$$TFPR(s) \equiv \frac{p(s)y(s)}{\sum_{i=1}^{N(s)} \kappa_i(s)} = \mu(s)R\,(1-\tau(s))\left(1 - \frac{\bar{k}}{\kappa(s)}\right), \tag{28}$$

where

$$\kappa(s) \equiv \frac{1}{N(s)} \sum_{i=1}^{N(s)} k_i(s) + \bar{k}$$

denotes average capital input per firm in sector s, inclusive of fixed costs.

Equation (28) highlights three sources of cross-sector dispersion in TFPR. First, markup heterogeneity across sectors—driven by variation in the number of potential firms $N(s)$—directly translates into TFPR dispersion. Second, sector-specific credit subsidies affect TFPR through the term $1 - \tau(s)$; preferential subsidies targeted toward high-markup sectors tend to compress TFPR dispersion, consistent with our empirical findings. Third, the presence of fixed operating costs implies that sectors with higher physical productivity exhibit higher TFPR, as fixed inputs account for a smaller share of total capital usage.

4.4 Aggregate TFP, markups, and welfare

Aggregate final output can be written as

$$Y = A\widetilde{K},$$

where A denotes aggregate productivity and $\widetilde{K}$ is aggregate capital net of fixed operating costs. Aggregate productivity can be expressed as a quantity-weighted harmonic mean of sectoral productivities:

$$A = \left(\int_0^1 \frac{y(s)}{Y} \frac{1}{a(s)} \, ds \right)^{-1}. \tag{29}$$

We define the aggregate markup as

$$\mu \equiv \frac{P}{R \int_0^1 (1 - \tau(s)) \, ds / A}, \tag{30}$$

that is, the ratio of the aggregate price index to aggregate marginal cost. Let

$$1 - \overline{\tau} \equiv \int_0^1 (1 - \tau(s)) \, ds$$

denote the average subsidy wedge. The aggregate markup can then be written as a harmonic mean of sectoral markups, weighted by sectoral revenue shares:

$$\mu = \left(\int_0^1 \frac{\omega(s)\,(1 - \overline{\tau})}{\mu(s)\,(1 - \tau(s))} \, ds \right)^{-1}. \tag{31}$$

Equation (31) implies that, as in Bai, Lu and Tian (2018), if all sectors receive identical credit subsidies, the introduction of subsidies does not affect the aggregate markup. Preferential credit subsidies influence the aggregate markup only through composition effects, by reallocating revenue shares across sectors. This channel operates even when sectoral markups themselves are unaffected except through the extensive margin.

Substituting equations (26) and (30) into (29), aggregate productivity can be expressed as

$$A = \left(\int_0^1 \left(\frac{\mu(s)\,(1-\tau(s))}{\mu\,(1-\overline{\tau})} \right)^{-\eta} a(s)^{\eta-1}\,ds \right)^{\frac{1}{\eta-1}}. \tag{32}$$

Equation (32) shows that dispersion in sectoral markups reduces aggregate productivity by distorting the allocation of production across sectors.

The efficient level of aggregate productivity associated with an efficient allocation is

$$A_{\text{eff}} = \left(\int_0^1 a_{\text{eff}}(s)^{\eta-1}\,ds \right)^{\frac{1}{\eta-1}}, \tag{33}$$

where efficient sectoral productivity is given by

$$a_{\text{eff}}(s) = \left(\sum_{i=1}^{N(s)} a_i(s)^{\gamma-1} \right)^{\frac{1}{\gamma-1}}. \tag{34}$$

In the absence of markup dispersion, sectoral and aggregate productivity coincide with their efficient counterparts given by equations (34) and (33). Markup dispersion therefore lowers aggregate productivity relative to the efficient benchmark.

Consistent with our definitions of firm- and sector-level TFPR, we define aggregate TFP as the ratio of aggregate output to total capital input, inclusive of both variable and fixed inputs:

$$\text{TFP} \equiv \frac{Y}{K} = A\left(1 - \frac{\overline{k}}{\kappa}\right), \tag{35}$$

where $\kappa \equiv K / \int_0^1 N(s)\,ds$. TFP loss can then be decomposed into losses due to aggregate productivity distortions and fixed operating costs:

$$\text{TFP Loss} \equiv \log A_{\text{eff}} - \log A + \left[\log\left(1 - \frac{\overline{k}}{\kappa_{\text{eff}}}\right) - \log\left(1 - \frac{\overline{k}}{\kappa}\right) \right]. \tag{36}$$

In our calibrated model, TFP loss arising from fixed operating costs is quantitatively negligible. Consequently, changes in TFP loss closely track changes in aggregate productivity.

Welfare is measured by final consumption per capita, C/L. In equilibrium, $C = Y$ and $L = 1$, so welfare coincides with aggregate output.

4.5 Preferential credit subsidies

We parameterize sectoral credit subsidies as a function of sectoral markups:

$$1 - \tau(s) = \left(\frac{\mu(s)}{\mu} \right)^{\frac{1}{\alpha} - 1}. \tag{37}$$

The subsidy is non-decreasing in sectoral markups, and the parameter $\alpha \geq 1$ governs the elasticity of subsidies with respect to markups. When $\alpha = 1$, $\mu(s)\,(1 - \tau(s)) = \mu(s)$, corresponding to the no-subsidy case. For $\alpha > 1$, sectors with higher markups receive relatively larger subsidies, increasing their output and revenue shares, as implied by equation (27). In the limit as $\alpha \to \infty$, $\mu(s)\,(1 - \tau(s)) = \mu$, fully eliminating cross-sector misallocation arising from markup dispersion.

This subsidy schedule is chosen for two reasons. First, it directly mirrors our empirical specification linking credit conditions to sectoral markups and provides a parsimonious way to parameterize the degree of preferential credit through α. Second, by subsidizing the rental cost of capital, this instrument directly lowers marginal production costs and prices, thereby expanding output in high-markup sectors and reducing cross-sector allocative distortions.

Substituting equations (27), (31), and (37) into (32) yields

$$A = \frac{\left[\int_0^1 \mu(s)^{\frac{1-\eta}{\alpha}} a(s)^{\eta - 1}\, ds \right]^{\frac{\eta}{\eta - 1}}}{\int_0^1 \mu(s)^{-\frac{\eta}{\alpha}} a(s)^{\eta - 1}\, ds}.$$

As $\alpha \to \infty$,

$$A \to \left(\int_0^1 a(s)^{\eta - 1}\, ds \right)^{\frac{1}{\eta - 1}}.$$

Comparing this expression with equation (33) shows that sectoral credit subsidies are sufficient to correct cross-sector misallocation due to markup dispersion. This result holds even though sector-level subsidies do not eliminate within-sector markup heterogeneity, implying that sectoral productivity $a(s)$ may still differ from its efficient counterpart $a_{\text{eff}}(s)$.

Finally, since total capital endowment is fixed, equation (36) implies that the effects of preferential credit policy on aggregate welfare, measured as the difference of log consumption between the case $\alpha > 1$ and the case $\alpha = 1$, equals the minus of the difference in aggregate TFP loss between these two cases:

$$\Delta \log C = -\Delta \text{TFP Loss}. \tag{38}$$

5 Quantifying the Model

This section quantifies the role of preferential credit subsidies in shaping aggregate productivity and welfare. Section 5.1 describes the parameterization and calibration of the benchmark economy. Section 5.2 evaluates the model's ability to replicate observed markup dispersion and other cross-sectional moments. Sections 5.3 and 5.4 then quantify the effects of preferential credit subsidies on aggregate productivity and welfare and assess the robustness of the main results to alternative values of key parameters.

5.1 Parameterization and calibration

We parameterize the model by jointly exploiting (i) a rich set of within- and across-sector concentration facts documented in the data and (ii) the structural mapping from these empirical concentration patterns to the parameters governing the productivity distribution, the number of producers per sector, and the elasticity parameters that shape markups. Appendix C describes the numerical algorithm used to compute the benchmark equilibrium and estimate the parameters.

Across sectors, the number of potential producers $N(s)$ is assumed to follow a geometric distribution with parameter $\zeta \in (0,1)$,

$$\Pr[N(s) = n] = (1-\zeta)^{n-1}\zeta.$$

Firm-level productivity is modeled as the product of a sector-specific and an idiosyncratic component,

$$a_i(s) = z(s)x_i(s), \tag{39}$$

where sectoral productivity $z(s) \leq 1$ is drawn i.i.d. across sectors from a Pareto distribution with shape parameter $\xi_z > 0$, independent of $N(s)$. Within each sector, the idiosyncratic components $\{x_i(s)\}_{i=1}^{N(s)}$ are drawn i.i.d. from a Pareto distribution with shape parameter ξ_x.

We jointly calibrate seven parameters,

$$\xi_z,\ \xi_x,\ \zeta,\ \eta,\ \gamma,\ \alpha,\ \bar{k},$$

to minimize the distance between a large set of model-generated moments and their empirical counterparts in Chinese manufacturing data. Panel A of Table 5 reports the targeted moments and their benchmark model values, while Panel B reports the resulting parameter estimates. We now summarize how the data discipline each group of parameters.

Number of producers, productivity, and fixed operating costs. The parameters ζ, ξ_z, ξ_x, and the fixed operating cost $\bar{k}$ are primarily disciplined by observed concentration patterns within and across sectors. The geometric parameter ζ governs the typical number of producers per sector, while the Pareto shape parameters ξ_z and ξ_x determine the extent of concentration across sectors and within sectors, respectively.

To discipline within-sector concentration, we target two moments summarizing the dominance of the largest firm in each sector: the mean and median of the top-firm revenue share. For each sector, we compute the largest producer's revenue share and then take the mean and median of this statistic across sectors.

Table 5 documents substantial concentration in the data. Within sectors, the largest producer accounts for roughly 20–30 percent of sales, and the median inverse Herfindahl index is 10.5. The benchmark model reproduces these patterns well. In the model, the largest firm accounts for an average of 35 percent of sectoral sales (30 percent in the data). The model also generates fat-tailed size distributions at both the sector and firm levels. The top 1 percent of sectors accounts for 27 percent of sales in the model (20 percent in the data), while the top 5 percent accounts for 38 percent of sales in the model (45 percent in the data). At the firm level, the top 1 percent of producers accounts for 32 percent of sales in the model (18 percent in the data), and the top 5 percent accounts for 47 percent of sales (46 percent in the data).

The model reproduces the lower tail of the sector size distribution closely: the 10th percentile of the number of producers per sector is three in both the model and the data. The median number of producers per sector is lower in the model (11) than in the data (40), reflecting the parsimonious nature of the geometric specification.

The implied productivity distribution $a_i(s) = z(s)x_i(s)$ is also fat-tailed. Most of the dispersion comes from the sectoral component, with $\xi_z = 0.63$, while idiosyncratic productivity is much less dispersed, with $\xi_x = 5.51$. The fixed operating cost is small, $\bar{k} = 0.002$, consistent with the presence of many small producers in the data.

The parameter α governs the sensitivity of credit subsidies to sectoral markup dispersion. Higher values of α strengthen the preferential allocation of credit toward high-markup sectors, allowing these sectors to expand output and capture larger revenue shares. At the firm level, higher α also lowers financing costs disproportionately for high-markup firms within a sector, amplifying concentration. As a result, measures such as top-sector revenue shares, sectoral HHIs, and the upper tail of the firm size distribution become more skewed as α increases.

Elasticities of substitution. The elasticities η and γ govern how market power responds to changes in market shares. We discipline these parameters by requiring the model to match the empirical relationship between inverse markups and revenue shares. Specifically, we estimate regressions of the form

$$\frac{1}{\mu_i(s)} = b_0 + b_1 \omega_i(s), \tag{40}$$

and require the model to match the ratio b_1/b_0. From equation (20),

$$\eta = \left(\frac{1}{\gamma} - \frac{b_1}{b_0} \frac{\gamma - 1}{\gamma} \right)^{-1}, \tag{41}$$

so the slope-to-intercept ratio restricts the admissible combinations of η and γ.

In the Chinese data, we estimate $b_0 = 0.90$ and $b_1 = -0.64$, implying $b_1/b_0 = -0.71$. The calibration sets $\gamma = 8.5$, yielding $\eta = 1.34$, which satisfies this restriction.

5.2 Markup Dispersion

Table 6 documents two distinct layers of markup heterogeneity in Chinese manufacturing—unconditional (firm-level) and sector-level—that are central for understanding the magnitude and structure of misallocation. Both dimensions are quantitatively relevant because dispersion in markups translates directly into dispersion in TFPR, generating efficiency losses both within sectors, through heterogeneous producer behavior, and across sectors, through variation in sectoral wedges. The table compares these data moments to their counterparts generated by the benchmark model.

At the firm level, markup dispersion in the data is relatively modest. The mean and median markups are 1.13 and 1.11, respectively, and the standard deviation of log markups is 0.07. Nevertheless, the upper tail is economically meaningful: the 95th percentile is 1.30 and the 99th percentile reaches 1.41. The benchmark model closely reproduces these features. It matches the center of the empirical distribution and generates a slightly thicker upper tail, with a 99th percentile of 1.66 compared to 1.41 in the data, while the model's log-standard deviation of markups (0.09) remains close to the empirical value. As a result, the model delivers a realistic degree of within-sector misallocation consistent with observed TFPR variation among Chinese firms.

A markedly different pattern emerges at the sector level. In the data, dispersion in sectoral markups is substantially larger than dispersion at the firm level. While the mean sectoral markup is only modestly higher than the unconditional mean (1.19 versus 1.13), the upper tail increases sharply: the 99th percentile of sectoral markups reaches 1.96, well above the firm-level 99th percentile of 1.41. The standard deviation of log sectoral markups rises to 0.14, roughly twice its firm-level counterpart. This amplification reflects the interaction of sectoral productivity, the number of active producers, and the concentration of market shares within sectors. Even when firm-level markup dispersion is limited, aggregation across firms operating under different degrees of oligopolistic competition naturally generates a thicker-tailed distribution of sectoral markups.

The benchmark model performs well in replicating this second layer of heterogeneity. It matches both the level and the shape of the sectoral markup distribution, generating a mean sectoral markup of 1.46 and a 99th percentile of 3.97, compared to 1.19 and 1.96 in the data. While the model produces a somewhat thicker upper tail, this difference is consistent with the abstraction from institutional constraints—such as price regulation or administrative guidance—that may limit markups in some Chinese industries. More importantly, the model reproduces the pronounced increase in dispersion when moving from firm-level to sector-level markups, with a sectoral log-standard deviation of 0.25 compared to 0.21 in the data.

Panel B of Table 6 reports the dispersion of TFPR and TFPQ and their correlation. In the data, TFPR is highly dispersed, with a standard deviation of 1.45, and is strongly positively correlated with physical productivity (TFPQ), with a correlation of 0.93. The benchmark model generates a much smaller degree of TFPR dispersion (0.11) but closely matches the strength of the positive relationship between TFPR and TFPQ, yielding a correlation of 0.98.[16] This correspondence highlights that the model embeds the correct mechanism: both within-sector heterogeneity and cross-sector differences in markups lead more productive firms and sectors to charge higher markups and supply inefficiently low output.

Taken together, Table 6 shows that markup dispersion in Chinese manufacturing, particularly at the sector level, is substantial. By replicating the key features of both unconditional and sectoral markup distributions, the benchmark model provides a disciplined quantitative foundation for the counterfactual analysis in Section 5.3, where we evaluate how preferential credit subsidies operate along the dimension of cross-sector markup dispersion to compress sectoral wedges and reduce aggregate TFP losses.

5.3 Roles of Preferential Credit Subsidy

Table 7 compares the benchmark economy—which incorporates empirically disciplined preferential credit subsidies—to a counterfactual economy with $\alpha = 1$, under which credit subsidies no longer respond to sectoral markups. Panel A shows that shutting down the preferential credit subsidy leads to substantially greater misallocation. Aggregate TFP losses

[16]The lower level of TFPR dispersion in the model reflects the fact that our model only considers markup distortions as a source of resource misallocation, while abstracting from other important sources, such as financial frictions and labor-market distortions, that have been emphasized in the recent literature on China.

nearly double, rising from 2.89 percent to 5.52 percent; sectoral TFPR dispersion increases by more than an order of magnitude, from 0.0064 to 0.0751; and the correlation between TFPR and markups rises sharply, from 0.61 to 0.98.[17] These changes indicate that, in the absence of preferential credit subsidies, high-markup, high-productivity sectors face substantially larger distortions. Overall, preferential credit subsidies increase welfare by 2.6 percent. This is despite an increase in aggregate markup, from 1.402 to 1.438.

Panel B highlights the sources of these aggregate differences. While the subsidy has little effect on within-sector concentration—as measured by inverse Herfindahl indices or top-firm revenue shares—it shifts revenue shares toward the top of the sectoral and firm-level distributions. Specifically, the fractions of sales accounted for by the top 1 percent and top 5 percent of sectors and producers increase under the benchmark subsidy regime. These shifts are modest in magnitude but consistent across both levels of aggregation. In the model, these top sectors are characterized by relatively high underlying productivity and high markups. When $\alpha > 1$, the credit subsidy lowers the effective cost of capital more strongly in precisely these sectors, mitigating the distortions that constrain their scale in the $\alpha = 1$ economy. The resulting reallocation of revenue shares reduces sectoral TFPR dispersion and weakens the TFPR–markup correlation observed in Panel A.

This reallocation mechanism also explains the behavior of the aggregate markup. Because the aggregate markup is a revenue-weighted harmonic mean of sectoral markups, a higher revenue share for high-markup sectors mechanically raises the aggregate markup, even when sectoral markups themselves are unchanged. Importantly, this increase reflects a composition effect rather than an increase in market power of individual firms.

Overall, the results in Table 7 show that preferential credit subsidies affect aggregate efficiency primarily by reallocating activity across sectors rather than by altering concentration within sectors. By reducing effective distortions faced by high-productivity, high-markup sectors, the subsidy modestly increases their equilibrium revenue shares and substantially compresses TFPR dispersion. These adjustments account for the large differences in aggregate TFP and welfare between the benchmark economy and the counterfactual economy without preferential credit subsidies.

5.4 Robustness Experiments

We next examine the sensitivity of our results to alternative parameter values relative to the benchmark calibration. In each robustness experiment, we vary one parameter at a time

[17] Consistent with the numerical results, deadweight losses associated with fixed operating costs are quantitatively small relative to aggregate productivity losses and vary little as α changes from 1 to 9.016. Consequently, nearly all of the reduction in TFP loss arises from improvements in aggregate productivity.

while holding all others fixed. Table 8 summarizes the results.

5.4.1 Role of γ

In the benchmark calibration, the within-sector elasticity of substitution is $\gamma = 8.5$. To assess the role of this parameter, we consider a lower value, $\gamma = 4$. With a lower γ, the model produces substantially less sales concentration both across and within sectors. The fraction of sales accounted for by the top 1 percent of sectors falls from 27 percent to 13 percent, and the fraction accounted for by the top 1 percent of producers declines from 38 percent to 20 percent. This reduction arises because a lower γ makes demand less sensitive to price differences within sectors, limiting the ability of highly productive firms and sectors with exceptionally productive firms to expand their sales.

Despite the reduction in concentration, lowering γ increases the aggregate markup from 1.43 in the benchmark economy to 1.57. As equation (20) implies, a lower γ reduces the demand elasticity faced by all firms, raising markups uniformly.[18] This broad upward shift in firm-level markups raises the aggregate markup even as sales become less concentrated.

A lower γ reduces TFP losses both with and without preferential credit subsidies. With subsidies, TFP losses decline from 2.89 percent to 0.48 percent; without subsidies, they fall from 5.52 percent to 3.01 percent. Two mechanisms drive this reduction. First, lowering γ narrows the gap between γ and η, weakening the transmission from market share heterogeneity to markup dispersion. Second, as equation (25) shows, a lower γ brings sectoral productivity $a(s)$ closer to its efficient counterpart $a_{\text{eff}}(s)$ by dampening the variation in wedges that distort firm-level productivity. Importantly, the welfare gains from preferential credit subsidies remain robust. When $\gamma = 4$, the model implies a welfare gain of 2.52 percent, compared to 2.62 percent in the benchmark calibration.

5.4.2 Role of Fixed Costs

To assess the role of fixed operating costs, we consider two alternative cases: no fixed costs ($\bar{k} = 0$) and high fixed costs ($\bar{k} = 0.01$). As shown in the last two columns of Table 8, changes in fixed costs primarily affect firm-level sales concentration rather than sector-level concentration. For example, with no fixed costs, the fraction of sales accounted for by the top 1 percent of producers rises to 37 percent, compared to 32 percent in the benchmark model. Lower fixed costs relax the zero-profit cutoff, allowing more marginal firms to operate and expanding the set of producers, which mechanically increases the unconditional top-share measure.

[18] For example, a lower γ increases the markup of an infinitesimal firm from $\gamma/(\gamma - 1)$.

At the same time, an increase in active firms reduces concentration within sectors, lowering sectoral and aggregate markups and compressing TFPR dispersion across sectors. Higher fixed costs have the opposite effect and tend to reduce the welfare gains from preferential credit subsidies. When $\bar{k} = 0.01$, the welfare gain from the subsidy falls to 2.41 percent, compared to 2.62 percent in the benchmark economy. With higher fixed costs, preferential credit subsidies operate more strongly along the extensive margin by lowering the cutoff productivity for operation. While this induces additional entry, it also lowers sectoral productivity, which is a harmonic mean of firm-level productivities.

Nevertheless, the quantitative impact of varying fixed costs is modest. As Table 8 shows, aggregate outcomes remain close to those in the benchmark calibration. This reflects the fact that, under oligopolistic competition, marginal firms that are induced to enter or exit have small market shares and therefore exert limited influence on aggregate productivity and welfare.

To summarize, the quantitative results show that preferential credit subsidies play a quantitatively important role in mitigating misallocation in Chinese manufacturing by operating primarily through cross-sector reallocation. The benchmark calibration and robustness exercises consistently indicate that these subsidies compress sectoral TFPR dispersion and reduce aggregate TFP losses, with welfare gains driven by shifts in activity toward high-productivity, high-markup sectors rather than changes in within-sector concentration. While the magnitude of markups, fixed costs, and substitution elasticities affects the level of misallocation, the central mechanism and the resulting welfare implications of preferential credit subsidies remain robust across alternative parameterizations.

6 Extension: Endogenous Entry

Our benchmark model highlights that preferential credit reallocates resources toward high-markup sectors and thereby improves allocative efficiency across sectors. However, the benchmark abstracts from firm entry and exit. Introducing endogenous entry adds additional forces that may either amplify or attenuate the benchmark gains. This section evaluates whether our main conclusions remain robust once firm entry and exit are allowed.

To keep the extension tractable while allowing for directed entry across sectors, we adopt a monopolistically competitive multi-sector framework with exogenous sectoral markup heterogeneity.[19] Within this environment, in addition to the cross-sector reallocation effect as

[19]Endogenous entry in oligopolistic models is computationally demanding because entrants internalize their impact on sectoral outcomes and the space of sectoral configurations is high dimensional. As a result, most existing work assumes undirected entry with random sector assignment after paying a sunk cost (Edmond, Midrigan and Xu, 2015, 2023). Because sector-specific credit subsidies require directed entry, we

in our benchmark model, preferential credit subsidies influence aggregate productivity and welfare through two additional channels via endogenous entry.

First, by reducing financing costs and relaxing operating and continuation cutoffs, subsidies weaken selection: lower-productivity firms that would otherwise not enter or would exit remain active, reducing average physical productivity within sectors. This mechanism captures the empirically observed association between subsidized credit and the prevalence of zombie firms. Second, preferential credit increases the mass of entrants in subsidized sectors. In the spirit of Eaton and Kortum (2002), a larger pool of entrants generates more ideas and raises the probability that superior technologies are implemented. This entry-driven innovation effect creates a within-sector productivity multiplier that increases with entry density and partially offsets the productivity losses induced by inefficient entry.

In this section, we provide a narrative description of the model with endogenous firm entry and exit, highlighting the new ingredients and new features of the model as compared with the benchmark economy. The formal setup of the model with endogenous entry is presented in Appendix E.

6.1 Environment

The economy consists of a continuum of sectors indexed by $s \in [0, 1]$. Final-good producers aggregate sectoral outputs using a CES technology across sectors, and within each sector output is produced by a continuum of differentiated intermediate-good firms under monopolistic competition. A representative household supplies capital inelastically, owns all firms, consumes the final good, and finances policy interventions through lump-sum taxes. Sector-specific credit subsidies continue to operate by reducing the effective user cost of capital faced by firms in each sector, following the same markup-linked subsidy schedule as in the benchmark economy. These elements mirror the benchmark environment and are summarized in Appendix E.1.

The key departure from the benchmark model is that the number of active firms in each sector is no longer fixed. Instead, firms must incur a sunk entry cost in order to operate, and entry decisions are endogenous. Potential entrants draw an idiosyncratic productivity level upon entry. Given sector-specific prices, subsidies, and competition conditions, only firms with sufficiently high productivity choose to operate. This generates a sector-specific productivity cutoff, denoted by $\underline{x}(s)$, such that firms with productivity below this threshold do not produce, while firms above the cutoff enter and remain active. The entry decision and the determination of the cutoff $\underline{x}(s)$ are described formally in Appendix E.2.

adopt a monopolistically competitive framework with exogenous sectoral markup heterogeneity.

Conditional on entry, firms produce using the same technology as in the benchmark model and compete monopolistically within sectors. Because all firms are infinitesimal, firm-level markups are constant within sectors, and sectoral markup heterogeneity is taken to be exogenous in this extension. This assumption allows the model to isolate the effects of entry and exit without introducing additional within-sector markup dynamics, consistent with the empirical evidence showing that preferential credit policies do not materially alter within-sector concentration patterns. The implications of monopolistic competition with endogenous entry are discussed in Appendix E.3.

Endogenous entry implies that both the mass of new entrants and the mass of active firms vary across sectors. Let $M(s)$ denote the mass of new entrants in sector s, and $N(s)$ the resulting mass of active firms after entry and exit decisions. These objects are jointly determined by the entry cost, the sectoral subsidy wedge, and the expected profitability of entry. Preferential credit subsidies affect these margins by lowering production costs and raising expected profits, thereby encouraging entry in subsidized sectors while simultaneously weakening selection by lowering the productivity cutoff $\underline{x}(s)$. The equilibrium determination of $M(s)$ and $N(s)$ is characterized in Appendix E.4.

In addition to selection effects, the model incorporates an innovation spillover channel associated with entry. Following the idea-discovery logic in the endogenous growth and trade literature, a larger mass of entrants increases the probability that high-productivity technologies are discovered and implemented. This mechanism is summarized by a sectoral productivity multiplier, denoted by $\varkappa(s)$, which scales effective sectoral productivity as a function of the mass of entrants. Sectors that attract more entry therefore benefit not only from increased competition but also from higher average productivity due to improved technology draws. The construction of the sectoral productivity multiplier $\varkappa(s)$ is detailed in Appendix E.5.

In sum, endogenous entry introduces two new margins through which preferential credit policies affect aggregate outcomes. On the one hand, by stimulating entry and innovation, credit subsidies can raise sectoral and aggregate productivity through the productivity multiplier $\varkappa(s)$. On the other hand, by lowering the productivity cutoff $\underline{x}(s)$, subsidies weaken selection and allow less productive firms to operate. The interaction of these forces determines the equilibrium mass of firms $N(s)$, the entry flow $M(s)$, and sectoral productivity in the extended model. Section 6.2 and 6.3 characterize these mechanisms formally and quantifies their contributions to aggregate TFP and welfare.

6.2 Sectoral and Aggregate Productivity

We retain the markup-linked credit subsidy schedule $\tau(s)$ from equation (37), so that higher-markup sectors receive larger subsidies when $\alpha > 1$. Relative to the benchmark, the key new endogenous objects are the productivity cutoff $\underline{x}(s)$, the mass of active firms $N(s)$, the mass of new entrants $M(s)$, and the sectoral productivity multiplier $\varkappa(s)$ capturing innovation spillovers—all of which now respond to the subsidy $\tau(s)$.

Sectoral productivity has three components:

$$a(s) = \underbrace{z(s)}_{\text{exogenous}} \cdot \underbrace{\varkappa(s)}_{\text{spillover}} \cdot \underbrace{\bar{x}(s)}_{\text{selection}} \tag{42}$$

where $z(s)$ is an exogenous sector-specific component, drawn, again from Pareto distribution, $\varkappa(s)$ is the sectoral productivity multiplier driven by innovation spillover, and $\bar{x}(s) \propto \underline{x}(s)$ is the average firm productivity determined by the survival cutoff.

Aggregate TFP and the associated TFP loss, measured relative to the efficient allocation without markup distortions, are defined using the same expressions as in the benchmark model (equations (35) and (36)). Under this formulation, the TFP loss can be decomposed into three components:

$$\text{TFP Loss} = \underbrace{\frac{\eta}{2\alpha^2}\sigma_\mu^2 + \left[\log\left(1 - \frac{\overline{k}}{\kappa_{\text{eff}}}\right) - \log\left(1 - \frac{\overline{k}}{\kappa}\right)\right]}_{\text{Allocative}} + \underbrace{\Psi_{\text{sel}}(\alpha; \bar{\mu}, \sigma_\mu^2, \sigma_{\mu z})}_{\text{Selection}} + \underbrace{\Psi_{\text{spill}}(\alpha, \theta; \bar{\mu}, \sigma_\mu^2, \sigma_{\mu z})}_{\text{Spillover}}, \tag{43}$$

where α is the policy parameter, η is the cross-sector elasticity of substitution, $\bar{\mu}$ is the mean of markups, σ_μ^2 is the variance of log markups, $\sigma_{\mu z}$ is the covariance between log markups and log sector-specific components, and θ governs the strength of innovation spillovers.

The first allocative term is decreasing in α: stronger targeting compresses TFPR dispersion; the second allocative term adjusts for the fixed operating costs. The selection term $\Psi_{\text{sel}} > 0$ captures the productive inefficiency due to the existance of zombie firms and is increasing in α. The spillover term $\Psi_{\text{spill}} < 0$ captures innovation gains from induced entry and is decreasing in α.

Unlike our benchmark economy, however, changes in TFP loss due to the introduction of preferential credit policy does not directly measure changes in welfare, as consumption equals total output net of entry costs. Specifically, consumption is given by $C = (1 - e)\,Y$, where e is the share of output absorbed by entry costs. Accordingly, welfare effects of preferential credit Changes in consumption can be represented by

$$\Delta \log(C) = -\Delta \text{TFP Loss} + \Delta \log(1-e). \tag{44}$$

6.3 Quantitative Results

We calibrate the model to match key moments from the NTSD data, including firm survival rates, revenue concentration, and the elasticity of sectoral productivity with respect to the mass of firms. Appendix E.7 describes the calibration procedure and the targeted moments in detail.

Table 9 reports the main quantitative results. Columns (1) and (2) present outcomes under the no-subsidy baseline ($\alpha = 1$) and under the estimated preferential credit policy ($\alpha = 9.016$), respectively. Column (3) considers a policy mix that combines credit subsidies with entry subsidies designed to offset the selection distortion induced by subsidized credit.

Three findings stand out. First, the allocative-efficiency channel remains the dominant mechanism through which preferential credit affects aggregate productivity. Relative to the no-subsidy case, introducing preferential credit reduces allocative-inefficiency losses by 5.54 percentage points (from 6.86 to 1.32 percent).

Second, the selection and innovation-spillover channels operate in opposite directions and partially offset each other. By lowering productivity cutoffs, credit subsidies weaken selection and increase the productive efficiency loss by 2.71 percentage points. At the same time, the induced expansion in entry strengthens innovation spillovers, contributing a 1.06 percentage points increase in productive efficiency. The net effect of these two additional forces brought by firm entry is therefore a modest 1.65 percent reduction in aggregate TFP, which is dominated by the reduction in TFP loss (5.54 percentage points) due to improvement in allocative efficiency.

Consistent with these mechanisms, Panel B shows that preferential credit reduces aggregate TFP loss by 3.80 percentage points and raises welfare by 3.65 percent. The magnitude of these gains is comparable to that obtained in our benchmark economy, where the corresponding welfare gain is 2.62 percent.

The selection distortion arises because credit subsidies lower the productivity cutoff $\underline{x}(s)$, allowing relatively unproductive firms to remain active. A natural policy response is to pair credit subsidies with entry subsidies that neutralize this effect. Specifically, suppose entry costs are subsidized according to $c_e(1-\tau^e(s))$, with $1-\tau^e(s) = 1-\tau(s)$, so that entry subsidies follow the same markup-linked schedule as credit subsidies. Under this policy mix, the productivity cutoff becomes independent of $\tau(s)$: the effect of credit subsidies on $\underline{x}(s)$ is exactly offset by the entry subsidy, while the impact on sectoral scale and entry, $M(s)$, is preserved.

The right-most column of Table 9 reports the resulting outcomes. The combined policy eliminates the selection distortion entirely while preserving—and strengthening—the innovation-spillover channel. As a consequence, the welfare gain rises from 3.65 percent under the credit-subsidy-only policy to 5.73 percent under the combined policies.

Overall, our main conclusions remain robust with endogenous entry. Preferential credit improves aggregate productivity and welfare primarily through cross-sector reallocation and entry-driven innovation spillovers, and these gains more than offset the productivity losses associated with weaker selection and zombie-firm survival.

7 Conclusion

This paper quantifies the role of preferential credit policies in shaping aggregate productivity and welfare. Using Chinese firm-level data, we document a robust positive relationship between sectoral markups and credit subsidies: sectors with higher markups and higher revenue-based productivity receive more favorable credit terms. This pattern is consistent with China's institutional framework, in which industrial policy explicitly targets sectors with high expected profitability and strong economic returns.

Motivated by these empirical facts, we develop a multi-sector quantitative model with endogenous markups and heterogeneous firms to assess the aggregate implications of preferential credit allocation. In the model, dispersion in markups generates cross-sector wedges that distort the allocation of capital and output, rendering high-markup sectors inefficiently small in the absence of intervention. Preferential credit policies that tilt subsidies toward such sectors reallocate activity in a manner that compresses these wedges and improves aggregate productive efficiency. Quantitatively, a subsidy schedule that increases with sectoral markups reduces aggregate TFP losses by roughly one half and delivers sizable welfare gains relative to a counterfactual without preferential targeting. These gains remain substantial in an extended framework with endogenous entry and exit, despite the additional trade-off between weakened firm selection and entry-driven productivity gains induced by preferential credit.

While the analysis in this paper focuses on the level effects of preferential credit subsidies on aggregate productivity and welfare, such policies are also likely to have important dynamic implications. Preferential credit and industrial support can shape industry dynamics by expanding production capacity and reducing average price–cost margins, even as concentration and scale increase endogenously.[20] Moreover, by sustaining high profit margins

[20]Using firm-level data from China's Annual Survey of Industrial Firms, Chen and Yuan (2025) document

for leading firms in targeted sectors, preferential credit may strengthen incentives for R&D investment and technological innovation, thereby fostering productivity growth over time. Finally, by directing financial resources toward innovative activities, these policies may influence the dynamic evolution of aggregate welfare. Exploring these dynamic channels within a unified framework remains an important direction for future research.

that major industrial policies articulated in successive Five-Year Plans during 1996–2015 led, on average, to a reduction in firm-level markups.

Table 1: Government Industrial Policy Documents Emphasizing High Profitability and Strong Economic Returns

Year	Policy Document	Key Phrases (Chinese)	English Translation
2010	Decision on Accelerating the Fostering and Development of Strategic Emerging Industries	"...**成长潜力大、综合效益好**的产业。"	"Industries with **large growth potential** and **strong economic returns**."
2012	12th Five-Year Plan for Strategic Emerging Industries	"**科学判断需求和技术趋势...提高发展质量和效益**。"	"**Assess future demand and technology trends... improve quality and returns**."
2018	Qiushi: Advanced Manufacturing	"价值链上**高利润**、**高附加值**的领域。"	"**High-profit**, **high–value-added** segments of the value chain."
2021	14th FYP: Manufacturing Upgrading	"迈向**价值链中高端...先进制造业集群**。"	"Move to **mid–high value chain**... build **advanced-manufacturing clusters**."
2023	NDRC: High-Quality Development of Real Economy	"**科技含量高、国际竞争力强、经济效益好**。"	"**High tech content**, **strong competitiveness**, **good returns**."
2025	SASAC: New-Quality Productive Forces	"**知识技术密集度高、经济效益好、附加值高**。"	"**Knowledge/technology-intensive**, **good returns**, **high value-added**."

Table 2: Estimations of the Effect of Markup on TFPR

	(1)	(2)
	TFPR	
	Level	Logarithm
Sectoral markup (μ)	21.233***	2.108***
	(0.815)	(0.068)
Sectoral controls (SOE share, export share)	Yes	Yes
Sector FE	Yes	Yes
N	684,663	684,663
R^2	0.061	0.111
Adj. R^2	0.060	0.109

Notes: This table reports regression estimates of the relationship between firm-level revenue productivity (TFPR) and sectoral markups. Column (1) uses TFPR in levels, while Column (2) uses log TFPR. Sectoral controls include SOE share and export share. Standard errors are clustered at the firm level and reported in parentheses. FE denotes fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Estimations of the elasticity of $1-\tau$ to sectoral markup

	OLS	**Reduced Form**	**First stage**	**Second stage**
Outcome	$y_{i,j,t}$ (1)	$y_{i,j,t}$ (2)	$\bar{\mu}_{i,t}$ (3)	$y_{i,j,t}$ (4)
$\mu_{i,t}$	-0.248			-7.238***
	(0.244)			(2.701)
$z_{i,t}^{BI}$		-0.582***	0.080***	
		(0.207)	(0.005)	
Sectoral controls: (SOE share, export share)	Yes	Yes	Yes	Yes
Exposure to baseline shares (SOE share, export share)	No	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	405,141	405,141	405,141	405,141
Clusters	4169	4169	4169	4169
R^2	0.033	0.033	0.929	0.031

Note: This table reports the regression estimates of β from the OLS and the IV approach. The dependent variable $y_{i,j,t}$ is $\log(1-\tau_{s,t}^{i})$. Exposure to baseline shares (Bartik controls) includes the interaction of year fixed effects with the industry-level exposure to baseline (2011) county characteristics: export share and SOE share. Standard errors are clustered at the county level and presented in parentheses. *, **, *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 4: Sectoral zombie ratio and subsidy rate (IV estimations)

	(1)	(2)	(3)	(4)
	Calculated τ		Predicted τ	
	Zombie ratio	Zombie ratio	Zombie ratio	Zombie ratio
Subsidy rate (τ)	6.078***	17.920	4.301***	4.101***
	(1.585)	(19.029)	(0.649)	(0.736)
Sectoral controls: (SOE share, export share)	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
N	3265	3265	3265	3265
R^2	0.579	0.606	0.647	0.726
$adj.R^2$	0.451	0.464	0.576	0.632

Note: This table displays four IV regression estimates on the relationship between the zombie ratio and subsidy rate, using official lending rates as the instrumental variable to address endogeneity. The firms' subsidy rate τ is calculated directly from NTSD data in columns 1 and 2, while in columns 3 and 4, it is predicted τ from Table 3. The sectoral τ are computed as simple averages of firm subsidy rate in columns 1 and 3, and are computed as weighted averages (by output) in columns 2 and 4. The outcome variable is the sectoral zombie ratio. FE = fixed effects. Standard errors are clustered at 4-digit sectoral level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Parameterization of the Benchmark Model

Panel A. Moments

	Data	Model		Data	Model
Within-sector concentration, sales revenue			*Size distribution sectors, sales revenue*		
Mean inverse HH	30.09	6.28	Fraction sales by top 0.01 sectors	0.2	0.27
Median inverse HH	10.49	5.7	Fraction sales by top 0.05 sectors	0.45	0.38
Mean top share	0.30	0.35			
Median top share	0.20	0.30			
Coefficients: markup on market share			*Size distribution producers, sales revenue*		
Ratio of coefficients b_1/b_0	-0.71	-0.71	Fraction sales by top 0.01 producers	0.18	0.32
			Fraction sales by top 0.05 producers	0.46	0.47
Across-sector concentration					
p10 inverse HH	1.63	2.11			
p50 inverse HH	10.49	5.71			
p90 inverse HH	70.18	10.91			
p10 top share	0.05	0.17			
p50 top share	0.20	0.30			
p90 top share	0.76	0.56			
p10 number producers	3	3			
p50 number producers	40	11			

Panel B. Parameter Values

γ	8.50	Within-sector elasticity of substitution
η	1.34	Across-sector elasticity of substitution
ξ_x	5.51	Pareto shape parameter, idiosyncratic productivity
ξ_z	0.63	Pareto shape parameter, sector productivity
ζ	0.04	Geometric parameter, number of producers per sector
$\overline{k}$	0.002	Fixed cost of operations
α	9.02	Elasticity of credit subsidy with respect to sectoral markups

Notes: Panel A reports empirical moments and their model counterparts used to discipline the benchmark calibration. Concentration measures follow Edmond, Midrigan and Xu (2015). The inverse Herfindahl index is computed as the inverse of the sum of squared revenue shares. "Top share" denotes the revenue share of the largest producer within a sector. Sector- and producer-level size distributions report cumulative revenue shares of the largest 1% and 5% of sectors and producers, respectively. The coefficient ratio b_1/b_0 is obtained from regressions of inverse markups on revenue shares and pins down the elasticities of substitution. Panel B reports calibrated parameter values.

Table 6: Markups in Data and the Benchmark Model

	Data	Benchmark
Panel A. Markup moments		
Aggregate markup		1.43
Unconditional markup distribution		
Mean	1.13	1.18
$p50$	1.11	1.13
$p75$	1.16	1.17
$p90$	1.22	1.24
$p95$	1.26	1.33
$p99$	1.41	1.66
SD log	0.07	0.09
Across-sector markup distribution		
Mean	1.49	1.46
$p50$	1.16	1.30
$p75$	1.23	1.40
$p90$	1.30	1.71
$p95$	1.43	1.92
$p99$	2.41	3.97
SD log	0.21	0.25
Panel B. Aggregate implications		
Corr(TFPR, TFPQ)	0.99	0.98
Std. TFPR	1.45	0.11
Std. TFPQ	1.74	1.82

Notes: Panel A reports firm-level and sector-level markup distributions in the data and the benchmark model. Firm markups are estimated using the production-function approach of De Loecker and Warzynski (2012). Sectoral markups are sales-weighted harmonic means of firm markups within four-digit manufacturing sectors, consistent with the model's aggregation. Panel B reports dispersion in revenue productivity (TFPR) and its correlation with physical productivity (TFPQ). TFPR and TFPQ are logged; "corr" denotes correlation, "Std." standard deviation.

Table 7: Roles of Preferential Credit Subsidy

	Benchmark	$\alpha = 1$
Panel A. Aggregate implications		
TFP Loss, percent	2.89	5.52
Aggregate output	29.31	28.56
VAR(TFPR_s)	0.0064	0.0751
Corr(log TFPR_s, log μ_s)	0.6088	0.9769
Aggregate markup	1.438	1.402
Panel B. Moments		
Mean inverse HH	6.28	6.42
Median inverse HH	5.70	5.81
Mean top share	0.35	0.35
Median top share	0.30	0.30
Fraction sales by top 0.01 sectors	0.27	0.26
Fraction sales by top 0.05 sectors	0.38	0.37
Fraction sales by top 0.01 producers	0.32	0.31
Fraction sales by top 0.05 producers	0.47	0.46
p10 inverse HH	2.11	2.10
p50 inverse HH	5.71	5.81
p90 inverse HH	10.91	11.29
p10 top share	0.17	0.17
p50 top share	0.30	0.30
p90 top share	0.56	0.56
p10 number of producers	3	3
p50 number of producers	11	11

Notes: The benchmark economy sets $\alpha = 9.016$ so that sectoral credit subsidies increase with sectoral markups as in equation (37); the counterfactual $\alpha = 1$ shuts down preferential targeting. TFP loss is computed as in equation (36). VAR(TFPR_s) is the cross-sector variance of log TFPR, where sectoral TFPR is defined in equation (28). "Aggregate output" denotes equilibrium final output. "Aggregate markup" is the revenue-weighted harmonic mean defined in equation (31). In Panel B, top-sector/top-producer moments report the revenue shares of the largest 1% and 5% of sectors/producers, respectively.

Table 8: Robustness Experiments

	Benchmark	Low γ	No fixed	High fixed
Fraction sales by top 0.01 sectors	0.27	0.13	0.27	0.27
Fraction sales by top 0.01 producers	0.32	0.20	0.37	0.29
Aggregate markup	1.43	1.58	1.42	1.48
VAR(TFPR_s)	0.0064	0.0044	0..0008	0.0613
TFP loss ($\alpha = 9.016$) (%)	2.89	0.48	2.85	2.94
TFP loss ($\alpha = 1$) (%)	5.52	3.01	5.56	5.40
Gains from subsidy policy (%)	2.62	2.52	2.71	2.46

Notes: Column "Low γ" refers to the case $\gamma = 4$. Column "No fixed" sets $\overline{k} = 0$, Column "High fixed" sets $\overline{k} = 0.01$.

Table 9: Roles of Preferential Credit Subsidy with Endogenous Entry

	No Subsidy $\alpha = 1$	Credit Subsidy $\alpha = 9.016$	Credit & Entry Subsidy $\alpha = 9.016$
Panel A. TFP loss relative to efficient level, percent			
Allocative inefficiency	6.86	1.32	2.08
Selection inefficiency	0.00	2.71	0.00
Innovation-spillover effect	−0.08	−1.06	−1.36
TFP loss	6.78	2.98	0.72
Panel B. Welfare relative to no subsidy case ($\alpha = 1$), percent			
$-\Delta$ TFP Loss	0.00	3.80	6.06
Δ Entry Cost	0.00	−0.15	−0.33
Δ Welfare	0.00	3.65	5.73

Notes: Panel A decomposes aggregate TFP losses relative to the efficient allocation into allocative inefficiency, selection inefficiency from endogenous entry and exit, and innovation-spillover effects from entry-driven idea generation, while Panel B reports welfare changes relative to the no-subsidy benchmark ($\alpha = 1$). Column (3) pairs credit subsidies with entry subsidies following the same markup-linked schedule, thereby neutralizing the selection distortion while preserving the effects of preferential credit on sectoral allocation and entry.

References

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer. 2015. "Indentification Properties of Recent Production Estimator." *Econometrica*, 83: 2411—-2451.

Atkeson, Andrew, and Ariel Burstein. 2008. "Pricing-to-market, trade costs, and international relative prices." *American Economic Review*, 98(5): 1998–2031.

Bai, Yan, Dan Lu, and Xu Tian. 2018. "Do Financial Frictions Explain Chinese Firms' Saving and Misallocation?" Unpublished Manuscript.

Bai, Yan, Keyu Jin, and Dan Lu. 2024. "Misallocation under Trade Liberalization." *American Economic Review*, 114(7): 1945—-1985.

Berger, David, Kyle Herkenhoff, and Simon Mongey. 2022. "Labor Market Power." *American Economic Review*, 112(4): 1147—-1193.

Bils, Mark, Peter J Klenow, and Cian Ruane. 2021. "Misallocation or mismeasurement?" *Journal of Monetary Economics*, 124: S39–S56.

Bond, Steve, Arshia Hashemi, Greg Kaplan, and Piotr Zoch. 2021. "Some unpleasant markup arithmetic: Production function elasticities and their estimation from production data." *Journal of Monetary Economics*, 121(1): 1–14.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-experimental shift-share research designs." *The Review of economic studies*, 89(1): 181–213.

Caballero, Ricardo J., Takeo Hoshi, and Anil K. Kashyap. 2008. "Zombie Lending and Depressed Restructuring in Japan." *American Economic Review*, 98: 1943—-1977.

Chen, Guifu, and Hongwei Yuan. 2025. "Key industrial policy, market competition and firms' markup: Evidence from China." *Economic Modelling*, 151: 107245.

David, Joel, and Venky Venkateswaran. 2019. "The Sources of Capital Misallocation." *American Economic Review*, 109: 2531–2567.

De Loecker, Jan, and Frederic Warzynski. 2012. "Markups and Firm-Level Export Status." *American Economic Review*, 102: 2437—-2461.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger. 2020. "The rise of market power and the macroeconomic implications." *The Quarterly journal of economics*, 135(2): 561–644.

Dipippo, Gerald, Ilaria Mazzocco, and Scott Kennedy. 2022. "Red Ink: Estimating Chinese Industrial Policy Spending in Competitive Perspective." Center for Strategic and International Studies.

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, Geography, and Trade." *Econometrica*, 70(5): 1741–1749.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu. 2015. "Competition, markups, and the gains from international trade." *American Economic Review*, 105(10): 3183–3221.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu. 2023. "How costly are markups?" *Journal of Political Economy*, 131(7): 1619–1675.

Fukuda, Shinichi, and Junichi Nakamura. 2011. "Why Did 'Zombie' Firms Recover in Japan?" *The World Economy*, 37: 1124–1137.

Gao, Xijie. 2025. "Zombie firms, state subsidies and aggregate productivity." *Economica*, 92(366): 507–547.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review*, 110: 2586—-2624.

Guner, Nezih, Gustavo Ventura, and Yi Xu. 2008. "Macroeconomic Implications of Size Dependent Policies." *Review of Economic Dynamics*, 11: 721—-744.

Hsieh, Chang-Tai, and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *Quarterly Journal of Economics*, CXXIV(4): 1403–1448.

Huang, S., and Y. Chen. 2017. "The distribution features and classified disposition of China's zombie firms." *China Industrial Economics*, 03: 24–43.

Kim, Minho, Munseob Lee, and Yongseok Shin. 2021. "The Plant-Level View of an Industrial Policy: The Korean Heavy Industry Drive of 1973." Washington University in St. Louis.

Levinsohn, James, and Amil Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *Review of Economic Studies*, 70: 317—-341.

Lin, Yifun, Mingxing Liu, and Qi Zhang. 2004. "Policy burden and enterprise's soft budgetary binding: a case study from China." *Management World*, 8(1): 81–89.

Liu, Ernest. 2019. "Industrial Policies in Production Network." *Quarterly Journal of Economics*, 134: 1883–1948.

Liu, Yongzheng, and Jie Mao. 2019. "How do tax incentives affect investment and productivity? Firm-level evidence from China." *American Economic Journal: Economic Policy*, 11(3): 261–291.

Lu, Yi, and Linhui Yu. 2015. "Trade Liberalization and Markup Dispersion: Evidence from China's WTO Accession." *American Economic Journal: Applied Economics*, 7: 221–253.

Midrigan, Virgiliu, and Daniel Yi Xu. 2014. "Finance and Misallocation: Evidence from Plant-Level Data." *American Economic Review*, 104(2): 422–58.

Nie, Huihua, Ting Jiang, Yuxiao Zhang, and Mingyue Fang. 2016. "Current Status, Causes and Countermeasures of Zombie Firms in China." *Macroeconomic Management (in Chinese)*, 9: 63–68.

Olley, Steven, and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunication Equipment." *Econometrica*, 64: 1264—-1273.

Peters, Michael. 2020. "Heterogeneous markups, growth and endogenous misallocation." *Econometrica*, 88: 2037—-2073.

Restuccia, Diego, and Richard Rogerson. 2008. "Policy distortions and aggregate productivity with heterogeneous establishments." *Review of Economic dynamics*, 11(4): 707–720.

Restuccia, Diego, and Richard Rogerson. 2017. "The Causes and Costs of Misallocation." *Journal of Economic Perspectives*, 31: 151—-174.

Tan, Yuyan, Zhibo Tan, Yiping Huang, and Wing Tye Woo. 2017. "The Crowding-out Effect of Zombie Firms: Evidence from China's Industrial Firms." *Economic Research Journal (in Chinese)*, 5: 322–364.

Internet Appendices

Not Intended for Publication

A Estimation of markups

A.1 Firm-level markups

Our theoretical framework features capital as the sole factor of production. When mapping the model to firm-level data, however, firms differ in their use of labor and intermediate inputs. To account for this heterogeneity, we allow for multiple inputs when estimating markups in the data. This subsection describes the construction of firm-level markups and their aggregation to the sector level.

Let firm i's production technology in year t be

$$Y_{i,t} = F_{i,t}(X_{i,t}, a_{i,t}), \tag{S1}$$

where $Y_{i,t}$ denotes real output, $X_{i,t}$ collects physical inputs—capital $K_{i,t}$, labor $L_{i,t}$, and intermediate inputs $M_{i,t}$—and $a_{i,t}$ is firm-specific productivity. The production function is assumed to be continuous and twice differentiable in all inputs.

Firms choose inputs to minimize variable costs subject to producing at least $\bar{Y}_{i,t}$:

$$\min_{L_{i,t},K_{i,t},M_{i,t}} \quad w_{i,t}L_{i,t} + r_{i,t}K_{i,t} + p^m_{i,t}M_{i,t} \tag{S2}$$

$$\text{s.t.} \quad F_{i,t}(L_{i,t}, K_{i,t}, M_{i,t}, a_{i,t}) \geq \bar{Y}_{i,t}, \tag{S3}$$

where $w_{i,t}$ is the wage, $r_{i,t}$ is the rental rate of capital, and $p^m_{i,t}$ is the price of intermediate inputs. The associated Lagrangian is

$$\mathcal{L} = w_{i,t}L_{i,t} + r_{i,t}K_{i,t} + p^m_{i,t}M_{i,t} + \lambda_{i,t}\left[\bar{Y}_{i,t} - F_{i,t}(L_{i,t}, K_{i,t}, M_{i,t}, a_{i,t})\right], \tag{S4}$$

where $\lambda_{i,t}$ is the marginal cost of producing an additional unit of output.

In principle, markups can be inferred from any flexible input. We focus on intermediate inputs for two reasons. First, capital is typically a dynamic state variable. Second, labor is often subject to non-market considerations in China, particularly for SOEs given their policy burdens (Lu and Yu, 2015). The first-order condition for intermediate inputs is

$$\frac{\partial \mathcal{L}}{\partial M_{i,t}} = p^m_{i,t} - \lambda_{i,t}\frac{\partial F_{i,t}}{\partial M_{i,t}} = 0. \tag{S5}$$

Rearranging (S5) and multiplying by $M_{i,t}/Y_{i,t}$ yields

$$\frac{\partial F_{i,t}}{\partial M_{i,t}}\frac{M_{i,t}}{Y_{i,t}} = \frac{1}{\lambda_{i,t}}\frac{p^m_{i,t}M_{i,t}}{Y_{i,t}} = \frac{P_{i,t}}{\lambda_{i,t}} \cdot \frac{p^m_{i,t}M_{i,t}}{P_{i,t}Y_{i,t}}, \tag{S6}$$

where $P_{i,t}$ denotes the firm's output price. The firm-level markup is therefore

$$\mu_{i,t} \equiv \frac{P_{i,t}}{\lambda_{i,t}} = \theta^m_{i,t} \left(\frac{p^m_{i,t} M_{i,t}}{P_{i,t} Y_{i,t}} \right)^{-1}, \tag{S7}$$

where $\theta^m_{i,t} \equiv \left(\frac{\partial F_{i,t}}{\partial M_{i,t}}\right)\left(\frac{M_{i,t}}{Y_{i,t}}\right)$ is the output elasticity of intermediate inputs and $\frac{p^m_{i,t} M_{i,t}}{P_{i,t} Y_{i,t}}$ is the intermediate-input expenditure share in revenue. Equation (S7) shows that markups can be recovered from the ratio of an input's output elasticity to its expenditure share.

A.2 Markup estimation

We estimate firm-level markups using the control-function approach of De Loecker and Warzynski (2012). A key feature of the implementation is that production functions are estimated separately by industry, allowing production technologies—including factor intensities and substitution patterns—to vary across sectors. This choice reduces the risk that measured markup dispersion reflects technological heterogeneity rather than allocative distortions, consistent with the strategy in Edmond, Midrigan and Xu (2015).

The intermediate-input expenditure share, $\left(\frac{p^m_{i,t} M_{i,t}}{P_{i,t} Y_{i,t}}\right)$ is computed using firms' expenditures on intermediate materials and sales revenue, which information is available in the NTSD. To recover the firm-specific output elasticity $\theta^m_{i,t}$, we assume a translog production function within each sector s:

$$\begin{aligned} y_{i,t} = a_{i,t} &+ \beta_l l_{i,t} + \beta_k k_{i,t} + \beta_m m_{i,t} + \beta_{ll} l^2_{i,t} + \beta_{kk} k^2_{i,t} + \beta_{mm} m^2_{i,t} \\ &+ \beta_{lk} l_{i,t} k_{i,t} + \beta_{km} k_{i,t} m_{i,t} + \beta_{lm} l_{i,t} m_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{S8}$$

where $y_{i,t}$, $l_{i,t}$, $k_{i,t}$, and $m_{i,t}$ denote the logs of output, employment, capital, and intermediate inputs, respectively. The terms $a_{i,t}$ and $\varepsilon_{i,t}$ capture (log) productivity and the error term. The coefficients $\{\beta_l, \beta_k, ...\}$ are specific to the 2-digit sector that firm i belongs to. For notational simplicity we suppress the sector index on $\boldsymbol{\beta}_s$.

After estimating (S8) for each sector, the output elasticity of intermediate inputs for firm i in sector s is

$$\hat{\theta}^m_{i,t} = \frac{\partial y_{i,t}}{\partial m_{i,t}} = \hat{\beta}_m + 2\hat{\beta}_{mm} m_{i,t} + \hat{\beta}_{lm} l_{i,t} + \hat{\beta}_{km} k_{i,t}. \tag{S9}$$

Because $\hat{\theta}^m_{i,t}$ depends on both sector-specific parameters and firm-level input choices, it accommodates heterogeneity in technology across sectors as well as within-sector differences in input intensities.

To obtain consistent estimates of the production-function parameters, we follow De Loecker and Warzynski (2012) and use a proxy-based control function to address simultaneity between productivity and input choices (building on Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2015)). Under the timing assumptions in Ackerberg, Caves and Frazer (2015), a firm's intermediate input demand is modeled as a monotonic function of its capital, labor, and productivity:

$$m_{i,t} = f_t(k_{i,t}, l_{i,t}, a_{i,t}), \tag{S10}$$

which can be inverted to express unobserved productivity as

$$a_{i,t} = g(k_{i,t}, l_{i,t}, m_{i,t}). \tag{S11}$$

Substituting into (S8), the first stage estimates

$$\begin{aligned} y_{i,t} =& g(k_{i,t}, l_{i,t}, m_{i,t}) + \beta_l l_{i,t} + \beta_k k_{i,t} + \beta_m m_{i,t} + \beta_{ll} l_{i,t}^2 + \beta_{kk} k_{i,t}^2 + \beta_{mm} m_{i,t}^2 \\ &+ \beta_{lk} l_{i,t} k_{i,t} + \beta_{km} k_{i,t} m_{i,t} + \beta_{lm} l_{i,t} m_{i,t} + \epsilon_{i,t} \end{aligned} \tag{S12}$$

or simply

$$y_{i,t} = \Phi_{i,t}(k_{i,t}, l_{i,t}, m_{i,t}) + \varepsilon_{i,t}, \tag{S13}$$

where $\Phi_{i,t}$ collects the polynomial in inputs and the proxy for productivity. This stage yields fitted values $\hat{\Phi}_{i,t}$ and residuals $\hat{\varepsilon}_{i,t}$. For any candidate parameter vector $\boldsymbol{\beta}$, implied productivity is recovered as

$$\begin{aligned} \hat{a}_{i,t}(\boldsymbol{\beta}) = \hat{\Phi}_{i,t} &- \beta_l l_{i,t} - \beta_k k_{i,t} - \beta_m m_{i,t} - \beta_{ll} l_{i,t}^2 - \beta_{kk} k_{i,t}^2 - \beta_{mm} m_{i,t}^2 \\ &- \beta_{lk} l_{i,t} k_{i,t} - \beta_{km} k_{i,t} m_{i,t} - \beta_{lm} l_{i,t} m_{i,t}. \end{aligned} \tag{S14}$$

In the second stage, productivity is assumed to follow a first-order Markov process,

$$\hat{a}_{i,t}(\boldsymbol{\beta}) = g(\hat{a}_{i,t-1}(\boldsymbol{\beta})) + \xi_{i,t}(\boldsymbol{\beta}), \tag{S15}$$

where $\xi_{i,t}$ is the innovation to productivity. We estimate $\boldsymbol{\beta}$ by GMM using moment conditions based on the orthogonality between $\xi_{i,t}$ and predetermined instruments:

$$E\left[\xi_{i,t}(\boldsymbol{\beta})\, \mathbf{Z}_{i,t}\right] = 0, \tag{S16}$$

where the instrument set includes current capital and lagged flexible inputs and their interactions:

$$\mathbf{Z}_{i,t} = \big[l_{i,t-1},\, k_{i,t},\, m_{i,t-1},\, l^2_{i,t-1},\, k^2_{i,t},\, m^2_{i,t-1},\, l_{i,t-1}k_{i,t},\, l_{i,t-1}m_{i,t-1},\, k_{i,t}m_{i,t-1}\big]. \qquad \text{(S17)}$$

Given the estimated sector-specific coefficients $\hat{\boldsymbol{\beta}}_s$, we compute $\hat{\theta}^m_{i,t}$ using (S9) and construct firm-level markups from (S7) as the ratio of the intermediate-input elasticity to the intermediate-input revenue share.

B Identification of Zombie Firms in Firm-level Data

We identify zombie firms based on their ability to service a benchmark level of interest payments. The approach follows the FN–CHK framework of Caballero, Hoshi and Kashyap (2008) and Fukuda and Nakamura (2011), which constructs a hypothetical minimum interest expense and compares it with firms' observed interest payments and operating earnings. In implementing this method, we follow Tan et al. (2017) and Huang and Chen (2017) in constructing calculating the hypothetical minimum interest rate payments. To distinguish true zombie firms from healthy firms experiencing temporary shocks, we further adopt the refinement proposed by Nie et al. (2016) and classify a firm as a zombie only if it satisfies the zombie criteria in two consecutive years (both year t and year $t-1$). The procedure is as follows.

1. **Construct the minimum required interest expense.** We compute the minimum interest payment that firm i should pay in year t under normal operation:

$$R^*_{i,t} = rs_{t-1}\, BS_{i,t-1} + \left(\frac{1}{5}\sum_{j=1}^{5} rl_{t-j}\right) BL_{i,t-1},$$

   where $BS_{i,t-1}$ and $BL_{i,t-1}$ denote short-term and long-term bank loans, respectively. Because the NTSD does not report detailed loan balances directly, we proxy short-term bank borrowing using short-term liabilities net of operating payables, and we proxy long-term bank borrowing using reported long-term liabilities.[21] The benchmark rates rs_{t-1} and rl_{t-j} are set to 0.9 times the official benchmark lending rates for the relevant

[21] Operating liabilities include accounts payable, value-added tax payable, income tax payable, wages payable, and employee benefits payable. Missing values are imputed using the corresponding payable items in other years for the same firm. We treat the year-end balance of income tax payable as one quarter of the cumulative annual amount (quarterly payments) and the year-end balances of value-added tax payable, wages payable, and employee benefits payable as one twelfth of the cumulative annual amounts (monthly payments).

maturities.[22]

Specification of benchmark rates. In our baseline results (Table 4 in the main text), the short-term benchmark rate (rs_t) is constructed as the arithmetic average of the official lending rates for maturities of six months or less and six months to one year. The long-term benchmark rate (rl_t) is constructed as the arithmetic average of the rates for maturities of one to three years, three to five years, and more than five years. This choice allows the required interest expense to reflect borrowing costs across the maturity distribution observed in firm liabilities.

2. **Impute interest income.** The NTSD reports net interest expense, $RN_{i,t}$ (interest expense net of interest income). To recover gross interest expense for comparison with benchmark payments, we first impute interest income:

$$RI_{i,t} = (CA_{i,t-1} - AR_{i,t-1} - INV_{i,t-1}) \cdot rd_t,$$

where $CA_{i,t-1}$, $AR_{i,t-1}$, and $INV_{i,t-1}$ denote current assets, accounts receivable, and inventories, respectively, and rd_t is the one-year benchmark deposit rate in year t.

3. **Compute the interest-payment gap and apply a profitability correction.** We compare actual net interest expense to the minimum required net interest expense and normalize by lagged borrowing $B_{i,t-1} = BS_{i,t-1} + BL_{i,t-1}$:

$$gap_{i,t} = \frac{RN_{i,t} - \left(R^*_{i,t} - RI_{i,t}\right)}{B_{i,t-1}}.$$

Under the FN–CHK criterion (Caballero, Hoshi and Kashyap, 2008), $gap_{i,t} < 0$ indicates that the firm pays an interest burden below the benchmark and is thus a zombie candidate. Fukuda and Nakamura (2011) note that this criterion may misclassify financially healthy firms with low borrowing costs as zombies; we therefore apply an earnings-based correction:

$$gapadj_{i,t} = \frac{EBIT_{i,t} - \left(R^*_{i,t} - RI_{i,t}\right)}{B_{i,t-1}}.$$

If $gapadj_{i,t} > 0$, i.e., if operating earnings are sufficient to cover the benchmark interest burden, the firm is reclassified as non-zombie.

The FN–CHK criteria alone, applied year by year, can still overstate zombification in

[22]From 1998 to 2011, the People's Bank of China set the lower bound of the lending-rate floating band at 0.9 times the benchmark rate for financial institutions.

environments where banks roll over distressed firms' obligations. As emphasized by Lin, Liu and Zhang (2004), rollover lending is common in China: overdue principal and interest may be refinanced into new loans, mechanically lowering measured interest burdens. To address this concern, and following Fukuda and Nakamura (2011) and Tan et al. (2017), we impose additional solvency and debt-dynamics filters. In our baseline classification, a firm is preliminarily labeled as a zombie in year t if it satisfies all of the following conditions: (i) pre-tax profits are below the benchmark net interest expense; (ii) the debt-to-asset ratio exceeds 50%; and (iii) liabilities in year t exceed liabilities in year $t-1$.

Finally, to reduce false positives arising from temporary shocks, we implement the persistence requirement in Nie et al. (2016): a firm is classified as a zombie in year t only if it is identified as a zombie in both year t and year $t-1$ under the baseline criteria. This requirement focuses the measure on chronic financial distress.

After identifying whether a firm is zombie or not, we compute the sectoral zombie ratio at the four-digit level as the fraction of zombie firms among all firms in the sector-year. The magnitude of the zombie firm ratios estimated through this approach aligns with findings from recent studies on the Chinese economy, such as Gao (2025), Tan et al. (2017), and Nie et al. (2016). These studies, which similarly account for the specific institutional and financial conditions in China, report zombie ratios of comparable levels, suggesting that our identification strategy—particularly with the inclusion of the persistence criterion—yields representative estimates of zombie firm ratios in China.

Robustness to alternative benchmark-rate specifications. To verify that our results are not driven by the specific choice of official lending rates used in constructing $R^*_{i,t}$, we conduct a robustness check following Tan et al. (2017). In the alternative specification, the short-term benchmark rate (rs_t) is set to the six-month-to-one-year lending rate, and the long-term benchmark rate (rl_t) is set to the five-year-and-above lending rate. We re-identify zombies under this alternative cost-of-capital measure and re-estimate the relationship between credit subsidies and sectoral zombie ratios. Table A2 shows that the estimated effects remain positive and statistically significant, confirming that our main results are robust to alternative constructions of the required minimum interest burden.

Table A1: Summary Statistics and Group Differences

Panel A. Summary statistics (4-digit sectoral level)

	Obs.	**Mean**	**Std. Dev.**	**P5**	**P25**	**P50**	**P75**	**P95**
Effective interest rate (%)	6260	2.678	1.628	0.860	1.864	2.551	3.250	4.617
Subsidy rate	6260	0.484	0.323	0.120	0.396	0.510	0.621	0.823
Zombie rate (%)	5976	14.702	16.988	0.000	0.000	11.589	21.739	44.445
SOE share (%)	6636	1.016	5.731	0.000	0.000	0.000	0.000	3.922
Export share (%)	4292	21.324	124.998	0.000	4.064	13.175	29.173	59.237

Panel B. Zombie firms vs. Non-zombie firms (Firm-level)

	Zombie firms		Non-zombie firms	
	Mean	Std. Dev.	Mean	Std. Dev.
Log(Revenue)	9.537	1.919	10.335	1.971
MRPK	1.414	1.595	1.766	1.429
Effective interest rate (%)	1.938	1.805	2.965	2.681

Note: Panel A presents 4-digit sector-year averages of firm-level data. The "%" symbol denotes percentage terms. "Effective interest rate (%)" represents the calculated effective interest rate faced by firms (sector-year averages). "Subsidy rate" refers to τ, the calculated subsidy rate as defined in the paper. "Zombie ratio (%)" indicates the percentage of zombie firms at the 4-digit sector-year level. "SOE share (%)" and "Export share (%)" respectively represent the proportion of state-owned capital in total capital and the portion of exports in output. "Std. Dev." stands for standard deviation. Panel B compares the mean and standard deviation of key variables between zombie and non-zombie firms.

Table A2: Robustness check: Sectoral zombie ratio and subsidy rate (IV estimations)

	(1)	(2)	(3)	(4)
	Calculated τ		Predicted τ	
	Zombie ratio	Zombie ratio	Zombie ratio	Zombie ratio
Subsidy rate (τ)	4.623***	12.579	3.029***	2.776***
	(1.283)	(13.481)	(0.550)	(0.605)
Sectoral controls: (SOE share, export share)	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
N	3265	3265	3265	3265
R^2	0.559	0.568	0.747	0.726
$adj.R^2$	0.445	0.437	0.676	0.632

Note: The table reports IV estimates of the relationship between sectoral zombie ratios and credit subsidies, instrumenting subsidy rates with official lending rates. Columns (1)–(2) use τ computed directly from firm-level NTSD data, while Columns (3)–(4) use τ predicted from Table 3. Sectoral τ is computed as a simple average of firm-level subsidies in Columns (1) and (3) and as an output-weighted average in Columns (2) and (4). The dependent variable is the sector-year zombie ratio. FE = fixed effects. Standard errors are clustered at the 4-digit sector level. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

C Algorithm to compute the model with endogenous markup

Algorithm:

1. Estimate b_0, b_1 from the following regression (sectoral markup and HHI index are from data) to make sure $\eta < \gamma$:

$$\frac{1}{\mu_i(s)} = \frac{\gamma - 1}{\gamma} - \left(\frac{1}{\eta} - \frac{1}{\gamma}\right)\omega_i(s) \tag{S18}$$

   Run regression:

$$\frac{1}{\text{Firm's Markup}} = b_0 + b_1 \text{ Firm's Market Share} \tag{S19}$$

$$\eta = \left(\frac{1}{\gamma} - \frac{b_1}{b_0}\left(\frac{\gamma - 1}{\gamma}\right)\right)^{-1} \text{ Cournot competition} \tag{S20}$$

2. Initial guess of parameters $\xi_z, \xi_x, \zeta, \gamma, \alpha, \overline{k}$

3. Draw firm-level productivity from two Pareto distributions (ξ_z, ξ_x)

4. Solve $\mu_i(s)$ and $\omega_i(s)$ by using the following equations given η and γ:

$$\frac{1}{\mu_i(s)} = \frac{\gamma - 1}{\gamma} - \left(\frac{1}{\eta} - \frac{1}{\gamma}\right)\omega_i(s) \tag{S21}$$

$$\omega_i(s) = \frac{\mu_i(s)^{1-\gamma} a_i(s)^{\gamma-1}}{\sum_{j=1}^{N(s)} \mu_j(s)^{1-\gamma} a_j(s)^{\gamma-1}} \tag{S22}$$

5. Sum up to sectoral level to get $\mu(s)$ and solve for subsidies given α:

$$\tau(s) = 1 - \left(\frac{\mu(s)}{\mu}\right)^{\frac{1}{\alpha} - 1} \tag{S23}$$

6. Calculate the moments from the model and data moments

7. Adjust the parameters to minimize distance between model implied moments and data moments

D Proof of Propositions and Lemmas

Derivation of Equation (25) From the definition of $a(s)$, we have

$$\begin{aligned}
a(s) &= \frac{y(s)}{\sum_{i=1}^{N(s)} y_i(s)/a_i(s)} \\
&= \left(\sum_{i=1}^{N(s)} \frac{y_i(s)}{y(s)} \frac{1}{a_i(s)}\right)^{-1} \\
&= \left(\sum_{i=1}^{N(s)} \frac{p_i(s)\, y_i(s)}{p(s)\, y(s)} \frac{p(s)}{p_i(s)} \frac{1}{a_i(s)}\right)^{-1} \\
&= \left(\sum_{i=1}^{N(s)} \left(\frac{p_i(s)}{p(s)}\right)^{-\gamma} \frac{1}{a_i(s)}\right)^{-1} \\
&= \left(\sum_{i=1}^{N(s)} \left(\frac{\mu_i(s)}{\mu(s)}\right)^{-\gamma} a_i(s)^{\gamma-1}\right)^{-1} a(s)^{\gamma}
\end{aligned}$$

Rearranging the above equation, we obtain equation (25).

Proof of Lemma 1. Plugging equation (16) into (12), we obtain

$$p(s)^{1-\gamma} = ((1-\tau(s))\, R)^{1-\gamma} \sum_{i=1}^{N(s)} \mu_i(s)^{1-\gamma} a_i(s)^{\gamma-1} \tag{S24}$$

Plugging equation (21) into (24), we have

$$\sum_{i=1}^{N(s)} \mu_i(s)^{1-\gamma} a_i(s)^{\gamma-1} = \mu(s) \sum_{i=1}^{N(s)} \mu_i(s)^{-\gamma} a_i(s)^{\gamma-1} \tag{S25}$$

Plugging equation (25) into (S25), we obtain

$$\mu(s) \sum_{i=1}^{N(s)} \mu_i(s)^{-\gamma} a_i(s)^{\gamma-1} = \mu(s)^{1-\gamma} a(s)^{\gamma-1} \tag{S26}$$

Plugging (S26) into (S24), we obtain (26) ■

Derivation of Equation (31) Plugging equation 29 into

$$\frac{R\int_0^1 (1-\tau(s))\,ds}{A},$$

we obtain

$$\frac{R\int_0^1 (1-\tau(s))\,ds}{A} \tag{S27}$$

$$= \int_0^1 \sum_{i=1}^{N(s)} \frac{R(1-\overline{\tau})}{a_i(s)} \frac{y_i(s)}{Y} ds \tag{S28}$$

$$= \int_0^1 \sum_{i=1}^{N(s)} \frac{p_i(s)(1-\overline{\tau})}{\mu_i(s)(1-\tau(s))} \frac{y_i(s)}{Y} ds \tag{S29}$$

$$= \int_0^1 \frac{1-\overline{\tau}}{1-\tau(s)} \sum_{i=1}^{N(s)} \frac{p_i(s)}{\mu_i(s)} \frac{y_i(s)}{Y} ds \tag{S30}$$

Plugging (S30) into the definition of aggregate markup (30) and rearranging, we can show that the aggregate markup is a revenue-weighted harmonic mean of firm markups, adjusted by the subsidy ratio.

$$\mu = \left(\int_0^1 \frac{1-\overline{\tau}}{1-\tau(s)} \sum_{i=1}^{N_s} \frac{1}{\mu_i(s)} \frac{p_i(s)\,y_i(s)}{PY} \right)^{-1} \tag{S31}$$

Rearranging (S31), and using the definition of $\omega(s)$ and the formula for $\mu(s)$ as in equationẽqrefeq:mu-sector, we obtain

$$\mu = \left(\int_0^1 \frac{1-\overline{\tau}}{1-\tau(s)} \frac{p(s)\,y(s)}{PY} \sum_{i=1}^{N(s)} \frac{1}{\mu_i(s)} \frac{p_i(s)\,y_i(s)}{p(s)\,y(s)} \right)^{-1}$$

$$= \left(\int_0^1 \frac{\omega(s)}{(1-\tau(s))\,/\,(1-\overline{\tau})} \frac{1}{\mu(s)} \right)^{-1} \tag{S32}$$

E The Model with Endogenous Entry

We present a tractable framework for analyzing preferential credit policy when firm entry and exit are endogenous and entry generates innovation spillovers. The environment extends the baseline model in two dimensions: (i) free entry, which introduces a selection effect; and (ii) innovation spillovers, which link entry to sectoral productivity.

E.1 Environment

Consumers. The economy is populated by a representative consumer endowed with a fixed aggregate capital stock K. The consumer owns both the capital stock and all firms, and therefore receives capital rental income as well as aggregate firm profits net of entry costs (introduced below in the firm problem). Any policy interventions considered later in the model are financed through lump-sum taxes levied on the consumer.

The consumer chooses consumption to solve

$$\max_{C} \quad \log(C) \quad \text{s.t.} \quad PC \leq RK + \Pi - T,$$

where R is the rental rate, Π is aggregate profits net of entry cost, and T is the lump-sum tax.

Sectors. Final output is a CES aggregate of sectoral composites:

$$Y = \left(\int_0^1 y(s)^{\frac{\eta-1}{\eta}} \, ds \right)^{\frac{\eta}{\eta-1}}, \qquad \eta > 1. \tag{S33}$$

Demand for sector s is

$$y(s) = \left(\frac{p(s)}{P} \right)^{-\eta} Y, \qquad P = \left(\int_0^1 p(s)^{1-\eta} \, ds \right)^{\frac{1}{1-\eta}}. \tag{S34}$$

Within each sector s, a continuum of varieties is aggregated as

$$y(s) = N(s)^{\frac{1}{1-\gamma}} \left(\int_{i \in I(s)} y_i(s)^{\frac{\gamma-1}{\gamma}} \, \mathrm{d}i \right)^{\frac{\gamma}{\gamma-1}}, \qquad \gamma > 1, \tag{S35}$$

where $N(s)$ is the mass of active firms (varieties). The scaling term rules out mechanical "love-of-variety" effects. Variety demand is

$$y_i(s) = \frac{y(s)}{N(s)} \left(\frac{p_i(s)}{p(s)} \right)^{-\gamma}. \tag{S36}$$

Firms. Firm i in sector s produces using variable capital $k_i(s)$:

$$y_i(s) = \varkappa(s) a_i(s) k_i(s), \qquad a_i(s) = z(s)\, x_i(s), \tag{S37}$$

where $\varkappa(s)$ is a sectoral spillover multiplier, $z(s)$ is an exogenous sector-specific component, and $x_i(s)$ is idiosyncratic productivity drawn from a Pareto distribution

$$G(x) = 1 - x^{-\xi}, \qquad x \geq 1,\ \xi > 0. \tag{S38}$$

Capital is rented at gross rate R. A sector-specific credit subsidy $\tau(s)$ reduces the user cost of capital to $R(1 - \tau(s))$.

Sectors face an exogenous wedge $\varrho(s)$ that acts as an effective output-market distortion. This wedge implies a sectoral markup

$$\mu(s) \equiv \varrho(s)\, \bar{\mu}, \qquad \bar{\mu} \equiv \frac{\gamma}{\gamma - 1}. \tag{S39}$$

Optimal pricing is a markup over marginal cost:

$$p_i(s) = \mu(s)\, \frac{R(1 - \tau(s))}{\varkappa(s) a_i(s)}. \tag{S40}$$

Each active firm pays a fixed operating cost of $\bar{k}$ units of capital:

$$c_f(s) = R(1 - \tau(s))\, \bar{k}. \tag{S41}$$

Define the productivity cutoff $\underline{x}(s)$ by the zero-profit condition. Then firm profits can be expressed in cutoff form:

$$\pi(x_i(s), \tau(s); s) = c_f(s) \left[\left(\frac{x_i(s)}{\underline{x}(s)} \right)^{\gamma - 1} - 1 \right]. \tag{S42}$$

A key tractability property is that (S42) is independent of $z(s)\varkappa(s)$.

E.2 Firm dynamics

Firms face idiosyncratic productivity risk through a two-state Markov process. In the normal state, effective productivity is $z(s)\varkappa(s)x_i(s)$. With probability $1-q$ the firm transitions into a low-productivity state where productivity becomes $z(s)\varkappa(s)\rho x_i(s)$, where $\rho \in (0,1)$.[23] Exogenous death occurs with probability $1-\phi$ each period.

Since $z(s)\varkappa(s)$ multiplies productivity in both states, the survival decision depends only on $x_i(s)$. A low-state firm exits if $\rho a_i(s) < \underline{x}(s)$, i.e. if $x_i(s) < \underline{x}(s)/\rho$.

Let $v^N(x_i(s);\tau(s))$ and $v^L(\rho x_i(s);\tau(s))$ denote continuation values in the normal and low states, respectively.

Conditional survivors. For firms with $x_i(s) \in [\underline{x}(s), \underline{x}(s)/\rho)$, a transition to the low state implies exit, so the low-state value is $v^L(\rho x_i(s);\tau(s)) = 0$. The normal-state value satisfies $v^N(x;\tau) = \pi(x;\tau) + \beta\phi q\, v^N(x;\tau)$, implying

$$v^N(x_i(s);\tau(s)) = \frac{c_f(s)}{1-\beta\phi q}\left[\left(\frac{x_i(s)}{\underline{x}(s)}\right)^{\gamma-1} - 1\right]. \tag{S43}$$

Persistent firms. For firms with $x_i(s) \geq \underline{x}(s)/\rho$, the transition to the low state does not force exit. The value function in the low state is $v^L(\rho x;\tau) = \pi(\rho x;\tau) + \beta\phi v^L(\rho x;\tau)$, that is, $v^L(\rho a;\tau) = \frac{\pi(\rho x;\tau)}{1-\beta\phi}$. The value function in the normal state is $v^N(x;\tau) = \pi(x;\tau) + \beta\phi[q\, v^N(x;\tau) + (1-q)v^L(\rho x;\tau)]$, which implies that $v^N(x;\tau) = \dfrac{\pi(x;\tau)}{1-\beta\phi q} + \frac{\beta\phi(1-q)\frac{\pi(\rho x;\tau)}{1-\beta\phi}}{1-\beta\phi q}$ or

$$v^N(x_i(s);\tau(s)) = \frac{c_f(s)}{1-\beta\phi q}\left[\left(\frac{x_i(s)}{\underline{x}(s)}\right)^{\gamma-1} - 1\right] + \frac{\beta\phi(1-q)}{(1-\beta\phi q)(1-\beta\phi)}c_f(s)\left[\left(\frac{\rho x_i(s)}{\underline{x}(s)}\right)^{\gamma-1} - 1\right].$$

E.3 Entry, cutoff, and the mass of firms

E.3.1 Free entry and cutoff

Potential entrants pay a constant entry cost c_e (in units of the final good) and draw x from G. Free entry requires $\beta\,\mathbb{E}[v^N(x;\tau(s))] = c_e$. Under Pareto G and the value function structure above, expected entrant value can be written as

$$\mathbb{E}[v^N(x;\tau(s))] = \int_1^\infty v^N(x;\tau(s))dG(x) = \chi \cdot c_f(s) \cdot (\underline{x}(s))^{-\xi}, \tag{S44}$$

[23] We adopt a two-state productivity structure for tractability. This abstraction does not imply that firms cannot experience positive sales growth in the data. Allowing for richer productivity dynamics would substantially increase model complexity but would not alter the core reallocation mechanism emphasized in this paper.

where the constant χ is

$$\chi = \frac{\rho^{\gamma-1}(1-\beta\phi) - \beta(1-q)\phi\rho^{\xi+1}(\xi-\gamma+1) + \beta\gamma(1-q)\phi\rho^{\xi+\gamma}}{\rho(1-\beta\phi)(\xi-\gamma+1)(1-\beta q\phi)}. \tag{S45}$$

Imposing $\beta\mathbb{E}[v^N] = c_e$ yields

$$\underline{x}(s) = \left(\frac{\beta\chi R(1-\tau(s))\bar{k}}{c_e}\right)^{\frac{1}{\xi}}. \tag{S46}$$

The cutoff depends only on policy ($\tau(s)$) and structural parameters—it is independent of $z(s)$, $\varkappa(s)$, or market size.

E.3.2 Mass of active firms and entrants

The cutoff in (S46) satisfies the zero-profit condition $\pi(\underline{x}(s), \tau(s); s) = 0$, which implies that the equilibrium mass of active firms satisfies

$$N(s) = (\mu(s)-1)\mu(s)^{-\gamma}(z(s)\varkappa(s))^{\gamma-1}(R(1-\tau(s)))^{1-\gamma}\left(\frac{\beta\chi}{c_e}\right)^{\frac{\gamma-1}{\xi}} c_f(s)^{\frac{\gamma-1-\xi}{\xi}} p(s)^{\gamma} y(s), \tag{S47}$$

which is equivalent to

$$N(s) = (\mu(s)-1)\mu(s)^{-\eta}(z(s)\varkappa(s))^{\eta-1}(R(1-\tau(s)))^{\frac{\eta(1-\xi)-1}{\xi}}\left(\frac{\beta\chi\bar{k}}{c_e}\right)^{\frac{\eta-1}{\xi}} \bar{k}^{-1}\lambda^{\eta-\gamma}P^{\eta}Y \propto (z(s)\varkappa(s))^{\eta-1},$$

where terms involving $\left(\lambda = \left(\frac{\xi}{\xi-\gamma+1}\right)^{\frac{1}{\gamma-1}}, P, Y\right)$ are common across sectors.

In stationary equilibrium, the mass of new entrants with productivity above the cutoff productivity (i.e., those entrants that are operative) is given by

$$M(s) = \Omega \cdot N(s), \tag{S48}$$

where $\Omega \equiv \frac{(1-\phi)+\phi(1-q)}{1+\frac{\phi(1-q)\rho^{\xi}}{1-\phi}}$ is a constant determined by firm dynamics parameters.

E.4 Innovation spillovers

The model incorporates innovation spillovers through the sectoral productivity multiplier $\varkappa(s)$. The idea is that entry activity generates knowledge spillovers that raise productivity for all firms in the sector, in the spirit of Eaton and Kortum (2002). We specify:

$$\varkappa(s) = \xi \tilde{M}(s)^{\theta} \tag{S49}$$

where $\tilde{M}(s)$ is a measure of entry intensity and $\theta \geq 0$ governs the strength of spillovers. A natural measure of entry activity is the mass of entrants $M(s)$. However, $M(s)$ scales with sector size—larger sectors have more entrants mechanically. Since $N(s) \propto (z(s)\varkappa(s))^{\eta-1}$ from the zero-profit condition, we define normalized entry mass:

$$\tilde{M}(s) \equiv \frac{M(s)}{z(s)^{\eta-1}} \tag{S50}$$

This measures entry intensity relative to the fundamental sector scale, removing the mechanical size effect.

The spillover specification creates a feedback loop: a higher $\varkappa(s)$ raises firm mass and entry, which further increases $\varkappa(s)$. This nonlinearity makes the model analytically intractable in general. We linearize around a symmetric benchmark to obtain closed-form expressions that cleanly decompose the channels through which policy affects aggregate TFP.

E.5 Sectoral and aggregate productivity

Sectoral productivity. Under Pareto productivity, average productivity among active firms is proportional to the cutoff:

$$\overline{x}(s) = \left(\frac{\xi}{\xi - \gamma + 1}\right)^{1/(\gamma-1)} \underline{x}(s), \tag{S51}$$

so sectoral net productivity decomposes into

$$a(s) = \underbrace{z(s)}_{\text{fundamental}} \cdot \underbrace{\varkappa(s)}_{\text{spillover}} \cdot \underbrace{\overline{x}(s)}_{\text{selection}}. \tag{S52}$$

Aggregate productivity. Using CES aggregation and the markup-linked credit subsidy schedule,

$$1 - \tau(s) = \mu(s)^{\frac{1}{\alpha}-1}, \qquad \alpha \geq 1, \tag{S53}$$

net aggregate productivity can be written as

$$A = \frac{\left[\int_0^1 \mu(s)^{\frac{1-\eta}{\alpha}} (a(s))^{\eta-1}\, ds\right]^{\frac{\eta}{\eta-1}}}{\int_0^1 \mu(s)^{-\frac{\eta}{\alpha}} (a(s))^{\eta-1}\, ds}. \tag{S54}$$

Productivity loss decomposition. We derive closed-form expressions by log-linearizing the entry and spillover conditions around a symmetric benchmark. This approximation yields a tractable characterization of productivity losses relative to the efficient equilibrium without markup heterogeneity, which can be decomposed into the following components:

$$\log A_{\text{eff}} - \log A = \underbrace{\frac{\eta}{2\alpha^2}\sigma_\mu^2}_{\text{Markup}} + \underbrace{\Psi_{\text{sel}}(\alpha; \bar{\mu}, \sigma_\mu^2, \sigma_{\mu z})}_{\text{Selection}} + \underbrace{\Psi_{\text{spill}}(\alpha, \theta; \bar{\mu}, \sigma_\mu^2, \sigma_{\mu z})}_{\text{Spillover}}, \tag{S55}$$

where $\sigma_\mu^2 \equiv \text{Var}(\log \mu(s))$ and $\sigma_{\mu z} \equiv \text{Cov}(\log \mu(s), \log z(s))$. The markup term decreases in α (better MRPK equalization). The selection term Ψ_{sel} is positive and increases in α (zombie drag). The spillover term Ψ_{spill} is negative and decreases in α (innovation gains).

E.6 TFP and welfare

Consistent with our benchmark model in Section 4, we define aggregate TFP as the ratio of aggregate output to total capital input, inclusive of both variable and fixed inputs.

$$\text{TFP} \equiv \frac{Y}{K} = A\left(1 - \frac{\overline{k}}{\kappa}\right),$$

where $\kappa \equiv K / \int_0^1 N(s)\, ds$. TFP loss can then be decomposed into losses due to aggregate productivity distortions and fixed operating costs:

$$\text{TFP Loss} \equiv \log A_{\text{eff}} - \log A + \left[\log\left(1 - \frac{\overline{k}}{\kappa_{\text{eff}}}\right) - \log\left(1 - \frac{\overline{k}}{\kappa}\right)\right].$$

These two definitions are exactly the same as in equations (35) and (36). Substituting (S55) yields the three-way decomposition:

$$\text{TFP Loss} = \underbrace{\frac{\eta}{2\alpha^2}\sigma_\mu^2 + \left[\log\left(1 - \frac{\overline{k}}{\kappa_{\text{eff}}}\right) - \log\left(1 - \frac{\overline{k}}{\kappa}\right)\right]}_{\text{Allocative}} + \underbrace{\Psi_{\text{sel}}(\alpha; \bar{\mu}, \sigma_\mu^2, \sigma_{\mu z})}_{\text{Selection}} + \underbrace{\Psi_{\text{spill}}(\alpha, \theta; \bar{\mu}, \sigma_\mu^2, \sigma_{\mu z})}_{\text{Spillover}},$$

The TFP analysis characterizes the efficiency of production but does not directly speak to welfare. To evaluate welfare, we therefore focus on aggregate consumption, which is pinned down by the representative household's problem. With stationary entry, the aggregate resource constraint is:

$$Y = C + c_e \int_0^1 N^e(s) ds,$$

In equilibrium, the household budget constraint implies

$$C = RK + \Pi - T = Y - c_e \int_0^1 N^e(s)ds.$$

Define entry-cost share as: $e \equiv \frac{c_e \int_0^1 N_s^e}{Y}$. Then we have

$$C = (1-e)\, Y = (1-e) \times \text{TFP} \times K.$$

Hence, for welfare comparison, we have

$$\Delta \log C = \Delta \log(\text{TFP}) + \Delta \log(1-e) = -\Delta\text{TFP Loss} + \Delta \log(1-e).$$

E.7 Calibration

We calibrate the model economy to match key data moments from the National Tax Survey Database (NTSD). The model is calibrated to an annual frequency. Table S3 summarizes all parameter values.

Standard Parameters. We set the discount factor $\beta = 0.96$ and the gross interest rate $R = 1.00$ (normalized). For the elasticity of substitution across sectors, we set $\eta = 5$, which lies in the commonly used range $[2, 10]$ and is frequently employed in quantitative exercises (e.g., Epifani & Gancia, 2011).

Markup Distribution. We calibrate the markup distribution using sector-level markups:

$$\log(\mu(s)) \sim \mathcal{N}(0.181, 0.209^2) \tag{S56}$$

Under monopolistic competition, the average markup satisfy $e^{0.181} = \gamma/(\gamma - 1)$, implying $\gamma = 6.04$.

Policy Sensitivity (α). We set the status quo policy sensitivity parameter to $\alpha = 9.02$, consistent with the benchmark model (see Panel B in Table 5).

Pareto Tail (ξ). We calibrate ξ to match the average revenue share of the top 5% of firms in 4-digit NTSD industries, which is 0.46. This target implies $\xi = 6.80$.

Specifically, note that the revenue of firm i in sector s is proportional to $x_i(s)^{\gamma-1}$, where $x_i(s)$ is idiosyncratic productivity drawn from a Pareto distribution with shape parameter ξ:

$$G(x) = 1 - x^{-\xi}, \qquad x \geq 1.$$

Let x^q denote the q-th quantile of the productivity distribution, i.e., $G(x^q) = q/100$. The revenue share of the top $(100-q)\%$ firms (those with productivity above x^q) is

$$\text{Share}(q) = \frac{\int_{x^q}^{\infty} x^{\gamma-1}\, dG(x)}{\int_1^{\infty} x^{\gamma-1}\, dG(x)}.$$

Evaluating these integrals under the Pareto distribution yields

$$\text{Share}(q) = \left(1 - \frac{q}{100}\right)^{\frac{\xi+1-\gamma}{\xi}}.$$

In the NTSD data, the average revenue share of the top 5% of firms in 4-digit manufacturing industries is 0.46. Setting $q = 95$ and using $\gamma = 6.04$, the calibration condition becomes

$$0.46 = \left(1 - \frac{95}{100}\right)^{\frac{\xi+1-6.04}{\xi}} = (0.05)^{\frac{\xi-5.04}{\xi}}.$$

Solving for ξ:

$$\xi = \frac{5.04 \cdot \log(0.05)}{\log(0.05) - \log(0.46)} \approx 6.80.$$

Firm Dynamics (ρ, ϕ, q). We jointly calibrate the productivity drop ρ, survival probability ϕ, and transition probability q using three data moments. Let f_t^n and f_t^l denote the mass of age-t firms in the normal and low productivity states, respectively. Starting from a unit mass of entrants ($f_0^n = 1$), the laws of motion are:

$$f_{t+1}^n = \phi q \cdot f_t^n \tag{S57}$$

$$f_{t+1}^l = \phi(1-q)\rho^{\xi} \cdot f_t^n + \phi \cdot f_t^l \tag{S58}$$

where ρ^{ξ} is the probability that a firm transitioning to the low state draws productivity above the survival threshold $\underline{x}/\rho$.

We capture firm entry and exit using survival ratios constructed from the firm age distribution rather than direct entry and exit rates. This choice reflects two features of the NTSD. First, NTSD is a repeated cross-sectional survey and does not reliably track firm exit, making exit rates particularly noisy. Second, the observed firm age distribution is left censored, as many firms enter the sample after inception. Focusing on survival ratios defined over the right tail of the age distribution mitigates these issues while preserving information about selection and exit hazards.

Specifically, we target the following three moments:

1) Zombie firm share. The ratio of low-state firms receiving subsidies to total firms:

$$\text{Zombie ratio} = \frac{\phi(1-q)\rho^{\xi}}{(1-\phi)+\phi(1-q)\rho^{\xi}} \cdot \bar{\tau} \tag{S59}$$

where $\bar{\tau}$ is the average subsidy rate.

2) Survival ratio (age 15+ to 10+). The fraction of firms surviving to age 15 or beyond, relative to those surviving to age 10 or beyond:

$$\frac{\sum_{t=15}^{\infty}(f_t^n + f_t^l)}{\sum_{t=10}^{\infty}(f_t^n + f_t^l)} \tag{S60}$$

3) Survival ratio (age 20+ to 15+). The fraction of firms surviving to age 20 or beyond, relative to those surviving to age 15 or beyond:

$$\frac{\sum_{t=20}^{\infty}(f_t^n + f_t^l)}{\sum_{t=15}^{\infty}(f_t^n + f_t^l)} \tag{S61}$$

The survival ratios discipline the exit hazard at different firm ages: the transition probability q governs how quickly firms fall into the low state, while ϕ determines overall survival. The parameter ρ controls the fraction of transitioning firms that survive.

From the NTSD, the survival ratio of firms aged 15+ to 10+ is 0.827, and the ratio of firms aged 20+ to 15+ is 0.884. Solving the nonlinear system yields $\rho = 0.615$, $\phi = 0.989$, and $q = 0.776$.

Spillover Elasticity (θ). The spillover multiplier $\varkappa(s) = \xi \tilde{M}(s)^{\theta}$ links entry mass to sectoral TFP. Since firm mass $N(s) \propto M(s)$, we calibrate θ by matching the reduced-form relationship between firm numbers and productivity at the sector level. Regressing log(TFP) on log(firm count) with sector and year fixed effects yields an elasticity of approximately $\theta = 0.012$.

Entry Cost and Overhead ($c_e, \bar{k}$). The overhead cost $\bar{k}$ affects the level of aggregate TFP but has no impact on misallocation or the TFP loss decomposition. The entry cost c_e does not affect productivity but enters welfare through the resource constraint. We implicitly calibrate c_e through the economy-wide entry cost share, targeting a value of 0.25% of GDP—reflecting the average venture capital investment share in China.[24]

Sector-specific Components ($\sigma_z, \sigma_{\mu z}$). While the markup distribution is directly estimated from the data, the dispersion of sector-specific components σ_z and their covariance with markups $\sigma_{\mu z}$ cannot be observed directly. We calibrate these parameters using the Simulated Method of Moments (SMM), fixing the marginal distribution of markups to match the

[24] https://mp.weixin.qq.com/s/ML_OAAUJl4_4JTXMF9GG6w

data and estimating the parameters governing the conditional distribution of fundamentals by matching moments of the sectoral revenue distribution.

Identification relies on the structural relationship between sectoral revenue, markups, and productivity. Under the CES demand system, sectoral revenue is proportional to $p(s)^{1-\eta}$. Using the pricing rule and substituting the equilibrium conditions, we derive the structural mapping:[25]

$$\text{Rev}(s) \propto \mu(s)^{\phi} \cdot z(s)^{\eta-1}, \tag{S62}$$

where $\phi = (1-\eta)\left[1 + \left(\frac{1}{\alpha} - 1\right)\left(1 - \frac{1}{\gamma}\right)\right]$ is a composite elasticity. By taking log, we can write

$$\log \text{Rev}(s) = \phi \log \mu(s) + (\eta - 1)\log z(s) + \text{const}. \tag{S63}$$

Since $\mu(s)$ is observed, the residual variation in $\text{Rev}(s)$ identifies the variance of $z(s)$, and the correlation between $\text{Rev}(s)$ and $\mu(s)$ identifies the covariance $\sigma_{\mu z}$.

Formally, we target three moments: (i) the covariance between sector-level log markups and log revenues, $\text{Cov}(\log \mu(s), \log \text{Rev}(s)) = 0.013$; (ii) the top 1% revenue share of 0.27; and (iii) the top 5% revenue share of 0.45. The SMM procedure minimizes the weighted sum of squared deviations between simulated and empirical moments:

$$\min_{\sigma_z, \sigma_{\mu z}} \sum_{m \in \mathcal{M}} w_m \left(\frac{\hat{m}^{\text{sim}} - \hat{m}^{\text{data}}}{\hat{m}^{\text{data}}}\right)^2. \tag{S64}$$

For each candidate parameter pair $(\sigma_z, \sigma_{\mu z})$, we draw 100,000 sectors from the joint distribution

$$\begin{pmatrix} \log \mu(s) \\ \log z(s) \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0.181 \\ 0 \end{pmatrix}, \begin{pmatrix} 0.209^2 & \sigma_{\mu z} \\ \sigma_{\mu z} & \sigma_z^2 \end{pmatrix}\right),$$

compute revenues using equation (S63), and calculate the simulated moments. Table S3 reports the fit. The estimation yields $\sigma_z = 0.385$ and $\sigma_{\mu z} = 0.014$.

[25] We estimate $(\sigma_z, \sigma_{\mu z})$ using the revenue equation without spillovers (i.e., $\theta = 0$) to isolate the baseline mapping between sectoral fundamentals and markups. Spillovers are modeled as a distinct amplification channel operating on top of this baseline, not as an additional source of heterogeneity.

Table S3: Calibration Parameters and SMM Fit

Panel A: Calibrated Parameters

Parameter	Value	Description	Source
β	0.96	Discount factor	Standard
R	1.00	Gross interest rate	Normalized
η	5	Cross-sector elasticity	Epifani & Gancia (2011)
γ	6.04	Within-sector elasticity	Mean markup $\bar{\mu} \approx 1.20$
ξ	6.80	Pareto tail	Top 5% revenue share
ρ	0.615	Low-state productivity factor	Survival/Zombie moments
ϕ	0.989	Survival probability	Survival/Zombie moments
q	0.776	Normal-state persistence	Survival/Zombie moments
α	9.02	Policy sensitivity	Main text estimation
θ	0.012	Spillover elasticity	TFP–firm mass regression
σ_z	0.385	Std. dev. of $\log z(s)$	SMM (Panel B)
$\sigma_{\mu z}$	0.014	$\text{Cov}(\log \mu(s), \log z(s))$	SMM (Panel B)

Panel B: SMM Targeted Moments

Moment	Data	Model
$\text{Cov}(\log \mu, \log R)$	0.013	0.013
Top 1% revenue share	0.27	0.27
Top 5% revenue share	0.45	0.45

Notes: We calibrate the model to match key moments from the NTSD data. Appendix E.7 describes the calibration procedure and the targeted moments in detail. Panel A reports calibrated parameters. Panel B compares targeted empirical moments to model-simulated counterparts from the SMM estimation of σ_z and $\sigma_{\mu z}$.

F Technical Details of the Endogenous-Entry Model

F.1 Profits

Each active firm pays a fixed operating cost of $\bar{k}$ units of capital. Thus the fixed cost in units of the final good is

$$c_f(s) = R(1-\tau(s))\,\bar{k}. \tag{S65}$$

Firm profits can be written as

$$\pi(x_i(s),\tau(s);s) = \Lambda(s)\left(\frac{z(s)\,\varkappa(s)\,x_i(s)}{R(1-\tau(s))}\right)^{\gamma-1} - c_f(s), \tag{S66}$$

where

$$\Lambda(s) \equiv (\mu(s)-1)\mu(s)^{-\gamma}\,p(s)^{\gamma}\,\frac{y(s)}{N(s)}. \tag{S67}$$

Define the productivity cutoff $\underline{x}(s)$ by the zero-profit condition $\pi(\underline{x}(s),\tau(s);s)=0$. Then profits can be expressed relative to the cutoff:

$$\pi(x_i(s),\tau(s);s) = c_f(s)\left[\left(\frac{x_i(s)}{\underline{x}(s)}\right)^{\gamma-1} - 1\right]. \tag{S68}$$

Expression (S68) is independent of $z(s)\varkappa(s)$. This invariance is central for tractability: $z(s)\varkappa(s)$ scales productivity in the same way for all firms in a sector, and therefore cancels out of the cutoff representation.

F.2 Linearization and closed-form decomposition

This section derives a closed-form decomposition of aggregate productivity losses by linearizing the entry and spillover conditions around a symmetric benchmark where $\mu(s)=\bar{\mu}$.

F.2.1 Linearization and Fixed Point

As noted earlier, the spillover $\varkappa(s)=\xi\tilde{M}(s)^{\theta}$ creates a nonlinear feedback loop: higher entry raises $\varkappa(s)$, which increases firm mass and induces further entry. We solve this fixed-point problem by linearizing around a symmetric benchmark where $\mu(s)=\bar{\mu}$.

Step 1: Log-linearize the equilibrium conditions. Taking logs of the firm mass expression and using the normalization $\tilde{M}(s)\equiv M(s)/z(s)^{\eta-1}$:

$$\log\tilde{M}(s) = (\eta-1)\log\varkappa(s) + \frac{\eta(1-\xi)-1}{\xi}\log(1-\tau(s)) + \log\left((\mu(s)-1)\mu(s)^{-\eta}\right) + \text{const} \tag{S69}$$

The spillover function is already log-linear:

$$\log \varkappa(s) = \log \xi + \theta \log \tilde{M}(s) \tag{S70}$$

Step 2: Approximate the markup term. The term $\log\big((\mu(s)-1)\mu(s)^{-\eta}\big)$ is nonlinear in $\log \mu(s)$. A first-order Taylor expansion around $\mu(s) = \bar{\mu}$ yields:

$$\log\big((\mu(s) - 1)\mu(s)^{-\eta}\big) \approx \text{const} + (\gamma - \eta)(\log \mu(s) - \log \bar{\mu}) \tag{S71}$$

where the coefficient $\gamma - \eta$ arises from the elasticity $\frac{d \log[(\mu-1)\mu^{-\eta}]}{d \log \mu}\Big|_{\mu=\bar{\mu}} = \frac{\bar{\mu}}{\bar{\mu}-1} - \eta = \gamma - \eta$, using $\bar{\mu} = \gamma/(\gamma - 1)$.

Step 3: Solve the fixed point. Substitute the spillover relation and the linearized markup term into the entry mass equation:

$$\log \tilde{M}(s) = (\eta - 1)\theta \log \tilde{M}(s) + (\gamma - \eta)(\log \mu(s) - \log \bar{\mu}) + \frac{\eta(1-\xi) - 1}{\xi} \log(1 - \tau(s)) + \text{const}$$

Collect terms in $\log \tilde{M}(s)$ on the left-hand side:

$$\big[1 - (\eta - 1)\theta\big](\log \tilde{M}(s) - \log \bar{\tilde{M}}^0) = \varepsilon^{\text{direct}}_{\tilde{M},\mu}(\log \mu(s) - \log \bar{\mu}) + \varepsilon^{\text{direct}}_{\tilde{M},\tau} \log(1 - \tau(s)) \tag{S72}$$

where we define the *direct* elasticities—the partial effects holding $\varkappa(s)$ fixed:

$$\varepsilon^{\text{direct}}_{\tilde{M},\mu} = \gamma - \eta, \qquad \varepsilon^{\text{direct}}_{\tilde{M},\tau} = \frac{\eta(1-\xi) - 1}{\xi}$$

Provided that $1-(\eta-1)\theta > 0$ (a stability condition ensuring the feedback loop converges), we obtain

$$\log \tilde{M}(s) - \log \bar{\tilde{M}}^0 = \varepsilon_{\tilde{M},\mu}(\log \mu(s) - \log \bar{\mu}) + \varepsilon_{\tilde{M},\tau} \log(1 - \tau(s)) \tag{S73}$$

with *amplified* elasticities that incorporate equilibrium feedback:

$$\varepsilon_{\tilde{M},\mu} = \frac{\gamma - \eta}{1 - (\eta - 1)\theta}, \qquad \varepsilon_{\tilde{M},\tau} = \frac{\eta(1-\xi) - 1}{\xi[1 - (\eta - 1)\theta]} \tag{S74}$$

The amplification factor $[1 - (\eta - 1)\theta]^{-1} > 1$ reflects the multiplier from the entry-spillover feedback loop.

F.2.2 Closed-form expression for sectoral productivity

Combining the cutoff expression, the spillover solution, and the policy rule, log sectoral productivity can be expressed (up to constants) as

$$\log A(s) = \log z(s) + \Phi\big(\log \mu(s) - \log \bar{\mu}\big) - \Xi \log \bar{\mu} + \text{const}, \tag{S75}$$

where the coefficients Φ and Ξ are

$$\Phi \equiv \theta\varepsilon_{\tilde{M},\mu} + \left(\theta\varepsilon_{\tilde{M},\tau} + \frac{1}{\xi}\right)\left(\frac{1}{\alpha} - 1\right), \qquad \Xi \equiv \left(\theta\varepsilon_{\tilde{M},\tau} + \frac{1}{\xi}\right)\left(\frac{1}{\alpha} - 1\right). \tag{S76}$$

Here Φ governs the cross-sectoral dispersion effect from markup heterogeneity, while Ξ captures captures the level effect from the policy rule.

F.2.3 Productivity-loss decomposition

Assume joint log-normality:

$$\log \mu(s) \sim \mathcal{N}(\log \bar{\mu}, \sigma_\mu^2), \qquad \log z(s) \sim \mathcal{N}(\mu_z, \sigma_z^2), \qquad \text{Cov}(\log \mu(s), \log z(s)) = \sigma_{\mu z}. \tag{S77}$$

Since sectoral productivity is log-linear in $(\log \mu(s), \log z(s))$ by equation (S75), the CES aggregator admits exact integration using the log-normal moment generating function. Let A_{eff} denote aggregate productivity in the efficient benchmark. The aggregate productivity loss is:

$$\log A_{\text{eff}} - \log A = \frac{\eta}{2\alpha^2}\sigma_\mu^2 - \Xi \log \bar{\mu} - \frac{\eta - 1}{2}\Phi^2\sigma_\mu^2 - (\eta - 1)\Phi\, \sigma_{\mu z}. \tag{S78}$$

To connect this expression to the allocative–selection–spillover decomposition in Section 6, decompose, write

$$\Xi = \Xi_{\text{sel}} + \Xi_{\text{spill}}, \qquad \Phi = \Phi_{\text{sel}} + \Phi_{\text{spill}}, \tag{S79}$$

where the selection components are the terms that remain when $\theta = 0$:

$$\Xi_{\text{sel}} = \Phi_{\text{sel}} = \frac{1}{\xi}\left(\frac{1}{\alpha} - 1\right), \qquad \Xi_{\text{spill}} = \theta\varepsilon_{\tilde{M},\tau}\left(\frac{1}{\alpha} - 1\right), \tag{S80}$$

and

$$\Phi_{\text{spill}} = \theta\left[\varepsilon_{\tilde{M},\mu} + \varepsilon_{\tilde{M},\tau}\left(\frac{1}{\alpha} - 1\right)\right]. \tag{S81}$$

The productivity loss decomposes into three channels:

Channel 1: Markup Dispersion. The term $\frac{\eta}{2\alpha^2}\sigma_\mu^2$ captures the standard allocative inefficiency from heterogeneous markups.

Channel 2: Selection. Define

$$\Psi_{\text{sel}}(\alpha; \bar{\mu}, \sigma_\mu^2, \sigma_{\mu z}) = -\Xi_{\text{sel}} \log \bar{\mu} - \frac{\eta - 1}{2} \Phi_{\text{sel}}^2 \sigma_\mu^2 - (\eta - 1)\Phi_{\text{sel}} \sigma_{\mu z} \tag{S82}$$

The first term reflects the zombie firm effect—credit subsidies lower cutoff productivity, allowing inefficient firms to survive. The second term captures how selection interacts with markup dispersion, while the third reflects misallocation arising from the correlation between markups and sector-specific components.

Channel 3: Spillover. Define

$$\Psi_{\text{spill}}(\alpha, \theta; \bar{\mu}, \sigma_\mu^2, \sigma_{\mu z}) = -\Xi_{\text{spill}} \log \bar{\mu} - \frac{\eta - 1}{2} \left(2\Phi_{\text{sel}}\Phi_{\text{spill}} + \Phi_{\text{spill}}^2\right) \sigma_\mu^2 - (\eta - 1)\Phi_{\text{spill}} \sigma_{\mu z} \tag{S83}$$

This channel collects all terms involving the spillover parameter θ and vanishes when spillovers are shut down ($\theta = 0$).

F.3 Neutralizing selection with entry subsidies

The cutoff expression reveals that credit subsidies distort firm selection:

$$\underline{x}(s) = \left(\frac{\beta\chi R(1 - \tau(s))\bar{k}}{c_e}\right)^{1/\xi} \tag{S84}$$

Suppose entry costs are also subsidized according to $c_e(1 - \tau^e(s))$ with $1 - \tau^e(s) = 1 - \tau(s)$. The cutoff becomes:

$$\underline{x}(s) = \left(\frac{\beta\chi R\bar{k}}{c_e}\right)^{1/\xi} \tag{S85}$$

eliminating the selection distortion while preserving the MRPK equalization benefit of credit subsidies.

Under combined policy, the entry mass equation gains an additional term from the entry subsidy:

$$\log \tilde{M}(s) = (\eta - 1) \log \varkappa(s) + \frac{\eta(1 - \xi) - 1}{\xi} \log(1 - \tau(s)) - \frac{\eta - 1}{\xi} \log(1 - \tau^e(s)) + \log\left((\mu(s) - 1)\mu(s)^{-\eta}\right) + \text{const}$$

When both instruments move with $\mu(s)$ according to the policy rules, the direct elasticity with respect to the policy wedge changes. Recall that under credit-only:

$$\varepsilon_{\tilde{M},\tau}^{\text{direct}} = \frac{\eta(1 - \xi) - 1}{\xi} = -\eta + \frac{\eta - 1}{\xi} \tag{S86}$$

The first term $(-\eta)$ is the operating profit effect; the second $(\frac{\eta-1}{\xi})$ is the selection effect through the cutoff. Under combined policy, the entry subsidy contributes $-\frac{\eta-1}{\xi}(1/\alpha-1)$ which exactly cancels the selection component, leaving:

$$\varepsilon_{\tilde{M},\tau}^{\text{direct, combined}} = -\eta \tag{S87}$$

The markup elasticity is unchanged: $\varepsilon_{\tilde{M},\mu}^{\text{direct, combined}} = \gamma - \eta$.

Solve the fixed point:

$$\varepsilon_{\tilde{M},\mu}^{\text{combined}} = \frac{\gamma-\eta}{1-(\eta-1)\theta}, \qquad \varepsilon_{\tilde{M},\tau}^{\text{combined}} = \frac{-\eta}{1-(\eta-1)\theta}. \tag{S88}$$

With neutralizing entry subsidies, the selection components vanish:

$$\Xi_{\text{sel}} = \Phi_{\text{sel}} = 0. \tag{S89}$$

The spillover components use the modified elasticities:

$$\Xi_{\text{spill}}^{\text{combined}} = \theta\varepsilon_{\tilde{M},\tau}^{\text{combined}}\left(\frac{1}{\alpha}-1\right) = \frac{-\theta\eta}{1-(\eta-1)\theta}\left(\frac{1}{\alpha}-1\right) \tag{S90}$$

$$\Phi_{\text{spill}}^{\text{combined}} = \theta\left[\varepsilon_{\tilde{M},\mu}^{\text{combined}} + \varepsilon_{\tilde{M},\tau}^{\text{combined}}\left(\frac{1}{\alpha}-1\right)\right] = \frac{\theta}{1-(\eta-1)\theta}\left[(\gamma-\eta)-\eta\left(\frac{1}{\alpha}-1\right)\right]. \tag{S91}$$

With $\Phi_{\text{sel}} = \Xi_{\text{sel}} = 0$, the three-channel decomposition becomes:

$$\log A_{\text{eff}} - \log A = \underbrace{\frac{\eta}{2\alpha^2}\sigma_\mu^2}_{\text{Markup dispersion}} + \left[\underbrace{-\Xi_{\text{spill}}^{\text{combined}}\log\bar{\mu} - \frac{\eta-1}{2}(\Phi_{\text{spill}}^{\text{combined}})^2\sigma_\mu^2 - (\eta-1)\Phi_{\text{spill}}^{\text{combined}}\sigma_{\mu z}}_{\text{Spillover}}\right]. \tag{S92}$$

Comment. The selection channel disappears entirely—no zombie firms, no misallocation from markup-fundamental correlation operating through cutoffs. The spillover channel remains but with a different magnitude: the entry subsidy removes the selection component from the entry response, leaving only the operating profit channel through which credit subsidies affect entry and hence innovation.

F.4 Neutralizing markups with output taxes

The markup $\mu(s)$ distorts relative prices across sectors. An output tax can undo this distortion directly. Suppose sector s faces a proportional output tax at rate $\tau^o(s)$, so that revenue per unit sold becomes $(1-\tau^o(s))\mu(s)mc_i(s)$, where $mc_i(s)$ is the marginal cost. By setting $\tau^o(s) = 1 - \frac{\bar{\mu}}{\mu(s)}$, the output tax can effectively eliminate sectoral markup heterogeneity. This leads to the limiting case where $\sigma_\mu \to 0$.

The TFP loss formula (S78) still applies, involving four terms:

$$\log A_{\text{eff}} - \log A = \underbrace{\frac{\eta}{2\alpha^2}\sigma_\mu^2}_{\text{(i)}} - \underbrace{\Xi \log \bar{\mu}}_{\text{(ii)}} - \underbrace{\frac{\eta-1}{2}\Phi^2\sigma_\mu^2}_{\text{(iii)}} - \underbrace{(\eta-1)\Phi\sigma_{\mu z}}_{\text{(iv)}}. \tag{S93}$$

When $\sigma_\mu \to 0$, all components of the productivity-loss decomposition vanish:

(i) Fundamental markup dispersion: This term vanishes as $\sigma_\mu^2 = 0$.

(ii) First-order term: This term captures the first-order impact of credit subsidies on productivity through both the selection and innovation-spillover channels. When markups are homogeneous, there is no role for capital subsidies to correct markup distortions, $\tau(s) = 0$ for all s. It then follows from (S76) that $\Xi = 0$, and the first-order term vanishes.

(iii) Second-order term: Both credit subsidy and innovation spillover can have a second order impact on markup dispersion, but all vanish with $\sigma_\mu^2 = 0$.

(iv) Covariance term: Since $\sigma_{\mu z} \propto \sigma_\mu = 0$, the covariance term also vanishes.

Therefore, an appropriately chosen output tax can fully eliminate the productivity loss associated with sectoral markup heterogeneity.