Trade and Decelerating Reallocation

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Preliminary

Abstract

A well-documented observation in the trade literature is that trade shocks often result in a protracted reallocation of productive factors. This paper investigates whether the shock itself, through the strategic responses it elicits from firms, actively contributes to this delay. Empirically, I show that the China trade shock is negatively associated with various measures of business dynamism. Theoretically, I propose a dynamic, two-country model of oligopolistic competition with trade and home-country firm dynamics to explain these facts. In my preferred industry-level instrumental-variables specification, increased import exposure accounts for roughly one-half of the recent decline in U.S. gross job reallocation.

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1. Introduction

Business dynamism describes the pace at which factors of production are reallocated from low- to high-productivity enterprises through the processes of job creation, job destruction, and firm entry and exit. Naturally, a trade shock affects all of these outcomes, leading to the question: to what extent can recent decades' declines in business dynamism be explained by rising import competition from abroad? Since the pace of reallocation is known to be a key driver of total factor productivity (TFP) growth, knowing the answer to this question is important (Foster et al., 2001). Consequently, this paper seeks to answer the above question through the lens of a quantitative endogenous growth model with trade in intermediate varieties.

Figure 1 plots the motivating time series. China became a member of the World Trade Organization (WTO) in December 2001: following its entry, the pace of job reallocation in the United States began a sharp decline, and the volume of imports from China to the United States began a sharp rise. By the end of the decade, job reallocation was 30% lower than at its decadal peak. Notably, this decline in job reallocation began *following* the conclusion of the early-2000s recession—which ended in November 2001—and continued unabated through the Great Financial Crisis (GFC) of 2007–2009.

Motivated by such developments, this paper presents a model and new empirical facts linking the recent decline in U.S. business dynamism to rising import penetration from China. In the model, the key force driving declining business dynamism is the classical Schumpeterian tradeoff between escape competition and strategic discouragement (Aghion et al., 2005; Acemoglu and Akcigit, 2012). In initially competitive industries, where home incumbents all have relatively similar production technologies, a trade shock—modeled as a reduction in bilateral iceberg trade costs—induces fierce competition among oligopolistically competitive domestic incumbents to attain leadership in both newly accessible foreign markets and newly contested domestic markets. Because home producers in these markets tend to be much farther ahead technologically than their foreign competitors, neither is particularly discouraged by the sudden emergence of a low-productivity foreign producer. In contrast, in initially uncompetitive industries—where, before the shock, domestic *leaders* hold a large technological advantage over both their domestic and foreign competitors—both foreign and home

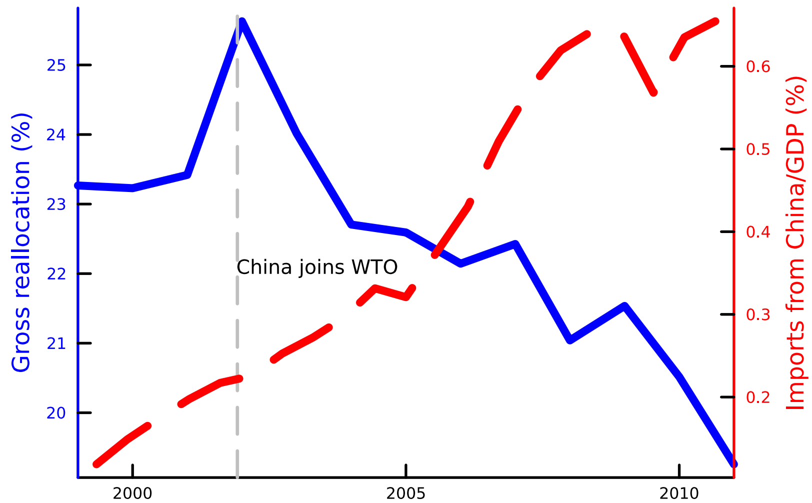


Figure 1: **Recent trends.** The solid blue line (left y-axis) plots the rate of gross reallocation in the United States between 1999 and 2011. The dashed red line (right y-axis) plots the value of imports from China, normalized by U.S. GDP, between 1999 and 2011. The dashed gray line denotes December 2001, when China joined the World Trade Organization (WTO).

laggards must engage in a protracted innovation race to earn market leadership. Doing so is costly. This induces strategic discouragement on the part of laggards; the leaders internalize the discouragement of the laggards and themselves reduce their efforts to stay far ahead of the competition. The net result is a less dynamic economy. In aggregate, these two forces compete with one another, and the balance is determined by the split of industries by competitiveness prior to the shock.

The emergence of such forces in the model is highly dependent on the chosen quantification. Therefore, I adopt a conservative estimation strategy: I discipline the model with moments exclusively drawn from U.S. business dynamics *prior* to the China shock; no information on U.S.–China trade or Chinese firm dynamics informs the estimation. To the extent that my model is capable of explaining the evolution of the macroeconomic data over the relevant period of analysis, then, it is entirely through the theoretical structure of the model.

I then expose my chosen quantification to a variety of shocks and trace the impulse response of the perfect-foresight transition. These shocks represent different hypotheses for how exposure to foreign competition might affect U.S. firms. I consider higher Chinese research productivity, increased knowledge spillovers from the United States to China, and lower bilateral trade costs. USTR (2023) and related work document concerns about the transfer or misappropriation of U.S. firms' intellectual property; I represent the associated increase in cross-border knowledge flows as a rise in η_{HF}. Among the three counterfactuals, the trade-cost reduction most closely matches the qualitative pattern in the data: it reproduces the direction of five of the six moment changes, although the magnitudes differ and the markup response has the opposite sign.

The quantitative analysis shows that the model can reproduce much of the pattern in the macroeconomic data, but does it do so through the channel outlined above? To answer this question, I augment the quantitative analysis with microdata. Adopting the instrumental-variables strategy of Acemoglu et al. (2016) and Borusyak et al. (2022), I find that a rise in import exposure from China is associated with a statistically significant decline in gross job reallocation and a statistically significant rise in productivity dispersion. In my preferred industry specification, increased import exposure accounts for roughly one-half of the decline in gross reallocation over the period of analysis. Running the same regressions in the model—by simulating a panel of home-country firms over the perfect-foresight transition—I recover elasticities comparable in magnitude to those from the empirical exercises. In both the model and the data, the effects are stronger in initially more concentrated industries, consistent with the Schumpeterian channels outlined at the outset.

My results extend our current understanding of how trade shocks propagate through the economy. A key finding of the China shock literature has been a puzzling slowness in reallocating factors of production—namely workers—from more affected to less affected sectors and firms (Autor et al., 2014, 2016). The pace of reallocation is, in reality, endogenous: firm decisions on how intensively to compete for market leadership are key determinants. To my knowledge, mine is the first paper to explain how trade shocks themselves are capable of slowing the pace of reallocation. Though the scope of this paper is positive, the result may have substantial implications for optimal trade and labor-market policy; the normative analysis is left for future work.

Literature review. This paper contributes to two distinct, rich literatures: on the China shock and on declining U.S. business dynamism.

The China shock literature has found profound impacts of rising import exposure from China on manufacturing employment. Directly, rising import exposure explains roughly 10–25% of the overall decline in U.S. manufacturing employment between 1990 and 2007 (Autor et al., 2013; Charles et al., 2019; Caliendo et al., 2019). Through input-output linkages, the estimated employment losses range from 2.0 million to 2.4 million jobs, with a key role assigned to China's accession to the WTO (Acemoglu et al., 2016; Pierce and Schott, 2016). Numerous auxiliary outcomes of interest have also been studied in the China shock literature. Though firm innovation is not the primary focus of this paper, my model is drawn from a class of models that is often used to study firm innovation outcomes, and the China shock, and trade shocks more broadly, have been found to have mixed effects on the innovation efforts and outcomes of affected firms (Bloom et al., 2016; Gong and Xu, 2017; Autor et al., 2020a; Hoberg et al., 2021; Liu et al., 2021; Chakravorty et al., 2024; Fadeev, 2023). My contribution to this literature is to bring in endogenous firm dynamics and general-equilibrium analysis in a fully dynamic setting. In doing so, I am able to explain slowness in the pace of reallocation. In this sense, the closest paper to my own is that of Caliendo et al. (2019). In their paper, frictions to reallocation are exogenous and all firms are ex ante and ex post identical. In my paper, reallocation is slowed by optimal firm decisions; firms are ex post heterogeneous; and there is endogenous growth and heterogeneity in firm market power. The drawbacks of my approach relative to theirs are an inability to study spatially heterogeneous outcomes in the home country and the restriction of my model to a two-country trade environment.

Most closely related empirically, Asquith et al. (2019) use establishment-level data to decompose the employment response to the China shock into job creation from establishment births and expansions, and job destruction from establishment deaths and contractions. Section 4.5 explains how their cumulative adjustment measures relate to my evidence on annual reallocation rates.

The literature studying declining business dynamism is similarly rich.[1] Much of the theoretical work in this literature has adopted modeling frameworks similar to my own, namely that class of models first put forward by Aghion and Howitt (1992) and Klette and Kortum (2004). I adopt an open-economy version of these models, similar to the ones studied in Akcigit et al. (2018), Choi and Shim (2024), and Sui (2023). Indeed, numerous complementary explanations for declining business dynamism have been pro-

[1] For a primer, see Decker et al. (2016b,c, 2017, 2020) and Akcigit and Ates (2021), among others.

posed, ranging from declining knowledge diffusion (Akcigit and Ates, 2021, 2023); declining financial discounts (Liu et al., 2022; Chikis et al., 2023); declining quality of laggard innovations (Olmstead-Rumsey, 2022); and positive shocks to fixed-cost-intensive technologies (Aghion et al., 2019; De Ridder, 2024). I do not claim to have the best or only explanation; rather, my contribution is to highlight a potentially novel, empirically relevant channel—international competition in product markets—through which domestic business dynamism can decline. In this sense, the closest paper to my own is Sui (2023), who shows that in the class of models studied, trade shocks have heterogeneous impacts on domestic leaders and domestic laggards, giving rise to forces that can produce a less dynamic economy.

The remainder of the paper proceeds as follows. Section 2 presents the model; Section 3 quantifies it. Section 4 provides further empirical support for the predictions of the model, and Section 5 concludes.

2. Model

In this section, I propose a two-country model of trade and endogenous growth. Time t is continuous ($0 \leq t < \infty$). There is potentially unbalanced trade in every period and no international trade in assets.[2]

2.1 Households and static equilibrium

There are two countries, H and F, indexed by c.[3] Each country has a mass L_c of homogeneous workers that are infinitely lived and that provide labor perfectly inelastically in each period. They choose streams of consumption and asset holdings to maximize lifetime utility:

$$\begin{aligned} \mathcal{U}_c = & \max_{\{C_c(t), A_c(t)\}_{t \geq 0}} \int_0^\infty e^{-\rho t} \log C_c(t) dt \\ \text{s.t.} \qquad & P_c(t)C_c(t) + \dot{A}_c(t) \leq r_c(t)A_c(t) + w_c(t)L_c + T_c(t) \end{aligned} \tag{1}$$

[2] Thus, any trade imbalance takes the form of an exogenous transfer. See Appendix D for details.

[3] These will alternatively be labeled "home" and "foreign."

where ρ is the rate of subjective discount; $w_c(t)$ is country c's wage at time t; $r_c(t)$ is country c's interest rate at time t, determined endogenously; $A_c(t)$ is country c's holdings of assets at time t; $T_c(t)$ is a lump-sum transfer for residents of country c; and $P_c(t)$ is the ideal price index of final-good consumption. In what follows, the home-country price index will be the numeraire so that $P_H(t) = 1$, without loss of generality. Intertemporal optimization on the part of country c households implies an Euler equation:

$$g_c(t) \equiv \frac{\dot{C}_c(t)}{C_c(t)} = r_c(t) - \rho \tag{2}$$

where, under balanced growth, $g \equiv g_c(t) + \frac{\dot{P}_c(t)}{P_c(t)}$ is common across all countries c.[4]

The final good is aggregated in each country under perfect competition according to a nested Cobb-Douglas, CES production function. There is a continuum of intermediate varieties indexed by $(i, j) \in \{H, -H, F\} \times [0, 1]$

$$Y_c(t) = \exp\left(\int_0^1 \log\left[\left(\psi_H^{1-\beta} y_{Hjc}(t)^\beta + \psi_H^{1-\beta} y_{-Hjc}(t)^\beta + \psi_F^{1-\beta} y_{Fjc}(t)^\beta\right)^{\frac{1}{\beta}}\right] dj\right) \tag{3}$$

where $(1-\beta)^{-1} \in (0, \infty)$ is the elasticity of substitution between a given variety (i, j) and (i', j) and $\psi_H, \psi_F \in (0, 1)$ satisfy $2\psi_H + \psi_F = 1$ and represent home bias. This gives rise to the ideal price index of the final good:

$$P_c(t) = \exp\left(\int_0^1 \log\left[\left(\psi_H p_{Hjc}(t)^{\frac{\beta}{\beta-1}} + \psi_H p_{-Hjc}(t)^{\frac{\beta}{\beta-1}} + \psi_F p_{Fjc}(t)^{\frac{\beta}{\beta-1}}\right)^{\frac{\beta-1}{\beta}}\right] dj\right). \tag{4}$$

In what follows I omit time indices where it causes minimal confusion. A firm is thus fully described by a triple (i, j, c) where $i \in \{H, -H, F\}$ denotes the firm (home leader; home laggard; and foreign incumbent); j denotes the industry-level variety it produces; and $c \in \{H, F\}$ denotes the country or market—used interchangeably—it is selling to.

Given demand, (3), each firm i in j faces a demand curve in market c:

$$y_{ijc} = \frac{\psi_{|i|} p_{ijc}^{\frac{1}{\beta-1}}}{\sum_{i'} \psi_{|i'|} p_{i'jc}^{\frac{\beta}{\beta-1}}} P_c Y_c \tag{5}$$

[4] Since the numeraire is the home-country final good, it can be shown that $\frac{\dot{P}_H(t)}{P_H(t)} = \frac{\dot{P}_F(t)}{P_F(t)} = 0$ along a balanced growth path (BGP).

where $|-H| = H$ is a slight abuse of notation. Firms produce with a common, linear production function in all markets they are active in

$$y_{ijc} = \frac{q_{ij} l_{ijc}}{1 + \tau_X \mathbb{1}\{c \neq |i|\}} \tag{6}$$

where q_{ij} is firm i's labor productivity; l_{ijc} is labor it hires for production for sales in market c; and $\tau_X \geq 0$ is a symmetric iceberg trade cost for selling in a foreign market.[5]

Assumption 1 *Given some initial level of labor productivity, $q_{ij}(0)$, labor productivity can take on a countable number of values along a quality ladder; the rungs of this ladder are indexed by a scalar parameter $\lambda > 1$ such that $\frac{q_{ij}}{q_{i'j}} = \lambda^{n_{ii'j}}$ where $n_{ii'j} \in \mathbb{Z}$ is the number of rungs along the quality ladder that firm i's labor productivity leads that of firm i' in variety j. Note that $n_{ii'j} = -n_{i'ij}$.*

Assumption 2 *Firms compete in prices (i.e. à la Bertrand).*

Assumptions 1 and 2 will make all objects from the static equilibrium solely a function of the relative gaps between home leaders and home laggards, $n_{HHj} \in \mathbb{N}$ and home leaders and foreign incumbents, $n_{HFj} \in \mathbb{Z}$, as well as the relative wage between home and foreign, $\frac{w_H}{w_F}$. Therefore, in what follows, I omit the index j wherever it causes minimal confusion. Firm i in line j, selling in market c, sets the following price and labor schedule given its share of the market, $z_{ijc} = \frac{p_{ijc} y_{ijc}}{\sum_{i'} p_{i'jc} y_{i'jc}}$:

$$p_{ijc} = \frac{1 - \beta z_{ijc}}{\beta (1 - z_{ijc})} (1 + \tau_X \mathbb{1}\{c \neq |i|\}) \frac{w_{|i|}}{q_{ij}} \tag{7}$$

$$l_{ijc} = \frac{P_c Y_c}{w_{|i|}} \frac{\beta z_{ijc}(1 - z_{ijc})}{1 - \beta z_{ijc}} \tag{8}$$

These choices give rise to static period profits, Π_{ijc}:

$$\Pi_{ijc} = \frac{z_{ijc} (1 - \beta)}{1 - \beta z_{ijc}} P_c C_c \tag{9}$$

Appendix A shows how to solve for market shares, z_{ijc}, given quality gaps, (n_{HHj}, n_{HFj}), and relative wages, $\frac{w_H}{w_F}$. For now, it suffices to know that—for a fixed relative wage $\frac{w_H}{w_F}$—

[5] A firm i draws its labor from country $|i|$.

z_{ijc} is weakly increasing in $(n_{ii'j}, n_{ii''j})$ for all $i, i', i'' \in \{H, -H, F\}$ and that this relationship is strict whenever $i \neq i'$ and $i \neq i''$.

Due to Assumptions 1 and 2, firms charge variable markups that are functions of $\boldsymbol{\sigma} = (i, n_{HH}, n_{HF})$ in each line j. Let $N \equiv \mathbb{N} \times \mathbb{Z}$ denote the state space and let $\boldsymbol{n} = (n_{HH}, n_{HF}) \in N$, where $n_{HH} \geq 0$ is the number of steps the home leader leads the home laggard and $n_{HF} \in \mathbb{Z}$ is the number of steps a home leader leads a foreign incumbent.[6] For the purposes of aggregation, it suffices to keep track of a probability mass function $\{\mu^{\boldsymbol{n}}\}_{\boldsymbol{n}}$, where $\mu^{\boldsymbol{n}} = \Pr\{j \text{ has gap pair } \boldsymbol{n}\}$. Numerically, I impose a finite upper limit on the number of steps a firm can lead its competitors.

2.2 Innovation

Firms undertake innovation in order to improve their own productivities. Doing so increases their market share and, hence, profits according to (9). A firm i hiring $G(x; B, \gamma)$ scientists at wage rate $w_{|i|}$ achieves a Poisson arrival rate of innovation x where:

$$G(x; B, \gamma) = \left(\frac{x}{B}\right)^{\frac{1}{\gamma}}. \tag{10}$$

$G(\cdot)$ is a cost function of R&D; $\gamma \in (0, 1)$ regulates its convexity and $B > 0$ is a cost shifter. Innovation is step-by-step or "slow," in the spirit of Acemoglu and Akcigit (2012). When a firm attains an innovation, its productivity evolves according to $q_{ij}(t + dt) = \lambda q_{ij}(t)$.

2.3 Knowledge diffusion

I will often speak of the firm i in j with the leading technology ($q_{ij} \geq \max_{i'} q_{i'j}$) as being "at the technological frontier." Firms that are behind the technological frontier can also improve their productivities by receiving knowledge spillovers from competitors. Knowledge flows both between and within countries. With exogenous Poisson intensity $\eta_{HH} \geq 0$, knowledge diffuses from the home leader, H, to the home laggard, $-H$; in like fashion, knowledge can flow from the foreign incumbent to the home incumbents, $\eta_{FH} \geq 0$, or from either of the home incumbents to the foreign incumbent,

[6] When a foreign incumbent leads the home leader, $n_{HF} < 0$.

$\eta_{HF} \geq 0$.[7] When a knowledge spillover occurs, the receiving firm i's productivity becomes the maximum of i's current productivity and the productivity of the sending firm i': $q_{ij}(t+dt) = \max\{q_{ij}(t), q_{i'j}(t)\}$.

2.4 Dynamic problem of the firm

I first consider the problem of the home leader in an industry with gap pair $\boldsymbol{n} = (n_{HH}, n_{HF})$—where $n_{HH} > n_{HF} > 0$ and $n_{HH} > 1$—in its recursive form. Let $V_i^{\boldsymbol{n}}$ denote the value of being a firm $i \in \{H, -H, F\}$ in an industry with gap pair $\boldsymbol{n}$.[8,9] The Hamilton–Jacobi–Bellman (HJB) equation for firm H is given by:

$$\begin{aligned}
r_H V_H^{\boldsymbol{n}} = \dot{V}_H^{\boldsymbol{n}} + (1-\tau_{HH})\Pi_{HH}^{\boldsymbol{n}} + (1-\tau_{FH})\Pi_{HF}^{\boldsymbol{n}} + \\
\max_{x_H^{\boldsymbol{n}}} \left\{ -(1-\tau_H^{\text{R\&D}}) w_H G(x_H^{\boldsymbol{n}}; B_H, \gamma) + x_H^{\boldsymbol{n}} \left(V_H^{\boldsymbol{n}+1} - V_H^{\boldsymbol{n}} \right) \right\} + \\
x_{-H}^{\boldsymbol{n}} \left(V_H^{n_{HH}-1, n_{HF}} - V_H^{\boldsymbol{n}} \right) + x_F^{\boldsymbol{n}} \left(V_H^{n_{HH}, n_{HF}-1} - V_H^{\boldsymbol{n}} \right) + \\
x_H^{\boldsymbol{n},E} \left(V_H^{n_{HH}-1, n_{HF}} - V_H^{\boldsymbol{n}} \right) + x_F^{\boldsymbol{n},E} \left(V_H^{n_{HH}, n_{HF}-1} - V_H^{\boldsymbol{n}} \right) + \\
\eta_{HH} \left(V_H^{0, n_{HF}} - V_H^{\boldsymbol{n}} \right) + \eta_{FH} \left(V_H^{n_{HF}, n_{HF}} - V_H^{\boldsymbol{n}} \right) + \eta_{HF} \left(\frac{1}{2} \left(V_H^{n_{HH}, 0} + V_H^{\boldsymbol{n}} \right) - V_H^{\boldsymbol{n}} \right)
\end{aligned} \tag{11}$$

where $\tau_H^{\text{R\&D}}$ is an R&D subsidy, and τ_{HH} and τ_{FH} are corporate taxes facing the firm in markets H and F. Entrant innovation intensities are given by $\{x_c^{\boldsymbol{n},E}\}_{c \in \{H,F\}}$; the entrant problem is detailed in Section 2.5. Equation (11) has the usual interpretation: the left-hand side equates the return from investing $V_H^{\boldsymbol{n}}$ dollars in the safe asset and earning the risk-free interest rate r_H with the expected return of holding the risky asset. Namely, owning firm H in an industry with gap pair $\boldsymbol{n}$ yields capital gains of $\dot{V}_H^{\boldsymbol{n}}$ and flow profits from sales in markets H and F, Π_{HH} and Π_{HF}, along with capital losses that accrue when competitors—home laggards and foreign incumbents along with potential entrants in both countries—achieve their own innovations or knowledge spills over (third, fourth, and fifth lines, respectively). The firm's choice, $x_H^{\boldsymbol{n}}$, is made to maximize the capital gain

[7] Conditional on the event that knowledge flowed from home to foreign, I assume there is a uniform probability of that flow originating from either of the two home incumbents. In some instances, then, the knowledge spillover is useless to the foreign incumbent—for example when $n_{HF} \leq n_{HH}$ (i.e. when the receiving firm is less behind the frontier than the sending firm).

[8] In the finite numerical approximation to N, I reflect transitions at the boundaries. See Appendix B.

[9] Below and throughout, addition and subtraction of scalars to and from vectors are elementwise.

of a successful innovation, $\Delta V_H^{\boldsymbol{n}} = V_H^{\boldsymbol{n}+1} - V_H^{\boldsymbol{n}}$, net of R&D costs, taking competitor strategies as given. Given the global convexity of (10), the equilibrium choice of innovation by the firm satisfies:

$$x_H^{\boldsymbol{n}} = \max\left\{ B_H \left[\frac{\Delta V_H^{\boldsymbol{n}}}{w_H(1-\tau_H^{\text{R\&D}})} B_H \gamma\right]^{\frac{\gamma}{1-\gamma}}, 0 \right\}. \tag{12}$$

The problem of the foreign incumbent can be formulated similarly. It will often be helpful to work with the scaled value functions, $v_i^{\boldsymbol{n}} = \frac{V_i^{\boldsymbol{n}}}{P_{|i|}C_{|i|}}$. Along a BGP, note that (2) implies that $r_{|i|} = \rho + \frac{\dot{C}}{C} + \frac{\dot{P}}{P}$ so that under the same restrictions as above for $\boldsymbol{n}$, the scaled value function of the foreign incumbent can be expressed as:

$$\begin{aligned}
\rho v_F^{\boldsymbol{n}} = (1-\tau_{HF})\pi_{FH}^{\boldsymbol{n}}\tilde{\psi}_{HF} + (1-\tau_{FF})\pi_{FF}^{\boldsymbol{n}} + \\
\max_{x_F^{\boldsymbol{n}}} \left\{ -(1-\tau_F^{\text{R\&D}})\omega_F G(x_F^{\boldsymbol{n}}; B_F, \gamma) + x_F^{\boldsymbol{n}} \left(v_F^{n_{HH}, n_{HF}-1} - v_F^{\boldsymbol{n}} \right) \right\} + \\
x_H^{\boldsymbol{n}} \left(v_F^{\boldsymbol{n}+1} - v_F^{\boldsymbol{n}} \right) + x_{-H}^{\boldsymbol{n}} \left(v_F^{n_{HH}-1, n_{HF}} - v_F^{\boldsymbol{n}} \right) + \\
x_F^{\boldsymbol{n},E} \left(0 - v_F^{\boldsymbol{n}} \right) + x_H^{\boldsymbol{n},E} \left(v_F^{n_{HH}-1, n_{HF}} - v_F^{\boldsymbol{n}} \right) + \\
\eta_{HH} \left(v_F^{0, n_{HF}} - v_F^{\boldsymbol{n}} \right) + \eta_{FH} \left(v_F^{n_{HF}, n_{HF}} - v_F^{\boldsymbol{n}} \right) + \eta_{HF} \left(\frac{1}{2} \left(v_F^{\boldsymbol{n}} + v_F^{n_{HH}, 0} \right) - v_F^{\boldsymbol{n}} \right)
\end{aligned} \tag{13}$$

where $\omega_c = \frac{w_c}{P_c C_c}$, $\pi_{cc'}^{\boldsymbol{n}} = \frac{\Pi_{cc'}^{\boldsymbol{n}}}{P_{c'}C_{c'}}$, and $\tilde{\psi}_{cc'} = \frac{P_c C_c}{P_{c'}C_{c'}}$. The remaining Hamilton-Jacobi-Bellman (HJB) equations are presented in Appendix B.

2.5 Entry

In each period t and each country $c \in \{H, F\}$ there is a unit mass of entrants who direct their entry to a particular sector j with gap pair $\boldsymbol{n}$. They choose an innovation intensity $x_c^{\boldsymbol{n},E} \geq 0$ under innovation cost function $G(\cdot; B_c^E, \gamma)$. If successful, they enter one step ahead of the less productive domestic incumbent; otherwise, they exit and are immediately replaced by a new entrant firm.[10] Let $\mathbb{M}_{\boldsymbol{n}}^{E,c}(i, \boldsymbol{n}') : \{H, -H, F\} \times N \to [0,1] = \Pr\{(i, \boldsymbol{n}') | \boldsymbol{n}, \text{Successful } c \text{ entrant innovation}\}$.[11] The recursive country c entrant prob-

[10] In industries where $n_{HH} = 0$, home entrants replace either home incumbent with equal probability.

[11] For example, in the example studied in Section 2.4, $\mathbb{M}_{n_{HH},n_{HF}}^{E,F}(F, n_{HH}, n_{HF}-1) = 1$—zero otherwise. See Appendix B for full specification.

lem is given by:

$$r_c V_c^{\boldsymbol{n},E} - \dot{V}_c^{\boldsymbol{n},E} = \max_{x_c^{\boldsymbol{n},E}} \left\{ -w_c G(x_c^{\boldsymbol{n},E}; B_c^E, \gamma) + x_c^{\boldsymbol{n},E} \sum_{i,\boldsymbol{n}'} \mathbb{M}_{\boldsymbol{n}}^{E,c}(i, \boldsymbol{n}') \left(V_i^{\boldsymbol{n}'} - 0 \right) \right\}. \tag{14}$$

2.6 Keeping track of the economy's state

The state of the economy is a probability mass function $\{\mu^{\boldsymbol{n}}\}_{\boldsymbol{n}}$ which gives the measure of industries $j \in [0,1]$ where the gap pair is $\boldsymbol{n}$.[12] At all periods t, it satisfies the Kolmogorov forward equation (KFE):

$$\frac{\mu^{\boldsymbol{n}}(t+dt) - \mu^{\boldsymbol{n}}(t)}{dt} = \text{Inflow}^{\boldsymbol{n}}(\{\mu^{\boldsymbol{n}}\}_{\boldsymbol{n}}) - \text{Outflow}^{\boldsymbol{n}}(\{\mu^{\boldsymbol{n}}\}_{\boldsymbol{n}}). \tag{15}$$

For the industry studied in Section 2.4:

$$\begin{aligned} \text{Inflow}^{\boldsymbol{n}}(\{\mu^{\boldsymbol{n}}\}_{\boldsymbol{n}}) = {} & x_H^{n_{HH}-1,n_{HF}-1} \mu^{n_{HH}-1,n_{HF}-1} + \eta_{FH} \mathbb{1}_{n_{HH}=n_{HF}} \sum_{n'_{HH} > n_{HF}} \mu^{n'_{HH},n_{HF}} \\ & + \left(x_{-H}^{n_{HH}+1,n_{HF}} + x_H^{(n_{HH}+1,n_{HF}),E} \right) \mu^{n_{HH}+1,n_{HF}} + \left(x_F^{n_{HH},n_{HF}+1} + x_F^{(n_{HH},n_{HF}+1),E} \right) \mu^{n_{HH},n_{HF}+1} \end{aligned} \tag{16}$$

and

$$\begin{aligned} \text{Outflow}^{\boldsymbol{n}}(\{\mu^{\boldsymbol{n}}\}_{\boldsymbol{n}}) = \Bigg(& \sum_{i \in \{H,-H,F\}} x_i^{\boldsymbol{n}} + \sum_{c \in \{H,F\}} x_c^{\boldsymbol{n},E} + \eta_{HH} \mathbb{1}_{n_{HH}>0} + \\ & \eta_{FH} \mathbb{1}_{n_{HH}>n_{HF}} + \eta_{HF} \mathbb{1}_{n_{HF}>0} \left(1 - \frac{1}{2} \mathbb{1}_{n_{HF}<n_{HH}} \right) \Bigg) \mu^{\boldsymbol{n}}. \end{aligned} \tag{17}$$

Complete formulae for $\text{Inflow}^{\boldsymbol{n}}$ and $\text{Outflow}^{\boldsymbol{n}}$ are given in Appendix C.

2.7 Equilibrium

A full statement of the model equilibrium is provided in Appendix D. For now, a truncated statement suffices. An equilibrium of the model presented above is a collection of

[12] Since $j \in [0,1]$, this measure can be thought of as a probability measure.

prices and quantities, Υ:

$$\Upsilon = \Bigg\{ \{Y_c(t), C_c(t), A_c(t), P_c(t), w_c(t), r_c(t)\}_{c\in\{H,F\}}, \\ \{y_{ijc}(t), p_{ijc}(t), l_{ijc}(t)\}_{i\in\{H,-H,F\}, c\in\{H,F\}}, \{x_i^{\boldsymbol{n}}(t), {}^c x_i^{\boldsymbol{n}}(t), v_i^{\boldsymbol{n}}(t)\}_{i\in\{H,-H,F\},\boldsymbol{n}\in N}, \\ \{x_c^{\boldsymbol{n},E}(t)\}_{\boldsymbol{n}\in N, c\in\{H,F\}}, \{\mu^{\boldsymbol{n}}(t)\}_{\boldsymbol{n}\in N} \Bigg\}_{t\in[0,\infty)} \tag{18}$$

such that all markets clear and all firms and households optimize. In calibrating the model, I focus on **balanced growth path** (BGP) equilibria; these are equilibria where all detrended nominal variables are time invariant. See Acemoglu and Akcigit (2012) for a proof of existence and uniqueness of balanced-growth-path equilibria in this class of models. Appendix E discusses a solution algorithm for the model.

2.8 Model extensions

In subsequent sections, I extend the model along the following lines to represent more realistically the various tradeoffs facing firms and countries under international competition for market leadership.

2.8.1 Offshore R&D

There is considerable offshore R&D activity that the model cannot currently account for (Fan, 2025). If research productivity is higher in country H than in country F, firm F may want to hire R&D labor in country H. Conversely, if the relative wage were lower in country F, then country H may want to hire research labor in country F. Generally, since $G(\cdot)$ is globally convex, to avoid diminishing returns, firms will generally want to spread out their R&D labor. In an extension, I allow for this cross-border activity. So long as firm i is restricted to drawing *production* labor from country $|i|$, tractability is maintained. The inner maximization problem of firm i becomes:

$$\max_{x_i^{\boldsymbol{n},|i|}, x_i^{\boldsymbol{n},\tilde{\mathcal{C}}(|i|)}} \Bigg\{ -\Big((1-\tau^{\text{R\&D}}_{|i||i|})w_{|i|}G(x_i^{\boldsymbol{n},|i|}; B_{|i|}, \gamma) + (1-\tau^{\text{R\&D}}_{\tilde{\mathcal{C}}(|i|)|i|})w_{\tilde{\mathcal{C}}(|i|)}G(x_i^{\boldsymbol{n},\tilde{\mathcal{C}}(|i|)}; B_{\tilde{\mathcal{C}}(|i|)}, \gamma)\Big) + \\ \left(x_i^{\boldsymbol{n},|i|} + x_i^{\boldsymbol{n},\tilde{\mathcal{C}}(|i|)}\right)\Delta V_i^{\boldsymbol{n}} \Bigg\} \tag{19}$$

where $\tilde{\mathcal{C}}(\cdot)$ is defined in Appendix B. The only additional modification is to account for cross-border R&D in labor market clearing (Appendix D).

2.8.2 Trade wars

Since 2018, there has been an ongoing trade war between the United States and China, in which each side has imposed tariffs on either a retaliatory or a preemptive basis, justified on national security grounds or on the grounds that the competing country is behaving unfairly. Following Choi and Shim (2024), in an extension, I introduce tariffs as an additional iceberg cost (levied after the fundamental iceberg cost). This affects the static equilibrium as follows:

$$y_{ijc} = \frac{q_{ij} l_{ijc}}{1 + \tau_X \mathbb{1}\{c \neq |i|\}} \frac{1}{1 + t_c \mathbb{1}\{c \neq |i|\}} \tag{20}$$

$$p_{ijc} = \frac{1 - \beta z_{ijc}}{\beta (1 - z_{ijc})} \left(1 + \tau_X \mathbb{1}\left\{c \neq |i|\right\}\right) \left(1 + t_c \mathbb{1}\{c \neq |i|\}\right) \frac{w_{|i|}}{q_{ij}} \tag{21}$$

where t_c is the tariff rate of country c.

2.8.3 National security costs

The trade war was undertaken, at least in part, on perceived national security grounds. To better study optimal policy, following Akcigit et al. (2024), I introduce a cost of losing leadership in certain industries. Let $\Omega_{cc'}$ be the measure of industries in country c where the leading firm is from country c'. I propose a quadratic cost denominated in country c's aggregate expenditure:

$$C(\Omega_{cc'}) = \begin{cases} \chi_0 \Omega_{cc'}^2 P_c Y_c & , c \neq c' \\ 0 & , c = c' \end{cases} \tag{22}$$

where χ_0 is a cost shifter. Results for these extensions will be presented in Appendix F.

2.9 Discussion of relevant model forces

Though explicit, analytical characterizations of the forces underlying the model are generally difficult to derive, the literature has pointed to several prominent ones that bear consideration for this paper's application.

1. **Escape competition effect.** This force was first introduced into the endogenous growth literature by Aghion et al. (2005) and is present in my model. It induces more innovation and dynamism in industries where firms are "neck-and-neck," or where n_{HH} and $|n_{HF}|$ are "small," because the rents from "winning the race"—getting to the frontier—are quite large relative to the cost.

2. **Discouragement effect.** In contrast, in industries where n_{HH} and $|n_{HF}|$ are large, there is likely to be strategic discouragement. Firms far behind the frontier recognize that a costly R&D race is unlikely to be won and that, even if won, victory is unlikely to have a positive present value. Leader firms anticipate laggards' reduced innovation incentives and engage in strategic accommodation. These discouragement forces are a focus of recent work by Liu et al. (2022). The cumulative effects of the escape competition and discouragement effects depend on the overall distribution of competition in the economy, as summarized by $\{\mu^{\boldsymbol{n}}\}_{\boldsymbol{n}}$.

3. **Market size effect.** There are powerful scale effects at play. All else equal, a larger population implies a lower marginal cost of production through a lower market-clearing wage. The implications for innovation are ambiguous. On the one hand, a larger labor force may induce firms to innovate less and rely more on cheap labor to win the competition for market share. On the other hand, a larger labor force implies a larger domestic market for goods, higher potential period profits, and thereby heightened efforts directed to winning the competition for market leadership through technology, q_{ij}.

3. Quantification

In this section, I quantify the theoretical model presented in Section 2.

3.1 Calibration strategy

I calibrate the model in one step. I assume the economy is in steady state in 1991. The two countries, H and F, correspond to the United States and China, respectively; I refer to them as home and foreign interchangeably. To discipline the initial BGP, I use only moments informative about U.S. business dynamism in 1991; neither trade data nor data from China are used to discipline the initial equilibrium.[13] Then, I shock the iceberg trade cost parameter, τ_X, by 50% and trace the impulse response of the model economy. Therefore, if the dynamics of the transition resemble reality, it is entirely through the mechanics of the model. I also experiment with shocks to China's research productivity and knowledge diffusion between the United States and China and find they have less explanatory power than a pure trade shock.

I choose moments that the firm-dynamics literature has identified as relevant for studying the decline in business dynamism in the first two decades of the 21$^{\text{st}}$ century: the growth rate of aggregate TFP; the rate of gross reallocation, a common measure of churn in the economy; the dispersion of firm growth rates; average markups; and the firm entry rate.

3.2 Externally calibrated parameters

Following the literature, I set the curvature parameter for R&D production, γ, to be 0.35 and the subjective rate of time preference, ρ, to be 5% on an annual basis (Acemoglu et al., 2018). I assume R&D labor and profits are subsidized and taxed, respectively, at a rate of 20%, common to both countries; these values are broadly in line with the literature (Akcigit and Ates, 2023). Since there are two home firms and one foreign firm in each industry, in order for there to be symmetry, I impose that $2\psi_H = \psi_F = 0.50$ (Choi and Shim, 2024). I choose the elasticity of substitution between varieties within the CES nest to be 6 following Broda and Weinstein (2006); the iceberg trade cost is externally calibrated to be 0.50 following Anderson and van Wincoop (2004). Lastly, I set the trade deficit to unity—$\Delta = 1$ (Appendix D). Of course, there is a meaningful trade deficit between the United States and China, and in future work, I hope to explore this issue in further detail.

[13]The one exception is the externally calibrated L_F, discussed in further detail in Section 3.3.

3.3 Discussion on choices of L_H and L_F

The last two parameters to be externally calibrated are L_H and L_F, the sizes of the home and foreign labor forces. These choices require careful justification: I normalize the home labor force to unity and set the foreign labor force to 65% of the home labor force. Since China, in 1991, had a population roughly five times larger than that of the United States, some discussion is in order.

3.3.1 Private sector, urban manufacturing employment

Due to the presence of considerable nontradable economic activity in both the United States and China—in contrast to the model, where all sectors are tradable—the relevant comparison is not between each country's total population or total labor force. The literature studying the China shock has typically focused on economic outcomes in manufacturing sectors, which I follow in Section 4 (Autor et al., 2013; Acemoglu et al., 2016).

Thus, to calibrate L_H and L_F, my analysis focuses on manufacturing employment in the United States and China. Data for the United States are readily available; data for China present challenges. As discussed by Banister (2005) and Benedetto (2018), nationwide manufacturing-employment counts for China are not consistently measured across sources and years, especially near the turn of the millennium. Practitioners often rely on data from China's National Bureau of Statistics (NBS)—specifically, the count of manufacturing workers in urban areas (Lardy, 2015). The remaining issue is whether to include the sizable urban manufacturing employment in state-owned enterprises (SOEs). Determining whether SOEs are major players in export markets is important: even if their motives are not well captured by the profit-maximizing behavior posited in the model, it would be difficult to justify excluding them if they are major exporters. However, Khandelwal (2015), in a comment on Hsieh and Song (2015), finds that 73% of exports by value during the China-shock period originated from the private sector, implying that SOE activity is likely to be segmented from the dynamics relevant for the model.

3.3.2 Innovation employment

In the model, labor is homogeneous: the same labor that is used for R&D is used for production. Therefore, there is an argument for using research employment as the relevant comparison between the United States and China, as this is likely to be the "rate-limiting" step.

3.3.3 Constructing the labor-force ratio

Based on the discussion in Section 3.3.1, I compare the number of manufacturing workers in the private sector in urban areas from Banister (2005) with the total number of manufacturing workers in the United States (from FRED) for the most recent post-1991 period after a structural break in the Chinese data. This yields a ratio of 0.66.[14] Second, using World Bank data, I obtain the number of researchers per million people in China and the United States for 1996—the most recent year for which data are commonly available—and multiply it by population to obtain the number of researchers in each country. This yields 0.64: for every researcher in China in 1996, there are $0.64^{-1} \approx 1.6$ researchers in the United States. I then take the simple average of these numbers to arrive at 0.65.

3.4 Internally calibrated parameters

The remaining parameters to be calibrated are the knowledge spillover parameters (η_{HH}, η_{FH}, η_{HF}); the productivity step size parameter, λ; and the scale parameters for R&D production (B_H, B_F, B_H^E, B_F^E) in both countries. I follow the literature and discipline these using simulated method of moments (SMM) (Lentz and Mortensen, 2008). Let $\Theta = (\eta_{HH} = \eta_{FH} = \eta_{HF}, \lambda, B_H, B_F, B_H^E, B_F^E)$ be a vector of free parameters and let $M(\Theta)$ be the vector of moments obtained through these parameters. I search for a Θ^* such that:

$$\Theta^* \in \arg\min_{\Theta} \left\{ \sum_{m \in M(\Theta)} w_m \frac{|\text{Model}_m - \text{Data}_m|}{\frac{1}{2}\left(|\text{Model}_m| + |\text{Data}_m|\right)} \right\} \tag{23}$$

where w is a vector of subjective weights. When calibrating, I set all weights to unity.

[14] Banister (2005) reports 11.44 million in 1998 (the most recent year after a structural break in the series); FRED reports 17.45 million in December 1998—$\frac{11.44}{17.45} \approx 0.66$.

Parameters				Moments			
Parameter	Description	Value	Source	Description	Model	Data	Source
L_H	Home-country labor force	1.00	Normalization	TFP growth rate, g	1.14%	0.91%	Fernald (2015)
L_F	Foreign-country labor force	0.65	FRED, World Bank, and Banister (2005)	Gross reallocation	23.98%	24.65%	BDS Decker et al. (2016c)
$\tau^H_{\text{R\&D}} = \tau^F_{\text{R\&D}}$	Subsidy rate	20.00%	Literature	Firm growth standard deviation	56.00%	50.19%	Decker et al. (2016c)
$\tau^H = \tau^F$	Tax rate	20.00%	Literature	Firm growth $P90 - P10$	63.99%	59.51%	Decker et al. (2016c)
ρ	Discount rate	5.00%	Literature	Mean markup	33.66%	39.50%	De Loecker et al. (2020)
$\psi_F = 2\psi_H$	Home bias	0.50	Externally calibrated	Firm entry rate	12.86%	10.59%	BDS Decker et al. (2016c)
γ	Curvature, R&D cost	0.35	Literature				
$(1-\beta)^{-1}$	Elasticity of substitution	6.00	Broda and Weinstein (2006)				
τ_X	Iceberg trade cost	0.50	Anderson and van Wincoop (2004)				
$\eta_{HH} = \eta_{FH} = \eta_{HF}$	Knowledge diffusion	0.05	SMM				
λ	Productivity step size	1.01	SMM				
B_H	Cost parameter, home R&D	6.72	SMM				
B_F	Cost parameter, foreign R&D	1.57	SMM				
B^E_H	Cost parameter, home entrant	0.80	SMM				
B^E_F	Cost parameter, foreign entrant	0.95	SMM				

Table 1: **Model calibration.**

3.5 Results

Table 1 shows the results of the model calibration. The quality of fit is quite good. The model economy features incumbent U.S. firms that have higher research productivity than their Chinese competitors; U.S. entrants and Chinese entrants appear to have roughly similar research productivities. Both the productivity step size parameter, λ, and the knowledge diffusion parameters, $\eta_{\cdot\cdot}$, have values broadly in line with those previously reported by the literature.

3.6 Implications of a trade shock for U.S. business dynamism

To what extent can various proposed shocks explain the decline in business dynamism witnessed over 1991–2007? In particular, was the China shock primarily (i) a trade shock, modeled as a reduction in τ_X; (ii) a research-productivity shock, modeled as a rise in B_F and B^E_F; or (iii) a knowledge-diffusion shock, modeled as a rise in η_{HF}? To answer these questions, I shock the calibrated model and compare BGPs. I then solve for and simulate the model's full transition.

3.6.1 A reduction in iceberg trade costs

China acceded to the World Trade Organization (WTO) in 2001. This accession made foreign markets more accessible to Chinese exporters and Chinese markets more accessible to foreign exporters. Thus, it is natural to think of this as a reduction in bilateral iceberg trade costs. To study whether this shock might induce the changes in business dynamism witnessed over the period in question, I shock the iceberg trade cost parame-

Moment	Data, $\Delta_{1991\to2007}$	Model, $\downarrow \tau_X$, $\Delta_{1991\to2007}$	Model, $\uparrow B_F, B_F^E$, $\Delta_{1991\to2007}$	Model, $\uparrow \eta_{HF}$
TFP growth rate, g	-31.47%	-0.44%	5.28%	3.84%
Gross reallocation	-9.45%	-3.83%	1.30%	1.04%
Firm growth standard deviation	-8.28%	-1.85%	0.53%	0.16%
Firm growth $P90 - P10$	-9.94%	-10.51%	1.90%	1.31%
Firm entry rate	-5.62%	-2.67%	1.10%	0.63%
Mean markup	35.67%	-6.48%	-0.04%	-0.10%

Table 2: **Comparison of BGPs in response to a 50% reduction in iceberg trade costs, τ_X.**

ter, τ_X, by 50%. The effect is shown in Table 2. A reduction in iceberg trade costs predicts changes with the same sign as the data for five of the six pre-shock moments; the counterfactual markup response differs from the observed response.[15]

3.6.2 A rise in Chinese research productivity

An alternative way of viewing the China shock is through a rise in the productivity of Chinese firms in generating innovations. This could arise because of large human-capital investments in China during the period in question or an easing of misallocation unleashed by widespread privatization during the intervening period (Hsieh and Song, 2015). A natural way to capture this is to shock the research productivities of incumbents and entrants. I test this by increasing B_F and B_F^E by 50%. The results are reported in Column (4) of Table 2; this shock predicts changes opposite in sign to the data for every moment.

3.6.3 Rising knowledge diffusion from the United States to China

Hoberg et al. (2021), Office of the United States Trade Representative (2023), and related work document concerns about the transfer or misappropriation of U.S. firms' intellectual property. I represent the associated increase in cross-border knowledge flows as a rise in η_{HF}. I therefore test the implications of a 50% rise in η_{HF}. The results are reported in Column (5) of Table 2; as with a rise in Chinese research productivity, this shock does not explain the evolution of the data over the period considered.

[15] The iceberg trade cost enters delivered marginal costs in Equation (7); equilibrium markups also depend on the distribution $\{\mu^n\}_n$.

	Gross reallocation			TFP dispersion			Growth rate dispersion		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Foreign share	-0.969***	-0.230*	-0.133	0.321***	0.168**	0.155*	-0.531***	-0.021	-0.003
	(0.10)	(0.11)	(0.13)	(0.06)	(0.06)	(0.08)	(0.10)	(0.11)	(0.14)
Δ Foreign share $\times$ Initial concentration	—	—	-0.175	—	—	0.024	—	—	-0.032
	—	—	(0.13)	—	—	(0.08)	—	—	(0.14)
Initial concentration control	—	✓	✓	—	✓	✓	—	✓	✓

Table 3: **Model regressions.** Standard errors are robust to heteroskedasticity. Sample size is 9,861 simulated industry-level observations.

3.7 Transition results

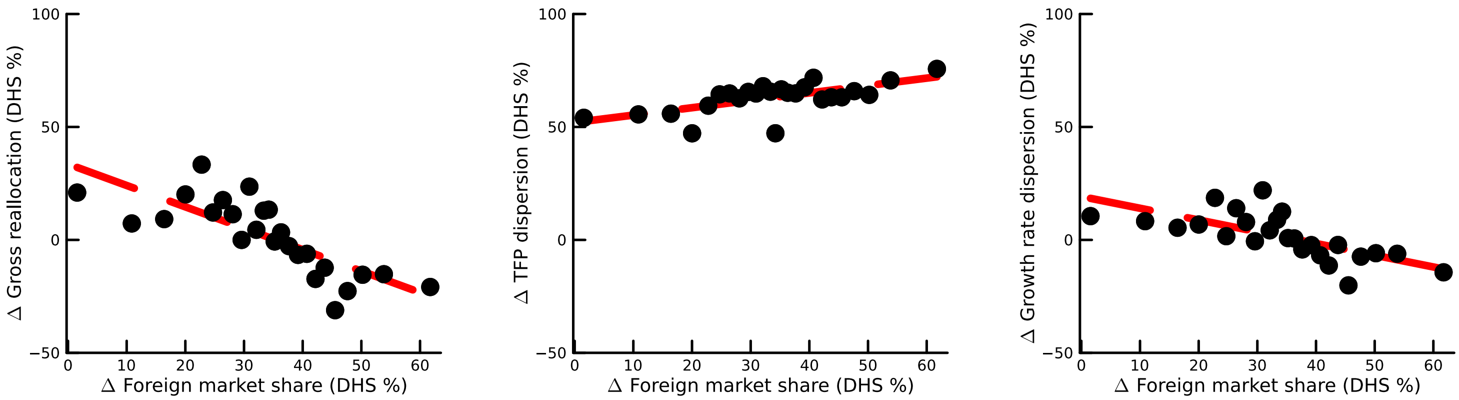
In this section, I solve the full transition of the calibrated model from Section 3.5, after reducing the iceberg trade cost parameter by 50%. Of particular interest is whether, cross-sectionally, industries that are more exposed to imports see larger declines in dynamism. This provides more direct evidence of what the steady-state results from Section 3.6 suggested. To run this regression, I simulate 9,861 industries—each composed of a home leader, home laggard, foreign incumbent, and two potential entrants—over the transition for 10 years. In the first 5 years, the iceberg parameter is 0.50; in the last 5 years it is 0.25. Then, I run the following first-difference regressions (all changes are à la Davis, Haltiwanger and Schuh 1998).

$$\Delta Y_{j,t\to t+\Delta t} = \alpha + \beta \Delta \text{Foreign share}_{j,t\to t+\Delta t} + \varepsilon_{jt} \tag{24}$$

$$\Delta Y_{j,t\to t+\Delta t} = \alpha + \gamma \text{Home concentration}_t + \beta \Delta \text{Foreign share}_{j,t\to t+\Delta t} + \varepsilon_{j,t} \tag{25}$$

$$\begin{aligned} \Delta Y_{j,t\to t+\Delta t} = \alpha + \gamma \text{Home concentration}_t + \beta \Delta \text{Foreign share}_{j,t\to t+\Delta t} + \\ \omega \Delta \text{Foreign share}_{j,t\to t+\Delta t} \times \mathbb{1}\{\text{Above median concentration}\}_{j,t} + \varepsilon_{j,t} \end{aligned} \tag{26}$$

Later, in Section 4, I run analogs of these regressions in the data. Equation (24) tests whether more import-exposed industries experience larger declines in various dynamism measures (β); Equation (25) tests the same hypothesis but controls for initial concentration (β); and Equation (26) asks whether more initially concentrated industries experience more pronounced declines in dynamism ($\beta + \omega$). The goal is to understand which forces elucidated in Section 2.9 might be driving the comparative statics in Table 2.



(a) **Gross reallocation.** (b) **TFP dispersion.** (c) **Growth rate dispersion.**

Figure 2: **Model regressions.** Plots are binscatter plots. Sample size is 9,861 simulated industry-level observations. Best-fit lines correspond to Columns (1), (4), and (7), respectively, of Table 3. Standard errors are robust to heteroskedasticity.

3.7.1 Gross reallocation

Results for gross reallocation are shown in Columns (1)–(3) of Table 3 and Figure 2a. Both unconditionally and conditional on initial domestic concentration, more import-exposed industries see larger decreases in dynamism. After interacting import exposure with initial concentration, the interaction estimate is no longer statistically significant at conventional levels, but the point estimates have the same direction: more import-exposed industries see larger declines in dynamism, with an additional decline in industries that were initially more concentrated. This is reminiscent of Aghion et al. (2005), where initially more concentrated industries experience strategic discouragement (Section 2.9).

3.7.2 TFP dispersion

Results for TFP dispersion are similar to those for gross reallocation. TFP dispersion rises more in industries that are more import-exposed, even after controlling for initial concentration. In the fully interacted regression, the point estimate has the same direction but is not statistically significant at conventional levels.

Due to lack of detailed, publicly available microdata, TFP dispersion is a nontargeted moment. Akcigit and Ates (2023) discuss why TFP dispersion may be a relevant moment for considering the decline in dynamism: if market leaders become many multiples more productive than market laggards, laggards may become discouraged and the economy may witness a decline in churn (proxied by gross reallocation) and overall competitiveness. Andrews et al. (2015) find evidence that leaders have indeed pulled far ahead of laggards during the period of analysis.

3.7.3 Growth rate dispersion

Growth rate dispersion has declined in the data and in the comparison between steady states in the model, as reported in Table 2. In the model, this result appears to correlate with changes in import exposure, but it is the weakest result: after controlling for initial concentration, the point estimate is not statistically significant at conventional levels.

To match how I treat the data, I use DHS employment-growth rates. In the model, these growth rates have a counterintuitive implication: conditional on survival, the most productive firms shrink in terms of their overall employment. This occurs because, when firms get very far ahead of their nearest competitors, strategic accommodation reduces their innovation incentives, while their high productivity allows them to charge a high price—essentially substituting markups for output—and thereby reduce overall employment. However, entry and exit still drive growth dispersion in the expected way.[16] In the aggregate, this counterintuitive behavior of firm employment growth does not prevent the model from matching the macroeconomic data over the period in question, but conditioning on initial concentration—where this behavior is more observable because of the presence of large incumbent leaders—leads to empirically ambiguous results.

4. Empirical evidence in support of the model

In this section, I explore more direct empirical evidence consistent with the model presented in Sections 2 and 3. I also present new facts linking declining U.S. business dynamism to rising import exposure from China, using both industry-level and geographic variation.

[16] Entering firms have DHS growth rates of $+200\%$; exiting firms have DHS growth rates of -200%.

4.1 Data

Data for studying the business dynamics of U.S. firms and establishments come from the Business Dynamics Statistics (BDS) of the U.S. Census Bureau (Chow et al., 2021). Import-penetration data are from Autor et al. (2013, 2014), and commuting-zone employment data are from Acemoglu et al. (2016). Total factor productivity (TFP) data come from the NBER-CES Manufacturing Industry Database (Becker et al., 2021). Data on productivity dispersion come from the U.S. Census Bureau's Dispersion Statistics on Productivity (DiSP) (Cunningham et al., 2023). Data on concentration in the manufacturing sector come from the 1992 Economic Census, publicly available on the Census Bureau's website.

4.2 Empirical strategy

I follow Autor et al. (2013) and Acemoglu et al. (2016) and define geographic and industry-based measures of changes to exposure to Chinese import competition as follows.

$$\Delta IP^{\text{Ind.}}_{j,t\to t+\Delta t} = \frac{\Delta M^{UC}_{j,t\to t+\Delta t}}{Y_{j,1991} + M_{j,1991} - X_{j,1991}} \tag{IND}$$

$$\Delta IP^{\text{Geo.}}_{c,t\to t+\Delta t} = \sum_j \frac{E_{c,j,t}}{\sum_{j'} E_{c,j',t}} \Delta IP^{\text{Ind.}}_{j,t\to t+\Delta t} \tag{GEO}$$

$\Delta M^{UC}_{j,t\to t+\Delta t}$ is the dollar-value change in imports from China to the United States in industry j between periods t and $t+\Delta t$; $Y_{j,1991}$ is total industry shipments in industry j in 1991; and $M_{j,1991} - X_{j,1991}$ is net industry j imports in 1991. $\Delta IP^{\text{Geo.}}_{c,t\to t+\Delta t}$ is the change in import penetration for commuting zone c between t and $t+\Delta t$; it is an employment-weighted average of the industry-level shocks.[17]

To assess how changes in Chinese import competition have affected outcomes of

[17]These weights may not sum to one because some employment in commuting zone c is in nontradable sectors, which, by default, have $\Delta IP^{\text{Ind.}}_{j,t\to t+\Delta t} = 0$. I follow Borusyak et al. (2022) and adjust for this in my regression analysis by controlling for the total initial-period share of tradable-sector employment in a commuting zone, interacted with a period dummy.

interest, I run the generalized regressions

$$\Delta Y_{j,t\to t+\Delta t} = \alpha_j + \delta_t + \beta \Delta IP^{\text{Ind.}}_{j,t\to t+\Delta t} + \mathbf{X}'_{j,0}\boldsymbol{\gamma} + \varepsilon_{j,t} \tag{27}$$

$$\Delta Y_{c,t\to t+\Delta t} = \delta_t + \beta \Delta IP^{\text{Geo.}}_{c,t\to t+\Delta t} + \mathbf{X}'_{c,0}\boldsymbol{\gamma} + \varepsilon_{c,t}. \tag{28}$$

Here, j denotes an industry; c denotes a commuting zone (CZ); and t denotes a period. α_j and δ_t are industry and period fixed effects, respectively.[18]

Where does identification come from? To fix ideas, in markets where American and Chinese firms compete, equilibrium outcomes respond to contemporaneous supply and demand shocks for American and Chinese varieties. The supply shock of interest for this paper is the rise in Chinese manufacturing productivity, which is potentially heterogeneous across specific subsectors, j, and would ideally be proxied by $\Delta IP^{\text{Ind.}}_{j,t\to t+\Delta t}$. However, realized $\Delta IP^{\text{Ind.}}_{j,t\to t+\Delta t}$ reflects simultaneous supply and demand shocks. Therefore, estimation of Equations (27) and (28) is confounded by simultaneity bias. To credibly identify β, I follow Acemoglu et al. (2016) and employ an instrumental-variables strategy, constructing foreign counterparts of $\Delta IP^{\text{Ind.}}_{j,t\to t+\Delta t}$.

$$\Delta IPO^{\text{Ind.}}_{j,t\to t+\Delta t} = \frac{\Delta M^{OC}_{j,t\to t+\Delta t}}{Y_{j,1988} + M_{j,1988} - X_{j,1988}} \tag{IND-O}$$

$$\Delta IPO^{\text{Geo.}}_{c,t\to t+\Delta t} = \sum_j \frac{E_{c,j,1988}}{\sum_{j'} E_{c,j',1988}} \Delta IPO^{\text{Ind.}}_{j,t\to t+\Delta t} \tag{GEO-O}$$

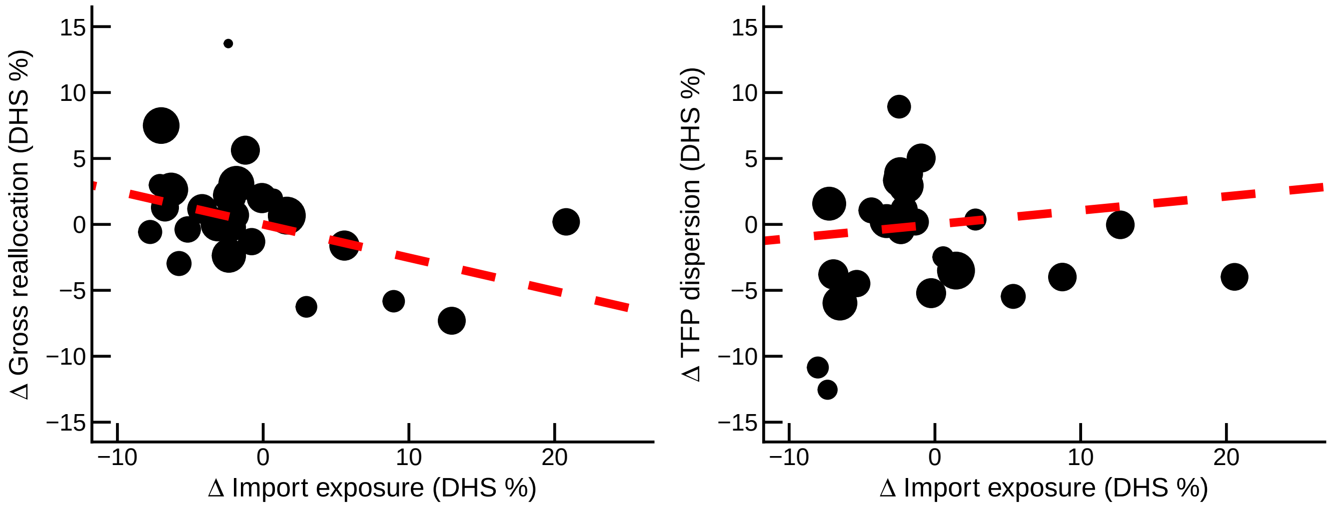
where the superscript O refers to a collection of eight high-income economies.[19,20] The identifying assumption is that industry demand shocks are uncorrelated across countries, but that industries' exposure to the Chinese manufacturing productivity shock is common.

An important challenge to consider in the above empirical strategy is the possibility of industry- or region-specific confounders. For example, if an industry or region was hit by a shock that is correlated with the China trade shock—and this shock goes

[18] Unless otherwise specified, for $\Delta Y_{j,t\to t+\Delta t}$, I follow Autor et al. (2020a) and consider growth rates à la Davis, Haltiwanger and Schuh (1998) (DHS growth rates): $\Delta Y_{j,t\to t+\Delta t} = \frac{Y_{j,t+\Delta t} - Y_{j,t}}{0.5(Y_{j,t+\Delta t} + Y_{j,t})}$. Thus, the β coefficients have the approximate interpretation of elasticities.

[19] These economies are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[20] I follow Acemoglu et al. (2016) and use 1988 employment shares for (GEO-O).



(a) **Gross reallocation.** (b) **TFP dispersion.**

Figure 3: **Binscatter for data.** Both panels use industry variation—Equation (IND). The change in import exposure is uninstrumented. Both panels project out year fixed effects. The dashed red line is the OLS best-fit line. The size of each dot is proportional to the weights used in the regressions in Tables 4 and 6.

unmodeled—β is no longer identified.[21] To address this, I add a battery of j-specific controls to (27) and (28) that, in the stacked first-difference specification above, remove industry- and region-specific trends.[22] For the industry-level regressions, out of concern for overfitting, I alternatively follow Acemoglu et al. (2016) and control for variation only at the single-digit supersector level.

By removing these industry-specific effects, the likelihood of confounding shocks is significantly diminished. I also provide falsification exercises using outcomes measured before the China trade shock (Table 5).

4.3 Declining business dynamism and import exposure

A large literature has explored the effects of rising Chinese import competition on employment in tradable sectors.[23] A somewhat distinct literature has focused on the secular decline in U.S. business dynamism.[24] To what extent, however, can rising Chinese import competition explain declining business dynamism?

To answer this question, I run industry- and commuting-zone-level regressions on common measures of business dynamism. Aligning with the nontargeted moments explored in Section 3.7, my chosen measures of dynamism are gross job reallocation and productivity (TFP) dispersion.[25] Figure 3 shows that the correlations in the data match those in the model. However, as discussed above, these correlations are confounded by simultaneity bias and industry-specific confounders.

Therefore, I estimate Equations (27) and (28). Results are shown in Table 4. Across specifications, a rise in import exposure—at either the industry or commuting-zone level—is associated with a decline in gross reallocation and a rise in productivity dispersion, consistent with the macroeconomic data and with the microdata generated by the model (Table 3).

Column (1) presents estimates from a two-stage least-squares (TSLS) regression with (IND-O) and (GEO-O) as the instruments for Panels A and B, respectively. A 1% rise in import exposure at the industry level is associated, on average, with a 0.32% decline in gross reallocation and a 0.27% rise in TFP dispersion. These are small but economically relevant elasticities. As a rough back-of-the-envelope calculation, the mean industry's 5.6% rise in import exposure implies a predicted 1.8% decline in gross reallocation. Because the mean industry experienced a 10.3% decline in gross reallocation between

[21]Examples could be the secular decline in manufacturing-sector activity (Charles et al., 2019) or the secular, broad-based decline in business-dynamism measures such as gross job reallocation (Decker et al., 2016b, 2017).

[22]Industry controls are at the j level (i.e., four-digit SIC fixed effects). Geographic controls are at the Census-division level (i.e., nine Census divisions). I do not include commuting-zone-level fixed effects because, following Borusyak et al. (2022), I control for initial tradable-sector employment in the commuting zone interacted with period dummies, which would be collinear with commuting-zone-level fixed effects.

[23]For example, see Autor et al. (2013); Acemoglu et al. (2016); and Pierce and Schott (2016).

[24]For example, see Decker et al. (2016b, 2017) and Akcigit and Ates (2021, 2023).

[25]Gross reallocation is the sum of the job creation and job destruction rates and is a common measure of dynamism in the economy. My concept of productivity is five-factor (capital, production labor, nonproduction labor, energy, and nonenergy materials) total factor productivity (TFP).

	Panel A: Industry variation		
	(1)	(2)	(3)
Gross reallocation	-0.315***	-0.281**	-0.768*
	(0.079)	(0.105)	(0.298)
TFP dispersion	0.271**	0.304**	0.838**
	(0.100)	(0.109)	(0.304)
	Panel B: Geographic variation		
Gross reallocation	-4.359*	—	-3.347*
	(1.637)	—	(1.568)

*—5% confidence; **—1% confidence; ***—0.1% confidence.

Table 4: **The effect of rising import competition on domestic business dynamism.** Column (1) lists the results of a TSLS regression in stacked first differences over 1991–1999 and 1999–2007 with period fixed effects—for Panel B, the controls are the commuting-zone-level sum of shares used to define the instrument in (GEO-O), interacted with period dummies as recommended by Borusyak et al. (2022). Column (2) lists the results of a TSLS regression in first differences over 1991–1999 and 1999–2007 with time and single-digit SIC fixed effects. Column (3) lists the results of a TSLS regression in first differences over 1991–1999 and 1999–2007 with period and four-digit SIC fixed effects—for Panel B, the controls are nine Census-division dummies and the commuting-zone-level sum of shares used to define the instrument in (GEO-O), interacted with period dummies as recommended by Borusyak et al. (2022). For Panel A, standard errors are clustered at the four-digit SIC-code level; observations are weighted by the average of 1990 and 1991 four-digit SIC-code employment. For Panel B, standard errors are clustered at the state level; observations are weighted by 1990 commuting-zone population. For "TFP dispersion," I map six-digit NAICS codes to four-digit SIC codes using the crosswalk of Autor et al. (2013). For "Gross reallocation," I map four-digit NAICS codes to four-digit SIC codes using the crosswalk of Autor et al. (2013).

1991 and 2007, these estimates account for roughly one-fifth of that decline.

One potential objection to lending the above analysis a causal interpretation is that sectors in which China has experienced rising productivity—and hence rising import exposure—may coincide with sectors experiencing secular declines in the chosen measures of dynamism. I first note that the declines in dynamism are widely acknowledged to be widespread across sectors, but most severe in retail trade and high tech (Decker et al., 2016a), both of which have zero exposure to trade in my data. To address this concern more directly, I add sectoral controls at the four-digit sector level (Column (3)), which, in the first-difference specification, remove sectoral trends from the identifying variation. Column (3) is my preferred specification. A back-of-the-envelope calculation using this specification attributes roughly one-half of the decline in gross reallocation to the rise in import exposure from China.[26]

Controlling for four-digit sector fixed effects is quite demanding because the identi-

[26] In Autor et al. (2013), Acemoglu et al. (2016), and related papers, standard practice is to load $\mathbf{X}_{j0}$ with many controls to address industry- or commuting-zone-level confounds. In contrast, my use of j-level fixed effects nonparametrically captures any j-level confounds that these papers' controls *parametrically* project out. For example, Acemoglu et al. (2016) use the change in the overall employment share for industry j between 1976 and 1991 as a control. In my specification, a j-level fixed effect would be perfectly collinear with this control and any other j-level control.

	With controls	No controls
Industry variation, 1979–1989	0.013	0.025
	(0.055)	(0.055)
Geographic variation, 1979–1989	-5.313*	-3.731
	(2.184)	(2.819)

Table 5: **Falsification tests.** The table shows the results of regressing changes in gross reallocation over 1979–1989 on the mean change in China import exposure over 1991–1999 and 1999–2007. Weights are given by sector employment shares in 1979. For industry variation, controls are the single-digit sector controls from Table 4. For geographic variation, controls are the Census-division controls along with the initial manufacturing-sector employment shares.

fying variation is at the four-digit sector $\times$ period level, and there are only two periods; this may raise concerns of overfitting. Therefore, I follow Acemoglu et al. (2016) and control for single-digit sector trends. Results are preserved and shown in Column (2).

Panel B repeats the above analysis at the commuting-zone level. Results are quantitatively much larger. Here, there are only two estimates because I am unable to control for commuting-zone-level fixed effects: the adjustment of Borusyak et al. (2022) would be perfectly collinear with a commuting-zone-level fixed effect. I interpret these results cautiously for the reasons described in the next paragraph.

As a final empirical exercise, I run falsification regressions of changes in business-dynamism outcomes during the decade before the shock on mean changes in import exposure over 1991–1999 and 1999–2007, with and without covariates. Evidence supporting the design would be estimates close to zero, with confidence intervals that exclude economically meaningful pretrends. Results are presented in Table 5.[27] For the most part, the estimated coefficients are close to zero or have the opposite sign and are statistically indistinguishable from zero. However, the controlled geographic estimate for gross reallocation is statistically significant and negative. I therefore interpret the Panel B estimates in Table 4 cautiously.

4.4 Schumpeterian theory

Aghion et al. (2005) observe that canonical theories of competition and innovation predict a negative correlation between the two. However, there is weak empirical evidence in support of this prediction. They build a model in which, in initially competitive industries, competition shocks are pro-innovation and pro-dynamism, while in initially

[27]Data for TFP dispersion do not extend far enough back in time to permit a falsification exercise.

	Panel A: Import exposure		
	(1)	(2)	(3)
Gross reallocation	-0.262***	-0.269**	-0.544*
	(0.072)	(0.096)	(0.243)
TFP dispersion	0.264*	0.290*	0.589*
	(0.128)	(0.135)	(0.265)
	Panel B: Import exposure $\times$ $\mathbb{1}\{$More concentrated$\}$		
Gross reallocation	-0.138	-0.130	-1.119*
	(0.138)	(0.151)	(0.436)
TFP dispersion	0.012	0.035	0.866*
	(0.156)	(0.178)	(0.379)

*—5% confidence; **—1% confidence; ***—0.1% confidence.

Table 6: **Regression results when interacted with initial concentration.** Panel A shows the regression loading for β in (29); Panel B shows the regression loading and standard error for ω. Column (1) has no controls. Column (2) controls for period and single-digit SIC fixed effects. Column (3) controls for period and four-digit SIC fixed effects. Weights are the same as those used in Table 4. Standard errors are clustered at the four-digit SIC level.

uncompetitive industries, competition shocks are anti-innovation and anti-dynamism. As discussed in Section 2.9, similar forces are nested within my model. The estimates in Table 3 provide some support for the view that escape-competition and strategic-discouragement forces drive the quantitative results. I test for similar relationships in the data by running the following regression:

$$\Delta Y_{j,t\to t+\Delta t} = \alpha_j + \delta_t + \beta \Delta IP^{\text{Ind.}}_{j,t\to t+\Delta t} + \omega \Delta IP^{\text{Ind.}}_{j,t\to t+\Delta t} \times \mathbb{1}\{\text{Above median concentration}\}_{j,0} + \mathbf{X}'_{j,0}\gamma + \varepsilon_{j,t}. \quad (29)$$

Following Autor et al. (2020b), I measure concentration using the share of sales accounted for by the top 20 firms in an industry in 1992.[28] Results are shown in Table 6. In the preferred specification—with period and sector fixed effects—more import-exposed industries undergo larger declines in dynamism; this effect is stronger in industries that are initially more concentrated, consistent with the evidence presented in Table 3 and with the theory.

4.5 Relationship to existing literature

Autor et al. (2013) and Acemoglu et al. (2016) show that regions and industries more exposed to Chinese import competition experienced steeper declines in employment.

[28] The 1992 Economic Census is the closest year to 1991 for which data are available.

At face value, my negative estimate for gross job reallocation is difficult to square with this result: accommodating an employment decline would seem to require greater job destruction and hence greater gross reallocation.

The distinction is between a cumulative net change and the pace of annual churn. The employment literature typically studies

$$\log E_{j,t+\Delta t} - \log E_{j,t}, \tag{30}$$

whereas my outcome is the change in the annual gross-reallocation rate, $GR_{j,t} = JC_{j,t} + JD_{j,t}$:

$$\Delta GR_{j,t\to t+\Delta t} = \frac{GR_{j,t+\Delta t} - GR_{j,t}}{0.5\left(GR_{j,t+\Delta t} + GR_{j,t}\right)}. \tag{31}$$

Employment can therefore decline over a period even if the annual pace of job creation and destruction is lower at its end.

The closest empirical antecedent is Asquith et al. (2019), who use NETS establishment data to decompose the employment response to the China shock into job creation from establishment births and expansions, and job destruction from establishment deaths and contractions. In their baseline manufacturing IV specification, import exposure substantially increases job destruction while leaving job creation approximately unchanged; establishment deaths account for more than 70% of the gross employment adjustment attributed to the shock. Their finding is therefore one of predominantly one-sided displacement through establishment closure, rather than offsetting creation and destruction.

Their estimates do not directly corroborate my negative reallocation coefficient: adding their job-creation and job-destruction responses implies greater cumulative gross adjustment. But neither do they identify the same object. Their measures are constructed over seven- to twelve-year windows and decompose the employment change between endpoints into contributions from establishment births, deaths, expansions, and contractions. My outcome instead measures how the annual rate of job creation plus destruction changes between those endpoints. The findings are thus consistent with an adjustment involving substantial establishment deaths within a period and a lower annual pace of churn at its end, although neither design identifies that complete within-period path.

This qualification also clarifies a limitation of my design. Because I measure changes in annual reallocation between endpoints, my estimates do not capture a transitory increase in job destruction occurring within the period and are not evidence against the establishment-death response documented by Asquith et al. (2019). Instead, they suggest that the shock not only displaces employment but is associated with a subsequent deceleration in the annual reallocation of productive factors.

5. Conclusion

This paper studies how the China trade shock affected U.S. business dynamism. In my preferred industry-level IV specification, increased import exposure accounts for roughly half of the observed decline in gross job reallocation. A dynamic two-country model of oligopolistic competition rationalizes this pattern through firms' innovation responses to increased foreign competition.

The framework also points to future research on optimal policy responses to trade shocks that slow reallocation in the broader economy.

References

Acemoglu, Daron and Ufuk Akcigit, "Intellectual Property Rights Policy, Competition and Innovation," *Journal of the European Economic Association*, 2012, *10* (1), 1–42.

— , David Autor, David Dorn, Gordon H. Hanson, and Brendan Price, "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, January 2016, *34* (S1), S141–S198.

— , Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr, "Innovation, Reallocation, and Growth," *American Economic Review*, November 2018, *108* (11), 3450–3491.

Aghion, Philippe and Peter Howitt, "A Model of Growth Through Creative Destruction," *Econometrica*, 1992, *60* (2), 323–351.

— , Antonin Bergeaud, Timo Boppart, Peter J. Klenow, and Huiyu Li, "A Theory of Falling Growth and Rising Rents," November 2019.

— , Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, "Competition and Innovation: an Inverted-U Relationship," *The Quarterly Journal of Economics*, May 2005, *120* (2), 701–728.

Akcigit, Ufuk and Sina T. Ates, "Ten Facts on Declining Business Dynamism and Lessons from Endogenous Growth Theory," *American Economic Journal: Macroeconomics*, January 2021, *13* (1), 257–298.

— and — , "What Happened to US Business Dynamism?," *Journal of Political Economy*, August 2023, *131* (8), 2059–2124.

— , — , and Giammario Impullitti, "Innovation and Trade Policy in a Globalized World," April 2018.

— , — , Josh Lerner, Richard R. Townsend, and Yulia Zhestkova, "Fencing off Silicon Valley: Cross-border venture capital and technology spillovers," *Journal of Monetary Economics*, January 2024, *141*, 14–39.

Anderson, James E. and Eric van Wincoop, "Trade Costs," *Journal of Economic Literature*, September 2004, *42* (3), 691–751.

Andrews, Dan, Chiara Criscuolo, and Peter N. Gal, "Frontier Firms, Technology Diffusion and Public Policy: Micro Evidence from OECD Countries," Technical Report, OECD, Paris November 2015.

Asquith, Brian J., Sanjana Goswami, David Neumark, and Antonio Rodriguez-Lopez, "U.S. Job Flows and the China Shock," *Journal of International Economics*, 2019, *118*, 123–137.

Autor, David, David Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu, "Foreign Competition and Domestic Innovation: Evidence from US Patents," *American Economic Review: Insights*, September 2020a, *2* (3), 357–374.

— , — , Lawrence F Katz, Christina Patterson, and John Van Reenen, "The Fall of the Labor Share and the Rise of Superstar Firms," *The Quarterly Journal of Economics*, May 2020b, *135* (2), 645–709.

Autor, David H., David Dorn, and Gordon H. Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, October 2013, *103* (6), 2121–2168.

— , — , and — , "The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade," *Annual Review of Economics*, October 2016, *8*, 205–240.

— , — , — , and Jae Song, "Trade Adjustment: Worker-Level Evidence," *The Quarterly Journal of Economics*, November 2014, *129* (4), 1799–1860.

Banister, Judith, "Manufacturing Employment in China," *Monthly Labor Review*, July 2005, *128* (7), 11–29.

Becker, Randy A., Wayne B. Gray, and Jordan Marvakov, "NBER-CES Manufacturing Industry Database (1958–2018, version 2021a)," 2021.

Benedetto, John, "Trends in Manufacturing Employment in the Largest Industrialized Economies During 1998–2014," U.S. International Trade Commission, Executive Briefings on Trade April 2018.

Bloom, Nicholas, Mirko Draca, and John Van Reenen, "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity," *The Review of Economic Studies*, January 2016, *83* (1), 87–117.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-Experimental Shift-Share Research Designs," *The Review of Economic Studies*, January 2022, *89* (1), 181–213.

Broda, Christian and David E. Weinstein, "Globalization and the Gains From Variety," *The Quarterly Journal of Economics*, May 2006, *121* (2), 541–585.

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro, "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock," *Econometrica*, 2019, *87* (3), 741–835.

Chakravorty, Ujjayant, Runjuan Liu, Ruotao Tang, and Long Zhao, "Firm innovation under import competition from low-wage countries," *The World Economy*, May 2024, *47* (5), 2063–2093.

Charles, Kerwin Kofi, Erik Hurst, and Mariel Schwartz, "The Transformation of Manufacturing and the Decline in US Employment," *NBER Macroeconomics Annual*, January 2019, *33*, 307–372.

Chikis, Craig, Jonathan Goldberg, and David López-Salido, "Financial discounts and creative-destruction dynamics," Working paper 2023.

Choi, Jaedo and Younghun Shim, "From Adoption to Innovation: State-Dependent Technology Policy in Developing Countries," IMF Working Paper 2024/154, International Monetary Fund July 2024.

Chow, Melissa C., Teresa C. Fort, Christopher Goetz, Nathan Goldschlag, James Lawrence, Elisabeth Ruth Perlman, Martha Stinson, and T. Kirk White, "Redesigning the Longitudinal Business Database," May 2021.

Cunningham, Cindy, Lucia Foster, Cheryl Grim, John Haltiwanger, Sabrina Wulff Pabilonia, Jay Stewart, and Zoltan Wolf, "Dispersion in Dispersion: Measuring Establishment-Level Differences in Productivity," *Review of Income and Wealth*, 2023, *69* (4), 999–1032.

Davis, Steven J., John C. Haltiwanger, and Scott Schuh, *Job Creation and Destruction*, Cambridge, MA: The MIT Press, January 1998.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger, "The Rise of Market Power and the Macroeconomic Implications," *The Quarterly Journal of Economics*, May 2020, *135* (2), 561–644.

De Ridder, Maarten, "Market Power and Innovation in the Intangible Economy," *American Economic Review*, January 2024, *114* (1), 199–251.

Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda, “Declining Business Dynamism: Implications For Productivity?,” Brookings Papers on Economic Activity September 2016a.

—, —, —, and —, “Declining Business Dynamism: What We Know and the Way Forward,” *American Economic Review*, May 2016b, *106* (5), 203–207.

—, —, —, and —, “Where has all the skewness gone? The decline in high-growth (young) firms in the U.S.,” *European Economic Review*, July 2016c, *86*, 4–23.

—, —, —, and —, “Declining Dynamism, Allocative Efficiency, and the Productivity Slowdown,” *American Economic Review*, May 2017, *107* (5), 322–326.

—, —, —, and —, “Changing Business Dynamism and Productivity: Shocks versus Responsiveness,” *American Economic Review*, December 2020, *110* (12), 3952–3990.

Fadeev, Evgenii, “Creative Construction,” Working paper 2023.

Fan, Jingting, “Talent, Geography, and Offshore R&D,” *The Review of Economic Studies*, March 2025, *92* (2), 1022–1060.

Fernald, John G., “Productivity and Potential Output before, during, and after the Great Recession,” *NBER Macroeconomics Annual*, January 2015, *29*, 1–51.

Foster, Lucia, John C. Haltiwanger, and C. J. Krizan, “Aggregate Productivity Growth: Lessons from Microeconomic Evidence,” in “New Developments in Productivity Analysis,” University of Chicago Press, January 2001, pp. 303–372.

Gong, Kaiji and Rui Xu, “Does Import Competition Induce R&D Reallocation? Evidence from the U.S.,” 2017.

Hoberg, Gerard, Bruce Yuan Li, and Gordon M. Phillips, “U.S.–China Innovation Competition,” April 2021.

Hsieh, Chang-Tai and Zheng (Michael) Song, “Grasp the Large, Let Go of the Small: The Transformation of the State Sector in China,” *Brookings Papers on Economic Activity*, 2015.

Khandelwal, Amit, “Comment on ‘Grasp the Large, Let Go of the Small: The Transformation of the State Sector in China’,” *Brookings Papers on Economic Activity*, 2015.

Klette, Tor Jakob and Samuel Kortum, "Innovating Firms and Aggregate Innovation," *Journal of Political Economy*, October 2004, *112* (5), 986–1018.

Lardy, Nicholas R., "Manufacturing Employment in China," Peterson Institute for International Economics December 2015.

Lentz, Rasmus and Dale T. Mortensen, "An Empirical Model of Growth through Product Innovation," *Econometrica*, 2008, *76* (6), 1317–1373.

Liu, Ernest, Atif Mian, and Amir Sufi, "Low Interest Rates, Market Power, and Productivity Growth," *Econometrica*, 2022, *90* (1), 193–221.

Liu, Qing, Ruosi Lu, Yi Lu, and Tuan Anh Luong, "Import competition and firm innovation: Evidence from China," *Journal of Development Economics*, June 2021, *151*, 102650.

Office of the United States Trade Representative, "2023 Special 301 Report," Office of the United States Trade Representative 2023.

Olmstead-Rumsey, Jane, "Market Concentration and the Productivity Slowdown," Working paper 2022.

Pierce, Justin R. and Peter K. Schott, "The Surprisingly Swift Decline of US Manufacturing Employment," *American Economic Review*, July 2016, *106* (7), 1632–1662.

Sui, Xiaomei, "Uneven Firm Growth in a Globalized World," Working paper 2023.

A. Solving the static equilibrium

Let $z^{\boldsymbol{n}}_{Hc}, z^{\boldsymbol{n}}_{-Hc}$ denote the equilibrium market shares of firms H and $-H$ in market $c \in \{H, F\}$ in a line j with gap $\boldsymbol{n} = (n_{HH}, n_{HF})$. Given ω_H, ω_F, and $\tilde{\psi}_{HH}$, prices as a function of market shares can be defined as:

$$\frac{p_{HH}}{p_{-HH}} = \lambda^{-n_{HH}} \frac{1-\beta z^{\boldsymbol{n}}_{HH}}{\beta(1-z^{\boldsymbol{n}}_{HH})} \frac{\beta(1-z^{\boldsymbol{n}}_{-HH})}{1-\beta z^{\boldsymbol{n}}_{-HH}} \tag{A.1}$$

$$\frac{p_{HH}}{p_{FH}} = \lambda^{-n_{HF}} \frac{\omega_H}{\omega_F} \tilde{\psi}_{HF} \frac{1}{\tau_X} \frac{1-\beta z^{\boldsymbol{n}}_{HH}}{\beta(1-z^{\boldsymbol{n}}_{HH})} \frac{\beta(z^{\boldsymbol{n}}_{HH}+z^{\boldsymbol{n}}_{-HH})}{1-\beta(1-z^{\boldsymbol{n}}_{HH}-z^{\boldsymbol{n}}_{-HH})} \tag{A.2}$$

$$\frac{p_{HF}}{p_{-HF}} = \lambda^{-n_{HH}} \frac{1-\beta z^{\boldsymbol{n}}_{HF}}{\beta(1-z^{\boldsymbol{n}}_{HF})} \frac{\beta(1-z^{\boldsymbol{n}}_{-HF})}{1-\beta z^{\boldsymbol{n}}_{-HF}} \tag{A.3}$$

$$\frac{p_{HF}}{p_{FF}} = \lambda^{-n_{HF}} \frac{\omega_H}{\omega_F} \tilde{\psi}_{HF} \tau_X \frac{1-\beta z^{\boldsymbol{n}}_{HF}}{\beta(1-z^{\boldsymbol{n}}_{HF})} \frac{\beta(z^{\boldsymbol{n}}_{HF}+z^{\boldsymbol{n}}_{-HF})}{1-\beta(1-z^{\boldsymbol{n}}_{HF}-z^{\boldsymbol{n}}_{-HF})}. \tag{A.4}$$

Using Equations (A.1)–(A.4), we can define an implicit system of equations that yields equilibrium market shares:

$$z^{\boldsymbol{n}}_{HH} = \frac{\psi_H}{\psi_H + \psi_H \left(\frac{p_{-HH}}{p_{HH}}\right)^{\frac{\beta}{\beta-1}} + \psi_F \left(\frac{p_{FH}}{p_{HH}}\right)^{\frac{\beta}{\beta-1}}} \tag{A.5}$$

$$z^{\boldsymbol{n}}_{-HH} = \frac{\psi_H}{\psi_H + \psi_H \left(\frac{p_{HH}}{p_{-HH}}\right)^{\frac{\beta}{\beta-1}} + \psi_F \left(\frac{p_{FH}}{p_{-HH}}\right)^{\frac{\beta}{\beta-1}}} \tag{A.6}$$

$$z^{\boldsymbol{n}}_{HF} = \frac{\psi_F}{\psi_F + \psi_F \left(\frac{p_{-HF}}{p_{HF}}\right)^{\frac{\beta}{\beta-1}} + \psi_H \left(\frac{p_{FF}}{p_{HF}}\right)^{\frac{\beta}{\beta-1}}} \tag{A.7}$$

$$z^{\boldsymbol{n}}_{-HF} = \frac{\psi_F}{\psi_F + \psi_F \left(\frac{p_{HF}}{p_{-HF}}\right)^{\frac{\beta}{\beta-1}} + \psi_H \left(\frac{p_{FF}}{p_{-HF}}\right)^{\frac{\beta}{\beta-1}}}. \tag{A.8}$$

Given an initial guess of $\{z^{\boldsymbol{n}}_{Hc}, z^{\boldsymbol{n}}_{-Hc}\}_c$, Equations (A.1)–(A.8) can be solved numerically.

B. HJB equations

Let $\mathbb{M}_{i,\boldsymbol{n}}(i', \boldsymbol{n}') : \{H, -H, F\} \times N \to [0, 1] = \Pr\{(i', \boldsymbol{n}')|(i, \boldsymbol{n}), \text{Successful innovation}\}$ be a conditional probability mass function such that $\sum_{i',\boldsymbol{n}'} \mathbb{M}_{i,\boldsymbol{n}}(i', \boldsymbol{n}') = 1$ for all $(i, \boldsymbol{n})$. $\mathbb{M}^{E,c}_{\boldsymbol{n}}(i', \boldsymbol{n}')$ is defined as in Section 2.5. For the finite numerical approximation, I reflect transitions at the boundaries.[29] For example, for $|n_{HF}| < \bar{n}_{HF}$:

$$\mathbb{M}_{H,(\bar{n}_{HH},n_{HF})}(i',\boldsymbol{n}') = \begin{cases} 1 & , n'_{HH} = \bar{n}_{HH}, n'_{HF} = n_{HF}+1, i' = H \\ 0 & , \text{otherwise} \end{cases} \tag{B.1}$$

$$\mathbb{M}_{H,(\bar{n}_{HH},\bar{n}_{HF})}(i',\boldsymbol{n}') = \begin{cases} 1 & , n'_{HH} = \bar{n}_{HH}, n'_{HF} = \bar{n}_{HF}, i' = H \\ 0 & , \text{otherwise} \end{cases} . \tag{B.2}$$

Let $\tilde{\mathcal{C}}(i)$ be the competitor country; for example, $\tilde{\mathcal{C}}(H) = F$. And let $\hat{\mathcal{C}}(i)$ be the domestic incumbent competitor; for example, $\hat{\mathcal{C}}(H) = -H$ and $\hat{\mathcal{C}}(F) = \emptyset$. Lastly, let all decisions $\boldsymbol{\sigma} = (H,(0,n_{HF}))$ be identical to those for $\boldsymbol{\sigma} = (-H,(0,n_{HF}))$.

Then, the Hamilton-Jacobi-Bellman equation for any firm $i \in \{H,-H\}$ can be written as:

$$\begin{aligned} r_{|i|}V_i^{\boldsymbol{n}} - \dot{V}_i^{\boldsymbol{n}} &= (1-\tau_{|i||i|})\Pi_{|i||i|} + (1-\tau_{\tilde{\mathcal{C}}(|i|)|i|})\Pi_{|i|\tilde{\mathcal{C}}(|i|)} + \\ &\max_{x_i^{\boldsymbol{n}}} \left\{ -(1-\tau_{|i|}^{\text{R\&D}})w_{|i|}G(x_i^{\boldsymbol{n}};B_{|i|},\gamma) + x_i^{\boldsymbol{n}} \sum_{i',\boldsymbol{n}'} \mathbb{M}_{i,\boldsymbol{n}}(i',\boldsymbol{n}') \left(V_{i'}^{\boldsymbol{n}'} - V_i^{\boldsymbol{n}}\right) \right\} + \\ &x_{\hat{\mathcal{C}}(i)}^{\boldsymbol{n}} \sum_{i',\boldsymbol{n}'} \mathbb{M}_{\hat{\mathcal{C}}(i),\boldsymbol{n}}(i',\boldsymbol{n}') \left(V_{\hat{\mathcal{C}}(i')}^{\boldsymbol{n}'} - V_i^{\boldsymbol{n}}\right) + x_{\tilde{\mathcal{C}}(|i|)}^{\boldsymbol{n}} \sum_{i',\boldsymbol{n}'} \mathbb{M}_{\tilde{\mathcal{C}}(|i|),\boldsymbol{n}}(i',\boldsymbol{n}') \left(V_i^{\boldsymbol{n}'} - V_i^{\boldsymbol{n}}\right) + \\ &x_{|i|}^{\boldsymbol{n},E} \sum_{i',\boldsymbol{n}'} \mathbb{M}_{\boldsymbol{n}}^{E,|i|}(i',\boldsymbol{n}') \left(\left(1 - \mathbb{1}_{i'=i} + \frac{1}{2}\mathbb{1}_{i=H,n_{HH}=0}\right) V_{\hat{\mathcal{C}}(i')}^{\boldsymbol{n}'} - V_i^{\boldsymbol{n}} \right) + \\ &x_{\tilde{\mathcal{C}}(|i|)}^{\boldsymbol{n},E} \sum_{i',\boldsymbol{n}'} \mathbb{M}_{\boldsymbol{n}}^{E,\tilde{\mathcal{C}}(|i|)}(i',\boldsymbol{n}') \left(V_i^{\boldsymbol{n}'} - V_i^{\boldsymbol{n}}\right) \\ &+ \eta_{HH}\left(V_{|i|}^{0,n_{HF}} - V_i^{\boldsymbol{n}}\right) + \eta_{FH}\mathbb{1}_{n_{HF}<n_{HH}} \left(\mathbb{1}_{n_{HF}<0}V_{|i|}^{0,0} + (1-\mathbb{1}_{n_{HF}<0})V_i^{n_{HF},n_{HF}} - V_i^{\boldsymbol{n}}\right) + \\ &\eta_{HF}\mathbb{1}_{n_{HF}>0}\left(\mathbb{1}_{n_{HF}>n_{HH}}\left(\frac{1}{2}V_i^{n_{HH},0} + \frac{1}{2}V_i^{n_{HH},n_{HH}}\right) + (1-\mathbb{1}_{n_{HF}>n_{HH}})\left(\frac{1}{2}V_i^{\boldsymbol{n}} + \frac{1}{2}V_i^{n_{HH},0}\right) - V_i^{\boldsymbol{n}}\right) \end{aligned} \tag{B.3}$$

[29] Note that reflection can imply nontrivial productivity spillovers. In practice, there is sufficiently small probability mass at the relevant boundaries that this is not a major concern.

and for $i = F$ as:

$$
\begin{aligned}
r_{|i|}V_i^{\boldsymbol{n}} - \dot{V}_i^{\boldsymbol{n}} = (1-\tau_{|i||i|})\Pi_{|i||i|} + (1-\tau_{\tilde{C}(|i|)|i|})\Pi_{|i|\tilde{C}(|i|)} + \\
\max_{x_i^{\boldsymbol{n}}} \left\{ -(1-\tau_{|i|}^{\text{R\&D}})w_{|i|}G(x_i^{\boldsymbol{n}}; B_{|i|}, \gamma) + x_i^{\boldsymbol{n}} \sum_{i',\boldsymbol{n}'} \mathbb{M}_{i,\boldsymbol{n}}(i',\boldsymbol{n}') \left(V_{i'}^{\boldsymbol{n}'} - V_i^{\boldsymbol{n}} \right) \right\} + \\
x_{\tilde{\mathcal{C}}(|i|)}^{\boldsymbol{n}} \sum_{i',\boldsymbol{n}'} \mathbb{M}_{\tilde{\mathcal{C}}(|i|),\boldsymbol{n}}(i',\boldsymbol{n}') \left(V_i^{\boldsymbol{n}'} - V_i^{\boldsymbol{n}} \right) + x_{-\tilde{\mathcal{C}}(|i|)}^{\boldsymbol{n}} \sum_{i',\boldsymbol{n}'} \mathbb{M}_{-\tilde{\mathcal{C}}(|i|),\boldsymbol{n}}(i',\boldsymbol{n}') \left(V_i^{\boldsymbol{n}'} - V_i^{\boldsymbol{n}} \right) + \\
x_{|i|}^{\boldsymbol{n},E}(0 - V_i^{\boldsymbol{n}}) + \\
x_{\tilde{\mathcal{C}}(|i|)}^{\boldsymbol{n},E} \sum_{i',\boldsymbol{n}'} \mathbb{M}_{\boldsymbol{n}}^{E,\tilde{\mathcal{C}}(|i|)}(i',\boldsymbol{n}') \left(V_i^{\boldsymbol{n}'} - V_i^{\boldsymbol{n}} \right) \\
+ \eta_{HH} \left(V_{|i|}^{0,n_{HF}} - V_i^{\boldsymbol{n}} \right) + \eta_{FH} \mathbb{1}_{n_{HF}<n_{HH}} \left(\mathbb{1}_{n_{HF}<0} V_{|i|}^{0,0} + (1-\mathbb{1}_{n_{HF}<0}) V_i^{n_{HF},n_{HF}} - V_i^{\boldsymbol{n}} \right) + \\
\eta_{HF} \mathbb{1}_{n_{HF}>0} \left(\mathbb{1}_{n_{HF}>n_{HH}} \left(\frac{1}{2} V_i^{n_{HH},0} + \frac{1}{2} V_i^{n_{HH},n_{HH}} \right) + (1-\mathbb{1}_{n_{HF}>n_{HH}}) \left(\frac{1}{2} V_i^{\boldsymbol{n}} + \frac{1}{2} V_i^{n_{HH},0} \right) - V_i^{\boldsymbol{n}} \right).
\end{aligned}
\tag{B.4}
$$

All that remains is to fully characterize $\mathbb{M}_{i,\boldsymbol{n}}(i',\boldsymbol{n}')$ and $\mathbb{M}_{\boldsymbol{n}}^{E,c}(i',\boldsymbol{n}')$ for all $(i,\boldsymbol{n})$ and all $(c,\boldsymbol{n})$, respectively.

$$
\mathbb{M}_{i,\boldsymbol{n}}(i',\boldsymbol{n}') = \begin{cases}
1 & , i = H, i' = H, n'_{HH} = n_{HH}+1, n'_{HF} = n_{HF}+1 \\
1 & , i = F, i' = F, n'_{HH} = n_{HH}, n'_{HF} = n_{HF}-1 \\
1 & , i = -H, i' = -H, n_{HH} > 1, n'_{HH} = n_{HH}-1, n'_{HF} = n_{HF} \\
1 & , i = -H, i' = H, n_{HH} = 1, n'_{HH} = 0, n'_{HF} = n_{HF} \\
0 & , \text{otherwise}
\end{cases}
\tag{B.5}
$$

$$
\mathbb{M}_{\boldsymbol{n}}^{E,c}(i',\boldsymbol{n}') = \begin{cases}
1 & , c = H, n_{HH} > 1, i' = -H, n'_{HH} = n_{HH}-1, n'_{HF} = n_{HF} \\
1 & , c = H, n_{HH} = 1, i' = H, n'_{HH} = 0, n'_{HF} = n_{HF} \\
1, & c = H, n_{HH} = 0, i' = H, n'_{HH} = 1, n'_{HF} = n_{HF}+1 \\
1, & c = F, i' = F, n'_{HH} = n_{HH}, n'_{HF} = n_{HF}-1 \\
0 & , \text{otherwise}
\end{cases}
.
\tag{B.6}
$$

C. KFE equations

Using (B.5) and (B.6) we can very easily characterize $\text{Inflow}^{\boldsymbol{n}}(\{\mu^{\boldsymbol{n}}\}_{\boldsymbol{n}})$ and $\text{Outflow}^{\boldsymbol{n}}(\{\mu^{\boldsymbol{n}}\}_{\boldsymbol{n}})$ for all $\boldsymbol{n}$. Combined with (15), this yields the fully specified Kolmogorov Forward Equations (KFE).

First, note that (17) is valid for all $\boldsymbol{n}$. That just leaves the inflows to be specified.

$$\begin{aligned}\text{Inflow}^{\boldsymbol{n}}(\{\mu^{\boldsymbol{n}}\}_{\boldsymbol{n}}) = \sum_{i',i'',\boldsymbol{n}'} \mu^{\boldsymbol{n}'} x_{i'}^{\boldsymbol{n}'} \mathbb{M}_{i',\boldsymbol{n}'}(i'',\boldsymbol{n}) + \sum_{c,i',\boldsymbol{n}'} \mu^{\boldsymbol{n}'} x_c^{\boldsymbol{n}',E} \mathbb{M}_{\boldsymbol{n}'}^{E,c}(i',\boldsymbol{n}) + \\ \eta_{HH} \mathbb{1}_{n_{HH}=0} \sum_{\boldsymbol{n}'} \mu^{\boldsymbol{n}'} \mathbb{1}_{n'_{HH}>0} + \eta_{FH} \mathbb{1}_{n_{HH}=n_{HF}} \sum_{\boldsymbol{n}'} \mu^{\boldsymbol{n}'} \mathbb{1}_{n'_{HH}>n_{HF}} + \\ \eta_{HF} \sum_{\boldsymbol{n}'} \mu^{\boldsymbol{n}'} \left(\mathbb{1}_{n'_{HH}>n_{HF}} \mathbb{1}_{n_{HH}=n_{HF}} \frac{1}{2} + (1-\mathbb{1}_{n'_{HH}>n_{HF}}) \left(\frac{1}{2}\mathbb{1}_{n_{HH}=n_{HF}} + \frac{1}{2}\mathbb{1}_{n_{HF}=0} \right) \right).\end{aligned} \tag{C.1}$$

D. Equilibrium

An equilibrium of the model is a collection of prices and quantities, Υ:

$$\begin{aligned}\Upsilon = \Big\{ & \{Y_c(t), C_c(t), A_c(t), P_c(t), w_c(t), r_c(t)\}_{c\in\{H,F\}}, \\ & \{y_{ijc}(t), p_{ijc}(t), l_{ijc}(t)\}_{i\in\{H,-H,F\},c\in\{H,F\}}, \{x_i^{\boldsymbol{n}}(t), {}^c x_i^{\boldsymbol{n}}(t), v_i^{\boldsymbol{n}}(t)\}_{i\in\{H,-H,F\},\boldsymbol{n}\in N}, \\ & \{x_c^{\boldsymbol{n},E}(t)\}_{\boldsymbol{n}\in N,c\in\{H,F\}}, \{\mu^{\boldsymbol{n}}(t)\}_{\boldsymbol{n}\in N} \Big\}_{t\in[0,\infty)}\end{aligned} \tag{D.1}$$

such that

1. **Intertemporal optimization.** Given prices, $\{P_c(t), w_c(t), r_c(t)\}$, households choose $\{C_c(t), A_c(t)\}$ optimally while satisfying their budget constraints—(1)–(2).

2. **Static optimization.** Given prices and demand $\{P_c(t), Y_c(t), w_c(t)\}$, firms choose $\{p_{ijc}(t), y_{ijc}(t), l_{ijc}(t)\}$ optimally—(5), (7), and (8). These imply static period profits, $\{\Pi_{cc'}(t)\}$.

3. **Markov perfection.** Given prices, period profits, competitor innovation decisions, and expected firm values $\{w_c(t), \Pi_{cc'}(t), {}^c x_i^{\boldsymbol{n}}(t), v_i^{\boldsymbol{n}}(t)\}$, firms choose their innovation decisions, $\{x_i^{\boldsymbol{n}}(t)\}$ optimally (i.e. satisfying the relevant Hamilton-Jacobi-Bellman

equations). As a consequence, innovation decisions are **symmetric**: $\{{}^{c}x_i^{\boldsymbol{n}}(t) = x_i^{\boldsymbol{n}}(t)\}$

4. **Market clearance.** All markets clear.

   (a) **Asset market clearance.**

$$A_H(t) = \sum_{\boldsymbol{n}} \mu^{\boldsymbol{n}}(t) \left(V_H^{\boldsymbol{n}}(t) + V_{-H}^{\boldsymbol{n}}(t) + V_H^{\boldsymbol{n},E}(t) \right) \tag{D.2}$$

$$A_F(t) = \sum_{\boldsymbol{n}} \mu^{\boldsymbol{n}}(t) \left(V_F^{\boldsymbol{n}}(t) + V_F^{\boldsymbol{n},E}(t) \right) \tag{D.3}$$

   (b) **Trade market clearance.** Let $\Delta(t) > 0$ represent a potentially exogenous trade deficit between home and foreign (the gross fraction by which home imports exceed home exports—balance is given by $\Delta(t) = 1$):

$$\frac{1}{\Delta(t)} \frac{\sum_{\boldsymbol{n}} \mu^{\boldsymbol{n}}(t) z_{FH}^{\boldsymbol{n}}(t)}{\sum_{\boldsymbol{n}} \mu^{\boldsymbol{n}}(t) \left(z_{HF}^{\boldsymbol{n}}(t) + z_{-HF}^{\boldsymbol{n}}(t) \right)} = \tilde{\psi}_{FH}(t). \tag{D.4}$$

   (c) **Goods market clearance.**

$$Y_H(t) = C_H(t) \qquad\qquad Y_F(t) = C_F(t) \tag{D.5}$$

   (d) **Labor market clearance.**

$$L_H(t) = \int_0^1 \left[\sum_{c\in\{H,F\}} \left(l_{Hjc}(t) + l_{-Hjc}(t) \right) + \tilde{l}_{Hj}(t) + \tilde{l}_{-Hj}(t) + \tilde{l}_{Hj}^{E} \right] dj \tag{D.6}$$

$$L_F(t) = \int_0^1 \left[\sum_{c\in\{H,F\}} \left(l_{Fjc}(t) \right) + \tilde{l}_{Fj}(t) + \tilde{l}_{Fj}^{E} \right] dj \tag{D.7}$$

   where

$$\int_0^1 \tilde{l}_{ij}(t) dj = \sum_{\boldsymbol{n}} \mu^{\boldsymbol{n}}(t) G\left(x_i^{\boldsymbol{n}}(t); B, \gamma \right) \tag{D.8}$$

$$\int_0^1 \tilde{l}_{cj}^{E}(t) dj = \sum_{\boldsymbol{n}} \mu^{\boldsymbol{n}}(t) G\left(x_c^{\boldsymbol{n},E}(t); B_c^E, \gamma \right). \tag{D.9}$$

E. Solution algorithm

I solve the model as follows.

1. I guess that the model converged to a BGP in T periods.

2. I posit a guess for $\{\omega_H(t), \omega_F(t), \tilde{\psi}_{HF}(t)\}_{t=0}^{T}$. Note that this guess must satisfy $0 \leq \omega_H(t) \leq \frac{1}{L_H(t)}$; $0 \leq \omega_F(t) \leq \frac{1}{L_F(t)}$; and $0 \leq \tilde{\psi}_{HF}(t) < \infty$.

3. Using this guess, I solve for the static equilibrium following the procedure described in Appendix A.

4. Adapting the HJBs for discrete time—I set $dt = 2^{-5}$ and shrink as necessary to ensure convergence—I solve the model backward from $t = T$ to $t = 0$. This gives me $\{\{x_c^{\boldsymbol{n},E}(t)\}_{c,\boldsymbol{n}}, \{x_i^{\boldsymbol{n}}(t)\}_{i,\boldsymbol{n}}\}_{t=0}^{T}$.

5. Using $\{\{x_c^{\boldsymbol{n},E}(t)\}_{c,\boldsymbol{n}}, \{x_i^{\boldsymbol{n}}(t)\}_{i,\boldsymbol{n}}\}_{t=0}^{T}$, I solve the KFEs forward. This gives me $\{\{\mu^{\boldsymbol{n}}(t)\}_{\boldsymbol{n}}\}_{t=0}^{T}$.

6. If the guess was correct—that the model converged to a BGP in T periods—continue. Otherwise return to step 1 and update T according to $T' = 2T$.

7. I check for the $\{\omega_H(t)', \omega_F(t)', \tilde{\psi}_{HF}(t)'\}_{t=0}^{T}$ that clear the trade and labor markets—Equations (D.4) and (D.6). If

$$\max_{t\in\{0,\dots,T\}} \left\{ ||(\omega_H(t)', \omega_F(t)', \tilde{\psi}_{HF}(t)')' - ((\omega_H(t), \omega_F(t), \tilde{\psi}_{HF}(t))'||_\infty \right\} < \epsilon \tag{E.1}$$

then stop: the model has converged. Otherwise, update the guess according to:

$$(\omega_H(t)'', \omega_F(t)'', \tilde{\psi}_{HF}(t)'')' = \lambda(\omega_H(t), \omega_F(t), \tilde{\psi}_{HF}(t))' + \\ (1-\lambda)(\omega_H(t)', \omega_F(t)', \tilde{\psi}_{HF}(t)')', \qquad \forall t, \lambda \in [0,1] \tag{E.2}$$

and return to step 3.

F. Model extensions

F.1 Offshore R&D activity

F.2 Optimal tariff policy