Entry Costs Rise with Growth

Peter J. Klenow

Stanford University, Stanford Institute for Economic Policy Research, and National Bureau of Economic Research

Huiyu Li

Federal Reserve Bank of San Francisco

Over time and across states in the United States, the number of firms is more closely tied to overall employment than to output per worker. In many models of firm dynamics, trade, and growth with a free entry condition, these facts imply that the costs of creating a new firm increase sharply with productivity growth. This increase in entry costs can stem from the rising cost of labor used in entry and weak or negative knowledge spillovers from prior entry. Our findings suggest that productivity-enhancing policies will not induce firm entry, thereby limiting the total impact of such policies on welfare.

I. Introduction

Suppose that new businesses are created with a fixed amount of output. Then a policy that boosts productivity can generate an endogenous expansion in the number of firms, with gains in welfare to the extent more

This project arose from a previous version with Albert Bollard entitled "Entry Costs Rise with Development." We thank research assistants Nathaniel Barlow, Patrick Kiernan, Jack Mueller, and Sam Tarasewicz for their excellent work. We are grateful for helpful comments from our discussant Ariel Burstein and from seminar participants at Stanford, the Federal Reserve Bank of San Francisco, Washington University, the Federal Reserve Bank of Philadelphia, the Society for Economic Dynamics at the University of Wisconsin, Madison, the National Bureau of Economic Research Summer Institute, and the Federal Reserve Bank of St. Louis. Opinions and conclusions herein are those of the authors and

Electronically published January 7, 2025

Journal of Political Economy Macroeconomics, volume 3, number 1, March 2025.

https://doi.org/10.1086/733979

firms entails more varieties. This multiplier effect through entry is analogous to the multiplier effect on output from physical capital accumulation in the neoclassical growth model. If instead entry requires a fixed amount of labor, however, then policies boosting productivity will fail to generate additional entry because entry costs rise with the price of labor.

Widely used models of firm dynamics, growth, and trade make different assumptions about entry costs. Some models assume entry costs are stable or stationary (e.g., a fixed output cost to invent a new product).[1] Other models assume entry costs rise as growth proceeds, say because entry requires a fixed amount of labor and labor becomes more expensive with growth.[2] Some studies do not take a stand but emphasize that the entry technology matters for the welfare impact of policies.[3]

Entry costs may also depend on knowledge spillovers from past entry. In the growth literature, it is common to assume spillovers from previous innovation to future innovation. This includes the classic models of Romer (1990) and Aghion and Howitt (1992) as well as many successors. Jones (1995) and Bloom et al. (2020) argue that such spillovers are limited or even negative.

Existing evidence is limited on how entry costs change with growth. The overall distribution of employment across firms and plants provides some indirect evidence. Laincz and Peretto (2006) report no trend in US average firm employment. Luttmer (2007, 2010) shows that entry costs proportional to average productivity are consistent with a stationary firm size distribution in various growth models. While our paper studies the secular trend in entry costs, Karahan, Pugsley, and Şahin (2023) use the free entry condition to infer whether entry costs are cyclical, and Gutiérrez and Philippon (2019) focus on the cross-industry relationship between the entry rate and Tobin's Q. Bento and Restuccia (2024) incorporate data on

---

do not necessarily represent the views of the Federal Reserve System, the Federal Reserve Bank of San Francisco, or the US Census Bureau. Any views expressed are those of the authors and not those of the US Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC projects no. 1440 (clearance request no. 5434) and no. 2441 (CBDRB-FY25-P2441-R11847). The authors have no relevant or material financial interests that relate to the research in this paper. The paper has been edited by Ariel Burstein.

[1] See Hopenhayn (1992), Hopenhayn and Rogerson (1993), Foster, Haltiwanger, and Syverson (2008), Clementi and Palazzo (2016), Gutiérrez, Jones, and Philippon (2021), David (2021), Boar and Midrigan (2022, 2024), and Karahan, Pugsley, and Şahin (2024).

[2] Examples include Lucas (1978), Grossman and Helpman (1991), Melitz (2003), Klette and Kortum (2004), Luttmer (2007), Bilbiie, Ghironi, and Melitz (2012), Acemoglu et al. (2018), Atkeson and Burstein (2019), Peters and Walsh (2021), Sterk, Sedlek, and Pugsley (2021), Hopenhayn, Neira, and Singhania (2022), and Baqaee, Farhi, and Sangani (2024).

[3] For example, Rivera-Batiz and Romer (1991), Atkeson and Burstein (2010), Bhattacharya, Guner, and Ventura (2013), a survey by Costinot and Rodríguez-Clare (2014), and Baqaee and Farhi (2021).

nonemployer establishments, and show that this affects inference about trends in average employment per firm.

In this paper, we provide evidence on how the average employment per firm varies with the level of overall labor productivity. We look over time and across states in the Business Dynamics Statistics (BDS) maintained by the US Census Bureau, in particular from 1978 through 2020. We combine this Census Bureau data with US Bureau of Economic Analysis (BEA) data on aggregate and state labor productivity. We argue that these simple empirical elasticities discipline the nature of entry costs in widely used models.

We find that average employment per firm is stable or increases with the level of labor productivity, both over time and across states. These patterns imply that revenue per firm increases sharply with growth. Firms evidently need more revenue to satisfy the free entry condition in places and times with higher market-wide labor productivity. If higher revenue is associated with higher operating profits, then entry costs must be bigger in order for the zero-profit condition to hold. We consider other possible explanations, however, such as trends in firm markups, exit rates, postentry growth rates, discount rates, selection, and industry composition. We will argue that these competing forces are too weak to explain why average employment per firm does not decline significantly relative to the extent of labor productivity growth.

We illustrate the implications of our empirical findings using two deliberately simple and stylized models. One model features long-run growth at the country level. The second model contains growing US states with mobility of workers and firms. In these models, entry costs can rise with growth simply because entry is labor intensive and labor becomes more expensive when productivity grows. Entry costs could also rise with growth because it is more costly for entrants to set up more technologically sophisticated operations as the economy advances (say because of limited or negative knowledge spillovers).[4] We use our empirical findings to estimate parameters governing the labor intensity of entry costs and the relationship between entry costs and the level of technology. We find that fitting our facts requires that entry be labor intensive and/or that knowledge spillovers be weak, thereby explaining why entry costs rise with growth.

We draw the following three conclusions for modeling and policy. First, if the choice is between fixed entry costs in terms of labor or output, our evidence favors denominating entry costs in terms of labor. Second, our

[4] Our evidence is relevant for total entry costs, which are the sum of technological and regulatory entry costs. In the *Doing Business* surveys, regulatory costs of entry (relative to GDP per capita) fall with development, as shown by Djankov et al. (2002). Thus rising technological entry costs with development may be needed to explain why employment per firm is higher in richer countries, as documented by Bento and Restuccia (2017).

evidence is consistent with at best weak knowledge spillovers for innovation embodied in entry. Third, productivity-enhancing policies have muted effects on entry, and hence are not amplified through endogenous entry.

The rest of the paper proceeds as follows. Section II provides two models to illustrate why we care about the nature of entry costs and to motivate our empirical design. Section III presents evidence on how the number of businesses varies with growth over time and across states in the United States and draws potential implications for entry costs. Section IV estimates entry technology parameters and discusses the welfare implications. Section V gauges the robustness of our empirical findings, and section VI concludes.

II. Simple Motivating Models

We first present a stylized love-of-variety model of a one-region economy to illustrate how the elasticity of entry costs with respect to growth matters for welfare. Then we extend the model to multiple regions à la Redding and Rossi-Hansberg (2017) and Redding (2022) to guide our cross-state empirical analysis. As both models are standard, we relegate the details on them to appendix A (appendixes A–D are available online). These models assume that the number of varieties is proportional to the number of firms. This is assumed in many other models, such as Peters and Walsh (2021). In appendix B we lay out a model with endogenous varieties per firm in which we recover the same estimating equation that we derive below.[5]

A. One-Region Model

We first consider a static, closed economy version of the Melitz (2003) model. The economy has a representative household endowed with L units of labor. Consumption per capita, which is proportional to the real wage w, is a measure of welfare in the economy. Consumption goods are produced by a perfectly competitive sector that uses intermediate goods as inputs and a CES production technology with elasticity of substitution σ. Profit maximization yields a downward-sloping demand curve for each intermediate good.

The intermediate goods sector is monopolistically competitive. Without loss of generality, we assume that all firms in this sector have the same

[5] We show in app. B that entry costs matter for welfare in other models, such as a version of the static Lucas span-of-control model, a static love-of-variety model with congestion in contemporaneous entry, and an endogenous growth model with expanding varieties per firm (rather than a single product per firm as in our baseline model).

production function, which is linear in labor inputs with technology level A.[6] Each intermediate goods firm takes demand for its product as given and chooses its output or price to maximize its profit. This yields the familiar relationship between the wage bill, revenue, and profit in each firm,

$$wl = \frac{\sigma - 1}{\sigma} py = (\sigma - 1)\pi. \tag{1}$$

Let L^y be the total amount of labor devoted to producing intermediate goods and N be the total number of intermediate goods produced. By symmetry of the intermediate goods production function, aggregate output is given by

$$Y = AL^y N^{1/(\sigma-1)}. \tag{2}$$

One unit of an entry good is required to create a variety, which is the equivalent to setting up an intermediate goods firm. We generalize the production technology of the entry good in Melitz (2003) to allow final goods to be an input into creating a new variety. In particular, we follow Atkeson and Burstein (2010, 2019) in assuming that the entry technology has the Cobb-Douglas form

$$N = A^e (Y^e)^{1-\lambda} (L^e)^{\lambda}, \tag{3}$$

where L^e and Y^e are the amount of labor and final output, respectively, used in creating varieties.

This specification of the entry technology nests various assumptions in the literature. For example, entry costs are as in (3) but with $\lambda = 1$ and $A^e_s = 1$ in Lucas (1978), Romer (1990), Melitz (2003), Luttmer (2007), and Hopenhayn, Neira, and Singhania (2022). When $\lambda = 0$ and $A^e_s = 1$, entry costs are as in Hopenhayn and Rogerson (1993), Foster, Haltiwanger, and Syverson (2008), David (2021), and Karahan, Pugsley, and Şahin (2024). Finally, entry costs may rise with labor productivity if, as in Berry and Waldfogel (2010), Cole, Greenwood, and Sanchez (2016), and Bento and Restuccia (2017), better production technologies carry higher setup costs (lower A^e).

Perfect competition in the constant returns to scale sector producing entry goods implies that the equilibrium cost and price of creating a variety in terms of consumption goods satisfy

$$p^e \propto \frac{w^{\lambda}}{A^e} \tag{4}$$

[6] We could allow postentry heterogeneity in firm technology and define $A \coloneqq (\mathbb{E}A_f^{\sigma-1})^{1/(\sigma-1)}$, where A_f is firm-level productivity.

and the labor share of revenue in entry goods production is

$$\frac{wL^e}{p^e N} = \lambda. \tag{5}$$

Free entry into producing intermediate goods firms (and varieties), with positive entry in equilibrium, implies that profit per variety equals the entry cost,

$$\pi = p^e. \tag{6}$$

Equations (3) and (6) are static because we have assumed for simplicity that firms are short lived. We consider postentry dynamics in section V.A.

Thus the one-shot equilibrium, given the triple $\{L, A, A^e\}$, consists of prices $\{w, p^e\}$ and allocations $\{C, N, Y, L^e, L^y\}$ such that (1) to (6) hold, and the following labor and goods market clearing conditions are satisfied:

$$L = L^y + L^e, \quad Y = C + Y^e.$$

We now consider how the welfare impact of a change in intermediate goods productivity A depends on the entry technology. In equilibrium, welfare (equivalently, the real wage) increases with A and the number of varieties,

$$w = \frac{\sigma - 1}{\sigma} AN^{1/(\sigma-1)},$$

and the change in welfare from a change in A is

$$\frac{\partial \ln w}{\partial \ln A} = 1 + \frac{1}{\sigma - 1}\frac{\partial \ln N}{\partial \ln A}.$$

An increase in A not only raises welfare directly (the first term, or 1), but also has the potential to improve welfare indirectly through variety expansion (the second term).

One can show that equilibrium variety satisfies

$$N \propto \frac{wL}{p^e}$$

such that the number of varieties depends on the value of labor relative to the entry cost. Combining this with equation (4) relating the real wage to p^e, we get

$$\frac{\partial \ln N}{\partial \ln A} = (1 - \lambda)\frac{\partial \ln w}{\partial \ln A}.$$

That is, the elasticity of variety with respect to A is larger when the share of output used in producing varieties $(1 - \lambda)$ is bigger. Higher A means more output, and some of this output is devoted to producing more varieties if the final good is used in entry ($\lambda < 1$). Incorporating this channel, the total impact of A on welfare is

$$\frac{\partial \ln w}{\partial \ln A} = 1 + \frac{1 - \lambda}{\sigma - 1 - (1 - \lambda)}$$

with the second term capturing the effect of variety expansion. A higher output share $(1 - \lambda)$ means more amplification.

The amplification of an increase in productivity depends negatively on the elasticity of substitution σ, because varieties are more valuable when substitutability is low. To illustrate the potential importance of variety expansion, consider the Broda and Weinstein (2006) estimates of $\sigma \approx 4$ at the 3-digit to 4-digit product level. For $\sigma = 4$, the increase in the total impact relative to the direct impact ranges from 50% when $\lambda = 0$ to 0% when $\lambda = 1$. Thus, for a plausible value of σ, the nature of entry costs matters immensely for the welfare impact of changes in A from technology or allocative efficiency.

The entry technology also influences the welfare impact of policies that affect the level of the population. As in Melitz (2003), increasing the population is like going from autarky to frictionless trade between two symmetric countries. In this case, the overall welfare effect is

$$\frac{\partial \ln w}{\partial \ln L} = \frac{1}{\sigma - 1}\left(1 + \frac{1 - \lambda}{\sigma - 1 - (1 - \lambda)}\right).$$

Just as with an increase in A, for an increase in L the amplification through variety expansion is 50% when $\lambda = 0$ and 0% when $\lambda = 1$.

Entry and amplification of productivity growth.—The above static model describes an economy in which entry technology can amplify the impact of changes in technology A and population L on the level of output per worker. Entry technology can potentially also amplify the impact of changes in the growth rates of technology and population on the growth rate of output per worker. A simple way to introduce endogenous growth of A_t is to let each firm j choose its productivity $A_t(j)$ in a way that builds on aggregate productivity in the previous period A_{t-1}. For simplicity, we assume the firms are short lived and make decisions in only one period. Suppose the entry efficiency A^e in a period is given by

$$A_t^e(A_t(j)) = N_{t-1}^{\phi} \exp\left[-\mu \frac{A_t(j)}{A_{t-1}}\right] \exp(\epsilon_t),$$

where N_{t-1}^{ϕ} captures spillover from the past stock of firms. A positive ϕ means there is positive spillover from the past entry to the efficiency of creating new firms. The second term reflects how the efficiency of entry may depend on the technology the firm chooses. A positive μ implies that entry costs rise with the productivity chosen by the entering firm.

The last term ϵ_t captures other factors affecting the efficiency of entry goods production. The first and third terms are common to all firms and are taken as given by each firm.

In each period, firms observe the entry efficiency shock ϵ_t and then decide $A_t(j)$. As before, entry costs in equilibrium are given by

$$p_t^e(A_t(j)) \propto \frac{(w_t/P_t)^\lambda}{A_t^e(A_t(j))}.$$

Profit maximization by intermediate goods producers and free entry imply that the choice of $A_t(j)$ by firm j satisfies[7]

$$\frac{\partial \ln \pi_t(j)}{\partial \ln A_t(j)} = \frac{\partial \ln p_t^e(A_t(j))}{\partial \ln A_t(j)}.$$

Since variable profits $\pi_t(j)$ are proportional to $A_t(j)^{\sigma-1}$, the firm's optimal choice of $A_t(j)$ satisfies

$$\sigma - 1 = \mu \frac{A_t(j)}{A_{t-1}},$$

and all firms choose the same growth relative to A_{t-1}. The growth of aggregate productivity is then

$$g_t^A \coloneqq \ln \frac{A_t}{A_{t-1}} = \ln \frac{\sigma - 1}{\mu}.$$

The growth rate increases with the elasticity of substitution σ and declines with the elasticity μ of entry costs with respect to growth in A. Following from this, entry efficiency in equilibrium is the same for all firms,

$$\ln A_t^e = \phi \ln N_{t-1} - (\sigma - 1) + \epsilon_t.$$

Consider the steady state with a constant ϵ_t and population growing at a constant rate of $g_L \coloneqq \ln(L_t/L_{t-1})$. The free entry condition implies that the number of firms grows at a constant rate

[7] Firms choose $A_t(j)$ to maximize profit postentry costs. Hence $A_t(j)$ satisfies the first-order condition

$$\frac{\partial \pi_t(A_t(j))}{\partial A_t(j)} = \frac{\partial p_t^e(A_t(j))}{\partial A_t(j)}.$$

At the equilibrium, we also have $\pi_t(A_t(j)) = p_t^e(A_t(j))$ and hence

$$\frac{\partial \ln \pi_t(A_t(j))}{\partial \ln A_t(j)} = \frac{\partial \pi_t(A_t(j))}{\partial A_t(j)} \frac{A_t(j)}{\pi_t(A_t(j))} = \frac{\partial p_t^e(A_t(j))}{\partial A_t(j)} \frac{A_t(j)}{p_t^e(A_t(j))} = \frac{\partial \ln p_t^e(A_t(j))}{\partial \ln A_t(j)}.$$

$$g^N := \ln \frac{N_t}{N_{t-1}} = \frac{g^L + (1-\lambda) g^{w/p}}{1-\phi}, \tag{7}$$

where the real wage grows at rate

$$g^{w/p} := \ln \frac{w_t/P_t}{w_{t-1}/P_{t-1}} = \frac{(\sigma-1)g^A + g^L/(1-\phi)}{\sigma - 1 - (1-\lambda)/(1-\phi)}. \tag{8}$$

The trend growth rate of the real wage is driven by the endogenous productivity growth g^A and by the growth in the national population g^L. The wage effects of these driving forces are amplified through entry when λ is less than 1. In addition, the wage effects can be amplified when there are positive spillovers from the past variety stock to the efficiency of creating new varieties ($\phi > 0$), or dampened when there are negative spillovers ($\phi < 0$). The intuition is similar to the multiplier effect that we detailed previously for the λ channel.

B. *Spatial Model*

Next we extend the simple one-region model to multiple regions.[8] This allows us to speak to evidence on changes in firm size not just at the national level but also at the state level. We view the cross-state evidence as more credible given that we can control for national trends in markups, firm age composition, and so forth.

1. Environment

The economy consists of $s = 1, 2, \ldots, S$ states and an exogenous mass of identical workers L. Each worker chooses one state to live in and to supply one unit of labor to the firms in that state. Ex ante identical firms choose one state in which to produce. The mass of workers living in each state L_s and the mass of firms in each state N_s are therefore endogenous. States differ in their endowment of housing H_s, intermediate goods productivity A_s, and entry efficiency A_s^e. Intermediate goods sent from state s' to state s incur an iceberg trade cost denoted by $d_{s,s'} > 1$ if $s \neq s'$ and $d_{ss} = 1$. We assume that the trade cost is symmetric ($d_{s,s'} = d_{s',s}$).

The government owns the housing in each state. It sets rent r_s for each unit of housing so that all available housing is used. Rents are then redistributed to each worker residing in the state as lump sum payment τ_s. The workers in state s own the firms in state s and receive equal shares of firm profits net of entry costs $(\pi_s - p_s^e)N_s/L_s$.

[8] The simple one-region model is a special case of the multiple-region model in which all regions are symmetric and households only derive utility from consumption.

2. Final Goods Production

In each state s, final goods are produced using the CES technology

$$Y_s = \left[\sum_{s'=1}^{S} \int_0^{N_{s'}} y_{s,s'}(j)^{(\sigma-1)/\sigma} dj\right]^{\sigma/(\sigma-1)},$$

where $y_{s,s'}(j)$ is the quantity of intermediate input variety j produced by firm j in state s' and sold to state s.

Let $p_{s,s'}(j)$ denote the price of this good in state s. Profit maximization by perfectly competitive final goods producers implies that the price of the final good in state s is

$$P_s = \left[\sum_{s'=1}^{S} \int_0^{N_{s'}} p_{s,s'}(j)^{1-\sigma} dj\right]^{1/(1-\sigma)}$$

and demand for each variety in state s is given by

$$\frac{y_{s,s'}(j)}{Y_s} = \left[\frac{p_{s,s'}(j)}{P_s}\right]^{-\sigma}.$$

3. Worker's Problem

The utility of a worker in state s is a Cobb-Douglas combination of consumption of the final good and housing:

$$U_s = \left(\frac{c_s}{\alpha}\right)^{\alpha}\left(\frac{h_s}{1-\alpha}\right)^{1-\alpha}, \quad \alpha \in (0, 1).$$

The worker maximizes U_s by choosing c_s and h_s subject to the budget constraint

$$P_s c_s + r_s h_s \leq w_s + (\pi_s - p_s^e)N_s/L_s + \tau_s =: v_s.$$

The consumer spends α share of their income v_s on consumption and the rest on housing:

$$P_s c_s = \alpha v_s, \quad r_s h_s = (1-\alpha) v_s.$$

Workers choose to live and work in the state that gives them the highest utility.

4. Entry Technology

To produce in state s, a firm buys an entry good that is produced using local labor l_s^e and the state's final consumption good y_s^e according to the Cobb-Douglas technology

$$N_s = A_s^e \left(\frac{l_s^e}{\lambda}\right)^{\lambda} \left(\frac{y_s^e}{1-\lambda}\right)^{1-\lambda}, \quad \lambda \in (0,1).$$

This is the same entry technology as the static one-region model except that the entry efficiency A^e can vary by state.

As before, we assume that the market for entry goods is perfectly competitive, so the equilibrium price of the entry good p_s^e/P_s increases with factor prices and declines with entry efficiency A_s^e:

$$\frac{p_s^e}{P_s} \propto \left(\frac{w_s}{P_s}\right)^{\lambda} \frac{1}{A_s^e}. \tag{9}$$

5. Intermediate Goods Firm's Problem

Intermediate goods producers in state s are ex ante identical and have the same productivity A_s after entry into state s. As a result, producers in each state make the same decision and we drop the firm j index. A firm in state s can produce y units of its variety using y/A_s units of labor. Since delivering a unit of the good from state s' to state s requires $d_{s,s'}$ units of the good, the labor input needed by a firm in state s' to deliver y units of goods to state s is given by

$$l_{s,s'} = y\frac{d_{s,s'}}{A_{s'}}.$$

Given this technology and the demand function in each state s, a firm in state s' chooses prices $p_{s,s'}$ for each destination state s to maximize postentry profits,

$$\sum_{s=1}^{S}\left(p_{s,s'} - w_{s'}\frac{d_{s,s'}}{A_{s'}}\right)\left(\frac{p_{s,s'}}{P_s}\right)^{-\sigma} Y_s.$$

The optimal price is a fixed markup over the marginal cost, where the firm charges a higher price for destinations with larger trade costs:

$$p_{s,s'} = \frac{\sigma}{\sigma-1}\frac{d_{s,s'}\, w_{s'}}{A_{s'}}.$$

The profit for selling to state s is thus

$$\pi_{s,s'} = \frac{p_{s,s'}\, y_{s,s'}}{\sigma},$$

and a firm enters in state s' if and only if its total profits across all destinations cover the entry cost:

$$\pi_{s'} := \sum_{s=1}^{S} \pi_{s,s'} \geq p^e_{s'}.$$

6. Closing the Model

Given L and $\{A_s, A^e_s, H_s, d_{s,s'}\}$ an equilibrium consists of prices $\{w_s, r_s, P_s, p^e_s\}$ in each location s and $p_{s,s'}$ for each trading pair (s, s'), and allocations $\{c_s, h_s, L_s, L^e_s, L^y_s, C_s, Y_s, Y^e_s, N_s, \tau_s, y_{s,s'}, l_{s,s'}\}$ such that for each state s

1. $\{c_s, h_s\}$ solve the worker's problem given prices and transfers;
2. $\{l_{s,s'}, y_{s,s'}, p_{s,s'}\}$ solve the intermediate goods firm's problem;
3. $\{L^e_s, Y^e_s\}$ solve the entry goods producer's problem;
4. the zero-profit condition for intermediate goods producers holds:

$$N_s(\pi_s - p^e_s) = 0, \quad \pi_s - p^e_s \geq 0, \quad N_s \geq 0;$$

5. land markets clear: $H_s = L_s h_s$;
6. labor markets clear: $L_s = L^e_s + L^y_s$ and $L = \Sigma_s L_s$;
7. final goods markets clear: $Y_s = C_s + Y^e_s$, where $C_s = L_s c_s$;
8. government budgets are balanced: $r_s H_s = \tau_s L_s$;
9. workers are indifferent between locations.

Since the model is standard, we refer readers to appendix A for the solution of the model. Next, we turn to how entry technology parameters modulate the welfare effects of changes in productivity.

7. Entry and Shocks to the Level of Productivity

Welfare depends on consumption and housing. Consumption is equal to the real wage in the equilibrium $c_s = w_s/P_s$ because of the household's budget constraint, the zero-profit condition for intermediate goods firms, and the balanced government budget condition. The real wage in turn is equal to

$$\ln \frac{w_s}{P_s} = \text{constant} + \frac{\ln A^e_s + \ln L + (\sigma - 1)\ln A_s + \ln(L_s/L) + (\sigma - 1)\ln(n_{s,s}) - \sigma \ln(b_{s,s})}{\sigma - 1 - (1 - \lambda)}, \tag{10}$$

where $b_{s,\,s}$ is the expenditure share in state s on local goods and $n_{s,\,s}$ is the share of production labor used to produce domestically consumed goods.

For illustration, consider symmetric states with the same initial values of $\{A_s, A^e_s, H_s, d_{s,s'}\}$. And consider a common change in A_s to clarify the model's properties. In this case, L_s/L, $n_{s,\,s}$ and $b_{s,\,s}$ do not change. As in the one-region model, the elasticity of the real wage in every state to the A_s shock is

$$\frac{\partial \ln w_s/P_s}{\partial \ln A_s} = 1 + \frac{1-\lambda}{\sigma - 1 - (1-\lambda)},$$

while the elasticity with respect to L and a common A_s^e shock is

$$\frac{\partial \ln w_s/P_s}{\partial \ln A_s^e} = \frac{\partial \ln w_s/P_s}{\partial \ln L} = \frac{1}{\sigma - 1}\left[1 + \frac{1-\lambda}{\sigma - 1 - (1-\lambda)}\right].$$

Since H_s/L_s does not change in response to shocks to the common values for A_s and A_s^e, the elasticity of consumption-equivalent welfare is the same as the elasticity of the real wage with respect to an A_s or an A_s^e shock. Consumption per capita increases when total population increases. However, housing per capita also declines. Hence the consumption-equivalent welfare impact of a shock to total population L is

$$\frac{1}{\sigma - 1 - (1-\lambda)} - \frac{1-\alpha}{\alpha}.$$

To recap, a smaller labor share in entry (lower λ) amplifies the positive effects on welfare from higher productivity, entry efficiency, or population.

8. Entry and Amplification of Productivity Growth

As in the one-region endogenous growth model in section II.A, we can extend the entry technology to

$$A_{st}^e(A_{s,t}(j)) = N_{s,t-1}^{\phi} \exp\left[-\mu \frac{A_{s,t}(j)}{A_{s,t-1}}\right] \exp(\epsilon_{st}),$$

so that entry costs for a firm in state s depend on the technology chosen by the firm relative to the lagged aggregate productivity in state s.

As before, the firm's optimal choice of $A_{st}(j)$ is given by

$$\sigma - 1 = \mu \frac{A_{st}(j)}{A_{s,t-1}},$$

and all regions have the same growth in A:

$$g_t^A := \ln \frac{A_{st}}{A_{s,t-1}} = \ln \frac{\sigma - 1}{\mu}.$$

At the steady state equilibrium where ϵ_{st}, amenities H_s, and trade costs $d_{s,s'}$ are constant and the national population grows at rate g^L, the number of firms in each state grows at rate

$$g_{st}^N = \frac{g_t^L + (1-\lambda) g_t^{w/p}}{1-\phi}, \tag{11}$$

which in turn implies that the real wage grows in all states at rate

$$g_{st}^{w/p} = \frac{(\sigma - 1)g_t^A + g_t^L/(1 - \phi)}{\sigma - 1 - (1 - \lambda)/(1 - \phi)}. \tag{12}$$

Again, like in the one-region model, the effects of g^A and g^L on the growth rate of the real wage are amplified through entry when λ is less than 1 or when there is positive spillover ($\phi > 0$).

III. Evidence on Entry Costs and Growth

Motivated by the previous section, we next consider what values of λ and ϕ are consistent with data on the number and productivity of US firms. The free entry condition is a zero-profit condition that equalizes average firm profits with the entry cost. Hence we can look at the relationship between firm profits and labor productivity over time and across states to infer how entry costs correlate with labor productivity. Another way is to look at the relationship between average employment per firm and labor productivity if the ratio of average payroll to average profit does not vary systematically with labor productivity. In this section, we examine the relationship between average employment and labor productivity because firm employment data are available for all industries. In section V, we show that our findings are robust to trends in the ratio of average payroll to average profit. We also directly examine the relationship between firm profits and labor productivity in manufacturing using restricted data from the Census of Manufacturing.

A. *Strategy for Estimating How Entry Costs Vary with Growth*

From the free entry condition and the solution to the firm's problem, we can derive the following equilibrium relationship between the average payroll of intermediate goods producer and the entry cost in each state:

$$\frac{w_s}{P_s}\frac{L_s^y}{N_s} = (\sigma - 1)\frac{\pi_s}{P_s} = (\sigma - 1)\frac{p_s^e}{P_s} = (\sigma - 1)\left(\frac{w_s}{P_s}\right)^{\lambda}\frac{1}{A_s^e}. \tag{13}$$

The first equality comes from production worker payroll per firm being proportional to firm profits, while the second equality comes from the free entry condition. The last equality derives from the entry technology that links entry costs with the real wage and entry efficiency.

Rearranging (13), we can look at how employment per firm varies with the real wage to infer how entry costs vary with the real wage:

$$\frac{L_s^y}{N_s} = (\sigma - 1)\left(\frac{w_s}{P_s}\right)^{\lambda - 1}\frac{1}{A_s^e}. \tag{14}$$

If entry uses only labor ($\lambda = 1$) and entry efficiency is constant, entry costs increase one for one with the real wage. Through the free entry condition, this implies that firm profits and hence firm payroll likewise increase one for one with the real wage. Since payroll is employment multiplied by the real wage, this further implies that employment per firm is invariant to changes in the real wage. In contrast, if entry uses only goods ($\lambda = 0$), then entry costs and payroll per firm are constant, which implies that employment per firm declines proportionately with the real wage.

As we will discuss later in this section, we have data on all workers (production and entry labor combined) and on gross state product (GSP). The model predicts a similar relationship between these data variables to what it predicts for production workers and real wages in (14). If σ and λ are the same across states, then production workers per firm are proportional to total employment per firm:

$$L_s = L_s^e + L_s^y = \frac{\lambda N_s p_s^e}{w_s} + L_s^y = \left(\frac{\lambda}{\sigma - 1} + 1\right) L_s^y.$$

We measure the real wage using local labor productivity GSP/L_s since

$$\frac{\mathrm{GSP}_s}{L_s} = \frac{N_s}{L_s}\sum_{s'}^{S}\frac{p_{s',s}y_{s',s}}{P_s} = \frac{N_s}{L_s}\frac{w_s}{P_s}\sum_{s'}^{S}\frac{\sigma}{\sigma - 1}l_{s',s} = \frac{\sigma}{\sigma - 1}\frac{w_s}{P_s}\frac{L_s^y}{L_s} = \frac{w_s}{P_s}\frac{\sigma}{\sigma - 1 + \lambda}.$$

Substituting the expressions for L_s and GSP_s/L_s into (14) yields the following equations involving observed variable and parameters:

$$\ln\frac{L_{st}}{N_{st}} = \text{constant} + (\lambda - 1)\ln\frac{\mathrm{GSP}_{st}}{L_{st}} - \phi \ln N_{s,t-1} - \epsilon_{st}. \tag{15}$$

Consistent with our growth model at the steady state, we can also look at the relationship between changes in employment per firm and changes in GSP per worker:

$$\Delta \ln\frac{L_{st}}{N_{st}} = (\lambda - 1)\Delta \ln\frac{\mathrm{GSP}_{st}}{L_{st}} - \phi\Delta \ln N_{s,t-1} - \Delta\epsilon_{st}. \tag{16}$$

This equation holds even if the elasticity of substitution σ and hence the ratio of payroll to revenue vary across states.

We will run OLS regressions corresponding to (15) and (16) to show that employment per firm is stable relative to variations in GSP per worker and the lagged number of firms. From the perspective of our model, these patterns imply that entry costs rise with labor productivity both across states and over time within states.

Although these regressions address the key question of whether entry costs rise with growth, the OLS regression coefficients do not correctly identify the parameters λ and ϕ that determine exactly why entry costs rise with growth. This is because the regressors (GSP_s and N_s) are endogenous to the residuals (entry efficiency ϵ_s) in this regression, according to our model. In section IV, we will use GMM to estimate the values of λ and ϕ in a model-consistent fashion.

B. *Empirical Patterns*

We use Business Dynamics Statistics (BDS) from the US Census Bureau on employment L_{st} and the number of firms or establishments N_{st} in each state. The models we described above feature a one-shot equilibrium that does not distinguish between new firms and incumbent firms. In the data, however, we apply our inference strategy to new firms separately from all firms. We use real gross value added from the Bureau of Economic Analysis (BEA) to calculate GDP_t and GSP_{st}. We describe the data in more detail in appendix C.

1. National Time-Series Evidence

Figure 1 displays the result of regressing log number of firms on log employment and log employment per firm on log GDP per worker, respectively, over time. The data are yearly from 1978 to 2020. Both bilateral relationships are strongly positive both economically and statistically. If we regress log firms on both log employment and log GDP per worker at the same time, the coefficient on log employment increases, whereas the coefficient on log GDP per worker becomes small and insignificant. If we

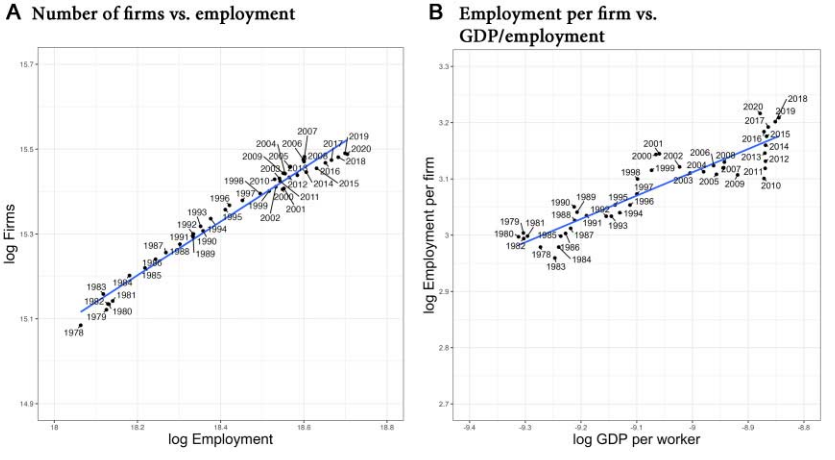

FIG. 1.—US national time series, 1978–2020. The number of firms and employment are from the US Census Bureau's Business Dynamic Statistics. Real GDP is from the US Bureau of Economic Analysis. In *A*, the slope coefficient is 0.63 (standard error 0.02) and the $R^2 = 0.98$. In *B*, the slope is 0.42 (0.03) and the R^2 is 0.85.

add a linear time trend to this multivariate regression, the coefficient on employment increases further and that on GDP per worker becomes modestly positive and significant. These results are consistent with entry costs being more labor intensive than goods intensive.

We now run OLS regressions based on (15) that are designed to explicitly get at how entry costs vary with growth. We add lagged firms to the regression in the spirit of the intertemporal knowledge spillovers (parameterized by ϕ) in our model.[9] Table 1 displays the result of regressing log employment per firm in the United States on log real GDP per worker and the lag of the log number of firms at the national level.[10] Using nonoverlapping 5-year averages generates similar results.

The column 1 of table 1 displays the results when imposing $\phi = 0$, which is consistent with the one-region love-of-variety model. Column 2 also estimates ϕ, which is consistent with the one-region endogenous growth model in section II.A. The regression using all firms and imposing $\phi = 0$ yields $\lambda^{\mathrm{OLS}} = 1.415$ (standard error 0.027), which implies an amplification of *negative* 12.1% (standard error 0.7%). Column 2 shows $\lambda^{\mathrm{OLS}} = 1.236$ (standard error 0.073) and $\phi^{\mathrm{OLS}} = -0.246$ (standard error 0.095), which implies that there was negative spillover from past entry. The amplification factor in this case remains mildly negative at -5.9% (standard error 2.1%).

These regressions using data on all firms do not control for the aging of firms as documented by Hopenhayn, Neira, and Singhania (2022) and Karahan, Pugsley, and Şahin (2024). Since older firms tend to be larger, the average employment of firms may have risen due to aging rather than entry costs. Columns 3 and 4 of table 1 run the same regression but using average employment of *new* firms as regressors, while keeping the explanatory variables the same.[11] We find that average employment of new firms and plants is stable relative to the rise in output per worker and rise in the number of firms. In column 3 where ϕ is restricted to be zero, we have $\lambda^{\mathrm{OLS}} = 0.907$ (standard error 0.055) and amplification = 3.2% (standard error 1.9%). In column 4, $\lambda^{\mathrm{OLS}} = 0.634$ (standard error 0.146), $\phi^{\mathrm{OLS}} = -0.356$ (standard error 0.191), and amplification = 9.9% (standard error 3.0%).

In sum, all the regressions using national data show that over the past four decades in the United States, average employment per firm has been increasing and average employment per new firm has been stable while labor productivity grew. The free entry condition in our baseline model interprets this pattern as a rise in entry costs with labor productivity so that amplification is modest. As mentioned, however, these OLS estimates

[9] The regression starts in 1979, the second year of data, when we add lagged number of firms.

[10] Table A2 (tables A1–A6 are available online) displays the results using establishments instead of firms.

[11] Using new firms, as opposed to all firms, controls for changes in the discount factor, postentry growth rate, and exit rate. We clarify this in sec. V.A.

TABLE 1
EMPLOYMENT PER FIRM ON GDP PER WORKER AND LAGGED NUMBER OF FIRMS

	National Sample, 1978–2020			
	All Firms		New Firms	
	(1)	(2)	(3)	(4)
λ^{OLS}	1.415	1.236	.907	.634
	(.027)	(.073)	(.055)	(.146)
ϕ^{OLS}		−.246		−.356
		(.095)		(.191)
R^2	.847	.864	.066	.170
Observations	43	42	43	42
Amplification (%)	−12.1	−5.9	3.2	9.9
	(.7)	(2.1)	(1.9)	(3.0)

NOTE.—Employment and firms are from the Business Dynamics Statistics of the US Census Bureau. Real output is from the US Bureau of Economic Analysis. Here λ^{OLS} is equal to 1 plus the regression coefficient on log output per worker, and ϕ^{OLS} is equal to -1 times the coefficient on log lagged number of firms. Amplification refers to the indirect effect of increases in productivity A through increased entry (variety), and is equal to $[(1-\lambda)/(1-\phi)]/[\sigma - 1 - (1-\lambda)/(1-\phi)]$. We evaluate it at $\sigma = 4$.

are not model consistent in that the residual reflects trends in entry costs that should affect the regressors. We carry out model-consistent GMM regressions in the next section.

2. State Panel Evidence

Figure 2 displays the result of regressing log number of firms on log employment and log employment per firm on log GSP per worker, respectively, across US states in 2020, the latest year of the BDS data. The number of firms in a state is strongly and positively related to the number of workers in the state, but employment per firm is not related to GSP per worker in the state. If we regress log firms on both log employment and log GDP per worker, the coefficient on log employment is unaffected, whereas the coefficient on log GDP per worker remains small and insignificant. These patterns hold for other years as well. They are consistent with entry costs being denominated in terms of labor rather than goods.

Our spatial model has predictions for the cross-state relationship between changes in state-level average firm size and the growth in real state output per worker—regression equation (16).[12] Table 2 displays the OLS regression results when we regress the change in log employment per firm on the change in log real GSP per worker and the change in log lagged number of firms using 1-year changes and cumulative 41-year changes, respectively. We use first differences to control for state fixed

[12] We run the growth regression with a constant to account for common trends in employment per firm due to factors such as aging.

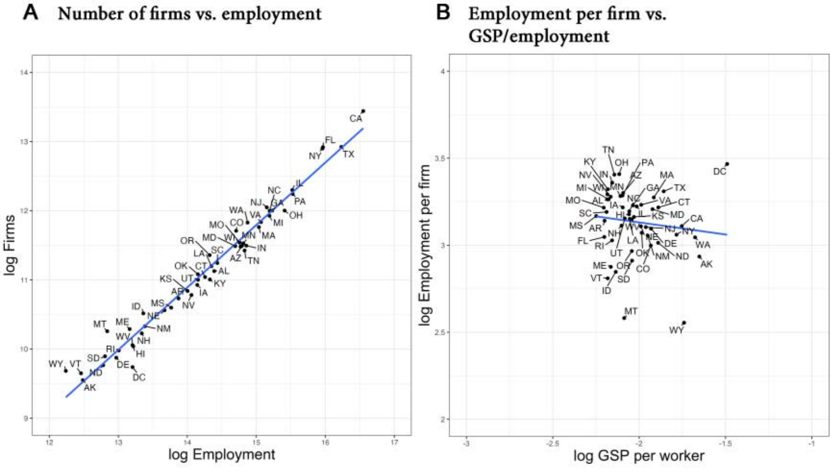

Fig. 2.—Across US states, 2020. The number of firms and employment in each state are from the US Census Bureau's Business Dynamic Statistics. Real GSP is from the US Bureau of Economic Analysis. In *A*, the slope coefficient is 0.90 (standard error 0.02) and the $R^2 = 0.97$. In *B*, the slope is -0.14 (0.16) and the R^2 is 0.01.

effects coming from state variation in price-cost markups, the entry cost shifter, and so forth.[13] We find that average employment per firm does not vary strongly with output per worker, which implies λ^{OLS} in the range of 0.69 to 0.95, depending on the horizon we use and whether we control for lagged number of firms. For the 41-year horizon, which perhaps corresponds the best to our long-run framework, the implied λ^{OLS} is 0.94 (standard error 0.10) when we control for the lagged number of firms. We do not find strong relationship between average employment per firm and lagged firms for state changes.[14]

Table 3 displays the results when we use average new firm employment, instead of average employment for all firms, as the dependent variable. The OLS estimates of λ are large and significant, while those for ϕ are larger than when using all firms. Amplification continues to be modest.[15]

IV. Inference on λ and ϕ

The previous section shows that average employment per firm is flat or rising in response to output per worker. Through the lens of the free entry

[13] We also find λ^{OLS} close to 1 and ϕ^{OLS} close to 0 when we run the level regression equation (15) with state fixed effects, with state and year fixed effects, and with state and industry-year fixed effects, respectively.

[14] Table A3 shows similar results when we run the regression using establishments instead of firms.

[15] See table A4 for results using new plants.

TABLE 2
Average Firm Size on GSP per Worker and Lagged Number of Firms

	Changes over Time, US States, 1978–2020			
	Horizon			
	41 Years		1 Year	
	(1)	(2)	(3)	(4)
λ^{OLS}	.954	.938	.694	.712
	(.07)	(.099)	(.014)	(.014)
ϕ^{OLS}		.085		−.047
		(.062)		(.021)
R^2	.004	.043	.194	.175
Observations	100	50	2,100	2,050
Amplification (%)	1.6	2.3	11.4	10.1
	(2.4)	(3.8)	(.6)	(.6)

Note.—Employment and firms are from the Business Dynamics Statistics of the US Census Bureau. Real output is from the US Bureau of Economic Analysis. Here λ^{OLS} is equal to 1 plus the regression coefficient on log output per worker, and ϕ^{OLS} is equal to −1 times the coefficient on log lagged number of firms. Amplification refers to the indirect effect of increases in productivity A through increased entry (variety), and is equal to $[(1-\lambda)/(1-\phi)]/[\sigma - 1 - (1-\lambda)/(1-\phi)]$. We evaluate it at $\sigma = 4$.

condition, this pattern is consistent with entry costs rising with growth. This section considers what values of λ and ϕ could explain why entry costs rise with growth.

As mentioned, our OLS estimates λ^{OLS} and ϕ^{OLS} based on (15) or (16) may be biased because the labor productivity regressor is endogenous to

TABLE 3
New Firm Size on GSP per Worker and Lagged Number of Firms

	Changes over Time, US States, 1978–2020			
	Horizon			
	41 Years		1 Year	
	(1)	(2)	(3)	(4)
λ^{OLS}	1.174	1.125	1.154	1.145
	(.091)	(.107)	(.105)	(.11)
ϕ^{OLS}		.282		.028
		(.067)		(.161)
R^2	.036	.302	.001	.001
Observations	100	50	2,100	2,050
Amplification (%)	−5.5	−5.5	−4.9	−4.7
	(2.7)	(4.4)	(3.2)	(3.4)

Note.—Employment and firms are from the Business Dynamics Statistics of the US Census Bureau. Real output is from the US Bureau of Economic Analysis. Here λ^{OLS} is equal to 1 plus the regression coefficient on log output per worker, and ϕ^{OLS} is equal to −1 times the coefficient on log lagged number of firms. Amplification refers to the indirect effect of increases in productivity A through increased entry (variety), and is equal to $[(1-\lambda)/(1-\phi)]/[\sigma - 1 - (1-\lambda)/(1-\phi)]$. We evaluate it at $\sigma = 4$.

TABLE 4
ESTIMATED VALUES OF λ AND ϕ

		λ		ϕ	
MODEL	ASSUMPTION	OLS	GMM	OLS	GMM
(1) National	$\epsilon_t \perp \ln \mathrm{Pop}_t$	1.415 (.027)	1		
(2) Spatial	$\epsilon_{st} \perp$ lagged birth rate$_{st}$	.954 (.070)	1		
(3) Spatial	$\epsilon_{st} \perp$ lagged birth rate$_{st}$, $\epsilon_{st} \perp \ln H_{st}$	.938 (.099)	1	.085 (.062)	−.141 (.006)

NOTE.—The term $\ln \mathrm{Pop}_t$ is civilian non-institutionalized population from the Census Bureau and 20-year lagged birth rate is the number of births per 1,000 from the National Center for Health Statistics. The term $\ln H_s$ is calculated from $\ln L_s - [\alpha/(1-\alpha)]\ln(Y_s/L_s)$ with $\alpha = 0.84$, where Y_s is state real output per worker from the BEA, and L_s is state employment from the BDS. For row 1, λ^{OLS} is from col. 1 of table 1. For rows 2 and 3, λ^{OLS} and ϕ^{OLS} are from cols. 1 and 2 of table 2. Here λ^{GMM} is restricted to be between 0 and 1. There is no standard error for λ^{GMM} at the upper bound of 1. The standard error of ϕ^{GMM} is the standard error when estimating ϕ^{GMM} while setting $\lambda = 1$.

the residual ϵ, which represents demeaned entry efficiency. Higher entry efficiency ϵ should induce more entry and thereby raise labor productivity through the love of variety. If entry efficiency ϵ is independent of the population and amenities H_s, however, then we can use these orthogonality conditions to consistently estimate λ and ϕ.[16] See appendix A for details.

The first row of table 4 displays our GMM estimates of λ based on national time series, restricting $\phi = 0$. For this case, we only need the single-moment condition that A^e is orthogonal to the national population. As the model does not allow $\lambda > 1$, we infer the corner value $\lambda = 1$ (labor-intensive entry). To estimate the parameters of the spatial model using cross-state data, we assume that entry efficiency A_s^e is orthogonal to the 20-year lagged birth rate used in Karahan, Pugsley, and Şahin (2024). Although this assumption means that their instrument is valid, it is not obvious why it should be relevant in our model. We therefore assume further that lagged population is correlated with amenities H_s across states. This might be a stand-in for forces outside the model, such as people preferring to live where they were born. But it could also be that amenities persist over time and attract population in the past and present. Results with lagged birth rate as an instrument are presented in the second and third rows of table 4. We continue to find $\lambda^{\mathrm{GMM}} = 1$.

[16] If there is serial correlation in entry efficiency, then lagged firms could be correlated with the residual. For the time series estimation, we can instrument lagged firms with national population. When we do this the results are similar.

TABLE 5
AMPLIFICATION OF REAL WAGE RESPONDS TO SHOCKS

	g^A Shock	g^L or $\Delta\epsilon$ Shocks
General case	$\frac{1-\lambda}{1-\phi} \times (\sigma - 1 - \frac{1-\lambda}{1-\phi})^{-1}$	$[(\sigma - 1)\frac{\phi}{1-\phi} + \frac{1-\lambda}{1-\phi}] \times (\sigma - 1 - \frac{1-\lambda}{1-\phi})^{-1}$
Special cases:		
$\lambda = 1, \phi = 0$		
(no amplification) (%)	0	0
$\lambda = 0, \phi = 0$		
(λ amplification) (%)	50	50
$\lambda = 0, \phi = .5$ (λ and ϕ		
amplification) (%)	200	500
GMM spatial estimate:		
$\lambda = 1, \phi = -.14$ (%)	0	−12

NOTE.—Entries show the response of log real wages to a 100% shock to productivity (A), employment (L), or entry efficiency (ϵ) minus the change when $\lambda = 1$ and $\phi = 0$, expressed as a percentage of the change when $\lambda = 1$ and $\phi = 0$. The last row provides the responses using our point estimates for λ and ϕ over time within US states (i.e., our "spatial" estimates). We assume $\sigma = 4$ throughout.

The estimated ϕ^{GMM} is -0.14 (standard error 0.01), which implies a modestly negative knowledge spillover. Such negative spillovers are in the spirit of Bloom et al. (2020).

We now consider the amplification of shocks at our estimated values of λ and ϕ. The first row of table 5 displays the amplification formula for the real wage response to shocks hitting the growth rates of productivity A, population, or entry efficiency. The second row shows the effect in the special case where $\lambda = 1$ and $\phi = 0$ (entry involves only a fixed amount of labor), under which there is no amplification through entry. The third row considers the special case when $\lambda = 0$ and $\phi = 0$ (entry involves only a fixed amount of output). We find 50% amplification to all three shocks in this special case. If we continue to assume entry costs denominated in output ($\lambda = 0$) but add a *positive* knowledge spillover, then the table indicates that amplification rises to 200% for productivity shocks and 500% for population or entry efficiency shocks.

The final row of table 5 calculates amplification under our GMM estimates of λ and ϕ. Since the estimated λ is 1 and ϕ is negative, we obtain little amplification. This suggests that shocks to productivity, population, and entry efficiency are only weakly amplified through induced changes in entry.

V. Empirical Robustness Checks

In this section we check the robustness of our finding that entry costs rise with growth by considering alternative explanations for the stability of employment per firm with respect to output per worker.

A. *Discount Rate, Postentry Growth Rate, and Exit Rate*

We used a one-shot model for illustration in the previous section, with no firm life-cycle dynamics. A natural question is whether the stability of employment per firm could reflect changes in the dynamics of firms after entry rather than entry costs rising with growth. Consider an extension of the illustrative model wherein each entrant f in period t draws initial productivity $A_0(f, t)$. After entry, their productivity grows at rate g and they exit at exogenous rate δ. Suppose entrants discount future profits at rate r and that g is sufficiently small relative to δ and r such that the present discounted value (PDV) of profits is finite. Let N^0 denote the number of new firms and L^0/N^0 the average employment of new firms. In this case, the stock of firms becomes

$$N_{st} = N_{s,t-1}(1-\delta) + N^0_{s,t}, \quad N^0_{s,t} = A^e_{s,t}(Y^e_{s,t})^{1-\lambda}(L^e_{s,t})^{\lambda},$$

and the free entry condition equalizes the entry cost with the sum of discounted profits

$$\frac{p^e_{st}}{P_{st}} \propto \frac{w_{st}}{P_{st}}\frac{L^0_{st}}{N^0_{st}}\sum_{a=0}^{\infty}\left[\frac{(1+g)^{\sigma-1}(1-\delta)}{1+r}\right]^a.$$

The new-firm results in tables 1 and 3 say that L^0/N^0 is stable relative to changes in output per worker over time and across states. In particular, the results for the 41-year average in table 3 potentially mitigate out-of-steady-state dynamics. Our interpretation is that g, r, and δ are stable and entry costs p^e/P rise proportionally with output per worker. An alternative explanation, however, is that entry costs p^e/P are constant but changes in g, r, and δ offset the changes in output per worker. For example, if the discount rate r rises with w/P, the postentry growth rate declines with w/P, or the exit rate rises with w/P, this could confound our inference about how entry costs change with growth.

While output per worker rose significantly over time in the United States, we did not see significantly higher interest rates or return to capital. See Gomme, Ravikumar, and Rupert (2011) and Farhi and Gourio (2018). We do not expect interest rates to vary significantly across states, meanwhile, as capital flows freely across states. Furthermore, studies document that firm exit rate by age has been stable over time while employment growth rate by age has been stable or increasing for older firms—see Hopenhayn, Neira, and Singhania (2022) and Karahan, Pugsley, and Şahin (2024). This suggests that the present discounted value of profit may have increased even faster with growth than implied by our regressions using new firm employment. Hence, we infer that entry costs rise with growth even after considering postentry dynamics.

For US manufacturing we can go a step further and directly calculate the present discounted value of profits. For a cohort of entering in year t, we calculate the expected PDV of profits using the average realized PDV of profits for a cohort. So our proxy for entry costs in period t is

$$\frac{1}{N_t^0}\sum_{f=1}^{N_t^0}\sum_{a=0}^{D_f}\beta(t,a)\pi_f(t,a), \tag{17}$$

where f indexes the entrants in the cohort, and D_f denotes the age of the entrant at the time of exit (death). Here $\pi_f(t, a)$ is the profit of entrant f from cohort t and age a and $\beta(t, a)$ is the discount factor.

Implementing the PDV measure requires us to estimate the flow of profits. Rather than trying to distinguish economic and accounting profits or variable and fixed costs, we estimate price-cost markups and combine our estimates with revenue to infer profits. Although estimating the level of markups is notoriously difficult, for our purposes we only need to know how markups vary over time. We use the over-time variation in the ratio of output to payroll.

We use establishment-level data from the US Census Bureau's Census of Manufacturing (CMF) for 1963 and quinquennially from 1972 to 2012. The CMF covers all establishments with employees. For our sample period, there are about 1.54 million unique establishments. We construct cohorts based on the first year each establishment appears in the data. This means that we drop all observations in 1963, because we cannot identify when these plants entered; we use the 1963 plants to determine which of the 1967 plants are entrants. We also drop plants that exit and then reenter, as their entry year is ambiguous. We drop all plant-years with negative or missing shipments, intermediate inputs, payroll, or employment.

We calculate the PDV of profits for each cohort in the following way. First, we multiply shipments by the profit share (implied by our time-varying ratio of shipment to payroll) to generate profits for each plant-year. We deflate all profits by the BEA manufacturing value added deflator.[17] We discount each year of real profits assuming a constant real interest rate $r = 0.05$. We calculate the PDV of real profits for each cohort using horizons of 0, 5, 10, and 15 years. A shorter horizon gives us more observations but covers less of a cohort's lifetime. The PDV for each cohort should be an unbiased estimate of its entry cost, given the zero-profit condition for entrants.

We use real manufacturing value added per worker each year to proxy for aggregate productivity. We deflate total value added per worker in each year by the BEA manufacturing value added deflator. We calculate the total value added and total number of workers by summing value added and employment across plants in each year.

[17] Since we only have data every 5 years, for each plant we interpolate real profit between years to generate yearly profits. We linearly interpolate the log of real profits, which is equivalent to fitting a constant growth rate of real profits between adjacent observations.

Across entering cohorts, we regress the log of the PDV of real profits on the log of real value added per worker in the year of the cohort's entry. Table 6 presents the results. At the 5 and 10 year horizons, the PDV of profits rises even more than one-for-one with labor productivity at the time of entry (a slope above 1). The standard errors are small (0.25 or less) and the R^2's are large (0.8 or higher). At the 15-year horizon the PDV of profits increases less than one-for-one with labor productivity at entry, but the connection is still quite positive (slope 0.65). Thus, at all horizons, it appears that entry costs rise strongly with average labor productivity in US manufacturing.

B. *Trends in the Aggregate Markup or Markdown*

The relationship between entry costs, average employment per firm, and the real wages is

$$\frac{p^e_{st}}{P_{st}} = \frac{1}{\sigma_{st} - 1}\left(\frac{wL}{PN}\right)_{st}.$$

Our baseline model assumes that the elasticity of substitution σ_{st} is either constant over time or homogeneous across states. Thus an alternative explanation for the stability of firm employment with respect to output per worker is that markups are declining (say because of σ rising) with output per worker. Similarly, extending our model to include time-varying markdowns would imply

$$\frac{p^e_{st}}{P_{st}} = \frac{1}{\eta_{st}}\left(\frac{wL}{PN}\right)_{st},$$

where η_{st} is the elasticity of labor supply. A lower η_{st} implies more labor market power for firms and a steeper markdown.

TABLE 6
PDV of Establishment Profits on Value Added per Worker

	US Manufacturing: 1967, 1972, ... , 2012			
	Horizon			
	0	5	10	15
Coefficient on ln Y/L	1.297	1.232	1.254	.648
	(.097)	(.191)	(.250)	(.151)
R^2	.957	.856	.807	.787
Number of cohorts	10	9	8	7
First cohort	1967	1967	1967	1967
Last cohort	2012	2007	2002	1997

Note.—US Census of Manufacturing (FSRDC project no. 1440, clearance request no. 5434) and the US Bureau of Economic Analysis. The table reports the regression coefficient from regressing log real PDV of profits by cohort on log real manufacturing output per worker at the time of entry. Horizon h means the PDV is calculated using profit streams from age 0 to age h.

Looking at the above expressions, we see that entry costs may be constant ($\lambda = 0$) even if average firm employment is constant because firm product and labor market power decline proportionally with output per worker over time or across states, such that $[1/(\sigma - 1)](w/P)$ or $(1/\eta)(w/P)$ in the above expressions is constant over time and across states. Intuitively, when entry costs are stable with respect to changes in output per worker, higher labor productivity reduces equilibrium average employment per firm. In the opposite direction, weaker product and labor market power (higher σ and η) raise employment per firm because more revenue is needed to generate the same amount of profits. In theory, equilibrium firm employment may not vary with output per worker because these two forces exactly cancel each other out.

Our regression of within-state changes in (16) controls for markup and markdown heterogeneity across states that can be picked up by state fixed effects—that is, σ and η variation across states but not over time. Over time in the United States, the PDV calculations in the previous section control for markup and markdown trends, at least for manufacturing. We also ran (16) with a time fixed effect to control for changes in markups and markdowns over time. Note that we cannot run this regression for the longest horizon in table 7 because we only have one period in that case. For the 10-year and 1-year horizons, we find similar coefficients to our baseline regression in table 2.

In addition to these robustness checks, it is worth noting that the literature tends to find rising or stable markups. See, for example, Autor

TABLE 7
AVERAGE FIRM SIZE ON GSP PER WORKER AND LAGGED NUMBER OF FIRMS

	CHANGES OVER TIME, US STATES, 1978–2020, WITH TIME FIXED EFFECTS			
	Horizon			
	10 Years		1 Year	
	(1)	(2)	(3)	(4)
λ^{OLS}	.626	.634	.688	.708
	(.048)	(.061)	(.014)	(.014)
ϕ^{OLS}		.016		−.066
		(.079)		(.022)
Within R^2	.385	.385	.201	.183
Observations	150	150	2,100	2,100
Amplification (%)	14.2	14.2	11.6	10.0
	(2.1)	(2.1)	(.6)	(.6)

NOTE.—Employment and firms are from the Business Dynamics Statistics of the US Census Bureau. Real output is from the US Bureau of Economic Analysis. Here λ^{OLS} is equal to 1 plus the regression coefficient on log output per worker, and ϕ^{OLS} is equal to -1 times the coefficient on log lagged number of firms. Amplification refers to the indirect effect of increases in productivity A through increased entry (variety), and is equal to $[(1 - \lambda)/(1 - \phi)]/[\sigma - 1 - (1 - \lambda)/(1 - \phi)]$. We evaluate it at $\sigma = 4$.

et al. (2020) and De Loecker, Eeckhout, and Unger (2020). Evidence for markdowns is more mixed; Berger, Herkenhoff, and Mongey (2022) report a decline in local labor market concentration between 1977 and 2013, while Yeh, Macaluso, and Hershbein (2022) find that markdowns declined and then increased over time.

C. *Industry Composition*

Our inference is based on a single-industry model. We can easily extend the inference to multiple industries. Suppose industry output is produced using the CES structure as in our baseline model. And suppose entry into an industry uses c_i units of the entry good. Then free entry into each industry implies that average employment in an industry is equal to $(\sigma - 1 + \lambda) c_i (p^e/w)$. Aggregate employment per firm is then the industry-weighted average of entry costs relative to wages:

$$\frac{L}{N} = (\sigma - 1 + \lambda) \frac{p^e \sum_i [(N_i/N) c_i]}{w}.$$

Therefore, the empirical pattern of stable L/N relative to output per worker still implies that entry costs $p^e \Sigma_i [(N_i/N) c_i]$ rise with growth. However, in addition to the entry technology channels (ϕ and λ) that work through p^e, the rise in entry costs can also be explained by reallocation toward industries with higher entry costs c_i. We can distinguish between the reallocation and entry technology channels by using a measure of average employment that is not affected by reallocation across industries. Let $\bar{s}_i$ be the average share of firms in industry i across years. If the free entry condition holds in each industry then

$$\sum_i \bar{s}_i \frac{L_i}{N_i} = (\sigma - 1 + \lambda) \frac{p^e}{w} \left(\sum_i \bar{s}_i c_i \right).$$

Changes in this fixed-weight average come purely from changes in p^e/w:

$$d \ln \left(\sum_i \bar{s}_i \frac{L_i}{N_i} \right) = d \ln \left(\frac{p^e}{w} \right).$$

The BDS data report employment and firms by NAICS 2-digit in each state-year for the business sector. We set s_i in each state to the 1978–2020 average NAICS 2-digit share of firms. Table 8 shows the same regression as table 2 but with the fixed weight on each industry in constructing average employment per firm on the left-hand side. The results are similar to the baseline in table 2.

D. *Selection on Entry*

Our inference strategy assumes the entrants do not know their productivity before entering and hence entry costs are proportional to average

TABLE 8
Average Firm Size on GSP per Worker and Lagged Number of Firms

	Changes over Time, US States, 1978–2020, Fixed Industry Weights			
	Horizon			
	41 Years		1 Year	
	(1)	(2)	(3)	(4)
λ^{OLS}	1.013	.988	.689	.721
	(.072)	(.102)	(.015)	(.015)
ϕ^{OLS}		.080		−.130
		(.064)		(.022)
R^2	.000	.032	.179	.168
Observations	100	50	2,100	2,000
Amplification (%)	−.4	.4	11.6	9.0
	(2.4)	(3.7)	(.6)	(.6)

Note.—Employment and firms are from the Business Dynamics Statistics of the US Census Bureau. Real output is from the US Bureau of Economic Analysis. Here λ^{OLS} is equal to 1 plus the regression coefficient on log output per worker, and ϕ^{OLS} is equal to -1 times the coefficient on log lagged number of firms. Amplification refers to the indirect effect of increases in productivity A through increased entry (variety), and is equal to $[(1-\lambda)/(1-\phi)]/[\sigma - 1 - (1-\lambda)/(1-\phi)]$. We evaluate it at $\sigma = 4$.

firm employment. If entrants know their productivity, however, then the free entry condition implies that entry costs are proportional to the employment of the marginal entrant rather than to average employment across all entrants.

In the case of Pareto-distributed entrant productivity, the size of the marginal entrant is proportional to that of the average entrant. In this case our finding that average entrant size increases with labor productivity is consistent with entry costs rising with growth. In the event of normally distributed entrant productivity, however, we need to examine other moments of the entrant size distribution. In particular, if the profit of the marginal entrant is pinned down by a constant entry cost denominated in terms of output, then we expect the dispersion of profits to increase with output per worker under normally distributed entrant productivity.

We can look at entrant dispersion in US manufacturing over time. Table 9 displays the results from regressing dispersion in PDV against real output per worker in US manufacturing. At all horizons, dispersion fails to increase with output per worker. Hence, we conclude that entry costs faced by the marginal entrant must also be increasing with output per worker.[18]

[18] Table A5 shows that average employment of firms with 1–4 employees is also stable with respect to output per worker across states. This is consistent with entry costs of marginal entrants rising with growth if the marginal entrants are in the smallest employee bin.

TABLE 9
Dispersion of PDV of Profits of New Establishments on Value Added per Worker

	US Manufacturing: 1967, 1972, ..., 2012			
	Horizon			
	0	5	10	15
Coefficient on Y/L	$-.091$	$-.099$	$-.018$	$-.374$
	(.068)	(.116)	(.157)	(.097)
R^2	.180	.093	.002	.748
Number of cohorts	10	9	8	7
First cohort	1967	1967	1967	1967
Last cohort	2012	2007	2002	1997

Note.—US Census of Manufacturing (FSRDC project no. 1440, clearance request no. 5434) and the US Bureau of Economic Analysis. The table reports the regression coefficient from regressing dispersion of log real PDV of profits by cohort on log real manufacturing output per worker at the time of entry. Horizon h means the PDV is calculated using profit streams from age 0 to age h.

E. *Measurement Error in Labor*

The modest relationship that we find between average employment per firm and labor productivity across time and states could be biased downward by measurement error in labor L. We check whether our results are driven by this division bias using employment from the County Business Patterns (CBP) to construct gross state product per worker but employment from the Business Dynamics Statistics to construct employment per firm. Table 10 displays the results.[19] The regression coefficients are similar to the baseline in table 2. We also checked for potential measurement errors by using Y/L^{CBP} to instrument for Y/L^{BDS}. The results are similarly reassuring, and are reported in table A6. Thus, our results do not appear to be from measurement error in L.

VI. Conclusion

In the United States, the number of workers per firm is stable or rises with output per worker over time and across states. This fact can be explained by a model in which entry costs rise with labor productivity. Entry costs can rise with productivity for multiple reasons. First, if entry is labor intensive then higher wages that go along with higher labor productivity raise the cost of entry. Second, the costs of setting up operations could be increasing with the level of technology. This may involve a negative knowledge spillover from past innovation à la Bloom et al. (2020). We leave it for future research to try to distinguish between these explanations.

[19] The longest horizon is shorter than in the baseline due to availability of CBP data.

TABLE 10
BDS Workers per Firm on GSP per CBP Worker and Lagged Number of Firms

	Changes over Time, US States, 1986–2020			
	Horizon			
	34 Years		1 Year	
	(1)	(2)	(3)	(4)
λ^{OLS}	.956	.950	.801	.803
	(.101)	(.098)	(.015)	(.015)
ϕ^{OLS}		.137		−.036
		(.069)		(.023)
R^2	.004	.082	.095	.097
Observations	50	50	1,700	1,700
Amplification (%)	1.5	2.0	7.1	6.7
	(3.5)	(3.9)	(.6)	(.6)

Note.—Employment and firms are from the Business Dynamics Statistics of the US Census Bureau and the County Business Patterns. Real output is from the US Bureau of Economic Analysis. Here λ^{OLS} is equal to 1 plus the regression coefficient on log output per worker, and ϕ^{OLS} is equal to -1 times the coefficient on log lagged number of firms. Amplification refers to the indirect effect of increases in productivity A through increased entry (variety), and is equal to $[(1-\lambda)/(1-\phi)]/[\sigma - 1 - (1-\lambda)/(1-\phi)]$. We evaluate it at $\sigma = 4$.

We draw out several implications for policy and modeling. First, policies that boost productivity need not boost entry of firms. Thus there is no amplification of the effect on aggregate productivity through entry. Second, if the modeling choice is between fixing entry costs in labor or output, it is more realistic to denominate in terms of labor. Third, we empirically corroborate the common assumption in endogenous growth models that the cost of innovation rises with the level of technology attained.

Throughout we assumed a close connection between firms and products—specifically, that each firm has the same number of products (which could be growing at a common rate). This assumption could be relaxed with sufficient data. An example is Berlingieri et al. (2024), who document how French firms differ in terms of their portfolio of products.

Data Availability

Code replicating the tables and figures in this article can be found in Klenow and Li (2024) in the Harvard Dataverse, https://doi.org/10.7910/DVN/N01UST.

References

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr. 2018. “Innovation, Reallocation, and Growth.” *A.E.R.* 108 (11): 3450–91.

Aghion, Philippe, and Peter Howitt. 1992. “A Model of Growth through Creative Destruction.” *Econometrica* 60 (2): 323–51.

Atkeson, Andrew, and Ariel Burstein. 2010. "Innovation, Firm Dynamics, and International Trade." *J.P.E.* 118 (3): 433–84.

———. 2019. "Aggregate Implications of Innovation Policy." *J.P.E.* 127 (6): 2625–83.

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2020. "The Fall of the Labor Share and the Rise of Superstar Firms." *Q.J.E.* 135 (2): 645–709.

Baqaee, David, and Emmanuel Farhi. 2021. "Entry vs. Rents: Aggregation with Economies of Scale." Working paper, Dept. Econ, Univ. California, Los Angeles.

Baqaee, David Rezza, Emmanuel Farhi, and Kunal Sangani. 2024. "The Darwinian Returns to Scale." *Rev. Econ. Studies* 91 (3): 1373–1405.

Bento, Pedro, and Diego Restuccia. 2017. "Misallocation, Establishment Size, and Productivity." *American Econ. J. Macroeconomics* 9 (3): 267–303.

———. 2024. "The Role of Nonemployers in Business Dynamism and Aggregate Productivity." Working Paper no. 25998 (July), NBER, Cambridge, MA.

Berger, David, Kyle Herkenhoff, and Simon Mongey. 2022. "Labor Market Power." *A.E.R.* 112 (4): 1147–93.

Berlingieri, Giuseppe, Maarten De Ridder, Danial Lashkari, and Davide Rigo. 2024. "Growth through Innovation Bursts." Working paper, Dept. Econ., ESSEC Bus. School.

Berry, Steven, and Joel Waldfogel. 2010. "Product Quality and Market Size." *J. Indus. Econ.* 58 (1): 1–31.

Bhattacharya, Dhritiman, Nezih Guner, and Gustavo Ventura. 2013. "Distortions, Endogenous Managerial Skills and Productivity Differences." *Rev. Econ. Dynamics* 16 (1): 11–25.

Bilbiie, Florin, Fabio Ghironi, and Marc Melitz. 2012. "Endogenous Entry, Product Variety and Business Cycles." *J.P.E.* 120 (2): 304–45.

Bloom, Nicholas, Charles I. Jones, John Van Reenen, and Michael Webb. 2020. "Are Ideas Getting Harder to Find?" *A.E.R.* 110 (4): 1104–44.

Boar, Corina, and Virgiliu Midrigan. 2022. "Efficient Redistribution." *J. Monetary Econ.* 131:78–91.

———. 2024. "Markups and Inequality." *Rev. Econ. Studies*, forthcoming.

Broda, Christian, and David E. Weinstein. 2006. "Globalization and the Gains from Variety." *Q.J.E.* 121 (2): 541–85.

Clementi, Gian Luca, and Dino Palazzo. 2016. "Entry, Exit, Firm Dynamics, and Aggregate Fluctuations." *American Econ. J. Macroeconomics* 8:1–41.

Cole, Harold L., Jeremy Greenwood, and Juan M. Sanchez. 2016. "Why Doesn't Technology Flow from Rich to Poor Countries?" *Econometrica* 84 (4): 1477–521.

Costinot, Arnaud, and Andrés Rodríguez-Clare. 2014. "Trade Theory with Numbers: Quantifying the Consequences of Globalization." In *Handbook of International Economics*, vol. 4, 197–261. Amsterdam: Elsevier.

David, Joel M. 2021. "The Aggregate Implications of Mergers and Acquisitions." *Rev. Econ. Studies* 88 (4): 1796–830.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger. 2020. "The Rise of Market Power and the Macroeconomic Implications." *Q.J.E.* 135 (2): 561–644.

Djankov, Simeon, Rafael La Porta, Florencio Lopez de Silanes, and Andrei Shleifer. 2002. "The Regulation of Entry." *Q.J.E.* 117 (1): 1–37.

Farhi, Emmanuel, and François Gourio. 2018. "Accounting for Macro-Finance Trends: Market Power, Intangibles, and Risk Premia." *Brookings Papers Econ. Activity* (Fall): 147–223.

Foster, Lucia, John Haltiwanger, and Chad Syverson. 2008. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *A.E.R.* 98 (1): 394–425.

Gomme, Paul, B. Ravikumar, and Peter Rupert. 2011. “The Return to Capital and the Business Cycle.” *Rev. Econ. Dynamics* 14 (2): 262–78.

Grossman, Gene M., and Elhanan Helpman. 1991. “Quality Ladders in the Theory of Growth.” *Rev. Econ. Studies* 58 (1): 43–61.

Gutiérrez, Germán, Callum Jones, and Thomas Philippon. 2021. “Entry Costs and Aggregate Dynamics.” *J. Monetary Econ.* 124:S77–S91.

Gutiérrez, Germán, and Thomas Philippon. 2019. “The Failure of Free Entry.” Working Paper no. 26001 (June), NBER, Cambridge, MA.

Hopenhayn, Hugo A. 1992. “Entry, Exit, and Firm Dynamics in Long Run Equilibrium.” *Econometrica* 60 (5): 1127–50.

Hopenhayn, Hugo, Julian Neira, and Rish Singhania. 2022. “From Population Growth to Firm Demographics: Implications for Concentration, Entrepreneurship and the Labor Share.” *Econometrica* 90 (4): 1879–914.

Hopenhayn, Hugo, and Richard Rogerson. 1993. “Job Turnover and Policy Evaluation: A General Equilibrium Analysis.” *J.P.E.* 101 (5): 915–38.

Jones, Charles I. 1995. “R&D-Based Models of Economic Growth.” *J.P.E.* 103 (4): 759–84.

Karahan, Fatih, Benjamin Pugsley, and Ayşegül Şahin. 2023. “How Free is Free Entry?” Manuscript, Dept. Econ., Univ. Notre Dame.

———. 2024. “Demographic Origins of the Startup Deficit.” *A.E.R.* 114 (7): 1986–2023.

Klenow, Peter, and Huiyu Li. 2024. “Replication Data for: ‘Entry Costs Rise with Growth.’” Harvard Dataverse, https://doi.org/10.7910/DVN/N01UST.

Klette, Tor Jakob, and Samuel Kortum. 2004. “Innovating Firms and Aggregate Innovation.” *J.P.E.* 112 (5): 986–1018.

Laincz, Christopher A., and Pietro F. Peretto. 2006. “Scale Effects in Endogenous Growth Theory: An Error of Aggregation Not Specification.” *J. Econ. Growth* 11 (3): 263–88.

Lucas, Robert E., Jr. 1978. “On the Size Distribution of Business Firms.” *Bell J. Econ.* 9 (2): 508–23.

Luttmer, Erzo G. J. 2007. “Selection, Growth, and the Size Distribution of Firms.” *Q.J.E.* 122 (3): 1103–44.

———. 2010. “Models of Growth and Firm Heterogeneity.” *Ann. Rev. Econ.* 2 (1): 547–76.

Melitz, Marc J. 2003. “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity.” *Econometrica* 71 (6): 1695–725.

Peters, Michael, and Conor Walsh. 2021. “Population Growth and Firm Dynamics.” Working Paper no. 29424 (October), NBER, Cambridge, MA.

Redding, Stephen J. 2022. “Trade and Geography.” In *Handbook of International Economics*, vol. 5, 147–217. Amsterdam: North-Holland.

Redding, Stephen J., and Esteban Rossi-Hansberg. 2017. “Quantitative Spatial Economics.” *Ann. Rev. Econ.* 9:21–58.

Rivera-Batiz, Luis A., and Paul M. Romer. 1991. “Economic Integration and Endogenous Growth.” *Q.J.E.* 106 (2): 531–55.

Romer, Paul M. 1990. “Endogenous Technological Change.” *J.P.E.* 98 (5): S71–S102.

Sterk, Vincent, Petr Sedlek, and Benjamin Pugsley. 2021. “The Nature of Firm Growth.” *A.E.R.* 111 (2): 547–79.

Yeh, Chen, Claudia Macaluso, and Brad Hershbein. 2022. “Monopsony in the US Labor Market.” *A.E.R.* 112 (7): 2099–138.