The Dynamics of Development: Innovation and Reallocation*

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Abstract

This paper proposes a quantitative model of endogenous firm dynamics to study growth acceleration episodes triggered by reforms. We find that reversals of entry distortions lead to persistent growth in TFP and declining average firm size, as in the experience of successful post-communist transitions. Removing idiosyncratic distortions results in a more protracted path of TFP and a rising average firm size, as in non-communist growth accelerations. When calibrating the reforms to China's liberalization, we find that the model accounts for one-third of the observed growth in TFP, while matching the dynamics of average firm size and income inequality.

Keywords: Transition dynamics, misallocation, innovation

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1 Introduction

China's economy changed dramatically between the early nineties and the 2000s, progressively liberalizing the economy from a severe misallocation of resources ((Hsieh and Klenow, 2009)) and high barriers to entry (Brandt et al. 2020). The economy grew spectacularly, entrepreneurship spurred, and the income distribution widened. Similarly transformative were the post-communist accelerations of countries in the former soviet union and, before these, the growth accelerations of the so-called Miracle Economies. This paper aims to understand the mechanisms underlying these episodes' macro and micro-level adjustments and to quantify the extent to which China's growth can be accounted for by the removal of measured distortions.

To that end, we propose a standard model of firm dynamics and apply it to China's economic liberalization since 1998, when micro-data needed to measure micro-distortions is readily available. We focus on two types of distortions and their reversals: the idiosyncratic distortions leading to resource misallocation and the barriers to entry rationalizing the large average firm size at the onset of the acceleration. We feed the pace of withdrawal of these distortions into the model, trace out the resulting transitional dynamics, and assess its ability to account for the properties of China's growth acceleration. We show that a model featuring endogenous entry, exit, and innovation of firms can account for the qualitative properties of China's transition path, up to one-third of its TFP growth, and almost all of the rising earnings inequality.

We set the stage for our quantitative analysis by revisiting the dynamics of growth acceleration episodes in the data. We apply Haussman et al.'s methodology to identify growth accelerations and classify them into those emerging from post-communist liberalizations and the rest of the episodes. We show that all accelerations are qualitatively similar in the aggregate, with rising TFP and investment rates, but are heterogeneous at the firm level: the average firm size declines during post-communist transitions but rises in the case of miracle economies and other growth acceleration episodes.

We then turn to the quantitative model to show that the relative relevance of idiosyncratic distortions and barriers to entrepreneurship can rationalize the heterogenous micro-level dynamics of the two growth accelerations. We compare the dynamics resulting from reforms where only one distortion is at play and then removed. We show that, as in the data, aggregate dynamics are qualitatively similar, with the model capturing the protracted growth of aggregate TFP and investment rates. At the micro level, however, we find a declining average firm size following the reversal of entry distortions, as in the experience of post-communist transitions, and an increasing average firm size in response to the removal of idiosyncratic distortions, as in the rest of the growth accelerations. Moreover, we show that transitions triggered by the reversal of entry distortions exhibit an initial drop in measured output but a faster convergence to the new steady state.

Lastly, we conduct our quantitative exploration of China's economic reforms since 1998, where idiosyncratic distortions and barriers to entry interact. We follow Hsieh and Klenow (2009) in measuring the former as wedges from the firms' optimal conditions. In particular, we compute the regression coefficient between the logarithm of distortions, log(TFPR), and the logarithm of firm-level productivity (TFPQ) from the Annual Survey of Industries between 1998 and 2005. We consider the value for 1998 as part of China's initial stationary allocation and consider the values after that as dictating the speed of reforms. In terms of entry distortions, we model these as a combination of overhead production costs and taxes to entrepreneurial profits. We calibrate their values by setting the profit tax and the fixed cost in the distorted stationary allocation to match the average firm size and the earnings share accounted for by the richest 1% of households in China in 1998. Then, we discipline the path of reversal of profit taxes to match the average firm size dynamics during the acceleration and let the dynamics of earnings inequality be used to validate the model's quantitative fit. Starting from the distorted stationary allocation and feeding the path of reversal of both distortions, we find that the model can account for one-third of the productivity growth evidenced by China between 1998 and 2011 and matches the dynamics of inequality remarkably closely.

The rest of the paper is organized as follows. Section 2 relates our work to the literature, in section 3 we provide the macro and micro facts that motivate our analysis, and section 4 presents the model with and without distortions. The calibration and quantitative analyses are in section 5. Lastly, we conclude.

2 Related Literature

Our study provides a unified framework for thinking about the short-run and long-run implications of various types of allocative distortions, spelling out the micro and macro behavior of the economy along development paths. It is therefore related to the large body of studies that have made contributions to each of these areas.

Our work is related to the burgeoning empirical and quantitative literature on misallocation and productivity, of which Hsieh and Klenow (2009), Bartelsman et al. (2013), and Restuccia and Rogerson (2008) are salient examples. We connect to this literature from two dimensions. First, we appeal to it as motivation for assigning a prominent role to resource misallocation in the construction of an initial allocation with low productivity and income per capita in the model. We follow their methodology to measure the extent of misallocation before the onset of our transition experiments, and their dynamics afterward. Secondly, we connect with the series of papers investigating the extent to which the dynamic responses from firms, such as innovation, entry, and exit, complement the static allocative responses in shaping long-run losses in productivity. Salient works in this area are Bhattacharya et al. (2013), Da-Rocha et al. (2017), Hsieh and Klenow (2014), and Akcigit et al. (2014). Our contribution is to characterize the importance of these mechanisms in the context of a relatively unexplored phenomenon: reform-driven growth accelerations.

Our focus on growth accelerations is also related to the literature evaluating the quantitative implications of growth theories for transition dynamics. Christiano (1989), King and Rebelo (1993), and Imrohoroglu et al. (2006) emphasize the shortcomings of the frictionless neoclassical model in accounting for features of transition dynamics in post-war growth accelerations. In particular, the neoclassical model failed at capturing the protracted rise of the rate of return to capital and the hump-shaped dynamics of the rate of investment. As shown by the authors, considering exogenous TFP growth and adjustment costs to the capital stock proved successful in reconciling the neoclassical model with the Japanese data. Our contribution is to develop a model that can account endogenously for the joint dynamics of TFP and investment rates while delivering rich firm-level implications to be validated against firm-level data. In our model, the protractedness of the TFP dynamics arises from convex innovation costs and stochastic innovation returns, which translate into a hump-shaped behavior of the investment rate without any friction in the accumulation of physical capital.

Our work is also close to the study of growth accelerations in Buera and Shin (2013). The authors develop a theory of transitions featuring heterogeneous entrepreneurs, entry and exit to production, and credit market imperfections. Motivated by the experience of seven Asian economies, the authors show that in the presence of financial frictions that delay capital reallocation, transition paths triggered by the removal of idiosyncratic distortions are characterized by paths of investment and interest rates that resemble the data. The model also yields an endogenous path for TFP, although on this front the model's convergence is substantially faster than in the data. Our relationship to this paper is twofold. Firstly, we update and extend the characterization of growth acceleration episodes, highlighting the divergent patterns between average firm size dynamics in post-communist transitions and the remaining cases. This distinction plays a critical role in motivating our consideration of entry and idiosyncratic distortions. Secondly, our model provides a complementary mechanism through which macroeconomic dynamics can depart from those of the standard neoclassical model. Rather than emphasizing barriers to factor reallocation, we show that the interaction between the economy's incentives to accumulate tangible capital, through household's investment decisions, and intangible capital, from firms' innovation efforts, can generate transition paths for output, investment, and TFP similar to those in the data in a frictionless setup.

The consideration of tangible and intangible forms of capital relates our paper to the work of Atkeson and Kehoe (2007). The authors develop a theory of development in which life-cycle dynamics are driven by age-dependent, exogenous stochastic accumulation of organizational capital and in which entering firms embody the best available technology. The trigger of development in their model stems from a sudden permanent improvement in the technologies embodied in new plants. Despite the resemblance of our model to theirs, there are several points of departure. First, as in the data, the life-cycle dynamics of firms in the frictionless steady state of our model are different from those of the distorted equilibrium. In turn, these differences are generated endogenously, from a theory of innovation that connects firm growth to allocative frictions. Secondly, the predictions about entry along the transition path in our model differ from those in Atkeson and Kehoe (2007). In the case of idiosyncratic distortions, entry is inefficiently encouraged by subsidies in the pre-reform steady state of our economy, which implies that our development paths are characterized by reductions in entrepreneurship, and increases in the average firm size. Lastly, because of our focus on growth accelerations, we follow a different strategy for parameterizing the pre-reform stationary equilibrium, appealing to firm-level data in low-income countries to discipline the choice of distortions that hinder output and productivity.

Lastly, our quantitative analysis of China's growth acceleration merits a discussion of the closely related work of Song et al. (2011). The authors propose a model with a private entrepreneurial sector and state-owned enterprises to understand the behavior of the savings rate, the rate of return on capital, and capital flows, during China's economic transition. As in Buera and Shin (2017), their emphasis is on financial frictions, which limit the access to credit by private entrepreneurs and encourage the accumulation of internal sources of financing for investment. Credit is mostly devoted to state-owned enterprises. In a context of heterogeneous but exogenous firm-level productivity, the authors show that the downsizing of the public sector leads to excess demand for financial assets that result in capital outflows. In our paper, we approach the Chinese acceleration from a different angle. While we propose a more reduced-form specification of entry distortions to implement features of a communist regime, we leverage this tractability to characterize more sharply the interaction between the underlying distortions and the innovation incentives of firms in a context of costless reallocation.

3 Motivating Facts

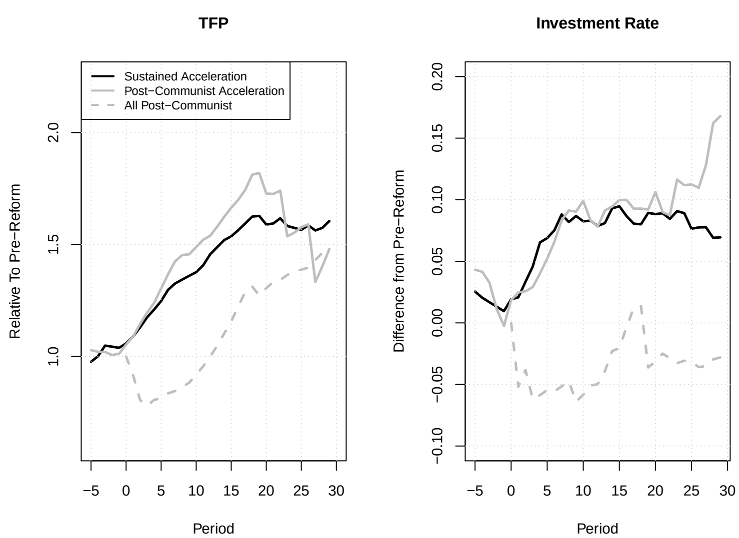
We set the stage for the quantitative model presenting some evidence characterizing aggregate and micro-level features of economic transitions. We consider separately two types of convergence episodes: sustained growth accelerations in the post-war period, identified appealing to the methodology of Hausmann et al. (2005), and post-communist transitions.[1] As we shall explain in greater detail below, we proceed in this way because of the fundamental differences in the adjustments occurring at the micro-level between these episodes, differences that we want to carefully account for in the theory that we develop later.

[1] In Hausmann et al. (2005) a growth acceleration starts in year t only if the following three conditions are met: (1) the average growth rate in the seven ensuing years (years t through $t+6$) is above 3.5 percent; (2) the average growth rate in the seven ensuing years is at least two percentage points higher than in the preceding seven years (years $t-7$ to $t-1$); and (3) the output per-capita in the ensuing seven years is above the previous peak. If more than one contiguous years satisfy all three conditions, the start of the growth acceleration is chosen to be the one for which a trend regression with a break in that year provides the best fit among all eligible years, in terms of the F-statistic. A *sustained* growth acceleration is one for which the average growth rate in the decade following a growth acceleration (years $t+7$ through $t+16$) is above 2 percent. We update the identification of growth accelerations applying the methodology to the most recent data in Penn World Tables 10.0 Zeileis (2021). The complete list of post-communist countries and the list of acceleration episodes picked up by the methodology is presented in Appendix A.

3.1 Aggregate and Firm-Level Features of Accelerations and Post-Communist Transitions

Consider first the dynamics of aggregate variables. Figure 3.1 shows the average behavior of TFP and investment rates in our selection of growth accelerations and post-communist transitions. The left panel plots the average dynamics of TFP. In the vertical axis, units are measured relative to the average value of TFP in the 5 years preceding the take-off.[2] For post-communist countries, we assume that all transitions start in 1990, so the corresponding line illustrates the ratio between the average of TFP across countries relative to the average value between 1985 and 1990.

Figure 3.1: Macroeconomic Features of Acceleration Episodes and Post-Communist Transitions



The left panel plots TFP dynamics for the simple average of post-communist transitions and acceleration episodes. The right panel illustrates the average of investment rates. The horizontal axis measures years with respect to the beginning of each episode, which we label period. For post-communist transitions we date such period to be 1990, while for growth accelerations, period is given by the country's specific date which we identify, using the methodology, as the start of the growth take-off. TFP dynamics are measured relative to the TFP level in period while the investment rates are expressed as absolute deviations from the period levels. A complete list of countries in each group is presented in Appendix A.

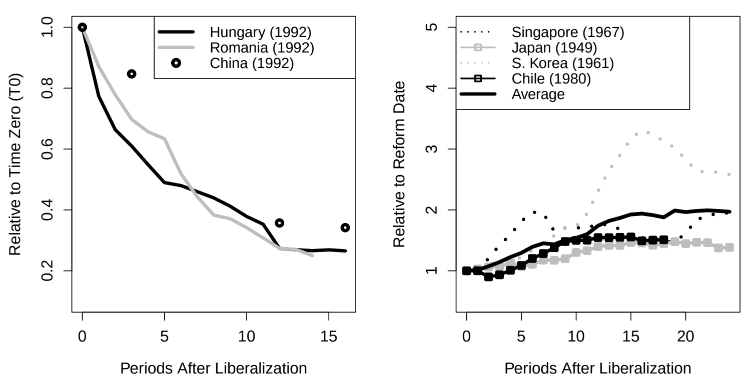
Despite the initial slump in the case of post-communist transitions, both TFP and investment rate increase over time. This pattern of behavior has been noted

[2]Since accelerations occur at different dates in each country, we construct a measure of average TFP dynamics as follows. For each country, we construct the time series of TFP during the acceleration years and we express them relative to the average value of TFP in the 5 years preceding the start of the acceleration; and then we average across countries.

before in the literature as a limitation of the standard neoclassical growth model, which is silent about TFP dynamics and predicts a decreasing path in the investment rate when converging towards an equilibrium with higher capital stock. In this context, one of the goals of our paper is to attempt to reconcile theory and data, by developing a quantitative model of transitions with endogenous TFP and investment rate dynamics.[3]

While exhibiting similar characteristics in the aggregate, acceleration episodes and post-communist transitions differ notably in the adjustments taking place at the micro-level, in particular regarding the size distribution of firms. To see this, figure 3.2 reproduces the dynamics of the average size of manufacturing firms, in terms of employment, for the subset of countries for which we were able to gather time-series average size data. We consider three post-communist cases, Hungary, Romania, and China, and four acceleration episodes, Singapore, Japan, Chile, and Korea. The former group of countries is plotted in the left panel and the latter group in the right one.

Figure 3.2: Average Size Dynamics during Acceleration Episodes and Post-Communist Transitions



Left panel illustrates average size dynamics for post-communist countries. Acceleration episodes are plotted on the right. Horizontal axes measure years after period 0, which corresponds to the year of reforms in the case of accelerations, and the first available year with firm level data in the case of post-communist transitions. Given the substantial differences in average size dynamics across growth accelerations, we also plot the behavior of the simple average of average size dynamics across these episodes. In all cases, the vertical axes measure the ratio of the average size relative to period 0.

[3]Christiano (1989), King and Rebelo (1993), Chen et.al. (2006), and Buera and Shin (2013) are salient examples of papers that have noted the conflict between the neoclassical growth model and macroeconomic data on transitions and developed extensions of the neoclassical model to bridge the gap between the two. See the literature review for a more thorough explanation of how our paper relates to this literature.

Figure 3.2 shows a divergence in the behavior of average firm size across episodes. While the average size increases by a factor of two 20 years into the acceleration, the typical firm shrinks by almost 70% in the post-communist case.

Several authors studied the behavior of the industrial sector in post-communist economies and emphasized the declining role played by large state-owned enterprises in favor of small privately-owned businesses. Maddison (1998) is perhaps the most eloquent of these explorations, showing data about the re-organization of production in China and the economies of former Soviet Union countries.[4] Our contribution is to extend this analysis to a more recent period and to revisit the previous findings through the lens of newer datasets.

Similarly, the fact that average firm size tends to increase with development has also been noted before in the literature. In fact, our data for average size dynamics during accelerations draw exactly from that in Buera and Shin (2013). What has not been equally emphasized before is that divergences from this average behavior can be driven by the nature of the underlying transformations taking place in the economy and that one such transformation that differs from the average is a post-communist liberalization.

3.2 From the Data to a Theory of Transitions

Growth accelerations tend to be highly unpredictable. However, large-scale economic reforms constitute one of the few successful predictors of growth acceleration, as shown by Hausmann et al. (2005) in the context of reduced-form regressions and by Buera and Shin (2013)'s narrative of the wave of reforms that preceded the growth accelerations in the so-called miracle economies. Supported by this evidence, this paper characterizes development dynamics that are triggered by economic reforms, defined as the removal of distortions in the economy.

The patterns of development described above, particularly the divergent dynamics in the average firm size, guide the identification of the family of distortions that are adequate for thinking about the allocations before each type of acceleration

[4]The following quote from Maddison (1998), referred to China, illustrates this point: *"There has been a huge expansion in industrial activity outside the state sector. In 1978 there were 265 000 collectives. By 1996 there were l.6 million. The number of private enterprises rose from zero to 6.2 million. The bulk of these are small-scale operations, most of them in rural areas, and run by individuals, townships, and village level governments. A major reason for the success of these new firms is that their labor costs are much lower than in state-owned enterprises, their capitalization is much more modest, and they are freer to respond to market demand. Many benefit from special tax privileges granted by local authorities."*

episode. For average growth accelerations, we interpret the data as suggestive of the predominance of allocative distortions and their dismantlement in understanding their growth dynamics.[5] The evidence shows that allocative distortions, identified as reduced form idiosyncratic wedges, tend to tax productive firms more heavily than unproductive ones, a feature that facilitates the survival of low productivity firms, discourages innovation, and, ultimately, reduces the scale of operations of the firms.[6] When dismantled, these types of distortions deliver dynamics of the average firm size that are consistent with what we observed for the average acceleration. For post-communist transitions, on the other hand, the dynamics of the average firm size suggest that barriers to the creation and operation of firms constitute a more prevalent source of distortion.[7] Distortions to entry concentrate production in fewer and larger firms and increase the average firm size, as in the allocation of centrally planned economies. Their dismantlement, then, is consistent with a spreading of production into more and smaller firms, which is what we found in the data. While the ability to replicate the patterns of micro-dynamics in the data will emerge by construction from the choice of distortions, it is the quantitative fit of this and other predictions of the theory as well as the relative contribution of the innovation and reallocation channels, that we seek to validate and uncover in the quantitative analysis.

4 Model

We study an economy populated by a single household composed of a continuum of agents. These agents are heterogeneous with respect to their ability to operate a production technology and run a business. The head of the household makes an occupational choice on behalf of each agent, choosing either to assign her to

[5]Throughout the paper, with average growth acceleration, we refer to all the sustained growth episodes that we identify from the data that are not originated by the dismantlement of a communist regime.

[6]The correlated nature of idiosyncratic distortions with respect to the distribution of firms' productivity is a pervasive property of resource misallocation around the world. Hsieh and Klenow (2007) first established this fact in the context of China, India, and the United States. Subsequent applications of this methodology in Latin America (Neumeyer and Sandleris, 2009 for Argentina; Casacuberta and Gandelman, 2009 for Uruguay, Camacho and Conover, 2010 for Colombia and Chen and Irarrazabal, 2015 for Chile) and Sub-Saharan Africa (Cirera et al., 2017) verify the generality of this feature of the data.

[7]More direct evidence is provided by Brandt et al. (2020), who show that entry barriers are the salient friction for explaining cross-regional growth disparities in China.

entrepreneurship and earn a risky profit or make her participate in the labor force, in exchange for a fixed wage. Each individual commits to participate in a risk-sharing agreement that insulates individual consumption from fluctuations in idiosyncratic income. In addition to occupational choices, the head of household chooses aggregate consumption and investment to maximize lifetime utility.

There are endogenous and exogenous forces for firm dynamics and resource reallocation. The endogenous component stems from entrepreneurs' investments in a risky innovation technology that controls the expected evolution of entrepreneurial ability over time, and their entry and exit decisions. The exogenous element results from idiosyncratic productivity shocks around the expected path. It is the endogenous decision of entrepreneurs to innovate together with the decision to enter and exit entrepreneurship that connects the life cycle and the size distribution of firms with policies and distortions to factor allocation.

We first present the details of the frictionless economy, which we take as a reference for the calibration of preferences and technological parameter values which are kept constants across countries. These parameters are calibrated to match data on the dynamics of firms and income inequality in the US, a relatively undistorted economy. Then we introduce an extension with distortions and calibrate it using information from growth accelerations.

4.1 Consumption and Savings Problem

The assumption of perfect sharing of idiosyncratic risk allows us to separate the consumption/investment decision from the occupational choices.

Taking wages and occupational choices as given, the household chooses consumption and investment in order to solve the following problem:

$$\max{}_{\{c_t,k_{t+1}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\sigma}}{1-\sigma}$$

subject to

$$c_t + k_{t+1} = w_t L_t^s + \Pi_t + (1 + r_t)\, k_t.$$

Aggregate labor supply and aggregate profits, L_t^s and Π_t respectively, are defined as follows:

$$L_t^s = \int (1 - o_t(z))\, dM_t(z)$$

and

$$\Pi_t = \int o_t(z)\, \pi_t(z)\, dM_t(z)\,,$$

where $o_t(z)$ is the outcome of the occupational choice of a household member with productivity z, being equal to 0 if she is a worker, and 1 is she is an entrepreneur; and $M_t(z)$ denotes the endogenous distribution of agents over productivity levels. All these objects will be characterized in detail below.

4.2 Occupational Choice

We assume that the head of the household chooses occupations for its members every period. Furthermore, we assume that movements in and out of entrepreneurship are costless. Therefore, the decision to allocate an individual into working for a wage or becoming an entrepreneur amounts to comparing the values associated with each activity.

When selected into entrepreneurship, agents produce the final good combining their idiosyncratic productivity, z, together with capital and labor into a Cobb-Douglas production function with decreasing returns to scale:[8]

$$y_t(z) = z^{(1-\alpha-\theta)} k_t(z)^{\alpha}\, l_t(z)^{\theta}\,.$$

We assume that there are perfectly flexible labor and capital rental markets every period, so that both capital and labor can be adjusted freely in response to changes in aggregate or idiosyncratic conditions. It follows that capital and labor choices are determined by the following static maximization problem:

$$\pi_t(z) = \max{}_{l,k} \left\{ z^{(1-\alpha-\theta)} k^{\alpha} l^{\theta} - w_t l - (r_t + \delta)\, k \right\}$$

which yields the following expressions for optimal capital and labor demands:

$$l_t(z) = \left(\frac{\alpha}{r_t+\delta}\right)^{\frac{\alpha}{1-\alpha-\theta}} \left(\frac{\theta}{w_t}\right)^{\frac{1-\alpha}{1-\alpha-\theta}} z$$

[8] The introduction of the productivity term raised to the $(1-\alpha-\theta)$ power is a normalization that simplifies the description of the stochastic process for productivity. As we will show below, firms' capital and labor demands become proportional to z when productivity is introduced in this way in the production function. This allows us to map the space of productivity levels z directly into the space of labor and capital demands.

and

$$k_t(z) = \left(\frac{\alpha}{r_t+\delta}\right)^{\frac{1-\theta}{1-\alpha-\theta}} \left(\frac{\theta}{w_t}\right)^{\frac{\theta}{1-\alpha-\theta}} z.$$

The indirect profit function associated with optimal capital and labor demands is given by:

$$\pi_t(z) = \left(\frac{\alpha}{r_t+\delta}\right)^{\frac{\alpha}{1-\alpha-\theta}} \left(\frac{\theta}{w_t}\right)^{\frac{\theta}{1-\alpha-\theta}} (1-\alpha-\theta)\, z.$$

Besides production decisions, entrepreneurs make investments in innovation. We adopt a process of technology upgrading and downgrading similar to that in Atkeson and Burstein (2010). Specifically, we assume that the growth rate of idiosyncratic productivity follows a simple binomial process, with an expected rate of growth that is determined by the firm's investments in innovation, and an exogenous standard deviation.

Let Δ denote the change in the logarithm of productivity that a firm can experience from one period to the other. Entrepreneurs use a research technology that yields a probability p of a technological upgrade (and probability $1-p$ of a downgrade) in return to investing $\chi(p,z)$ units of labor. We assume a convex function for the cost of innovation of the following form:

$$\chi_t(p,z) = z \times \mu \left(e^{\phi p} - 1\right)$$

Notice that the innovation cost is scaled by the current productivity of the entrepreneur. As we will explain below, this is an important assumption that allows the model to be consistent with innovation patterns of large firms in the U.S, which is our target economy for the calibration of parameters that are kept constant across economies. We will also explain the relevance of the scale parameter μ and the elasticity parameter ϕ to replicate properties of the size distribution and firm life-cycle dynamics in the U.S.[9]

Taking capital and labor demands from the static profit maximization problem,

[9] The process for idiosyncratic productivity can be interpreted as a binomial approximation to a geometric Brownian motion, with an exogenous standard deviation Δ, and endogenous drift $(2p_t(z)-1)\,\Delta$.

entrepreneurs' innovation-decision solves the following optimization problem:

$$\begin{aligned} v_t^E(z) &= \max_p \Bigg\{ \pi_t(z) - w_t \chi(p,z) \\ & \qquad + \frac{1}{1+r_{t+1}} \left[p v_{t+1}\left(z e^{\Delta}\right) + (1-p)\, v_{t+1}\left(z e^{-\Delta}\right) \right] \Bigg\} \end{aligned} \tag{4.1}$$

with $v_t^E(z)$ standing for the value of an entrepreneur with productivity z in period t, and $v_t(z)$ denoting the value of an individual in period t with productivity z, facing the decision to become an entrepreneur or working for a wage. We will come back to this value below, once we characterize the value of a worker.

Unlike entrepreneurs, we abstract from modeling workers' efforts in developing entrepreneurial ability. We assume that while working for a wage, agents get a random draw of entrepreneurial ability from a known stationary distribution $F(z)$ that they can exploit the following period if they find it profitable to do so. In particular, we assume that an individual in the labor force with current entrepreneurial ability z gets to keep it for the following period with probability ψ, and gets a random draw from the distribution $F(z)$ with probability $(1-\psi)$. The same process governs the evolution of the entrepreneurial ability of agents that join the labor force after having exited from operating a business. These agents will keep their accumulated stock of knowledge with probability ψ, and will get random draws with probability $(1-\psi)$.

Our probabilistic representation of the arrival of entrepreneurial ideas among workers allows us to be consistent with two key properties about the behavior of entrants in the data: 1) the rate of establishment entry and exit, and 2) the average size of entrants relative to incumbents. We will see below that consistency with these facts is important for the properties of a firm's life-cycle dynamics, and for shaping the responses to reforms.

It follows from the above that the value of a worker is simply defined by the wage rate in the period, plus the discounted expected value of resetting occupations in the following period:

$$v_t^{\omega}(z) = w_t + \frac{1}{1+r_{t+1}} \left[\psi v_{t+1}(z) + (1-\psi) \int v_{t+1}\left(z'\right) dF\left(z'\right) \right]$$

with the value of an agent before making an occupational choice given by

$$v_t(z) = \max\left\{v_t^E(z), v_t^\omega(z)\right\}.$$

4.2.1 Aggregation and Definition of Equilibrium

At any given point in time, all individuals in the economy will be distributed over the space of entrepreneurial productivity. We denote the fraction of individuals with productivity less than or equal to z with $M_t(z)$. We need to characterize the evolution of this distribution to be able to aggregate individual decisions and compute equilibrium prices.

Say we start with a given distribution $M_t(z)$ at the beginning of period t. Entrepreneurs move across productivity levels in accordance to their innovation-decisions, while workers do so in response to the stochastic process of productivity. Combining these processes leads to the following law of motion for the distribution of agents across productivity levels:

$$\begin{aligned} M_{t+1}(z) &= M_t(z) + \int_z^{ze^{\Delta}} (1-p_t(x))\, o_t(x)\, dM_t(x) - \int_{ze^{-\Delta}}^{z} p_t(x)\, o_t(x)\, dM_t(x) \\ &\quad - (1-\psi)\int_0^z (1-o_t(x))\, dM_t(x) \\ &\quad + (1-\psi) F(z) \int_0^\infty (1-o_t(x))\, dM_t(x) \end{aligned} \tag{4.2}$$

The first two terms refer to the individuals that worked as entrepreneurs in period t and transition to (remain in) the set with productivity in $[0, z]$ after a period. Those with productivity level $x \in \left(z, ze^{\Delta}\right]$ downgrade to $xe^{-\Delta} < z$ with probability $1 - p_t(x)$, and those with productivity level $x \in \left(ze^{-\Delta}, z\right]$ upgrade to $xe^{\Delta} > z$ with probability $p_t(x)$. The last two terms refer to workers. A fraction $1-\psi$ of workers with ability less than z get a new productivity. Among all the workers that get a new productivity, a fraction $(1-\psi)F(z)$ have a new draw less than or equal to z.

A *competitive equilibrium* in this economy is given by sequences of choices by the head of the household $\{c_t, k_{t+1}, o_t(z)\}_{t=0}^{\infty}$; sequences of entrepreneurs' decisions $\{l_t(z), k_t(z), p_t(z)\}$; sequences of interest rates and wage rates $\{r_t, w_t\}$; and a distribution of agents over productivity $\{M_t(z)\}$; such that given an initial capital stock K_0 and a given distribution of talent draws for workers $F(z)$, household's and firm's decision solve their dynamic optimization problems and capital and labor markets clear

$$\int \left[l_t(z) + z\mu e^{\phi p_t(z)} \right] o_t(z)\, dM_t(z) = \int (1 - o_t(z))\, dM_t(z)$$

and

$$\int k_t(z)\, o_t(z)\, dM_t(z) = K_t,$$

and the distribution of entrepreneurial productivity evolves according to (4.2).

Similarly, a *long run equilibrium* of this economy is one where individual decisions, aggregate quantities, and prices are constant, and the distribution of productivity is stationary.

4.2.2 Output and Productivity

A well known property of our model with decreasing returns to scale and frictionless factor markets is that the production side of the economy aggregates into the following aggregate production function:

$$Y_t = \left[\int o_t(z)\, z dM_t(z) \right]^{(1-\alpha-\theta)} (K_t^s)^{\alpha} \left(L_{p,t}^s \right)^{\theta}$$

where $L_{p,t}$ stands for aggregate labor demand for the production of the final good only:

$$L_{p,t} = \int l_t(z)\, o_t(z)\, dM_t(z)$$

Measured TFP, in turn, can be computed from the following expression:

$$\begin{aligned} TFP_t &= \left[\int o_t(z)\, z dM_t(z) \right]^{(1-\alpha-\theta)} \left(L_{p,t}^s \right)^{\theta} \\ &= \left[\frac{\int o_t(z)\, z dM_t(z)}{\int o_t(z)\, dM_t(z)} \right]^{(1-\alpha-\theta)} \left(\int o_t(z)\, dM_t(z) \right)^{1-\alpha-\theta} \left(L_{p,t}^s \right)^{\theta}. \end{aligned} \tag{4.3}$$

Notice that we made an adjustment to the measure of TFP_t so that it is comparable with the measured used development accounting studies. The expression reflects the fact that output is deflated using the entire labor force, which has a unit measure, regardless of occupation, while in the model only a subset of the agents are involved in the production of goods. The other fraction, workers in innovation, make intangible contributions that we assume go unmeasured in GDP.

4.3 Introducing Distortions

As mentioned earlier, our approach for characterizing transitions is to emphasize the role of distortions. The exploration of growth acceleration episodes and post-communist transitions suggested that we investigate idiosyncratic distortions that misallocate resources across firms and entry distortions that distort the occupational choices and increase the average firm size.

Idiosyncratic distortions are modeled as productivity-dependent taxes to the firms' revenues, while entry distortions are implemented through taxes to the profits of the firms gross of innovation expenses and overhead production costs.[10] The productivity dependence of idiosyncratic distortions is a pervasive feature of misallocation in developing countries and has been used to characterize distortions in many studies[11]. The profit taxes, on the other hand, are less standard. We appeal to taxes to the profits of firms, gross of innovation expenses, to capture the barriers to the creation of private enterprises that characterize the functioning of centrally planned economies. In the model, this type of taxation discourages entrepreneurship, hinders private innovation, and concentrates production into fewer and bigger firms. In addition, a profit tax is a natural instrument to capture the nature of a communist regime, where profits are ultimately collectivized, or captured by the party elite. Fixed production costs are a complementary instrument to profit taxes that help the model replicate the micro-level features of China's economy at the onset of its economic liberalization. In particular, these instruments allow us to jointly capture the average firm size and the concentration of earnings among the richest households prior to the reforms.

Formally, let $\tau_t(z)$ and τ_t^{π} denote the revenue and profit tax rates corresponding to a firm with productivity z in period t. Notice that the profit tax is identical across firms, while revenue taxes are idiosyncratic to the firm's productivity, according to the following function:

$$[1 - \tau_t(z)] = \left(\frac{z}{z_{I,t}}\right)^{-\upsilon_t(1-\alpha-\theta)}. \tag{4.4}$$

[10] Notice that our analysis seeks to capture the degree of misallocation stemming from the correlation of distortions with productivity only, without consideration of uncorrelated dispersion. Uncorrelated dispersion would further misallocate resources and drag TFP, and their removal help account for the dynamics of TFP. In this sense, our result should be interpreted as a lower bound on the contribution of idiosyncratic distortions.

[11] See, for instance, Bento and Restuccia (2017) and Fattal-Jaef (2022)

The productivity-elasticity of the distortion profile υ_t controls the degree of a linear relationship between the logarithm of the marginal revenue product of the firm ($TFPR$) and the logarithm of physical productivity ($TFPQ$). As explained in greater detail in the calibration section, we appeal to China's firm-level data to estimate the regression coefficient between these variables to discipline its parameterization. The productivity index $z_{I,t}^{(1-\alpha-\theta)}$ separates firms into those that get a revenue subsidy from those that get a revenue tax and hence determines the average distortion in the economy. This parameter is neutral for the resource misallocation that the distortions induce, but shapes the rate of return to capital in the distorted allocation, and therefore the investment rate. We explain how we calibrate this parameter in the context of the quantitative analysis.

In terms of the profit tax, it can be shown that a flat profit tax has a direct effect on occupational choices, innovation, and, thereby, the average firm size and inequality. We appeal to data on average size and inequality statistics to calibrate the profit tax in the quantitative analysis.

We now turn to incorporating the profit and revenue taxes into the optimization problems of the agents. Consider first the value of an entrepreneur with productivity z and associated revenue and profit taxes $\tau_t(z)$ and τ_t^{π}. This is given by the following expression:

$$v_t^E(z) = max_{p_t} \left\{ \begin{array}{c} [1-\tau_t^{\pi}]\,\pi_t(z,\tau_t(z);w_t,r_t) - w_t\chi_t(p,z) - f_c \\ + \left(\frac{1}{1+r_t}\right)\left[p_t v_{t+1}\left(ze^{\Delta}\right) + (1-p_t)\,v_{t+1}\left(ze^{-\Delta}\right)\right] \end{array} \right\} \tag{4.5}$$

which in addition to the tax distortions, also reflects the fixed cost of production f_c

Profit taxes have a direct effect on the firm's incentives to innovate but have no implication for the entrepreneur's choice of labor and capital demands. Revenue taxes, on the other hand, do interfere with factor demand and profitability, as reflected in the firm's static profit maximization problem:

$$\pi_t(z,\tau_t(z);w,r) = \max{}_{l_t(z),k_t(z)} \left\{(1-\tau_t(z))\,z^{(1-\alpha-\theta)}k_t^{\alpha}l_t^{\theta} - w_t l - (r_t+\delta)\,k\right\}$$

with optimal policies

$$l_t(z) = \left(\frac{\alpha}{r_t+\delta}\right)^{\frac{\alpha}{1-\alpha-\theta}} \left(\frac{\theta}{w_t}\right)^{\frac{1-\alpha}{1-\alpha-\theta}} z\left[1-\tau_t(z)\right]^{\frac{1}{1-\alpha-\theta}}$$

and

$$k_t(z) = \left(\frac{\alpha}{r_t+\delta}\right)^{\frac{1-\theta}{1-\alpha-\theta}} \left(\frac{\theta}{w_t}\right)^{\frac{\theta}{1-\alpha-\theta}} z\left[1-\tau_t(z)\right]^{\frac{1}{1-\alpha-\theta}}$$

and value

$$\pi_t(z,\tau_t(z);w,r) = \left(\frac{\alpha}{r_t+\delta}\right)^{\frac{\alpha}{1-\alpha-\theta}} \left(\frac{\theta}{w_t}\right)^{\frac{\theta}{1-\alpha-\theta}} (1-\alpha-\theta)\, z\left[1-\tau_t(z)\right]^{\frac{1}{1-\alpha-\theta}}.$$

A feature of the value of entrepreneurship worth highlighting is that profit taxes affect the operating profits of the entrepreneur gross of the expenditure on innovation. In the context of the theory, this assumption is necessary in order to ensure that the profit tax indeed distorts the innovation decision of the entrepreneur. To the extent that the profit taxes are intended to capture the distortions to managers' incentives to invest in technology under a communist regime, these taxes must have a non-neutral effect over the rate of return to innovation relative to the marginal cost of innovation expenses. It is to accomplish this goal that we set the tax to affect operating profits gross of innovation expenses.

The calibration of profit tax rests on its implications for earnings inequality. In the model, the earnings of an individual with entrepreneurial ability z is given by:

$$E_t(z) = \left[1-o_t(z)\right] w_t + o_t(z)\, \pi_t^E(z)$$

where $o_t(z)$ encodes the agents' occupational choices, being equal to 1 for entrepreneurs and equal to 0 for workers, and $\pi_t^E(z)$ denotes the after tax entrepreneurial earnings, given by:

$$\pi_t^E(z) = (1-\tau_t^\pi)\,\pi_t(z) - w_t\chi(p_t,z) - f_c$$

Lastly, we conclude the section revisiting the definitions of aggregate output and productivity in the version of the economy with distortions:

$$Y_t = \frac{\left[\int z\left(1-\tau(z)\right)^{\frac{\alpha+\theta}{1-\alpha-\theta}} o_t(z)\, dM_t(z)\right]}{\left[\int z\left(1-\tau(z)\right)^{\frac{1}{1-\alpha-\theta}} o_t(z)\, dM_t(z)\right]^{\alpha+\theta}} \left(K_t^s\right)^\alpha \left(L_{p,t}^s\right)^\theta \tag{4.6}$$

and

$$TFP = \frac{\left[\int z\left(1-\tau\left(z\right)\right)^{\frac{\alpha+\theta}{1-\alpha-\theta}} o_t\left(z\right) dM_t\left(z\right)\right]}{\left[\int z\left(1-\tau\left(z\right)\right)^{\frac{1}{1-\alpha-\theta}} o_t\left(z\right) dM_t\left(z\right)\right]^{\alpha+\theta}} \left(L_{p,t}^s\right)^{\theta}. \tag{4.7}$$

The misallocation effect of revenue taxes is manifested in the aggregation of individual productivity, which now reflects the inefficiency in the distribution of capital and labor across producers. The dynamic effects of revenue and profit taxes, which operate through distortions to innovation, are captured in the distribution of firms across productivity levels $M_t\left(z\right)$.

5 Quantitative Exploration

We organize the presentation of the quantitative analysis as follows. Firstly, to understand the mechanisms in the model, we characterize the economy's response to reforms that dismantle idiosyncratic distortions or entry barriers only. A distinguishing feature of this exercise is that the reforms are implemented abruptly, as opposed to feeding the smooth path of reversal in our calibration to China, so that the resulting transitional dynamics are purely attributable to the model's mechanisms. Next, we evaluate the quantitative merit of the theory in the context of China's economic liberalization since 1998. This important episode presents an opportunity to evaluate our theory since we count with data to tightly calibrate the degree of distortions at the initial conditions and to discipline the rate of reversal of the distortions along the transition paths. Using our quantitative theory as measurement device, we assess how much of the observed TFP growth since China's liberalization can be accounted for by the calibrated reversal of the distortions, as well as evaluate the model's ability to account for the changes in the firm size and income distributions.

5.1 Calibration

There are 8 parameters that remain invariant across the types of economies that we consider: the coefficient of relative risk aversion σ, the labor and capital shares in production α and θ, the subjective discount factor β, the scale and the convexity parameters in the innovation cost function μ and ϕ, the capital depreciation rate δ, and the arrival rate of entrepreneurial ability among worker ψ. In addition, we must specify and parameterize the distribution of entrepreneurial ability types among workers. Parameters are calibrated within the stationary equilibrium of the undistorted economy targeting moments in the U.S. economy.[12]

For the coefficient of relative risk aversion, we set $\sigma = 1.5$, which is standard in the macroeconomics literature. We set $\beta = 1/(1 + 0.04)$, to target a 4% yearly interest rate, and set the annual capital depreciation rate at $\delta = 0.06$. In terms of factor shares in the production technologies, given a value of the span of control $1 - \alpha - \theta$, we calibrate $\alpha/(\alpha + \theta) = 1/3$, so that 1/3 of the income going to non-entrepreneurial factors is paid to to capital. For the probability that workers get a new draw of entrepreneurial ability, $(1 - \psi)$, we set $\psi = 0$ so that workers update their entrepreneurial talent every period.

The span of control $\alpha + \theta$ is calibrated jointly with the parameters of the innovation cost function, μ and ϕ, and the innovation step Δ, to match the concentration of earnings in the top 1% of the population, the employment share in the top 10% of the firm size distribution, the average employment ratio between firms aged 21-25 to 1 year old, and the log dispersion of the distribution of employment growth rates for large firms. Finally, we assume that the distribution of entrepreneurial abilities is Pareto, with a productivity lower bound equal to one and a tail parameter η that we calibrate to match the ratio between the average employment of entrants relative to the average employment of incumbents.[13] The parameter values resulting from this strategy are reported in table 1

Table 1: Calibration of Common Parameters across Economies

	US data	Model	Parameter
Top 1 % Earnings Share	18.5%	18.5%	$\alpha + \theta = 0.71$
Top 10% Employment Share	0.76	0.77	$\mu = 4.8e - 05$
Employment Age 21-25 relative to Age 1	3.95	3.83	$\phi = 10$
Std Dev. Employment Growth rate	0.25	0.25	$\Delta = 0.25$
Empl. Ratio Entrants to Incumbents	18.9%	18.9%	$\eta = 4.46$

The top 1% earnings share for the US is taken from Khun and RÃos-Rull (2015). We report the average of the top 1% share between 2007 and 2013. The top 10% employment share, the average employment ratio between 21-25 and 1 year old firms, and the average employment ratio between entrants and incumbents were computed from Business Dynamics Statistics database for the year 2007. Numbers are for the manufacturing sector. Standard deviation of employment growth rates for large firms are reported in Atkeson and Burstein (2010).

[12] As a robustness check, we solved for a distorted version of the U.S. economy, keeping parameters values fixed at the baseline calibration, but feeding an estimate of the productivity-elasticity of idiosyncratic distortions for the U.S., which Hsieh and Klenow (2007) report to be equal to $\nu = 0.138$. We find that these mild distortions generate a weak contraction in the TFP relative to an undistorted benchmark, in the order of 5%

[13] In appendix F, we further explore the goodness of fit of the Pareto assumption comparing the size distribution of firms at entry with the data

5.2 Distortions and Reforms

We now discuss the strategy for calibrating the parameter values governing the distortions in the model and their paths of reversal during China's economic liberalization since 1998. These are given by a sequence of slopes and scale parameters of the revenue tax profile, υ_t and $Z_{I,t}$, a sequence of profit taxes, τ_t^{π}, and a value for the fixed costs of production f_c. As a reminder, we are modeling China's communist regime as a combination of taxes to the profits gross of innovation expenses and fixed production costs, which mimic the barriers to entry and the egalitarian forces that characterize these regimes, and idiosyncratic distortions.

The idiosyncratic distortion profile is parameterized by the productivity-elasticity υ_t and the scaling parameter $Z_{I,t}$. We calibrate the productivity-elasticity estimating the regression coefficient between the logarithm of $TFPR$ and the logarithm of $TFPQ$ between 1998 and 2005. The data stems from the Annual Surveys of Industrial Production for the years 1998 through 2005. These surveys are conducted by the National Bureau of Statistics covering the universe of industrial firms (both privately-owned and state-owned) with sales above 5 million RMB (equivalent to roughly $600,000). We take the estimate for 1998 as the one characterizing the initial stationary allocation. We define $TFPR$ and $TFPQ$ exactly as in Hsieh and Klenow (2009). The scaling parameter Z_I, which shapes the average distortion in the economy, has a direct mapping on the capital-output ratio in the stationary equilibrium. Hence, we calibrate its values in 1998 and 2011 to replicate China's capital-output ratio in these years. The parameter values governing the idiosyncratic distortions in the initial and terminal steady states are reported in table 2

The profit tax and the fixed production cost are calibrated to match statistics of the firm size and earnings distribution. As said earlier in the text, these reduced-form instruments are intended to tractably capture the various elements that hinder private entrepreneurial activity and compress the earnings distribution in a communist regime such as China's in 1998. Our strategy for their calibration is to appeal to observable outcomes on which these instruments exert a first-order effect. To this end, we set the average firm size and the earnings share accounted for by the richest 1% of households in 1998 as empirical moments. We target an average firm size of 3.1 times the average firm size in the U.S. manufacturing sector and a top earnings share of 8% which we draw from the World Inequality Database (Piketty et al. 2019). The strategy results in a fixed production cost of $f_c = 48.1$, equivalent to 57% of the average profits gross of innovation expenses and fixed costs in the initial steady state, and a profit tax $\tau_0^{\pi} = 0.4$. These parameter values are also reported in table 2

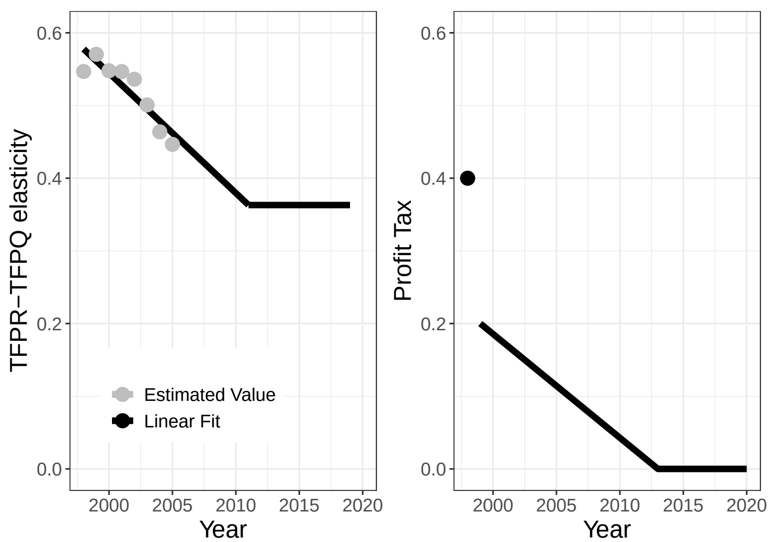
Table 2: Calibration of Distortions in China's Initial and Terminal Stationary Equilibrium.

	Value in 1998	Source/Target	Value in 2011	Source/Target
Productivity-Elasticity of Distortions, ν	0.578	Regression coefficient $log\,(TFPR)$ on $log\,(TFPQ)$, Annual Surveys of Industrial Production 1998	0.36	Projected regression coefficient of $\log\,(TFPR)$ on $\log\,(TFPQ)$ for 2011
Scale-Parameter of Distortions, Z_I	10.05	Capital-output ratio 1998	32.07	Capital-output ratio 2011
τ^{π}	0.4	Earnings Share top 1% richest Households, World Inequality Database	0	Assumption
f_c	48.1	Average firm size in China relative to the U.S. in 1998, equal to 3.1	48.1	Assumption based on persisting entry Barriers Brandt et al. (2020)

Note: The data for the estimation of regression coefficients between $log\,(TFPR)$ and $log\,(TFPQ)$ stems from the Annual Survey of Industrial producers for the years 1998-2005. The capital-output ratios are drawn from the Penn World Table Database, version 10.0 Zeileis 2021, Feenstra et al. 2015. The earnings data for China in the World Inequality Database draws from Piketty et al. 2019.

The pace of reversal of the distortions during the reform is disciplined as follows. For idiosyncratic distortions, we fit a linear trend to the time series of regression coefficients of $log\,(TFPR)$ and $log\,(TFPQ)$ estimated from the firm-level data between 1998 and 2005. The linear trend allows us to project the evolution of idiosyncratic distortions beyond the estimating period into 2011, which is the last year in our aggregate data. We assume that in the terminal steady-state, idiosyncratic distortions stabilize at the level projected for 2011. The evolution of the scaling parameter $Z_{I,t}$ is set to converge linearly between 1998 and 2011 from the initial an the terminal values. In terms of the profit taxes, we also feed a linear path of reversal disciplined to match the pace reduction of the average firm size in China during the acceleration. In this way, while the average firm size dynamics will be replicated by construction, the implied dynamics of inequality will be untargeted, and hence can be used as validation for the model's mechanisms. In terms of the fixed production cost, we assume they remain at the initial steady state's level, in reflection of the pervasive entry distortions that still characterize China's economy (Brandt et al. 2020). The resulting paths of the productivity-elasticity of idiosyncratic distortions and the profit taxes are plotted in figure 5.1.

Figure 5.1: Calibration of Distortions and Reforms

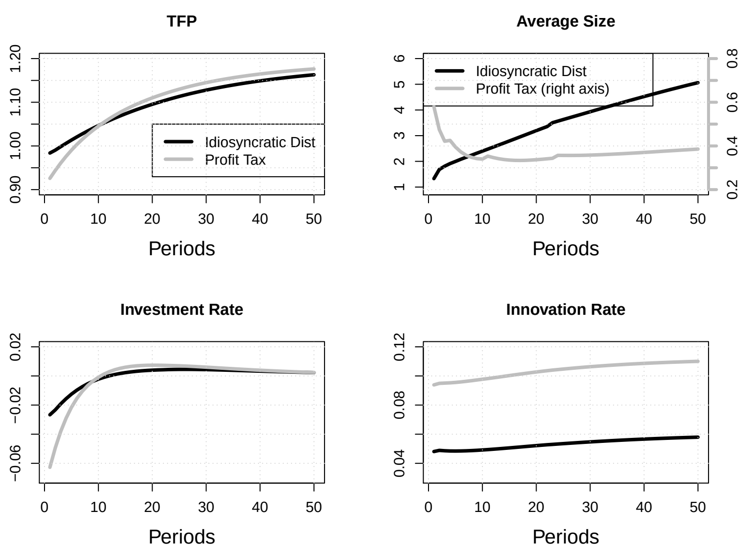


NOTE: The left panel illustrates the regression coefficient between $log\,(TFPR)$ and $log\,(TFPQ)$ for the period 1998-2011. The dots correspond to the point estimates from China's Annual Survey of Industrial Production for 1998 through 2005. We define $log\,(TFPR)$ and $log\,(TFPQ)$ as in Hsieh and Klenow 2009. The solid line illustrates a linear fit on the estimated values projected on to 2011. We assume that reforms stabilize in 2011, and the productivity-elasticity of idiosyncratic distortions remain constant a the 2011 level. The initial steady state is represented by the elasticity estimate for 1998. The right panel illustrates the calibration of the profit tax. The solid dot corresponds to our calibration for 1998, while the solid line corresponds to the reform. The initial value is calibrated, jointly with the fixed production cost, targeting the earnings share of the richest top 1% of households and the average firm size. The solid line is calibrated to replicate the average firm size dynamics during the transition.

5.3 Exploring the Mechanisms: Idiosyncratic Distortions vs Profit Taxes

In the quantitative exploration of China's development since 1998, the resulting dynamics compound the protracted nature of the reform with the model's propagation forces. To isolate and understand the contribution of the model's mechanisms, we consider a series of reforms where only the mechanisms in the model are at work. We achieve this in two ways. First, but considering one reform at a time, that is, considering an economy with idiosyncratic distortions only and studying a transition after reversing these distortions, and similarly with an economy with a profit tax only. Secondly, we trigger transitional dynamics as a once and for all removal of the distortion instead of endowing the model with a protracted path of reversal, as in the full quantitative analysis. A detailed explanation of the parameterization of distortions in each of the initial stationary allocations is provided in Appendix B.1

Figure 5.2: Transition Dynamics: Idiosyncratic Distortions vs Entry Distortions



TFP and $Average\,Size$ are measured as ratio with respect to the initial steady state values . The Investment rates and innovation expenditure rates are measured as absolute deviations from the distorted steady state ratios.

Figure 5.2 shows that the model can capture the qualitative features of growth accelerations in the data. In particular, the model delivers a protracted path for measured TFP and a hump-shaped behavior of the investment rate. The underlying mechanisms leading to such an outcome depend on the type of distortion being removed. When lifting idiosyncratic distortions, the main driver of aggregate dynamics is firms' innovation decisions. Absent any reallocation friction, the allocative efficiency gains accrue immediately. Moreover, the removal of distortions encourages the most productive firms to innovate, accelerating convergence. However, the enhanced incentives to innovate by the most productive firms coexist with the disincentive to innovate among the least productive ones, who benefited from the distorted environment. Given the stochastic nature of entrepreneurial ability, it takes time for these firms to exit the market, a force that protracts the transition. When lifting the profit tax, on the other hand, the most relevant force protracting the transition is given by the difference in the distribution of entrepreneurial talent between entering firms and incumbents. The distribution of entrepreneurial ability at entry is calibrated to match the life-cycle growth of firms in the U.S. which requires a substantial gap between the average productivity of entrants and incumbents. When removing the profit tax, a burst of new entrepreneurs enters the market, increasing the density on the left tail of the productivity distribution. As these entrepreneurs innovate and their abilities follow their stochastic course, the distribution converges sluggishly to the stationary one, protracting the dynamics of productivity in the aggregate[14]. The properties of the innovation profiles along the transition dynamics as well as the evolution of the productivity distribution of firms in both reforms, are discussed in greater detail in appendix B.2

While leading to comparable dynamics in the aggregate, removing of each type of distortion leads to divergent dynamics at the firm level. In a distorted stationary allocation subsidizing low-productivity firms and taxing highly productive ones, the number of firms increases relative to the undistorted level, reducing the average firm size in equilibrium.[15] When removing these distortions, the average size increases

[14] The stochastic component of the evolution of idiosyncratic productivity is a feature that distinguishes our model from a neoclassical model of capital accumulation with adjustment costs. Even in a model with exogenous innovation, which dispenses from the protractedness induced by convex innovation costs, the transition may be protracted and feature a hump-shaped investment. One example of this case is when we remove entry barriers in a context of exogenous innovation, discussed in appendix B.2 and illustrated in figure B.2. There, the transition is driven purely by the stochastic shocks to idiosyncratic productivity, which drive the convergence of the productivity distribution at entry to the stationary one. Because the shock process induces a sluggish convergence of the productivity distribution, it leads to a hump-shaped dynamics of the investment rate. This case would be akin to a neoclassical growth model with exogenous productivity growth and frictionless capital accumulation, as in Imrohoroglu et al. (2006), the difference being that TFP growth would not be entirely exogenous but resulting from an endogenous burst of entry.

[15] The conditions under which the number of firms rises in economies with productivity-dependent idiosyncratic distortions are discussed in greater detail in . In models where the life-cycle dynamics

along the transition to an undistorted equilibrium. By discouraging entrepreneurship, profit taxes exert the opposite effect, concentrating production into fewer firms and increasing the average size. When lifted, the average size declines along the convergence dynamics. The contrasting dynamics of the average firm size in response to removing each type of distortion helps rationalize the dynamics of average firm size in post-communist relative to the rest of the growth accelerations. As we show in the case of China, where both idiosyncratic distortions and profit taxes interact, achieving the large average size at the onset of China's economic liberalization requires that the latter dominate the former. In the case of the rest of the accelerations, it is the idiosyncratic distortion that must have a stronger effect.

Figure 5.2 also reveals notable differences in the speed of transition depending on the nature of the reform. While measured TFP declines abruptly following a reversal of the profit tax\, it recovers faster, achieving a half-life that is four years lower than in the case of idiosyncratic distortions. Exploring the changes in the distribution of innovation efforts across firms and the evolution of productivity distribution helps understand this differential response. There is a burst of entry upon lifting the profit tax, and all firms shift their innovation profiles upwards. As a result, the economy reallocates labor towards innovation and firm creation, both of which are not capitalized in national income and product accounts[16], dragging on aggregate productivity on impact. Thereafter, however, the burst in innovation materializes, and aggregate productivity accelerates. When removing the productivity-dependent idiosyncratic distortions, only the most productive firms that increase innovation. However, few productive firms are in the initial productivity distribution, leading to a minimal impulse on aggregate productivity. Moreover, the least productive firms, which enjoyed subsidies under the distorted regime and cut down on innovation after the reform, drift slowly towards exit due to the stochastic nature of the productivity process, holding down the growth in aggregate productivity. Combined, these two forces explain the more sluggish convergence relative to the case of entry distortions.

of productivity are such that firms start with lower productivity on average than the average productivity of incumbents, distortions that favor low productivity firms and tax high-productivity ones represent a subsidy to entry.

[16]The Bureau of Economic Analysis in the US has started incorporating some forms of intangible investment, such as software and entertainment, into the National Income and Product Accounts. However, as argued by Corrado et al. (2006) the majority of intangible investment still goes unmeasured in national accounts. Thus, we take the approach of treating payments to labor that go into intangible capital accumulation, which in the model corresponds to payments to labor devoted to innovation as an expense rather than an investment. Furthermore, these adjustments are not made in the national accounts of the countries and periods under study.

The appendix B.2 develops these intuitions in greater detail.

A final noteworthy property of both transitions is the hump-shaped dynamics of investment. As in Imrohoroglu et al. (2006)'s analysis of the post-war Japanese economy, accounting for TFP growth was essential in generating the hump-shaped dynamics of the investment rate. In our model, the TFP dynamics are generated endogenously through the innovation incentives triggered by implementing reforms. However, unlike Imrohoroglu et al. (2006), the investment rate first drops on impact before engaging in sustained growth. This temporary decline is an implication of the endogenous nature of TFP and consumption smoothing, which requires the investment of resources for innovation purposes and induces households to preserve consumption by reducing the investment rate[17].

5.4 Accounting for China's Development Since 1998

Equipped with an understanding of how idiosyncratic distortions and profit taxes contribute to shaping transitional dynamics in the model and with a calibration strategy for the path of reversal of distortions, we proceed to evaluate the extent to which the reform can account for the observed growth in TFP in China between 1998 and 2011. We begin discussing the long-run implications of the mix of distortions at the initial and the terminal allocations and then characterize the transitional dynamics.

5.4.1 Long-Run Implications

Consider first the long-run implications of the calibrated reforms in the model. Table 3 reports the values of GDP, TFP, the number of entrepreneurs, and the average firm size in the steady-state with 2011 distortions relative to the steady-state with distortions calibrated to 1998. The table also reports the earnings share of the top 1% richest individuals in the population as absolute differences between the initial and terminal values. The first column shows the long run effects of the baseline reform, where both idiosyncratic distortions and profit taxes are removed, and the

[17] One way to mitigate or reverse the initial investment decline is through capital adjustment costs. This friction would precipitate the accumulation of physical capital albeit at the expense of slowing down innovation. The fall in the investment rate, however, does not occur in our full calibration of China. There, we allow the scaling parameter of the idiosyncratic distortion profile to target the capital-output ratio observed in 2011. Since this is notably higher than the starting capital-output ratio of 1998, it implies an investment subsidy that makes households willing to increase both innovation and physical capital accumulation, at the expense of lower consumption.

second column reports the results from a partial reform where only the productivity-elasticity of distortions is alleviated.

Table 3: Steady State Analysis: Terminal vs Initial Allocations

	Baseline Reform	Misallocation Only Reform
GDP	1.42	1.09
TFP	1.19	1.10
Entrepreneurs	2.06	0.62
Av. Size	0.48	1.61
Top 1% (difference between steady states)	0.08	0.03

NOTE: Table 3 shows the values of GDP, TFP, the number of entrepreneurs, and the average firm size in the steady-state with 2011 distortions relative to the steady-state with distortions calibrated to 1998. In the first column, both idiosyncratic distortion and profit taxes are reversed according to their calibrated values in table2. In the second column, only the productivity-elasticity of distortions is reduced to its 2011 value, leaving the other components of the mix of distortions in 1998 unchanged.

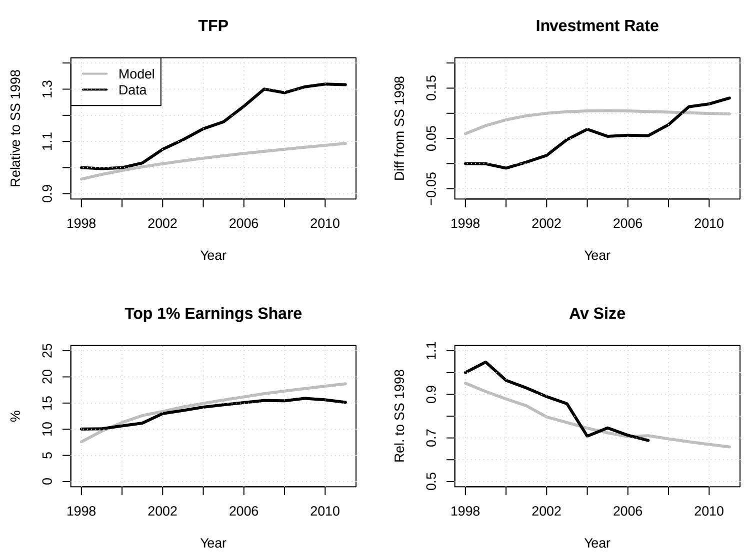
The reversal of distortions in the baseline reform generates a long-run TFP growth of 19%. The average firm size declines by almost 50%, largely explained by a doubling of the rate of entrepreneurship in the economy. The second column in table 3 allows disentangling the contribution of each distortion. Aggregate TFP increases by half as much under the partial reform, dictating that idiosyncratic distortions and profit taxes each contribute in almost equal shares to the total TFP gains. At the micro-level however, the implications of each distortion are notably different. As shown when exploring the model's mechanisms, the alleviation of idiosyncratic distortions in isolation generates a decline in the rate of entrepreneurship and an increase in the average firm size, a result that is counter to the evidence and that emphasizes the importance of withdrawing barriers to entrepreneurship in accounting for China's growth. Moreover, the comparison between the full and partial reforms yields significant differences in the growth of income inequality. In the full reform, the rise in inequality is on par with the one observed in the data, whereas abstracting from the profit-tax reform accounts for less than half of the observed increase.

5.5 Development Dynamics

Here we conduct the quantitative evaluation of the model's development dynamics for China's growth acceleration. The construction of the reforms involved feeding a linear fit of the observed path of reversal of the productivity-elasticity of idiosyncratic distortions into the model as well as a protracted reversion of profit taxes. The calibration of the speed of reversion of profit taxes and the value of the average idiosyncratic distortions was determined so that, by construction, the predicted transitional dynamics will be able to match the dynamics of the average firm size and the value of the investment rate in the terminal stationary equilibrium. The evaluation of the model, then, is based on two non-targeted moments: the fraction of the observed TFP growth that the model can account since the inception of the reforms until 2011 and the dynamics of the top earnings inequality relative to the data.

Figure 5.3 illustrates the dynamics of TFP, the investment rate, the top 1% earnings share and the average firm size. The solid black line corresponds to the dynamics in the model, and the light gray line represents the data. We report the TFP and the average firm size relative to their value in the initial steady-state, the top 1% earnings share as percentages, and the investment rate as differences from the initial steady state.

Figure 5.3: Post-Communist Transition Dynamics: China 1998-2011



The data for TFP corresponds Penn World Table's (Zeileis 2021) $rtfnpa$ measure of TFP between 1998 and 2011, linearly detrended by an annual TFP growth of 0.85% in the U.S. The investment rates is the raw data for the period from the same source. The average size data is the same as in section 3. The top income share is drawn from the World Inequality Database, Piketty et al. (2019)). TFP and the average size are expressed as ratios with respect to 1998 values, where, in the case of the model, 1998 stands for the calibration of the economy to the distortions in that year. The investment rate and the ratio of innovation expenditure over GDP are expressed as absolute differences.

The model predicts a protracted growth in aggregate productivity that can account for one-third of the TFP growth in the data. As discussed in the earlier, the protractedness of TFP allows for a hump-shaped behavior of the investment rate during the transition. Unlike Imrohoroglu et al. 2006, who appeal to an exogenous path of TFP growth to attain a hump-shaped behavior of the savings rate in post-war Japan, our model delivers such an outcome through the endogenous response of innovation decisions of firms to the changes in the economy's underlying distortions. The endogenous path of aggregate productivity also translates into a hump-shaped dynamics for the rate of return to capital, which we portray in the right panel of figure 5.4. Quantitatively, the investment rate follows closely the overall dynamics in the data, although as said earlier, the quantitative fit is an outcome of the calibration strategy for the terminal value of the scaling component of the idiosyncratic distortion profile, $Z_{I,2011}$, which we set to achieve China's capital-output ratio in 2011.[18]

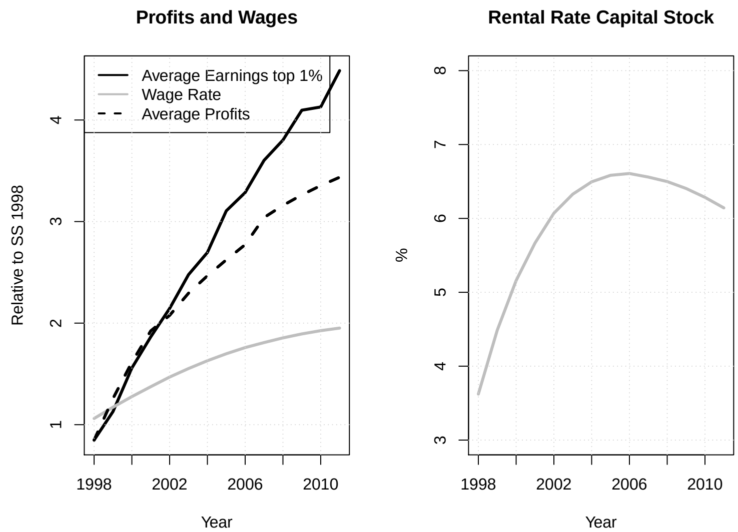
The aggregate behavior of the model is underlaid by dynamics of the average firm size and the earnings in inequality that resembles the data. While we calibrated the pace of reversal of the profit taxes to replicate the observed behavior of the average firm size, the dynamics of inequality were non-targeted. The growth in earnings inequality arises, on one hand, from the reduction of profit taxes, which increases the share of earnings that entrepreneurs can appropriate and, on the other hand, from the higher expenses on innovation, which widens the earnings gap between wage earners and business owners and concentrates income among the most talented entrepreneurs. These properties can be seen in figure 5.4, which depicts the dynamics of the wage rate, the average entrepreneurial profits, and the average earnings among the richest entrepreneurs.

We conclude the quantitative exercise with an exploration of the relative contribution of each component of China's reforms, the alleviation of idiosyncratic distortions and the removal of profit taxes, in explaining the aggregate and micro-level dynamics predicted by the model. To do so, we compute a partial reform where only the productivity-elasticity of distortions follows its calibrated path of reversal, while the profit tax remains at its initial steady state value.

Figure 5.5 shows that the abstracting from the elimination of profit taxes re-

[18] Along the transition, the investment rate increases too promptly. As discussed in footnote 16, the dynamics could be smoother, and therefore closer to the data, if we were to introduce adjustment cost to investment.

Figure 5.4: Profits, Wages, and the Rate of Return to Capital



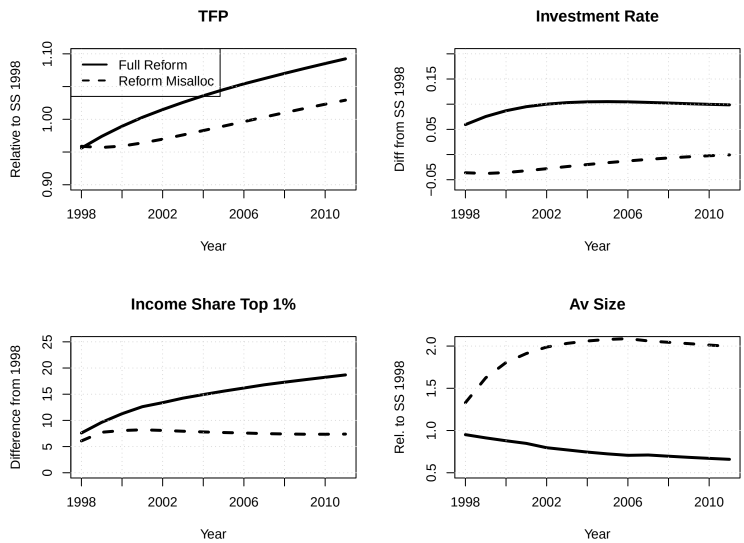
duces the aggregate productivity growth to half as much as the one yielded by the full reform and is accompanied by micro-level dynamics that are counterfactual. The micro-level dynamics, in turn, are at odds with China's experience. First, the average firm size increases in the transition to the new stationary allocation, an implication which is consistent with our analysis of section 5.3 but one that is counterfactual. Moreover, the increase in top income inequality is also substantially lower than the growth generated by the full reform. When profit taxes are kept in place, the incentive to increase innovation expenses is subdued, thereby mitigating the divergence between entrepreneurial profits among the top entrepreneurs, the average entrepreneurial profit, and the wage rate.

6 Conclusion

In this paper we presented a quantitative model of economic transitions to aid in understanding the macro and micro patterns of development dynamics in post-war acceleration episodes and post-communist transitions.

Our model builds upon recent theories of firm-level innovation, with entry, exit, and a stationary firm size distribution. We innovated upon these theories by interacting the built-in mechanisms of the model with two types of allocative distortions,

Figure 5.5: Decomposition of Post-Communist Transitions: Full Reform vs Reducing Idiosyncratic Distortions



Note: The figure reports the transitional dynamics of the TFP, the Investment Rate, the Income Share of the Top 1% earnings, and the average firm size under the baseline reform (Full Reform) and under a partial reform where the productivity elasticity of the idiosyncratic distortions follows its calibrated path, and the capital-output ratio and the profit tax remain fixed at their initial values (Reform Misalloc). The TFP and the average firm size are reported relative to their 1998 values, the top earnings share is presented in percentage, and the investment rate is reported as absolute difference from the initial steady-state.

idiosyncratic distortions and profit taxes, and by characterizing the transition dynamics. Furthermore, our analysis exploits the time-series dimension in existing empirical studies of misallocation in developing countries to come up with a novel strategy to discipline reforms. This allowed us to explore the quantitative behavior of the model in the context of a calibrated path of dismantlement of distortions.

Our findings suggest that our theory can account for the salient features of development dynamics in acceleration episodes. A property of our findings is that, despite dispensing from frictions to resource reallocation, e.g., financial frictions, the model can deliver a protracted path of growth in the rate of investment and in the TFP. A key feature for the sustained growth in these variables is our theory of innovation, and the co-existence of heterogeneous incentives to invest in intangible capital along transition paths. There, the incentives to spur innovation from new and previously taxed entrepreneurs interact with a decline in innovation incentives from older cohorts of firms with relatively low productivity. As a result from this tension, it takes several years for the TFP to attain its new steady state level.

The quantitative evaluation of the model in the context of China's growth acceleration reveals that there is still a large fraction of the observed productivity growth that the model cannot account for. In future research, we shall investigate plausible extensions to the model that may shed light on the missing forces. One potential avenue is the consideration of an open economy and the possibility that, either through the competitive effects of international trade or through the direct diffusion from multinational production, the model could account for a closer share of observed productivity growth in the data. Another abstraction in our current analysis that would help the model explain a higher share of the observed growth in TFP in China is the uncorrelated component of the dispersion in marginal revenue products. Accounting for uncorrelated dispersion would induce rank-reversal and magnify the allocative inefficiency, forces that would increase the productivity effect of distortions.

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A Data Description

We first provide a list of the countries captured as accelerations by the methodology of Hausmann et.al (2005) and the full list of post-communist transitions.

For these countries, we construct the average of TFP and investment rate dynamics relative to the acceleration year, or relative to the liberalization year in the case of a post-communist transition, which we date to be 1990. The underlying data comes from Penn World Tables version 10.1. TFP is taken directly from the variable $rtfpna$ in the database, while the investment rate is given by csh_i. The lines in figure 3.1 correspond to simple averages among countries within each group.

Average size dynamics for Singapore, Japan, and Korea 3.2 are constructed based on the data in Buera and Shin (2013). The average firm size for Chile and Romania was constructed from the supplementary material accompanying Bartelsman et al. (2009). For Hungary, the data comes from Varela (2017).

In terms of computing the average size dynamics for China, we have two data sources that we use for different purposes: the Census Yearbooks for 1995, 2004, and 2008; and the Annual Survey of Industrial Production conducted by the National Bureau of Statistics for the years 1998 through 2007. Since part our calibration of

Table 5: List of All Sustained Accelerations, Successful Post-Communist Transitions, and All Post-Communist Transition Countries

Sustained Growth Accelerations				Successful Post-Communist	All Post-Communist
Albania	1994	Morocco	1958	Russia	Russia
Armenia	2001	Morocco	2000	Estonia	Georgia
Belgium	1960	Mexico	1963	Uzbekistan	Estonia
Bulgaria	2001	North Macedonia	2003	Armenia	Moldova
Belarus	1998	Mali	1985	Azerbaijan	Kyrgyzstan
Botswana	1968	Mali	1993	Turkmenistan	Uzbekistan
Canada	1963	Myanmar	1991	Bulgaria	Tajikistan
Chile	1975	Mongolia	2002	Belarus	Armenia
Chile	1987	Mozambique	1996	Kazakhstan	Azerbaijan
China	1961	Mauritius	1971	North Macedonia	Turkmenistan
China	1979	Mauritius	1984	Czech Republic	Bulgaria
China	1993	Malawi	1965	Hungary	Belarus
China	2002	Malaysia	1968	Latvia	Kazakhstan
Congo	1968	Namibia	2000	Lithuania	North Macedonia
Colombia	2003	Nigeria	1958	Poland	Czech Republic
Costa Rica	1965	Pakistan	1961	Romania	Hungary
Denmark	1958	Panama	1966	Slovakia	Latvia
Dominican Republic	1992	Panama	1989	Albania	Lithuania
Dominican Republic	2005	Panama	2004	China	Poland
Egypt	1959	Peru	2003	Vietnam	Romania
Egypt	1978	Poland	1994	Laos	Slovenia
Spain	1960	Portugal	1960		Slovakia
Spain	1984	Portugal	1985		Albania
Ethiopia	2004	Romania	1971		China
Finland	1968	Romania	2002		Vietnam
United Kingdom	1983	Rwanda	1996		Laos
Ghana	2007	Sudan	1995		Ukraine
Equatorial Guinea	1990	Singapore	1968		
Greece	1960	Singapore	1989		
Hong Kong	2002	Singapore	2002		
Indonesia	1968	El Salvador	1992		
Indonesia	2003	Slovakia	2002		
Ireland	1959	Chad	1999		
Ireland	1987	Thailand	1958		
Japan	1958	Thailand	1965		
Kazakhstan	1998	Thailand	2002		
Cambodia	2000	Turkmenistan	2002		
Republic of Korea	1964	Trinidad and Tobago	1995		
Republic of Korea	1984	Tunisia	1968		
Laos	1979	Turkey	1982		
Laos	1990	Turkey	2003		
Laos	2007	Taiwan	1961		
Sri Lanka	1977	Tanzania	1999		
Sri Lanka	1991	Uzbekistan	2004		
Sri Lanka	2005	Viet Nam	1991		
Lithuania	1998				

the Chinese economy in 1998 relies on matching the average size ratios with the US, we need to make sure that the dataset covers most firms in the economy in order to avoid biasing the calibration of the underlying distortion. Thus, for calibration purposes, we appeal to data from the Census Yearbooks as reported in Brandt et al. (2014). They report the total number of firms and the employment level from the Census Yearbooks of 1995, 2004, and 2008, allowing us to compute the average size in these years. The average size for 1995, our calibration target in the model, amounts to 166 workers. We plot this number along with the other two available data points in figure 3.2[19] of motivating facts.

We appeal to the alternative dataset, the NBSsurveys, to provide a longer and more continuous point of comparison for the model with respect to predictions about the evolution of average firm size during the reforms. The Annual Survey of Industrial Production conducted by the National Bureau of Statistics covers all non-state firms with 5 million yuan in revenue or more. Even though we find this data useful for illustrating the evolution of the average firm size for a longer period of time (see figure 5.3), appealing to it for calibration purposes would have delivered a much higher value of the flat component of the profit tax distortion. That is because in the surveys, the average size of an industrial firm in China in 1998 was 341 workers, twice as large as the magnitude emerging from the Census. Matching this target would have required a stronger disincentive to entrepreneurship in the model.

B Reforms to Understand the Model's Mechanisms

Here we present the calibration strategy underlying the reforms considered in section 5.3 and provide more details of the micro-level adjustments described in the text.

B.1 Parametrization

We consider two types of reforms, one that dismantles idiosyncratic distortions and one that reverses taxes to the profits of the firms. As said, both distortions feature prominently at the onset of China's transformation, hence we it is important to uncover how the reversal of each of them contributes to shaping the transitional dynamics.

[19] The figure also shows a data point for 1993. We thank Gueorgui Kambourov for calculating this number for us. The source is the same as in Brandt et.al (2014), which did not report number of firms and employment data for the year 1993 in their work.

We parametrize the distortions and the reforms in a simple and stark fashion. Firstly, we choose relative high values of distortions in the distorted steady state to magnify the forces in the model. More precisely, we pick slope of the idiosyncratic distortion profile and the profit tax rate to attain, in each case, a 20% reduction in TFP relative to an undistorted allocation. When considering idiosyncratic distortions, the average value of the distortion has an effect over the economy's capital to output ratio in the steady state. In this exploratory stage of the paper, we opt to abstract from these steady state changes in the investment rate so that we can assess the model's ability to trace the qualitative properties of the investment rate in the accelerations data without any interference from the distortion profile other than its effect on the dynamics of TFP. To this end, then, we adjust the scale parameter Z_I in the idiosyncratic distortion profile to keep the capital-output ratio fixed across the stationary allocations. Secondly, we consider once and for all reversals of distortions as triggers of transitional dynamics. Table 4 summarizes the outcome of the calibration procedure.

Table 4: Parametrization of Distortions in Simple Experiments

	Parameter Value	Target
Productivity-elasticity of distortions υ	0.35	$\frac{TFP(undistorted)}{TFP(idiosyncratic-distortions)} = 1.2$
Profit tax τ^{π}	0.74	$\frac{TFP(undistorted)}{TFP(profit-taxes)} = 1.2$
Scale parameter Z_I	5.47	$\frac{K}{Y} = 2.36$
Fixed cost f_c	0	

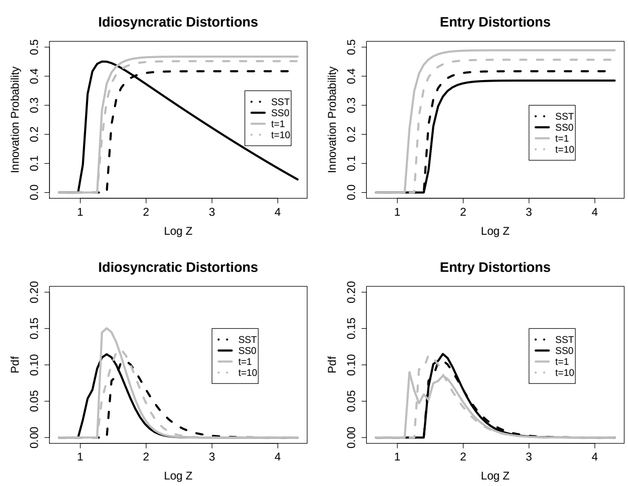
Parameter values apply to model economies with one type of distortion at a time. Values are set so that model's long run growth in TFP from achieving the undistorted steady state allocation matches the 20% detrended TFP growth observed in the data for an average acceleration.

B.2 Micro-Level Adjustments

The differential response of the economy response to reforms that remove entry and idiosyncratic distortions can be understood by exploring the micro-level adjustments, particularly the response in the distribution of innovation efforts across firms over time and the evolution of the productivity distribution. We illustrate these objects in figure B.1. The top two panels depict the response of innovation probabilities as a function of the firms' underlying physical productivity ($TFPQ$) at a number of representative points of the transition: the initial steady-state ($SS0$) ,the terminal steady-state (SST), and periods 1 and 10 ($t = 1, t = 10$). Similarly, the bottom two panels depict the productivity distribution of firms at the same instances of the transition path.

Figure B.1 shows that both entry and idiosyncratic distortions depress innovation incentives, but idiosyncratic distortions have a disproportionate effect among the most productive firms in the economy (lines labeled $SS0$ in the top figures). This distinguishing feature of idiosyncratic distortions manifests in the properties of the productivity distribution. The share of firms at the top of the distribution declines sharply under idiosyncratic distortions (line $SS0$ of bottom left figure) whereas it shows almost no change under entry distortions (line $SS0$of bottom right figure). As a result, when reforms are implemented and innovation intensities recover, aggregate innovation expenses increases strongly in the case of entry distortions, where there is a high share of highly productive firms to take advantage of the improved incentives to innovation, while it does so by about half as much in the case of idiosyncratic distortions, where there share of such firms is significantly smaller.

Figure B.1: Innovation Profiles and Productivity Distributions



The top panel plots the innovation profiles in the initial and terminal steady states, and periods 1 and 10 along the transition following reforms that reverse idiosyncratic (top left) and entry (top right) distortions. The bottom panels illustrate the *pdf* of the distribution of physical productivity (TFP) at the same points of the transition.

The sharper increase in the rate of innovation helps rationalize the stronger decline and the speedier recovery of TFP when removing entry distortions. As the economy expands innovation efforts and increases entry, it reallocates labor towards to innovation and firm creation, both of which are not capitalized in national income and product accounts[20]. Therefore, aggregate productivity declines on impact. Thereafter, the properties of the productivity distribution at the onset of the reforms discussed above allows for a quicker recovery than in the event of removing idiosyncratic distortions.

B.3 The Role of Innovation and Reallocation

How do endogenous innovation and resource reallocation contribute to shaping the dynamics of development?

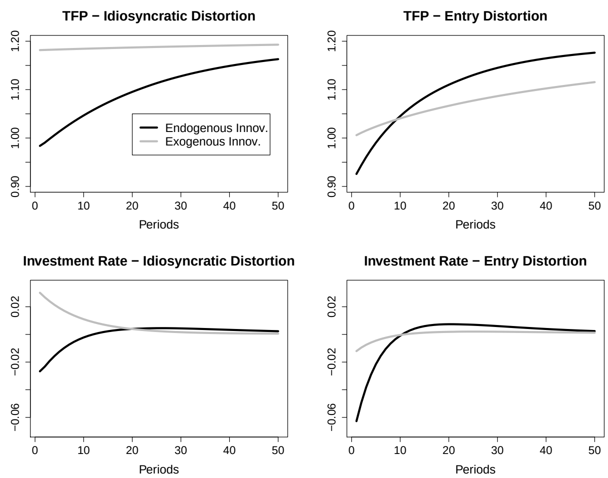
We evaluate reforms that dismantle idiosyncratic and entry distortions considering separately cases where innovation is endogenous, as in the previous section, or exogenous, in which case resource reallocation is the sole force driving the transition. To represent an economy with exogenous innovation, we endow firms with the same innovation profile as in the undistorted stationary allocation with endogenous innovation. Firms do not have to invest in achieving this innovation profile and hence, do not have a technology to innovate more or less as a result of distortions, so firm dynamics are exogenous. Recall that all experiments calibrate distortions so as to achieve the same TFP growth (see table 4)

Consider first the role of innovation and reallocation for the behavior of macroeconomic variables in figure B.2. There, we plot TFP and the investment rates for each type of reforms overlaying the cases with endogenous and exogenous innovation.

The main message of the figure is the differential contribution of endogenous innovation to the speed of convergence of TFP across reforms. When dismantling idiosyncratic distortions, an active response in the firms' expenses on innovation is essential for adding protractedness to the dynamics. Conversely, in the case of entry distortions, the dynamics of TFP under exogenous innovation experience almost no change on impact but are substantially more protracted throughout the transition

[20] The Bureau of Economic Analysis in the US has started to incorporate some forms if intangible investment, such as software and entertainment, into the National Income and Product Accounts. However, as argued by Corrado et al. (2006) the majority of intangible investment still goes unmeasured in national accounts. Thus, we take the approach of treating payments to labor that go into intangible capital accumulation, which in the model corresponds to payments to labor devoted to innovation, as an expense rather than an investment. Furthermore, these adjustments are not done in the national accounts of the countries and periods under study.

Figure B.2: Transition Dynamics: Idiosyncratic Distortions vs Entry Distortions



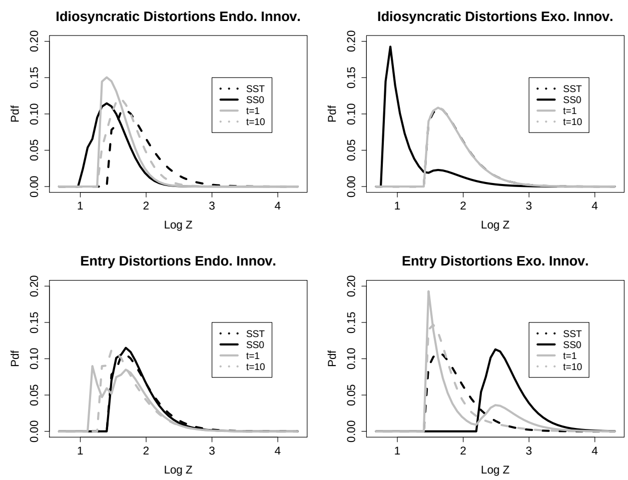
TFP is measured as ratio with respect to the initial steady state values . The Investment rates is measured as absolute deviations from the distorted steady state ratios.

than in the baseline with endogenous innovation.

The productivity distributions are, again, illustrative of the mechanisms underlying the contribution of endogenous innovation to the speed of transitions. Consider first the case of reversing idiosyncratic distortions, which are depicted in the top two panels of figure B.3. The case with exogenous innovation (top right) shows that there is a substantial increase in entrepreneurship in the distorted stationary allocation, manifested in the notable shift to the left of the productivity distribution. However, as soon as distortions are lifted and the selection of entrepreneurs improves, the distribution converges almost immediately to the undistorted stationary one and, hence, so does aggregate TFP. With endogenous innovation, the immediate productivity gain upon reversal of the misallocation is more muted, given that the productivity distribution (labeled $t = 1$) is still far from the stationary one. As innovation expenses pay off, the distribution shifts to the right, but 10 periods into the transition the distribution has not yet settled into the stationary one. The protracted pace of convergence in the distribution feeds into the dynamics of aggregate TFP.

When the reforms lift entry distortions, the drivers of the speed of transition are reversed. With exogenous innovation (bottom right), the immediate effect of the reform is to create a burst in the entry of new entrepreneurs that makes the distribution of firms across productivity be almost entirely dominated by the distribution of entrants (line labeled $t = 1$). Thereafter the distribution converges to the stationary one at a pace dictated by the exogenous stochastic process of firm dynamics. When allowing for endogenous innovation (bottom left), the burst in entry also leads to a contraction in the right tail of the distribution. However, as firms increase their expenses in innovation, the convergence of the distribution is accelerated.

Figure B.3: Innovation Profiles and Productivity Distributions



The top two panels illustrate the *pdf* of the distribution of physical productivity (TFP) at various points of the transition for economies with endogenous (top left) and exogenous (top right) innovation, under a reform eliminating idiosyncratic distortions. The bottom figures illustrate the same objects for the case of reforms reversing entry distortions.

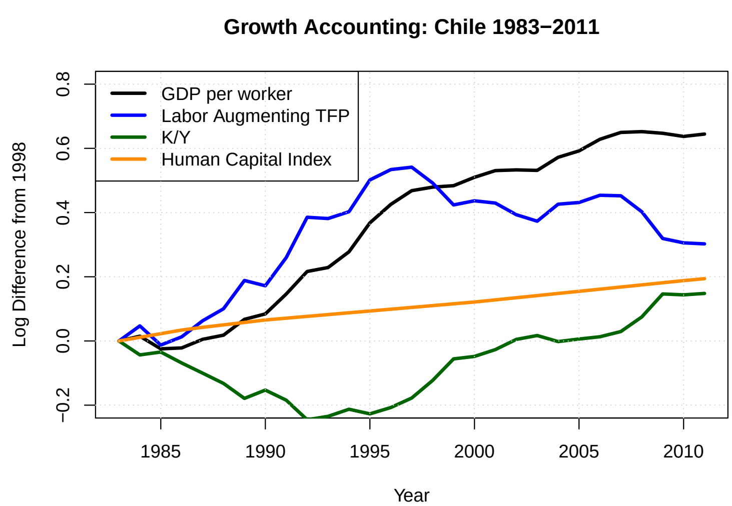
The difference in the behavior of TFP help rationalize the behavior of investment dynamics. With exogenous innovation and idiosyncratic distortions, the immediate jump in TFP induces a neoclassical-shaped response of investment, increasing on impact and converging to the steady state level from above.[21] In the case of entry distortions, investment dynamics are qualitatively similar, and intricately related to the protracted adjustment in TFP. However, when innovation is endogenous, the economy postpones investment so as to invest in innovation at the same time it preserves consumption smoothing.

[21] Recall that the idiosyncratic distortions were calibrated so that the capital to output ratio was undistorted. Thus, the behavior of investment dynamics cannot be attributed to an investment specific component of idiosyncratic distortions.

C Chile's Growth Acceleration 1985-1996

In earlier versions of the manuscript, we considered Chile's growth acceleration between 1985 and 2011 as a complementary case study to the quantitative analysis of China's development since 1998. Considering Chile's acceleration was motivated by the availability of firm-level data covering the acceleration period, a key ingredient for a tight calibration of the pace of reversal of distortions in the model. However, while the Chilean acceleration surpasses the criterion for counting as a sustained growth acceleration, it is one that is very contaminated by cyclical elements, driven by the strong recovery the economy was undergoing after a deep recession in the early 1980s. Moreover, as shown in the growth accounting exercise depicted in figure C.1, it is only in the early years that the acceleration was fueled by rapid and sustained TFP growth, the ingredient of the acceleration that our theory seeks to account for, whereas it was physical and capital accumulation that became the primary driving forces in the second half of the period. In this section we present the results from the complementary case study.

Figure C.1: Growth Accounting: Chile's Growth Acceleration

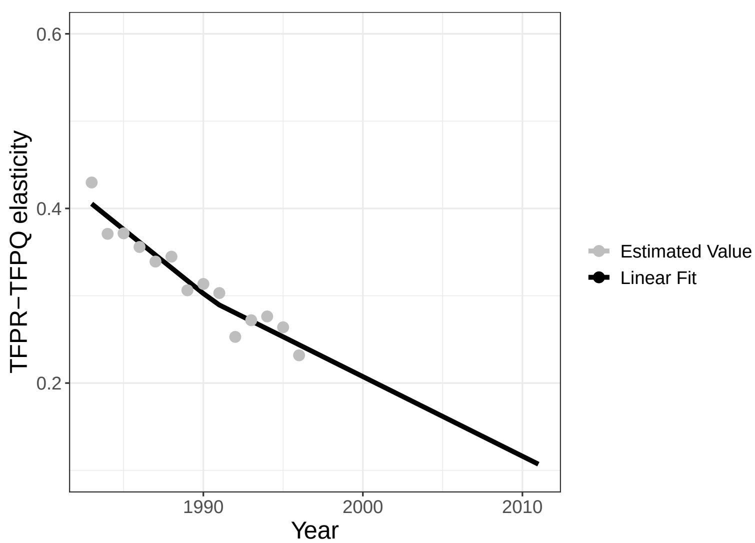


Note: The data for the growth accounting exercise stems from the Penn World Tables Database Zeileis (2021). We decompose real GDP per worker, as $\frac{Y}{L} = TFP^{\frac{1}{1-\alpha}} \left(\frac{k}{y}\right)^{\frac{\alpha}{1-\alpha}} hc$, where real GDP is measured according to $rgdpna$ in the data, L is the number of employed agents, k is $rkna$, and hc is the human capital index provided by the data. The labor share, $(1-\alpha)$, is given by the labor share reported in the data, $lbsh$, for the year 2011.

C.1 Calibration of Chile's Growth Acceleration

We think of Chile's economy prior to its growth take-off as subject to idiosyncratic distortions, and model its acceleration as driven a protracted alleviation of these distortions. Based on Chile's ENIA (Encuesta Nacional Industrial Anual), a yearly industrial survey covering the universe of manufacturing plants with 10 or more workers[22], we estimate the productivity-elasticity of idiosyncratic distortions. As before, the productivity elasticity is estimated as the regression coefficient between the $log\,(TFPR)$ and $log\,(TFPQ)$, where $TFPR$ and $TFPQ$ are measured exactly as in Hsieh and Klenow (2009). Similarly to how we proceed in the quantitative analysis of China's development since 1998, we fit a linear trend to the regression coefficients, which we use to extrapolate the elasticities outside the estimation period until 2011, the year in which we assume the reform stalls and distortions stabilize. The result from this calibration strategy is illustrated in figure C.2.

Figure C.2: Productivity-Elasticity of Distortions in Chile



Note: The figure illustrates the regression coefficient between $log\,(TFPR)$ and $log\,(TFPQ)$ for the period 1984-2011. The dots correspond to the point estimates from Chile's ENIA (Encuesta Nacional Industrial Anual) for 1984 through 1996. We define $log\,(TFPR)$ and $log\,(TFPQ)$ as in Hsieh and Klenow 2009. The solid line illustrates a linear fit on the estimated values projected on to 2011. We assume that reforms stabilize in 2011, and the productivity-elasticity of idiosyncratic distortions remain constant a the 2011 level. The initial steady state is represented by the elasticity estimate for 1984.

[22]We work with the version of the ENIA that is provided in Chen and Irarrazabal (2015)'s replication material, downloadable from https://www.economicdynamics.org/codes/13/13-61/pack_finalversion.zip

We dispense from profit taxes but continue to rely on fixed costs of production to replicate the average firm size in Chile prior to the acceleration. Since we appealed to profit taxes to characterize the egalitarian forces and the barriers to private entrepreneurship that are characteristic of a communist regime, we do not see these taxes as pertinent to think about Chile's acceleration. However, for consistency with a calibration strategy that seeks to start-off the economy at a level of the average firm size that is consistent with the data, we preserve the fixed cost specification.

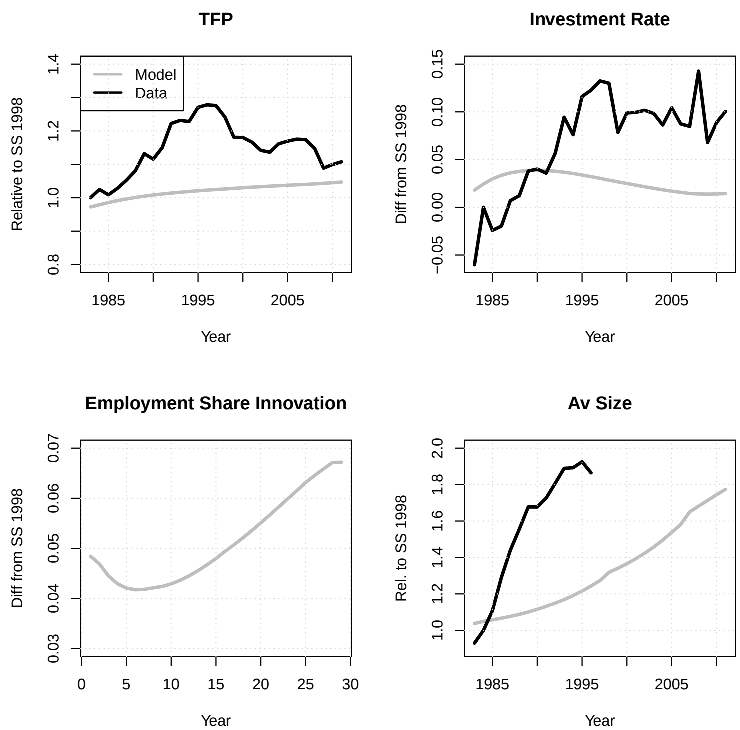
A property of Chile's development dynamics that does not align well with that of the average growth acceleration is the behavior of the investment rate. At the onset of the acceleration, the investment rate declines strongly, constituting a significant drag on aggregate growth, and then recovers abruptly so that at the point where the TFP impulse stalls, the capital-output ratio starts to increase. This deviation in the behavior of the investment rate from the pattern exhibited by the average growth acceleration carries consequences for the calibration of the average idiosyncratic distortion in the economy, controlled by the parameter Z_{It} in the idiosyncratic distortion profile. This parameter was set to reconcile the growth in the capital output ratio in the model with that of the data. In China's acceleration this could be achieved parsimoniously, due to the somewhat monotonic rise in the capital-output ratio throughout the transition. This is not the case under Chile's cyclical behavior of the investment rate. For this reason, we decided to abstract from seeking to match the behavior of the capital output ratio, and preserve the value of Z_I in 1984 and in 2011, the initial and terminal points of the transition, to attain a common capital-output ratio.

C.2 Development Dynamics

Figure C.3 shows the development dynamics under Chile's calibrated reforms. Although the model can almost fully account for the overall growth in TFP from the beginning until the end of the period, it cannot capture the fast rise in TFP in the first decade of the acceleration nor it can it explain the decline thereafter. As said, the smooth impulse implied by the calibrated reform, leads to a more protracted growth in aggregate productivity and cannot generate contractions.

The atypical behavior of the investment rate during Chile's acceleration cannot be accounted for by the model either. While we could have improved the model's fit by adjusting the average idiosyncratic distortion to attain a higher level of the capital to output ratio at the end of the acceleration period, the model would not have been

Figure C.3: Development Dynamics: Chile's Growth Acceleration 1984-2011



Note: The data for TFP is constructed from the Penn World Tables Database (Zeileis 2021). We construct TFP using $rgdpna$ as the measure of real GDP, the product of the population and the human capital index ($pop * hc$) as the measure of the labor input, and $rkna$ as the measure of the capital stock. We fixed the labor share at the value reported by the data for the year 2011, $lsh(2011)$. Once the series of TFP is construct it, we linearly de-trend it assuming an annual productivity growth in the U.S. of 0.85%. The investment rate is drawn directly from the Penn World Tables. We construct the average firm size from the ENIA (Encuesta Nacional Industrial Anual), extracted from the replication material for Chen and Irarrazabal (2015). The average firm size is defined as the ratio between total employment and the total number of firms.

able to capture the cyclical behavior of the investment rate. The model does capture, however, the qualitative property of an increasing pattern of the investment rate, which is a virtue derived from the endogenous response of innovation decisions and the resulting effect on the rate of return to capital.

Lastly, the interaction between occupational choices, innovation expenses, and the reversal of idiosyncratic distortions leads to a rise in the average firm size, as in the data. Quantitatively, however, the rise predicted by the model is more protracted than the one observed in Chile.

C.3 Life-Cycle of Firms during Acceleration Episodes

In addition to the interest in the literature in documenting cross-country differences in the firm size distribution, recent studies have shifted the focus towards investigating differences in the life-cycle growth of firms between developed and developing economies.[23] Because of data limitations, most current empirical investigations of the cross-country differences in the life-cycle of firms has been carried out inferring the life-cycle from the cross-sectional distributions of employment across ages, instead of tracking the life cycle of a cohort.

In this section we investigate the accuracy of this approximation in the context of an economy undergoing a growth acceleration. For this purpose, we compare the evolution of the cross-sectional distribution of employment across ages at various points of the transition path, alongside the life-cycle growth of the cohort of firms that enters the economy at the onset of the reform. We choose Chile's acceleration as illustrative example, given the simpler nature of the its reform in the model, entailing the withdrawal of a single distortion.

Specifically, figure C.4 illustrates the cross-sectional distribution of employment and age at Chile's initial steady state (labeled ss 1980), at the post-reform steady state (ss Chile post-reform), and for the years 1980 (period 1 of reform), 1995, and 2011. The figure also depicts the life-cycle growth of the cohort born in 1980.[24]

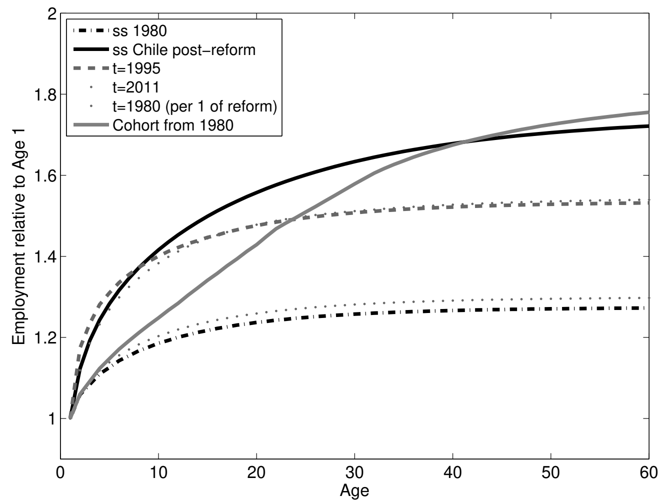
Figure C.4 shows that the protractedness displayed by the aggregate productivity in figure C.3 is underlaid by a comparable sluggishness in the convergence of the cross-sectional life-cycle of employment. After making a small upward jump in the period of the reform (see line labeled t=1980), by the year 2011 it is still quite far from having converged to the stationary distribution of the terminal stationary allocation (ss Chile post-reform)

In terms of understanding the source of this sluggishness, recall that the shape of the cross-sectional life-cycle is determined by a combination of age and cohort effects. On the one hand, newly created firms are innovating at a pace consistent with the more friendly economic environment and are, therefore, making the life-cycle look steeper. On the other hand, older cohorts comprise low productivity, formerly subsidized entrepreneurs whose protection is being withdrawn by the reform and are consequently cutting down on innovation and headed towards exit. Since these low

[23] Hsieh and Klenow (2014) being the most salient study in this family of papers.

[24] It is a proper life-cycle in the sense that we kept track of the time series evolution of employment for a given cohort, conditional on survival.

Figure C.4: Life Cycle of Firms during Acceleration Episodes: Chile 1980-2011



productivity firms have accumulated investments in productivity, the productivity process implies that it takes time for these firms to drift down towards the exit threshold. Hence, they contribute to making the life-cycle look flatter.

The sluggishness in the convergence of the cross-sectional distribution of employment across age raise a word of caution to using it as an input to back out the underlying idiosyncratic distortions in the economy. Suppose a researcher were to observe the cross-sectional distribution of employment over age for Chile in 2011, and one were to use a stationary model of firm dynamics to infer the degree of allocative distortions that are necessary to replicate the cross-sectional life cycle in the data.[25] Since the life cycle of firms in the cross section of the model for 2011 is well below the one at the new steady state, the researcher would back out distortions that are more severe than those that are actually underlying the economy in 2011, point at which the profile of distortion adopts it lowest estimated value and stabilizes. Had the researcher been able to construct the life-cycle of a cohort of firms, the imputed degree of distortions would have been milder, and closer to the actual degree of distortions in 2011, given that the life-cycle of the cohort is closest to the cross-sectional life cycle consistent with the steady state associated with the distortions of 2011.

[25]This is the kind of counterfactual constructed in Hsieh and Klenow (2014) to quantify the aggregate implications of the differences in the life-cycle of firms between the U.S., India, and Mexico

D Self-Employment and the Number of Firms: Evidence and the Model's Predictions

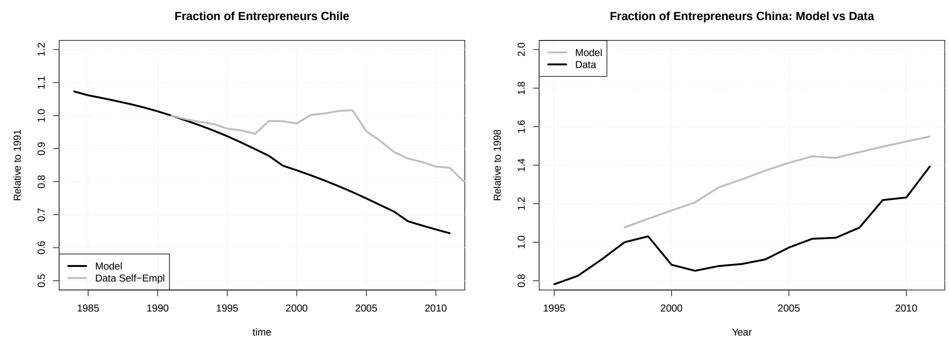
The paper stresses the behavior of the average firm size as the relevant empirical counterpart to assess the implications of distortions on the rate of entrepreneurship and the firm-size distribution. However, being an entrepreneurial model of firm entry and exit, it is useful to review evidence that more directly speaks to this margin of adjustment.

To this end, figures D.1 and D.2 report the dynamics of the rate of self-employment and the number of firms along China's and Chile's growth accelerations. Both these metrics have merits and limitations in capturing the notion of a firm in the model. Self-employment, on one hand, better reflects entrepreneurial activity from individuals that are on the margin of entrepreneurial activity or seeking for work in the labor market, but is less likely to reflect the innovation and growth potential of that entrepreneurial firms exhibit in the model. The number of firms, on the other hand, is subject to the opposite trade-off. Stemming from China's Annual Survey of Industries, which covers firms beyond a certain size, it captures firms with a certain number of employees and stock of capital, but also captures businesses with a more sophisticated ownership structure whose survival is less linked to an occupational choice from the entrepreneur. Since, as we show below, both measures exhibit a similar behavior, we argue they provide empirical validity to the channels in the model.

Turning, then, to the results, let us begin with figure D.1, which illustrates the fraction of entrepreneurs in the model and the fraction of self-employed in the labor force for China and Chile. We see that in both cases the model captures the direction of change in the rate of self-employment, except for the 1995-2005 period in Chile, and the 1999-2001 period in China. Despite these non-monotonicities, we interpret the evidence as supportive of the model.

To complement the above, we turn now to discussing the implications of adopting the number of firms as the empirical counterpart for firms in the model. We can see in figure D.2 that a similar validation for the model's mechanisms emerges under this metric, albeit with different quantitative fit. In particular, the model falls short of capturing the spike in the number of firms in China between 2003 and 2005, while it over-predicts the decline in the number of firms in the early years of Chile's acceleration, and under predicts it towards the end.

Figure D.1: Self-Employment in Model and Data



Note: Chile's data on Self-Employment is drawn from the International Labor Organization's ILO-stat database. Both the model and the data are normalized to be equal to one in 1991, which is the first data point. Self-Employment in China is drawn from China's Statistical Yearbooks of 2018, and is defined as the ratio of Self-Employed individuals in urban areas over the total number Urban Employed Persons. The data is measured relative to its value in 1998, and the model is measured relative to the initial steady state, which is calibrated to the distortions measured for 1998.

E Decomposition of TFPR into Capital and Output Distortions

The paper adopts $TFPR$ as the summary of idiosyncratic distortions in the data, and uses the properties of the distribution of $TFPR$ to discipline the distribution of revenue taxes in the model. However, $TFPR$ is defined by a combination of "output distortions" and "capital distortions", as labeled in Hsieh and Klenow (2009). To assess the extent to which each ingredient is contributing to the overall dynamics of $TFPR$, we provide a decomposition in the figures that follow.

As a quick reminder, $TFPR$ is proportional to capital and output distortions in the following fashion

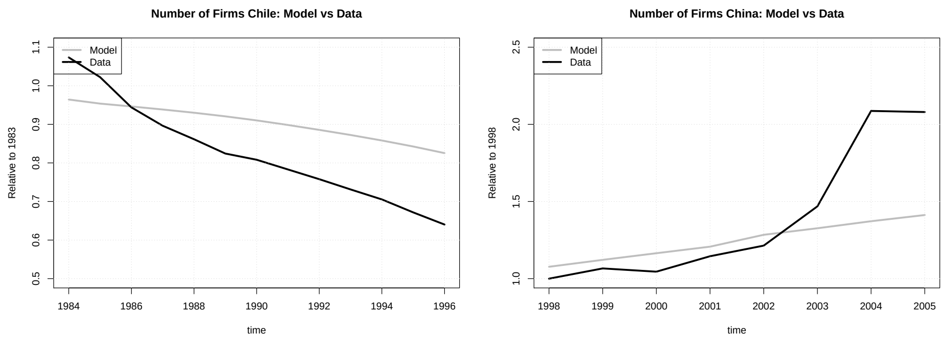
$$TFPR_i \ltimes \frac{(1+\tau_{ki})^{\alpha}}{(1-\tau_{yi})}$$

Based on this definition, our approach to addressing the decomposition is to construct two alternative counterfactual measures of $TFPR$ in which one distortion is shut down at a time

$$log\left(\frac{TFPR_i\,(\tau_y=0)}{\overline{TFPR}}\right) = log\left[\frac{(1+\tau_{ki})^{\alpha}}{\overline{TFPR}}\right]$$

$$log\left(\frac{TFPR_i\,(\tau_k=0)}{\overline{TFPR}}\right) = log\left[\frac{\frac{1}{(1-\tau_{yi})}}{\overline{TFPR}}\right]$$

Figure D.2: Number of Firms in Model and Data



Note: The number of firms in Chile are aggregated from Chile's "Encuenta Nacional Industrial Anual" (ENIA) for the period 1983-1996. The number of firms in China is computed from the Annual Survey of Industries for the years 1998-2005.

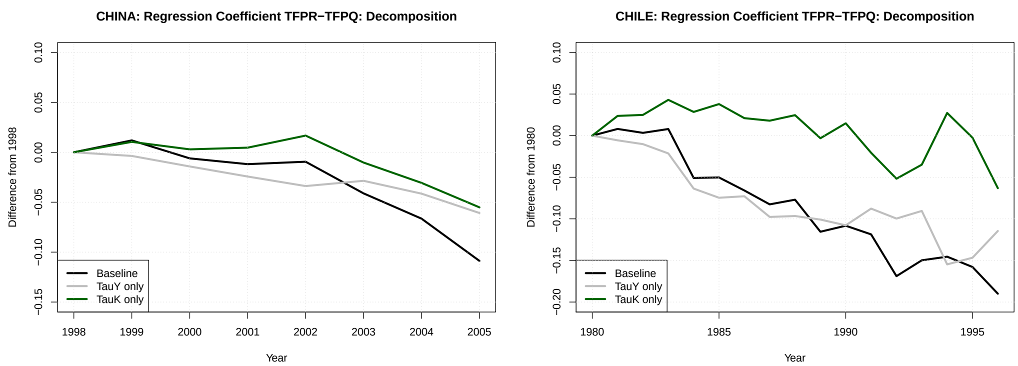
where $log\left(\frac{TFPR_i^K}{\overline{TFPR}}\right)$ is the log of $TFPR$ assuming the only distortion is the capital one, relative to the industry average $TFPR$, and where $log\left(\frac{TFPR_i^y}{\overline{TFPR}}\right)$ is the same object assuming the output distortion is the only active distortion.

Equipped with these alternative definition, we separately compute their regression coefficients with respect to $log\left(\frac{TFPQ_i}{\overline{TFPQ}}\right)$. In the context of the model, where capital distortions create a wedge in the cost of renting capital, a decline in the capital-distortions' elasticity with respect to $TFPQ$ implies that, during acceleration episodes, more productive firms become more able to increase their capital labor ratios. A decline in the output distortion's elasticity, on the other hand, implies that the more productive firms become more able to increase size attracting labor and capital in proportion to their technological shares. With respect to TFP, however, a decline in both types of elasticity is indicative of higher incentives for more productive firms to innovate.

The results for Chile and China are plotted in figure E.1, where the vertical axis measures the evolution of the regression coefficients as differences from their respective values in the first period of the respective samples.

In Chile, Figure E.1 shows that the output distortion's elasticity (gray line) tracks the overall elasticity very closely throughout the entire period, whereas the capital distortion (green line) shows a milder and noisier decline starting in 1985. In China, the figure shows that the output distortion's elasticity (gray line) falls the most between 1998 and 2002, with the capital distortion (green line) playing a bigger role since 2003.

Figure E.1: Output and Capital Distortions and the Dynamics of TFPR/TFPQ Elasticity



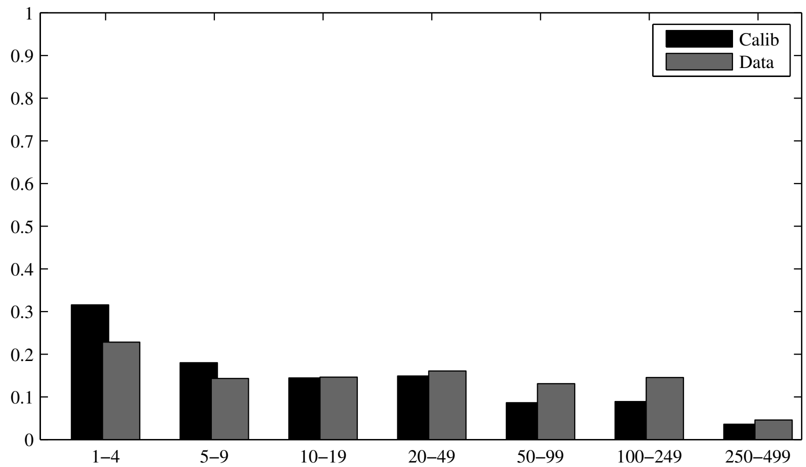
Given our primary goal of accounting for TFP dynamics, and that we are seeking to do so though the interaction between endogenous firm dynamics and the productivity-dependent component of distortions (abstracting from reallocation barriers), we find the evidence to provide support for our approach of loading all of the $TFPR/TFPQ$ elasticity on the output component.

F Calibration of the Size Distribution of Entrants

Besides calibrating the shape parameter η to match moments of the size distribution of entrants in the data, we can further explore the goodness of fit of the Pareto assumption by comparing the entire employment size distribution of entrants with the data. We plot the employment-weighted distribution of entrants in figure F.1.

The figure shows that while the Pareto distribution tracks closely the empirical distribution of entrants, it slightly under-predicts the shares towards the right tail of the distribution. There are two features of the equilibrium that are affected by the properties of the size distribution of entrants: the dynamics of employment over the life-cycle and the speed of convergence along transitional dynamics. Since large firms innovate more intensively, a smaller share at the top decreases the speed of employment growth over the life-cycle conditional on survival, and delays the speed of convergence. We experimented with a Log-Normal distribution, and found that aggregate and micro-level implications are largely unaffected once parameter values are re-calibrated to satisfy the empirical targets, specially the ones referring to the average size of entrants relative to incumbents and the employment ratio between

Figure F.1: Employment Weighted Size Distribution of Entrants: Model and Data



Note: The data corresponds to the employment-weighted distribution of firm sizes from the Business Dynamics Statistics database for the manufacturing sector in 2007. The unit of analysis are firms, and entrants are identified as firms with age equal to zero. Data points for firms with employment greater than 499 are undisclosed in the database.

21-25 and 1 year old firms.