Online Appendix: "The Dynamics of Development: Innovation and Reallocation"

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1 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 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.

1.1 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[1], we estimate the productivity-elasticity of idiosyncratic distortions. As before, the productivity elasticity is

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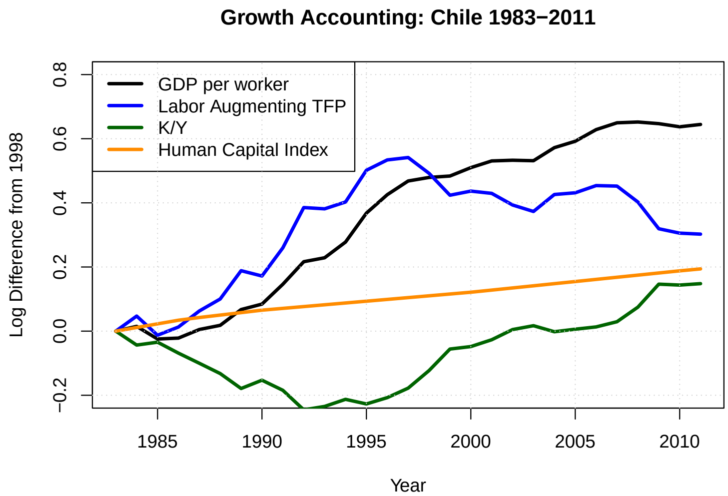
[1] We work with the version of the ENIA that is provided in Chen and Irarrazabal [2015]'s replication material, downloadable from https://www.economicdynamics.org/codes/13/13-61/pack_finalversion.zip

Figure 1: Growth Accounting: Chile's Growth Acceleration



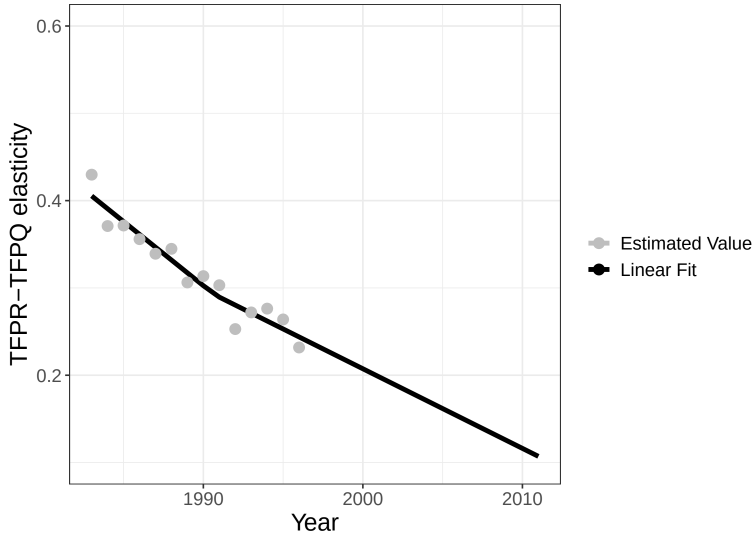
Note: The data for the growth accounting exercise stems from the Penn World Tables Database Zeileis [2021]. We decompose real GDP per worker, as $\frac{Y}{L} = TFP^{\frac{1}{1-\alpha}} \left(\frac{k}{y}\right)^{\frac{\alpha}{1-\alpha}} hc$, where real GDP is measured according to $rgdpna$ in the data, 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.

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 2.

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

Figure 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.

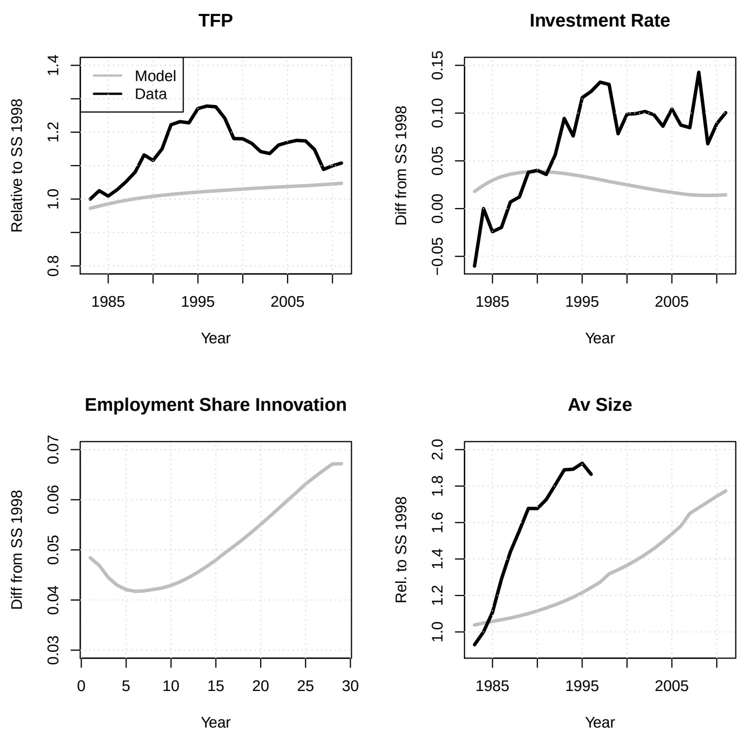
for the calibration of the average idiosyncratic distortion in the economy, controlled by the parameter Z_{It} in the idiosyncratic distortion profile. This parameter was set to reconcile the growth in the capital output ratio in the model with that of the data. In China's acceleration this could be 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.

1.2 Development Dynamics

Figure 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 ac-

Figure 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.

counted 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 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.

1.3 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.[2] 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 4 illustrates the cross-sectional distribution of employment and age at Chile's initial steady state (labeled ss 1983), at the post-reform steady state (ss Chile post-reform), and for the year 2011. The figure also depicts the life-cycle growth of the cohort born in 1983.[3]

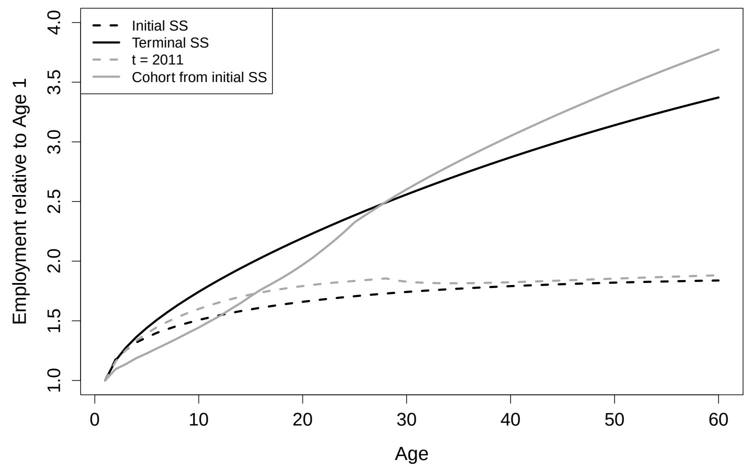
Figure 4 shows that the protractedness displayed by the aggregate productivity in figure 3 is underlaid by a comparable sluggishness in the convergence of the cross-sectional life-cycle of employment. By the year 2011 it is still quite far from having converged to the stationary distribution of the terminal 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

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

[3] 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 4: Life Cycle of Firms during Acceleration Episodes: Chile 1980-2011



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 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.[4] 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.

[4]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

2 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 5 and 6 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.

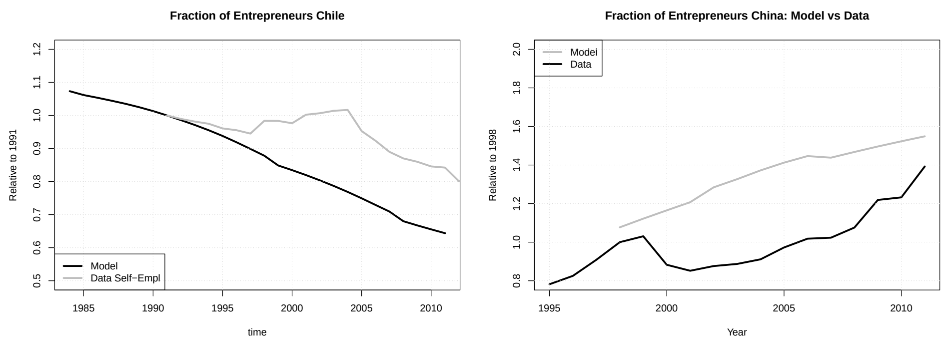
Turning, then, to the results, let us begin with figure 5, which illustrates the fraction of entrepreneurs in the model and the fraction of self-employed in the labor force for China and Chile. We see that in both cases the model captures the direction of change in the rate of self-employment, except 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 6 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.

3 Decomposition of TFPR into Capital and Output Distortions

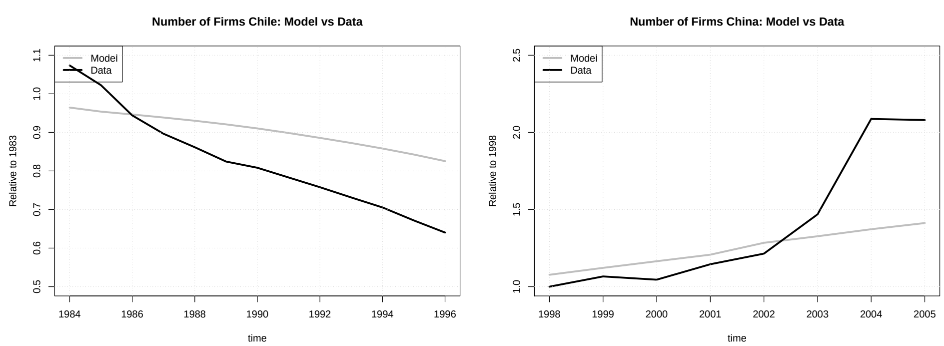
The paper adopts $TFPR$ as the summary of idiosyncratic distortions in the data, and uses the properties of the distribution of $TFPR$ to discipline the distribution of revenue taxes

Figure 5: Self-Employment in Model and Data



Note: Chile's data on Self-Employment is drawn from the International Labor Organization's ILOstat 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.

Figure 6: 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.

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

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

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

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.

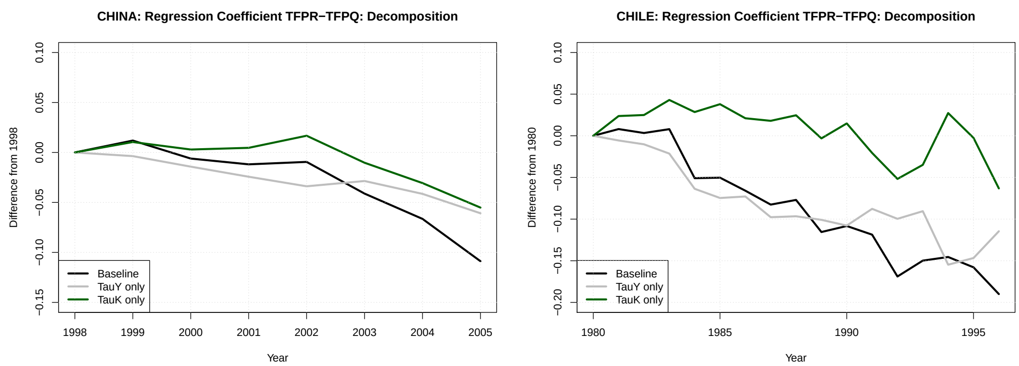
Equipped with these alternative definition, we separately compute their regression coefficients with respect to $log\left(\frac{TFPQ_i}{\overline{TFPQ}}\right)$. In the context of the model, where capital distortions create a wedge in the cost of renting capital, a decline in the capital-distortions' 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 7, 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 7 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.

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

Figure 7: Output and Capital Distortions and the Dynamics of TFPR/TFPQ Elasticity



provide support for our approach of loading all of the $TFPR/TFPQ$ elasticity on the output component.

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