Finance and Growth:
Firm Heterogeneity and Creative Destruction[*]

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Abstract

The empirical literature on macro-finance has provided a plethora of new micro-data and evidence on how finance shapes the heterogeneous responses of firms to shocks. Quantitative models of creative destruction are uniquely suited to study the heterogeneous firm level effects and the aggregate consequences of finance. This chapter provides an overview of these literatures, highlighting the theoretical connections, and provides evidence from recent financial crises on the importance of firm heterogeneity in financial frictions for creative destruction.

1 Introduction

There is an extensive literature on the interplay of finance and growth. The comprehensive review of Levine [2005] shows that countries with better functioning banks and markets grow faster. Levine [2005] points to several channels underlying this relationship: better allocation of capital, better financial intermediation, better monitoring of investments, and higher quality of investment. The review by Aghion et al. [2018] adds to this list the importance of finance in Schumpeterian models of innovation-led growth, especially when firms are subjects to financial frictions.

Finance is at the heart of any innovation-based growth model. In fact, entrepreneurs have to collateralize their ideas in order to seek funding to finance R&D [Mann, 2018, Hochberg et al., 2018], while the payoff to innovation is often back-loaded requiring continuous financing well before generating cash inflows. Because of the forward looking nature of innovation, interest rate fluctuations play a key role in innovation decisions today and can potentially affect the path of aggregate productivity well into the future. Moreover, because firm heterogeneity is key in models of innovation led growth [Akcigit and Kerr, 2018, Acemoglu et al., 2018], the allocative role of the financial system also plays a central role selecting the set of active firms. While Aghion et al. [2018] show how to incorporate financial frictions in a simple version of Aghion and Howitt [1992], they call for more effort in modeling finance within the new generation of innovation led growth with firm dynamics that are uniquely suited to face the richness of the micro data.

In a globalized world, the channels in Levine [2005] have become more complex. In fact, financial intermediaries operate on a global scale making financial conditions largely exogenous to firms, financial institutions, and policy makers in financially integrated economies [Rey, 2013]. Moreover, the field of international finance has seen an explosion in the availability of detailed micro data linking financial and real choices at the firm level in several countries. The potential exogeneity of financial flows and the availability of micro data makes international finance the ideal field to study the intersection of finance and growth. This field is an ideal laboratory to understand how finance shapes firm's decisions potentially affecting the process of creative destruction. In fact, sudden stop episodes provide large exogenous financial variation with a precise timing.[1]

Financial crises cast a long shadow on output [Cerra and Saxena, 2008, Reinhart and Rogoff, 2009] and aggregate productivity [Meza and Quintin, 2007, Pratap and Urrutia,

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[1]A sudden stop is a typical financial crises in small open economies. It is characterized by sharp capital outflows and strong reversals of the current account.

2012, Hardy and Sever, 2021]. This persistence is indicative of dynamic distortions in productivity growth that can cause economic scarring and output hysteresis. Firm level evidence points to granular productivity losses caused by financial factors [Hallward-Driemeier and Rijkers, 2013, Duval et al., 2020, Manaresi and Pierri, 2019, De Ridder, 2019, Besley et al., 2020]. Moreover, finance shows rich heterogeneity at the firm level.[2] For example work by Rey [2013], Coimbra and Rey [2017], Kalemli-Özcan [2019], Di Giovanni et al. [2017] provides evidence that larger banks lend more and larger firms borrow more. Moreover, small firms are relatively more innovative but at the same time, small and young firms are also more financially constrained [Akcigit and Kerr, 2018, Gopinath et al., 2017, Dinlersoz et al., 2019]. In this chapter we review some of this empirical evidence and we provide new evidence based on micro data from several countries to understand how financial crises trigger selection in the entry and exit margins.

Despite abundant empirical evidence and the suitability of the creative destruction framework to model firm heterogeneity, there have been few bridges unifying the innovation led growth models with the international business cycle quantitative literature. In fact, most of the Schumpeterian models that explore the interlinks between finance and growth are continuous time models solved along a non-stochastic balanced growth path. The key obstacle when integrating innovation based models with firm dynamics based on Klette and Kortum [2004] into stochastic models of crises is the limitations of discrete time. Despite recent advances in numerical solutions for continuous time business cycle models [Brunnermeier and Sannikov, 2016, Achdou et al., forthcoming], the dynamic stochastic general equilibrium (DSGE) literature has been mainly developed in discrete time. In fact, the main goal of the quantitative DSGE literature is to relate to the time series properties of the data, and the nature of data is discrete [Fernández-Villaverde and Guerrón-Quintana, 2021].

To overcome this challenge, we use a simplified version of the solution developed by Ates and Saffie [2021] to provide a tractable path that allow for creative destruction and firm dynamics to be integrated to the workhorse quantitative models of international finance [Mendoza, 1991, 2010]. This mapping preserves the richness and tractability of Klette and Kortum [2004] allowing the models to speak directly to firm-product data not only during tranquil times but also during crises. This class of models generate the hysteresis documented by the empirical literature and provide a testable micro-foundation for the channels that generate the economic scarring. Moreover, the

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[2]Other financial channels include the role of ownership and risk taking in innovation [Aghion et al., 2013, Penciakova, 2018], the development of venture capital [Ates, Greenwood et al., 2018, Akcigit et al., 2019], or how to collateralize intangible assets [Amable et al., 2010, Mann, 2018].

framework can be extended to capture firm heterogeneity and financial frictions that can be directly contrasted to granular and aggregate data.

2 Financial Crises and Productivity

There has been a large increase in corporate debt pre-global financial crisis in most countries, most prominently in Southern European countries as shown below in Figure 1. Investment to GDP also declined most for these set of countries as shown on the same figure on the right panel.

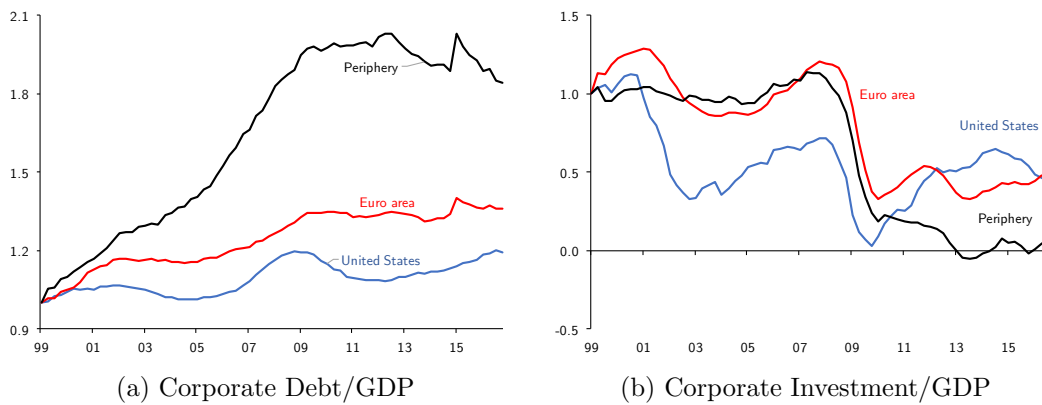
(a) Corporate Debt/GDP
(b) Corporate Investment/GDP

Figure 1: Corporate Debt and Investment to GDP: Europe and U.S.

SOURCE: See Kalemli-Özcan et al. [2018] for original data sources as these figures re-produced from that paper. Corporate debt is credit to nonfinancial corporations granted by banks and non-banks, scaled by total economy GDP (left-hand side panel (a)). Corporate investment is net fixed capital formation of non-financial corporations, scaled by total economy GDP (right-hand side panel (b)) Quarterly data for the period 1999 to 2017. Values are indexed at 1 for 1999Q1. Periphery group of economies comprises Greece, Ireland, Italy, Portugal, and Spain.

It is also the case that, high debt countries, pre-crisis, not only decrease investment most post-crisis, the investment stays sluggish in these countries for a long time. As shown in Figure 2 it takes a long time in terms of investment to recover after a financial crisis. This figure plots four panels for firm investment where firm can be a high or low leverage firm located in a periphery or center European country. As shown in the top left panel, periphery countries where firms had high leverage before the crisis, had experienced the largest drop in investment and took longest to recover. We also know that it takes a long time to recover in terms of GDP after financial crisis. So we really do not observe any Solow style recovery, as depicted in Figure 3.

A natural question is that why firms accumulate debt during booms and what does this imply for TFP?. Firm heterogeneity in accessing finance plays a key role, with
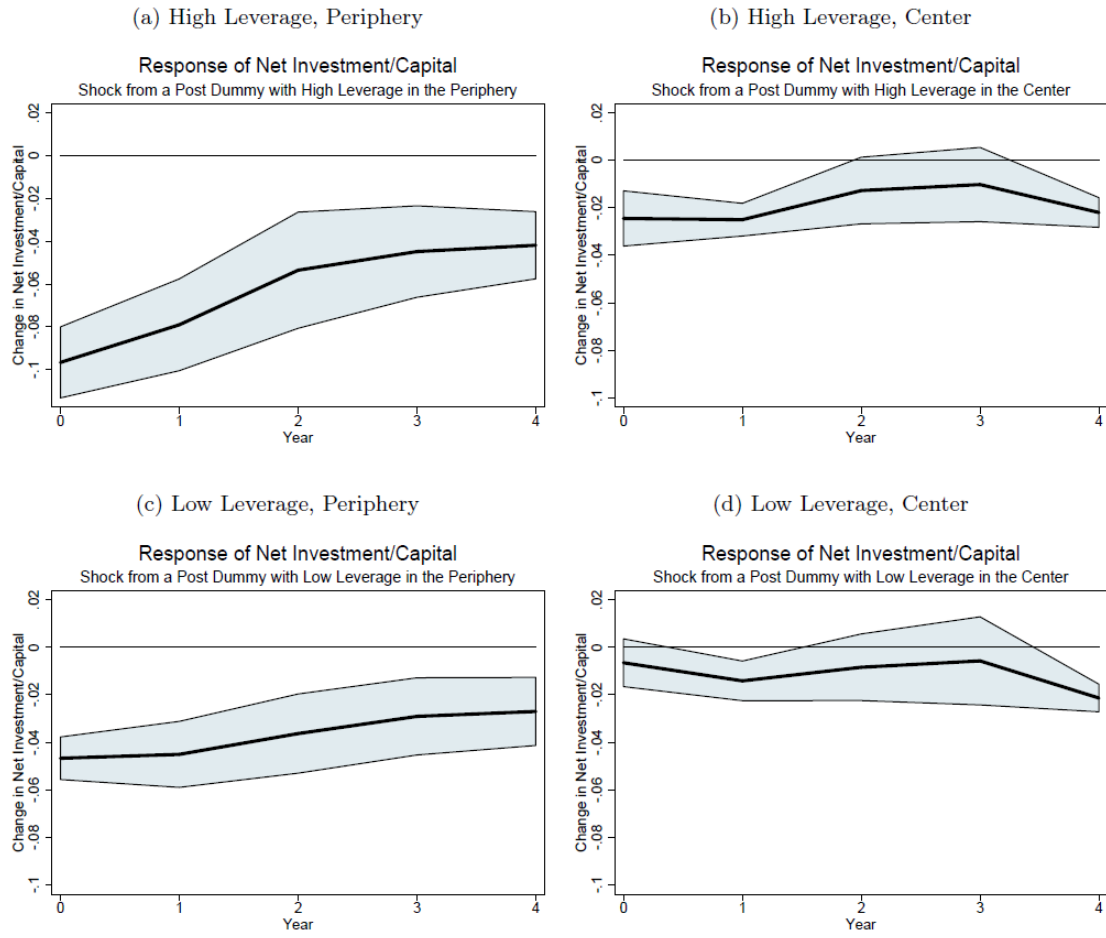
Figure 2: Firm Debt Overhang and Investment in Europe–No recovery after 5 years
Source: Kalemli-Özcan et al. [2018]. See Figure 1 for the variable and country group definitions.

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ASIAN CRISES

| Indonesia | Korea | Malaysia | Thailand |

DEBT CRISES

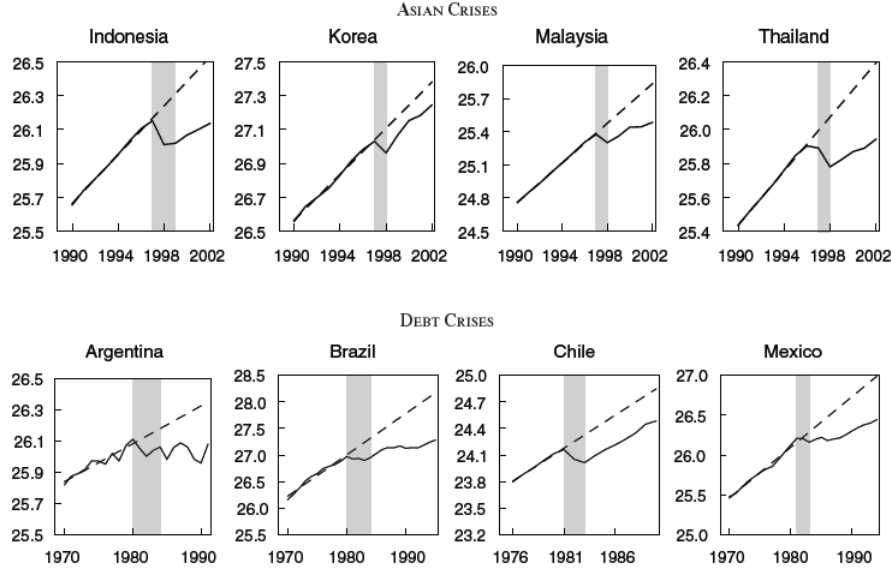| Argentina | Brazil | Chile | Mexico |

FIGURE 1

Figure 3: Sluggish GDP Recovery

Source: Cerra and Saxena [2008].

implications on aggregate productivity when all firms face a lower interest rate during booms. A decrease in real interest rate increases desired capital for all firms. However, while large firms with high net worth can borrow and invest, facing lower returns to capital, smaller firms with low net worth cannot borrow and invest and hence face higher returns to capital. This type of dispersion in returns to capital across firms within a narrowly defined 4-digit sector leads to a decline in aggregate productivity of that sector.

Is there any evidence for such size-dependent constraints? The answer is yes as shown in Gopinath et al. [2017], where small firms are much more constrained relative to large firms as large firms are more leveraged.

To dig deeper into the selection effect before and after the crisis, we run a regression at the firm level, where we regress entry into a certain sector (top panel) and exit from a certain sector (bottom panel) on firm productivity and firm productivity interacted with the foreign finance in that sector. We did this before and after the 2008 crisis.

As shown in Table 1, our results are striking. Financial crisis trigger selection in terms of entry and exit and this is more powerful in sectors with more foreign finance.

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Table 1: Selection and Productivity During Crises

Entry Rate-Sector

	(1)	(2)	(3)	(4)
	Before Crisis	After Crisis	Before Crisis	After Crisis
Firm TFP	-0.0004**	0.0007**	-0.0004*	0.0005**
	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Firm TFP x Foreign Finance			-0.0004	0.0014**
			(0.0007)	(0.0006)
Foreign Finance			-0.0001	-0.0053
			(0.0034)	(0.0033)

Exit Rate-Sector

	(1)	(2)	(3)	(4)
	Before Crisis	After Crisis	Before Crisis	After Crisis
Firm TFP	-0.0004	-0.0017**	-0.0001	-0.0011*
	(0.0005)	(0.0008)	(0.0004)	(0.0006)
Firm TFP x Foreign Finance			-0.0013	-0.0034**
			(0.0010)	(0.0016)
Foreign Finance			0.0088	0.0270***
			(0.0060)	(0.0076)
Observations	1926409	1219387	1907641	1211350
R-squared	0.562	0.808	0.571	0.811
FirmFE	Yes	Yes	Yes	Yes
Country×SectorFE	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes

NOTES: 'Firm TFP' is a firm level variable estimated via: $\log y_{it} = d_t(s) + \beta^\ell(s) \log \ell_{it} + \beta^k(s) \log k_{it} + \log Z_{it} + \epsilon_{it}$, where i is firm, s is sector, $d_t(s)$ is a time fixed effect for the given sector, y_{it} denotes nominal value added divided by the two-digit output price deflator, ℓ_{it} denotes the wage bill divided by the same output price deflator, and k_{it} denotes the (book) value of fixed assets divided by the aggregate price of investment goods. $\beta^\ell(s)$ denotes the elasticity of value added with respect to labor and $\beta^k(s)$ denotes the elasticity of value added with respect to capital. These elasticities vary at 24 industries defined by their two-digit industry classification. Our estimation uses the methodology developed in Wooldridge [2009] and hence we refer the reader to his paper for details of the estimation process. Given our estimated elasticities $\hat{\beta}^\ell(s)$ and $\hat{\beta}^k(s)$, we then calculate firm (log) productivity as $\log Z_{it} = \log y_{it} - \hat{\beta}^\ell(s) \log \ell_{it} - \hat{\beta}^k(s) \log k_{it}$. 'Foreign Finance' is a sector level variable, referring to sectoral FDI and foreign ownership and comes from Akcigit et al. [2018b].

3 Creative Destruction and Aggregate Risk

3.1 A Simple Model of Creative Destruction

The first step to study the interaction between financial crises and growth is to combine dynamic models featuring aggregate risk and endogenous technical change. Because of the tractability and simplicity of the Romer [1990] framework, the literature extending DSGE models to feature endogenous productivity has focused on this non-Schumpeterian framework when developing quantitative tools. In fact, Barlevy [2004] shows that the cost of business cycles is amplified when stationary shocks affect the number of varieties in a Romer [1990] product space. Comin and Gertler [2006] study the ability of endogenous growth to generate low-frequency cycles in an otherwise standard close economy Real Business Cycle (RBC) model.[3]

Closer to our purposes, Queralto [2020] and Guerron-Quintana and Jinnai [2019] combine Comin and Gertler [2006] with the financial crisis model of Gertler and Karadi [2011] to document that crises can generate hysteresis in productivity by affecting the creation of new varieties. In these models, a financial crisis increases the cost of developing new varieties and decreases the discounted value of future profits, therefore permanently decreasing the number of available products with respect to a counter-factual economy that was able to avoid the crisis. Because in the Romer [1990] framework there is no post-entry dynamics and every homogeneous product line is unaffected by other firms' expansion decisions, these models could not be contrasted with the richness of the micro-financial-data documented in Section 2.[4]

The main challenge when mapping creative destruction models with firm dynamics in the spirit of the Klette and Kortum [2004] extension of Aghion and Howitt [1992] is that the DSGE literature has been built in discrete time, while creative destruction models take advantage of the tractability of continuous time. To better understand the convenience of continuous time let's consider the problem of an incumbent firm in Klette and Kortum [2004]. An incumbent firm with n products optimally chooses innovation effort (L units of labor) to generate an innovation on a new product line with a Poisson arrival rate X.[5] The cost function is given by:

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[3]This framework has been extended beyond a closed economy to study cross-country spillovers [Gavazzoni and Santacreu, 2020, Comin et al., 2014] and it has been used to study sovereign default crises [Gornemann, 2014] and exchange rate fluctuations [Gornemann et al., 2020].

[4]Aghion et al. [2014a, 2015] provide an excellent discussion of the tractability and limitations of the Romer [1990] framework when compared to the Schumpeterian paradigm.

[5]Because there are a continuum of products and innovation is un-directed, the event of landing on a product line already owned by the firm has zero probability.

$$X = \xi n^{1-\gamma} L^\gamma = n\xi \left[\frac{L}{n}\right]^\gamma \quad \Rightarrow x = \xi l^\gamma, \tag{1}$$

where small cases represent values normalized by the number of product lines. Then, an incumbent maximizes firm value according to the following value function:

$$rV_n - \dot{V} = n\pi - n\Delta\left[V_{n-1} - V_n\right] + n\left[\max_x \left\{x\left(V_{n+1} - V_n\right) - w\left(\frac{x}{\xi}\right)^{\frac{1}{\gamma}}\right\}\right], \tag{2}$$

where V_n is the value of a firm with n products, π are the per product profits, $\dot{V}$ represents the instantaneous change on the value, Δ is the endogenous creative destruction rate, and w is the wage.[6] Note that, a firm with n products only experiences three possibles outcomes: i) neither winning nor losing a product, ii) winning a new product, or iii) losing an existing product. In fact, because of continuous time, those are the only relevant outcomes to consider. In any instant, the probability of winning and loosing multiple products lines is practically nil. This convenience is lost when combining Klette and Kortum [2004] into a classical DSGE framework. In fact, in discrete time, every period a firm could loose or win multiple products. Ates and Saffie [2021] develop a mapping to discrete time that keeps the tractability of the original framework to study the long-run productivity effect of financial crises. In particular, they assume that expansion and destruction probabilities are governed by binomial processes. Therefore, a firm with n products that optimally chooses an innovation rate x will win k new products with probability:

$$\mathbb{B}(k, n, x) = \binom{n}{k} x^k (1-x)^{n-k}, \tag{3}$$

and loose $\tilde{k}$ products when facing the aggregate creative destruction rate Δ according to:

$$\mathbb{B}(\tilde{k}, n, \Delta) = \binom{n}{\tilde{k}} \Delta^{\tilde{k}} (1-\Delta)^{n-\tilde{k}}. \tag{4}$$

Because we want to study aggregate financial crises we also introduce aggregate risk to the economy denoting the stochastic history by s^t. Then, the discrete time problem

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[6]Because of the log-log structure in production and the Bertrand monopolistic competition assumption, profits are independent of the product specific productivity and only depend on the relative productivity between the leader and the closest follower.

of an incumbent becomes:

$$
\begin{aligned}
V_n(s^t) \;=\;& \max_{x_n(s^t)} n\left[\pi(s^t) - w(s^t)\left(\frac{x_n(s^t)}{\xi}\right)^{\frac{1}{\gamma}}\right] \\
+\;& E_t\left[m(s^{t+1})\sum_{\tilde{k}=0}^{n}\mathbb{B}\left(\tilde{k},n,\Delta(s^t)\right)\sum_{k=0}^{n}\mathbb{B}\left(k,n,x_n(s^t)\right)V_{n-\tilde{k}+k}(s^{t+1})\bigg|\, s_t\right] \quad (5)
\end{aligned}
$$

where $m(s^{t+1})$ denotes the stochastic discount factor of the household that owns the firms.[7] Note that, because firms are atomistic we can assume that the two binomial processes are independent and, therefore, separable. The combination of the two binomial processes characterizes the probability distribution of a firm with n products to transition in only one period to any number of products in $[0, 2n]$ instead. Beside being able to capture all potential firm level transitions, this framework also preserves the proportionality of the value function that has made the Klette and Kortum [2004] so popular in the creative destruction literature. In fact, we can guess and verify that $V_n(s^t) = nV_1(s^t)$. This means that every firm invests the same amount per product. By replacing the guess, factoring the future value of a product and using the properties of the binomial distribution, Equation (5) simplifies to:

$$
\begin{aligned}
V_1(s^t) \;=\;& \max_{x(s^t)} \pi(s^t) - w(s^t)\left(\frac{x(s^t)}{\xi}\right)^{\frac{1}{\gamma}} \\
+\;& E_t\left[m(s^{t+1})\left(1 - \Delta(s^t) + x(s^t)\right)V_1(s^{t+1})\big|\, s_t\right]. \quad (6)
\end{aligned}
$$

The optimal innovation effort per product line is therefore independent of the total number of products that the firm has:

$$
x^*(s^t) = \Gamma_0\left[\frac{E_t\left[m(s^{t+1})V_1(s^{t+1})\big|\, s_t\right]}{w(s^t)}\right]^{\frac{\gamma}{\gamma-1}}, \quad (7)
$$

where Γ_0 is a constant. To model entry of new firms, define $M(s^t)$ as the mass of new entrepreneurs trying to start a business. We assume that when $M(s^t)$ entrepreneurs pay κ unit of labor each to enter, only $M(s^t)^\upsilon$ with $\upsilon < 1$ become next period mono-product firm, we get the following entry rate:

$$
M^*(s^t) = \Gamma_1\left[\frac{E_t\left[m(s^{t+1})V_1(s^{t+1})\big|\, s_t\right]}{w(s^t)}\right]^{\frac{1}{\upsilon-1}}, \quad (8)
$$

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[7]The innovation investment at time t materializes in product transitions at time $t+1$. Entry of new firms also takes one period to materialize.

where Γ_1 is a constant. Combining the innovation from entrants and incumbents we get the aggregate creative destruction rate:

$$\Delta(s^t) = M^*(s^t) + x^*(s^t)$$

To link these innovation decisions to productivity growth we need more structure on the production side of the economy. For simplicity, we assume that intermediate varieties are produced accordingly to the following production function:

$$y_i(s^t) = q_i(s^t)l_i(s^t), \tag{9}$$

where $q_i(s^t)$ is the efficiency in the production of product line i and $l_i(s^t)$ represents the labor used in production.[8] Furthermore we assume that innovations by incumbents or entrants on a given product line increase the product-level technology by a factor of $(1 + \sigma)$ with $\sigma > 0$ being the step size. These products are aggregated by a final good producer with the following technology:

$$\ln Y(s^t) = z(s^t) + \int_0^1 \ln y_i(s^t)di, \tag{10}$$

where $Y(s^t)$ is the unique final good and $z(s^t)$ is an aggregate efficiency shock. Following Aghion and Howitt [1992] if we assume Bertrand monopolistic competition we can show that profits and labor per product are independent of the product-specific efficiency $q_i(s^t)$, in particular:

$$\pi(s^t) \quad = \quad \frac{\sigma}{1 + \sigma}Y(s^t) \tag{11}$$

$$l(s^t) \quad = \quad \frac{Y(s^t)}{w(s^t)(1 + \sigma)} \tag{12}$$

Moreover replacing Equation (9) in Equation (10) we obtain:

$$Y(s^t) = e^{z(s^t)}A(s^t)l(s^t), \tag{13}$$

where $A(s^t)$ is the endogenous productivity level defined by:

$$A(s^t) = e^{\int_0^1 \ln q_i(s^t)di}. \tag{14}$$

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[8] Any technology with constant marginal cost would lead similar tractability. For example, a Cobb-Douglas aggregation of capital and labor.

Endogenous productivity growth is generated by creative destruction such that:

$$\ln A(s^t, s_{t+1}) - \ln(A(s^t)) = \Delta(s^t) \ln(1 + \sigma)$$

$$\text{or} \quad \frac{A(s^t, s_{t+1})}{A(s^t)} = 1 + g\left(s^t, s_{t+1}\right) = (1 + \sigma)^{\Delta(s^t)}, \tag{15}$$

where $g\left(s^t, s_{t+1}\right)$ is the growth rate of the endogenous productivity index. When a shock triggers fluctuations in $\Delta(s^t)$, Equation (15) provides a mapping to productivity growth generating hysteresis in the productivity index from Equation (14) and therefore, in every growing variable.

Note that the stochastic framework retains the tractability of its continuous time counterpart allowing for a stochastic analysis beyond the balanced growth path. A corollary of the linearity of the value function in the number of products is that the size distribution is not needed when solving the model. Nevertheless, the size distribution is a well defined object that can be used to estimate the parameters of the model and validate entry, exit, and size transitions at the firm level. Because there is a continuum of products we can use the law of large numbers to track the distribution of firms. In particular, denote by $\Omega_n(s^t)$ the mass of firms with n products. The law of motion of this distribution is characterized by a system of dynamic equations that only depend on the innovation rate of incumbents and the mass of entrants:

$$\Omega_1(s^t) = M^*(s^{t-1}) + \sum_{n=1}^{\infty} \Omega_n(s^{t-1}) \sum_{k=0}^{1} \mathbb{B}\left(k, n, x^*(s^{t-1})\right) \mathbb{B}\left((k+n-1, n, \Delta(s^{t-1}))\right)$$

$$\Omega_{\tilde{n}>1}(s^t) = \sum_{n=\mathbb{I}^+(\frac{\tilde{n}}{2})}^{\tilde{n}} \left\{ \Omega_n(s^{t-1}) \sum_{k=\tilde{n}-n}^{n} \mathbb{B}\left(k, n, x^*(s^{t-1})\right) \mathbb{B}\left(k - (\tilde{n}-n), n, \Delta(s^{t-1})\right) \right\}$$

$$+ \sum_{n=\tilde{n}+1}^{\infty} \left\{ \Omega_n(s^{t-1}) \sum_{k=0}^{\tilde{n}} \mathbb{B}\left(k, n, x^*(s^{t-1})\right) \mathbb{B}\left(k - (\tilde{n}-n), n, \Delta(s^{t-1})\right) \right\},$$

where $\mathbb{I}^+(a)$ refers to the integer closest to a such that $\mathbb{I}^+(a) \geq a$.[9] The first equation has two terms, the first one tracks the entry of new firms with one product while the second term tracks firms that used to have more than 1 product and contracted to exactly 1 product. The second line shows an analogous law of motion for categories of firms with more than one product where the first component are firms that started with less than $\tilde{n}$ products and had net gains that left them at $\tilde{n}$, while the second term reflects firms that were above $\tilde{n}$ and experienced net losses that left them exactly at

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[9]A firm with n products can become a firm with $n' \in [0, 2n]$ in one period, so, at most it can double its size in one period.

$\tilde{n}$.[10]

Having shown the tractability of the mapping between continuous time creative destruction models and their discrete time counterpart, we proceed to introducing financial crises into this simple framework.

3.2   Financial Crises and Aggregate Productivity

The simplest way to introduce aggregate risk and financial crises is to follow the framework of Mendoza [1991] used by Neumeyer and Perri [2005] and Uribe and Yue [2006] to study the effects of interest rate shocks in small open economies. Equation (10) introduced an aggregate efficiency shock. We will use the problem of the household to introduce our second aggregate shock. Without loss of generality, we assume logarithmic utility and a fixed supply of hours normalized to unity. In particular, the representative household solves the following problem:

$$\max_{C(s^t),B(s^t)} \sum_{t=0}^{\infty} \beta^t \mathbb{E}\left[\ln C(s^t)|s_0\right] \qquad \text{subject to:}$$

$$C(s^t) \leq w(s^t) + B(s^{t-1})R(s^{t-1}) + T(s^t) - B(s^t) - \frac{\psi}{2}Y(s^t)\left(\frac{B(s^t)}{Y(s^t)} - \bar{b}\left(1+\bar{g}\right)\right)^2,$$

where C is consumption of the only final good in the economy, B represents holding of the non-contingent bonds, and T are lump sum transfers from the profits of the intermediate good producers. The interest rate follows an AR(1), this is the second shock of the model. The last term in the borrowing constraint is a bond holding cost used to eliminate non-stationary debt dynamics in small open economies forcing the debt to output ratio to converge to $\bar{b}\left(1+\bar{g}\right)$ in the long-run [Schmitt-Grohé and Uribe, 2003], the parameter ψ is typically set to a small number that does not influence the dynamic properties of the model.[11] The stochastic discount factor of the household is given by:

$$m(s^{t+1}) = \beta \frac{C(s^t)}{C(s^{t+1})} \qquad (16)$$

In this simple model, the key determinant of the stochastic discount factor is the interest rate shock. In fact, as borrowing becomes more expensive, it is more taxing to stabilize consumption. Under a pure aggregate efficiency shock borrowing can always

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[10]The condition that ensures that the mass of products is always equal to one is given by $\sum_{n=1}^{\infty} n\Omega_n(s^t) = 1$.

[11]The final good is the only tradable good. The model features endogenous trade and current account imbalances.

be used to partially smooth consumption. A financial crisis is typically modeled as an increase in the interest rate coupled with a negative aggregate demand shock. To understand the effect of these crises in aggregate productivity we need to understand how these shocks affect creative destruction. In particular, how their effect propagates in Equations (7) and (8). Three objects determine this pass-through: 1) the stochastic discount factor, 2) the next period value of a product line, and 3) the current wage. Combining Equations (13) and (12) we get:

$$w(s^t) = \frac{e^{z(s^t)}A(s^t)}{1 + \sigma} \tag{17}$$

Therefore, when aggregate efficiency is low, aggregate output (Equation (10)) and profits (Equation (11)) decrease but so does the wage (Equation (17)). Therefore, given the high persistence of productivity shocks, as a first order effect we expect the ratio of next period value of a product line and this period wage to be fairly stable in response to aggregate efficiency shocks. Moreover, as we discussed earlier, the stochastic discount factor is typically stable under pure aggregate efficiency shocks. Therefore, in this simple framework, aggregate efficiency shocks do not generate significant changes in creative destruction rate and therefore do not trigger significant hysteresis in productivity.[12] This is not the case for pure financial shocks. In fact, interest rate shocks while triggering negligible effects in current profits and wages [Mendoza, 1991], generate wide swings on the stochastic discount factor ultimately shaping the response of the rate of creative destruction. Thus, stationary interest rate shocks generate hysteresis in aggregate productivity. Therefore, models of creative destruction can rationalize why financial crises cast large shadows [Cerra and Saxena, 2008, Reinhart and Rogoff, 2009]. These models also provide an endogenous connection between high interest rates and low productivity, a correlation typically assumed in the financial crises literature [Neumeyer and Perri, 2005, Uribe and Yue, 2006, Mendoza, 2010].

3.3 Firm Heterogeneity and Model Performance

The exposition so far has not levered all the power of the creative destruction framework. In fact, the literature of creative destruction has included rich heterogeneity that shapes macro dynamics and policy design [Acemoglu et al., 2018]. This richness can be carried to the discrete time DSGE literature and it is just as important when studying financial crises. The tractability of the framework allows for heterogeneity

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[12]Changes in preferences and the inclusion of other frictions can generate some pass-though but the main economic force behind this stability is always present.

beyond size and productivity. For instance, Ates and Saffie [2021] consider two types of firms that differ on the productivity advantage that they generate when they innovate in a given product allowing for dynamic selection effects during crises. In fact, the model is able to replicate the firm level dynamics exhibited in Chile during the 1998 financial crisis triggered by the Russian default. During the crises, fewer firms enter but a larger fraction of the firms are high type. Selection also implies that high type incumbents are less likely to exit during the crises. This micro-founded composition channel that shapes the productivity effect of a financial crises, cannot be modeled outside the creative destruction framework and was therefore absent in the Romer [1990] based DSGE literature. From a quantitative perspective, creative destruction is economically significant. In fact, ignoring selection and firm dynamics overestimates the consumption equivalent welfare cost of the crisis by 60%.

For Ates and Saffie [2021], a financial crisis is a large exogenous shock to the interest rate. Newer generation of models of financial crises are based on Mendoza [2010], where an occasionally binding borrowing constraint triggers a financial crises after a bad combination of shocks. These models can nest regular business cycles and large financial crises in a single framework. Benguria et al. [2020] show how creative destruction can be incorporated in these richer models of crises further allowing for heterogeneous innovations, endogenous real exchange rate fluctuations, and exporting entry and exit at the intermediate product level consistent with Akcigit et al. [2018a]. Thereby showing that DSGE models with creative destruction can display rich firm heterogeneity and elaborated financial crises. We will use their results to illustrate the quantitative behavior of this class of models.

First, from a microeconomics perspective, the model generates well defined size distributions. Because of data limitations models of creative destruction have typically identified plants or patents with products when validating the size distribution [Akcigit and Kerr, 2018]. Benguria et al. [2020] have access to novel data for the portfolio of domestic and exporting products of Chilean manufacturing firms. Therefore, they use for the first time product level data to validate their firm dynamic model. Figure 4 shows the (non-targeted) performance of the model in terms of the ergodic distribution. Panels 4a and 4b show that the model can replicate the product portfolio of exporters and non-exporter firms and Panel 4c shows that the model also mimics the overall firm size distribution in terms of workers. Moreover, the model replicates firm level product-portfolio dynamics during the Chilean sudden stop of 1998. Therefore, the creative destruction DSGE framework allows aggregate models to be estimated and validated using granular data.

Second, Figure 5 uses their financial crisis results to illustrate how these models

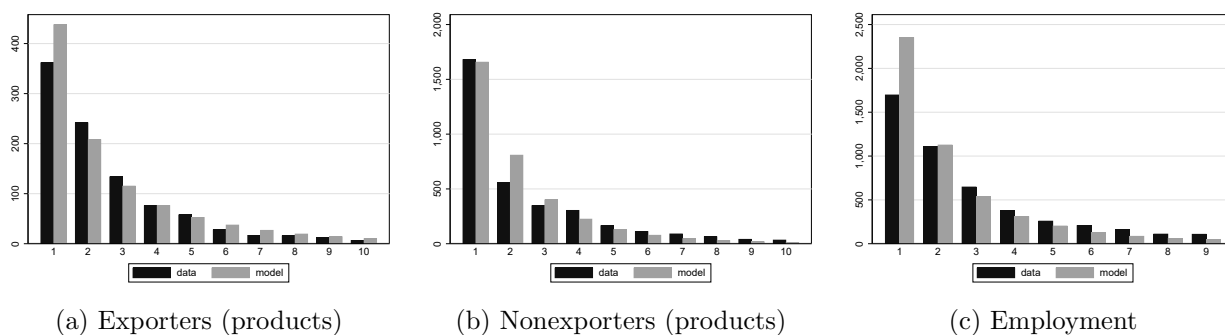(a) Exporters (products)   (b) Nonexporters (products)   (c) Employment

Figure 4: Benguria et al. [2020]: Size Distribution in Normal Times

SOURCE: Benguria et al. [2020]. NOTES: Panel a shows the distribution of the total number of products sold by exporting firms in the data and in the simulated model. Panel b does the same for non-exporting firms. Panel c shows the distribution of total employment in the data and in the simulated model. Employment is reported in multiples of the employment of the smallest firm.

can generate hysteresis and how firm heterogeneity shapes the response of endogenous productivity. Panel 5a shows the dynamics of GDP in the model on a window of four years around a Sudden Stop (SS) and compares it with the 20 years trend that preceded the financial crisis. The model generates a boom before the crisis and persistent hysteresis in GDP even four years after the event. Panel 5b shows the source of this hysteresis. In fact, the productivity index deviates from its trend due to the slowdown in creative destruction during the crisis. The model in Benguria et al. [2020] features semi-endogenous growth so there is a convergence in productivity levels in the long-run.[13] Even under semi-endogenous growth, productivity is below its pre-crisis trend for 30 years. Third, the counter-factual analysis in Panel 5b shows the role of heterogeneity when studying financial crises. In fact, it is the decrease in incumbents effort to enter the domestic market at the product level that drives the productivity drop in impact, while the effort of incumbents to start exporting their domestic products drives the recovery from the crisis.

In a nutshell, creative destruction can be incorporated into DSGE models without compromising the richness of its connection to granular data. Moreover, models of financial crises provides new avenues for studying the importance of firm heterogeneity when studying productivity dynamics.

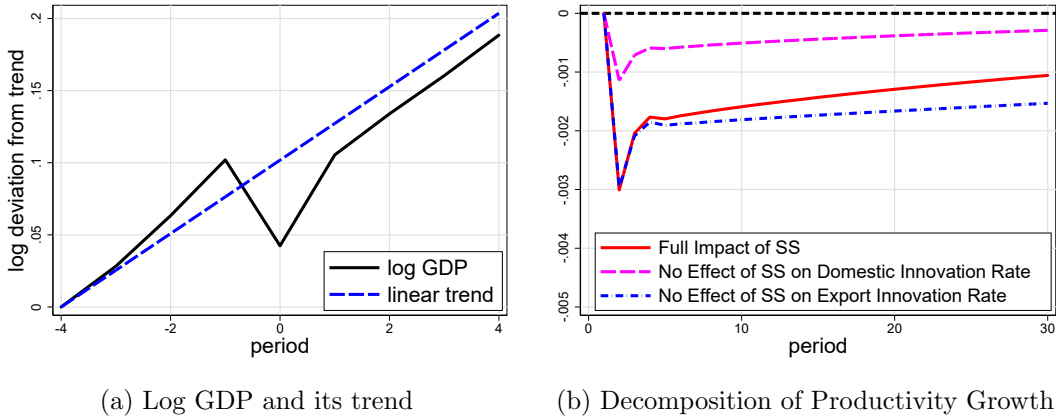[13]The foreign market grows exogenously and acts as a attractor for the small open economy.

16

| (a) Log GDP and its trend | (b) Decomposition of Productivity Growth |

Figure 5: Sudden Stops and Hysteresis

3.4   Firm Level Financial Frictions

So far we have not deviated from the tractability of the Klette and Kortum [2004] model where the linearity of the value function on the number of products allows the researcher to abstract from the size distribution when solving the model. Nevertheless, size does matter for both, innovation and finance. On the one hand, Akcigit and Kerr [2018] show that small firms are more productive and more intensive in R&D investment. Therefore, they introduce decreasing returns to scale in the production function of ideas depicted in Equation (1). On the other hand, Gopinath et al. [2017] show that small firms are more financially constrained than large firms. They propose a size based borrowing constraint at the firm level to capture this restriction. Both of these changes break the linearity of the value function. Although the literature has documented that financial frictions shape the business cycle properties of R&D, productivity, and the desirability of stabilization policies [e.g., Aghion et al., 2010, 2012, 2014b], firm dynamic models with financial constraints and aggregate risk [e.g., Khan and Thomas, 2013] have largely ignored the Schumpeterian forces of creative destruction. Because incorporating these firm level frictions in quantitative models of firms dynamics and creative destruction with aggregate risk has been an elusive challenge, we conclude this chapter showing how the firm level problem can be defined and solved using numerical methods.[14]

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[14]Schmitz [2021] solves a similar problem than the one depicted in this sub-section. He simplifies the problem by assuming away the inter-temporal investment-saving decision at the firm level and assuming that incumbents can only win or loose one product per period.

The incumbent problem in Equation (5) can be modified to accommodate firm level financial constraints and a cost advantage in innovation for small firms. In particular, an incumbent firm chooses innovation intensity and debt holdings to solve the following recursive problem:

$$
\begin{aligned}
V(S) \;=\; & \max_{x(S),d'(S)} n\left[\pi(S) - w(S)\left(\frac{x(S)}{\xi}\right)^{\frac{1}{\gamma}} n^{\chi}\right] - (1+r)d + d'(S) \\
& + \; E_t\left[m(S')\sum_{\tilde{k}=0}^{n}\mathbb{B}\left(\tilde{k},n,\Delta(S)\right)\sum_{k=0}^{n}\mathbb{B}\left(k,n,x(S)\right)V_{n-\tilde{k}+k}(S')\,\middle|\,S\right] \quad (18)
\end{aligned}
$$

subject to:

$$
n\pi(s^t) - (1+r)\,d - nw(S)\left(x(S)\right)^{\xi} n^{\chi} \le d'(S) \le F(n), \quad (19)
$$

where $S = (r, z, d, n, \Phi(n,d))$ denotes the relevant state variables, including the joint distribution of debt and number of products $\Phi(n,d)$. Constraint (19) shows that the firm has to borrow to finance innovation effort if operational cash flows plus savings are not sufficient to cover the innovation cost. The constraint also shows that borrowing is limited and that the limit is a function of the size of the firm.[15] Note that, the decreasing returns in the production of innovation ($\chi \in (0,1)$) and the size dependent borrowing constraint allow the model to encompass the findings of Akcigit and Kerr [2018] and Gopinath et al. [2017]. These features also break the linearity of the value function such that size now matters: n firms each with one product and d debt stock each will make different decisions per product line than one firm with n products and $n*d$ total debt. The distribution $\Phi(n,d)$ is therefore needed to solve the model as firms need to predict, not only future wages but also aggregate growth and aggregate creative destruction. Therefore, to solve this problem, techniques akin to Krusell and Smith [1998] must be implemented.[16]

This framework is a promising avenue to study how capital inflows might shift innovation towards larger and less productive firms and away from small and more productive firms slowing down aggregate productivity growth. It can also be used to understand how precautionary motives generate resource hoarding incentives among innovative firms. In fact, anticipating a potential financial crisis, firms can postpone innovation to build a financial buffer.

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[15]In this model, a size constraint can also be interpreted as an earning based constraint consistent with the evidence in Lian and Ma [2021] and Drechsel et al. [2019].

[16]A comparison of numerical methods can be found in Terry [2017].

4   Conclusion

The innovation led framework of growth has emerged as a new paradigm locating firms and entrepreneurs at the hart of technological progress. Since the very beginning, finance was at the heart of Schumpeter's economic framework. Soon after the formalization of his growth theory by Grossman and Helpman [1991] and Aghion and Howitt [1992] the empirical literature showed that Schumpeter was right [King and Levine, 1993] and that finance and growth cannot be studied in isolation. In fact, innovation requires financing for an idea that has yet to produce value, therefore, saving and borrowing are essential for innovation. Moreover, innovation is forward looking in nature and thus subject to the inter-temporal pounding of interest rates. This relationship is particularly important during financial crises, when capital is scarce and the future looks grim.

Recent developments in the empirical literature have used financial crises as quasi natural experiments to understand how finance can shape firm dynamics and creative destruction. Financial crises cast long shadows in output and productivity that last decades. Because young and small firms are an important driver of productivity enhancement [Akcigit and Kerr, 2018] and they are also more financially vulnerable [Gopinath et al., 2017], when liquidity is scarce we are likely to see sizable distortions to creative destruction.

As discussed by Aghion et al. [2018], the literature has struggled to jointly model financial frictions in Schumpeterian models of firm dynamics [Klette and Kortum, 2004], therefore, quantitative models have lagged behind the richness of the recent empirical analysis linking finance and productivity. This chapter proposed a path forward that allows macro models with financial crises to incorporate rich creative destruction features and match firm dynamics. The key is to provide a tractable discrete time framework that can be incorporated into large DSGE models [Ates and Saffie, 2021]. This framework allows, not only to provide a micro foundation for the large shadows cast by financial crises, but also to use granular data when estimating and validating DSGE models. Because the DSGE literature has been dominated by discrete time models [Fernández-Villaverde and Guerrón-Quintana, 2021], we propose a discrete time version of the creative destruction literature. An interesting future avenue for research is to use continuous time DSGE models [Achdou et al., forthcoming] to nest models of creative destruction.[17]

The framework presented in this chapter can be used beyond the study of financial

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[17]This avenue is largely unexplored as the applications of continuous time DSGE models has been to heterogeneous household models with nominal frictions.

crises. In fact, monetary policy surprises also have persistent effects in output [Brunnermeier et al., 2021] and they trigger real effects through financial channels [Aghion et al., 2014b, 2019] especially in small and medium sized firms [Caglio et al., 2021]. Therefore, a rich creative destruction framework is likely to help us understand the long-run consequences of monetary policy and its optimal design. Some studies have used Romer [1990] based models to study the financial channel of monetary policy [Moran and Queralto, 2018, Garga and Singh, 2021] contrasting their findings with aggregate VAR dynamics. Future research could consider using the Schumpeterian framework of creative destruction and firm dynamics to understand the role of heterogeneity and speak not just to the aggregate data, but also to the granular evidence in the literature.

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