Essays on Economic Structure and Growth
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Dedication

To my parents, my grandparents and all the beautiful things in my life

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Abstract of Dissertation

Essays on Economic Structure and Growth

My dissertation essays explore factors that determine changes in economic structure over time. First, I study the role of productivity growth differences across industries in driving structural change in the long run. Second, I find in the short run that economic structure is skewed away from industries that depend on external funds or have difficulty raising external finance during recessions. Third, I investigate the role of financial institutions in industry growth. I show that better bank competition encourages growth by disproportionately benefiting industries that are more dependent on external finance.

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Chapter 1

Introduction

Economic development is a joint process of economic growth and economic restructuring. It is important to understand the underlying factors that drive structural change before we derive any policy implications, make predictions and draw conclusions about the links between economic structure and growth. This dissertation investigates the technological and institutional factors that contribute to economic structure and growth, in the long- and short-run contexts.

The first chapter studies structural change in the long run. In particular, I investigate the role of persistent productivity differences in structural change and growth. In the long run, the applied theory literature has focused on the agriculture and services sectors (e.g., Ngai and Pissarides, 2007, Acemoglu and Guerrieri, 2008, Duarte and Restuccia, 2010). However, I study "stages of diversification" , which is a broader pattern of structure change along the development path, among disaggregated manufacturing industries.

The stages of diversification pattern is as follows. Countries appear to start out with employment concentrated in a few industries and sectors, diversifying until reaching a certain threshold in income per capita, after which they begin to re-specialize. In other words, industrial specialization is U-shaped along the development path. Imbs and Wacziarg (2003, hereafter IW) refer to this pattern as "stages of diversification." However, the literature has not previously developed an explicit, quantifiable theoretical model that attempts to account for the stages of diversification in IW. This chapter shows that persistent productivity differences across industries can account for observed patterns of "stages of diversification", using a multi-industry growth model with capital along an unbalanced growth path. It contributes to the literature by proposing an explicit mechanism behind "stages of diversification" based on differential TFP growth rates across industries, and providing quantitative evidence to account for the dynamics of industrial structures in development.

The second chapter studies structural change in the short run. In the short run, how economic structure is affected by recessions is not known. The only exception, to my knowledge, is Braun and Larrain (2005, henceforth BL). BL show that recessions have a financial component in that growth in industries that tend to rely heavily on external finance is disproportionately hit in recessions. In my paper, I conduct a more general study applying their method to a set of industry technological characteristics.

Theory also suggests several technological factors that underlie financing constraints. For example, Hart and Moore (1994) argue that fixed assets help raise external finance as they are more liquid and hence more effectively used as collateral than assets that are intangible. The same is true of productive assets that are durable, or that are non-specific. On the other hand, Myers and Rajan (1998) argue that the liquidity of assets could make them less suitable as collateral, as they could be more easily disposed of against the interests of creditors. Thus, a variety of technological factors could affect the ability to borrow – yet it is not known which are the empirically relevant ones, nor what is the sign of the relationship.

My second paper explores the technological factors that lead certain industries to be more sensitive to recessions. The aim is to narrow down the most empirically relevant technological determinants of credit constraints with regard to short run fluctuations, as well as to identify other technological factors that might interact with recessions.

The third chapter examines how economic structure has changed with the current financial crisis. The European banking sector has been hit hard by the recent financial crisis. Many banks incurred large losses and only managed to stay in business with exceptional support from national governments and central banks. The efficiency and structure of the banking system has been found to have significant implications for growth and economic structure, which begs the question of how economic structure may have been affected by the financial crisis. Increased competition in the financial sector could result in lower costs, higher efficiency across banks, better quality of financial services and therefore greater access to finance by non-financial firms and households. Improved access to finance and a lower cost of capital may promote growth of other industries, especially those dependent on external finance. Some research investigates the linkage between bank competition and industry growth, and shows that financially dependent industries grow faster in countries with strong bank competition (Claessens and Laeven, 2005). My paper evaluates the degree of bank competition before and after the financial crisis and the impact of bank competition on growth and employment, as well as revisiting the issue whether the introduction of the European Economic and Monetary Union (EMU) and the euro have had any impact on bank competition in the euro area. I find that the recent global financial crisis led to a fall in competition in several countries, especially where large credit and housing booms preceded the crisis. This paper further evaluates the impact of bank competition on industry growth. The growth results show that better bank competition encourages growth by disproportionately benefiting industries that are more dependent on external finance, especially by encouraging labor investment, rather by capital investment and productivity improvement.

Chapter 2

Structural change in the long run: the role of productivity growth

2.1 Introduction

It is known that countries appear to start out with employment concentrated in a few industries and sectors, diversifying until they reach a certain threshold in income per capita, after which they begin to re-specialize. In other words, industrial specialization is U-shaped along the development path. Imbs and Wacziarg (2003, hereafter IW) refer to this pattern as "stages of diversification."

There are several factors suggested in the literature that may lead to the U-shaped stages of diversification. IW suggest that the interaction of trade and economic development is the driver of industrial specialization. Higher aggregate income enables an economy to diversify, while openness to trade encourages economies to specialize in those industries in which they have a comparative advantage. So, in their view economic development and trade jointly determine the stages of diversification. Koren and Tenreyro (2007) interpret the "stages" in terms of shifts in resources between sectors with differing levels of volatility. They argue that poor countries tend to specialize in industries with high volatility, while rich countries specialize in industries with low volatility.

However, before we conclude that the stages of diversification are driven by these factors, we need to understand how economic structure evolves under autarky, and compare autarkic outcomes to the stylized facts of how economic structure varies along the development path. The existing literature about the stages of diversification omitted one important factor, namely, productivity growth. This paper shows that persistent productivity growth differences across industries can account for observed patterns of economic restructuring along the development path. Thus, an important characteristic of the process of economic development is the reallocation of resources among industries with different rates of productivity growth. The results therefore support a productivity-driven theory in accounting jointly for economic development and for structural change.

I show this using a multi-sector model that highlights TFP growth differences across manufacturing industries, in a closed economy and in the absence of industry volatility. I calibrate initial productivity levels so as to reproduce the composition of manufacturing in each of the countries in the IW data set in the starting year. Then, I allow the structure of the model economies to evolve over time as a result of persistent productivity growth differences across industries, calibrated to U.S. data. Along the development path, the labor shares of different industries evolve due to differences between their TFP growth rates. Using the model-generated series of industrial diversification and applying the same non-parametric method as IW, I am able to replicate the U-shaped stages of diversification found in IW. The results are robust to a number of variations in the calibration procedure. I conclude that disparities in TFP growth across industries can account for differences in economic structure along the development path. To my knowledge, the literature has not previously developed an explicit, quantifiable theoretical model that attempts to account for the stages of diversification in IW.

The intuition behind the model is simple. Suppose that there are two goods that are substitutes. Differences in TFP growth rates will lead to an increase in the output share of the industry with high productivity growth, as the good it produces will register a decline in its relative price.[1] However, if the economy starts out being specialized in the other industry, then the economy will diversify as the share of the other industry decreases and the one with the most rapid productivity growth gradually catches up, until half of the resources are devoted to each industry, after which it will appear to specialize again. The economy will display a "U" shaped pattern of specialization as countries grow.

Notably, the results suggest that goods within manufacturing are substitutes so that, within manufacturing, resources should shift towards high-TFP growth industries. This is exactly what I find in the data, underlining the empirical relevance of the productivity mechanisms in the paper for understanding the process of economic development.

[1] Conversely, suppose the goods are complements. Then, persistent differences in TFP growth rates will lead to an increase in the GDP share of the industry with the slowest productivity growth. This case turns out not to be empirically relevant for understanding structural change within manufacturing. In Samaniego and Sun (2012), I extend the model to replicate the stages of diversification across broad sectors, not just within manufacturing.

The model builds on Ngai and Pissarides (2007) by performing a rigorous quantitative analysis of the implications of productivity-driven structural change for a large set of countries. Ngai and Pissarides (2007) show that persistent productivity differences across sectors can result in structural change, and study conditions under which this may occur along a balanced growth path. However, they focus on the behavior of agriculture and services (as do most studies of structural change), and do not study "stages of diversification."[2] My analysis is based on an unbalanced growth path and focuses on more disaggregated manufacturing industries. In addition, I find that the restrictions Ngai and Pissarides (2007) identify that are required for a balanced growth path with structural change do not hold empirically – specifically, the elasticity of substitution across capital goods is not equal to one – so my analysis requires the computation of a multi-industry growth model along an unbalanced growth path.[3] Moreover, I focus on an equilibrium where the initial condition for the capital stock satisfies the Euler equation at date zero, which I refer to as an Euler growth path. However, the results do not rely on this condition. Acemoglu and Guerrieri (2008) allow both productivity growth rates and capital shares to vary across industries. However, I do not find clear evidence that differences in capital shares are related to the "stages." Instead, I do find evidence

[2]Ilyina and Samaniego (2012, henceforth IS) conjecture but do not explore the possibility of a U-shaped specialization pattern over time, not in relation to GDP per person.

[3]This is something that to my knowledge has not been done before in an infinite-horizon multi-industry model with capital accumulation, and my methodology may be of independent interest. Rogerson (2008), Duarte and Restuccia (2010) and others compute transition dynamics in growth models with many industries: however, their models do not have capital so there are no intertemporal decisions.

that countries systematically shift resources between industries with different rates of productivity growth, as predicted by my model. Therefore, to emphasize the productivity mechanism in my paper, I assume that capital intensity is the same for all industries in my model (as do Ngai and Pissarides (2007)).

Duarte and Restuccia (2010) examine the impact of productivity differences across countries in agriculture and services on aggregate productivity, but my experiment is different. I assume that the rate of productivity growth in a given industry is constant across countries, and focus on accounting for economic structure rather than aggregate productivity. My model is also much more disaggregated, allowing me to provide a more detailed picture of industrial structure along the development path within manufacturing. Indeed, a contribution of the paper is to account for the largely hitherto-neglected patterns of structural change within manufacturing. The assumption that the industry TFP growth rate does not vary across countries is driven by the nature of the experiment, as it allows me to talk of high- and low-TFP growth industries. It is also consistent with the finding in Rodrik (2012) that there is unconditional convergence in labor productivity across countries among disaggregated manufacturing industries. Still, I perform a variety of robustness checks to examine the importance of this assumption, finding that the results are robust to significant variation in TFP growth rates across countries.

The results in this paper do not imply that other factors, e.g., trade, might not account for differences in economic structure. However, I show that these alternatives are not required to generate the observed stylized facts. Future work may sort out the relative contribution of one or other factors to patterns of economic structure along the development path.

The rest of the paper is organized as follows. Section 2.2 describes the link between industry productivity differences and industrial diversification in a simple heuristic framework. Section 2.3 presents a general equilibrium model economy with many industries and characterizes the equilibrium. Section 2.4 calibrates the model economy with a focus on manufacturing, and reports the results concerning the evolution of industrial structure in the model economy within manufacturing. Section 2.5 discusses extensions and possibilities for future work.

2.2 Diversification and TFP Growth Differences

2.2.1 Economic structure along the development path

IW use a nonparametric methodology to investigate the relationship between industrial diversification and income. Manufacturing industry data are drawn from the INDSTAT3 database distributed by UNIDO, and data on aggregate income per capita are from the Penn World Tables. The industry share is defined as the share of manufacturing employment or value added.

IW use the Gini coefficient of industry shares ($GINI_{c,t}$) to measure the degree of industrial concentration in any country c at date t: the more equal the industry shares (i.e., the lower the Gini), the more diversified the economic structure. Then, they apply a procedure related to robust locally weighted scatterplot smoothing

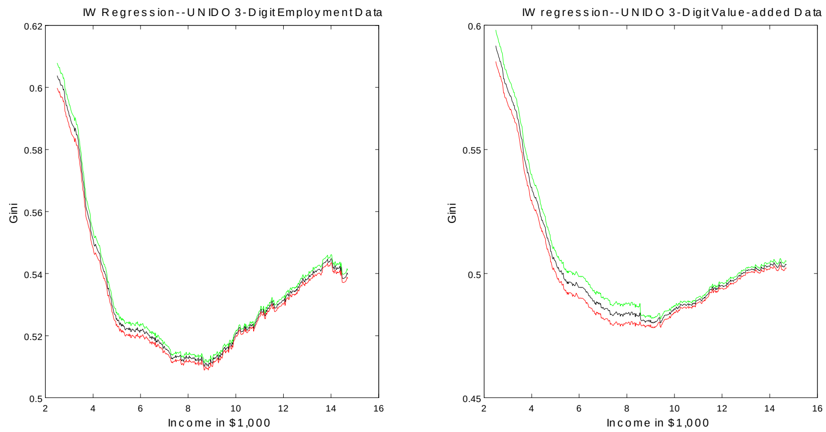

Figure 2.1: IW Regression–Employment and Value-added Data

(lowess) to uncover the link between income per capita $GDP_{c,t}$ and specialization. Specifically, they regress the Gini coefficients of industrial specialization on income per capita with country fixed effects, using rolling income windows.

$$GINI_{c,t} = \hat{\alpha}_c(x) + \hat{\beta}(x)\, GDP_{c,t} + \varepsilon_{c,t},\; GDP_{c,t} \in [x - \Delta/2, x + \Delta/2]\,. \qquad (2.1)$$

The income interval Δ is fixed in each regression ($\$5,000$ in 1985 dollars) and the midpoint x of the interval gradually moves away from the previous income range (the increment across regressions is \$25). Then, they plot the fitted Gini coefficients estimated at the midpoint of the income interval in each regression. They find a U-shaped relationship between Gini coefficients and income levels. Their U-shaped relationship is robust using both employment and value added data within manufacturing[4]. Figure 2.1 reproduces their main results.

[4] IW also provide evidence that the relationship is robust across broader sectors. This paper will focus on manufacturing industries.

2.2.2 Productivity and economic structure

To illustrate the main mechanisms in my model, consider the following simple setup. Suppose there are N competitive industries, with production functions of the form:

$$y_{it} = A_{it} K_{it}^{\alpha} n_{it}^{1-\alpha} \tag{2.2}$$

where $A_{it} = A_{i0} g_i^t$. The growth factor g_i may vary across industries, but capital shares α are assumed to be constant to highlight the productivity mechanism.

Producers solve the problem

$$\max_{k_{it}, n_{it}} \{ p_{it} y_{it} - w_t n_{it} - r_t K_{it} \} \tag{2.3}$$

subject to (2.2), where p_{it} is the price of good i, w_t is the wage and r_t is the rental rate of capital. For now, the series for w_t and r_t may be arbitrary.

Assume these goods are consumed and that preferences are CES, so that, if $\mathbf{y}_t$= $\{y_{1t}, ..., y_{Nt}\}$, then

$$u(\mathbf{y}_t) = \left[\sum_{i=1}^{N} \xi_i \times y_{i,t}^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}}, \quad \sum_{i=1}^{N} \xi_i = 1 \tag{2.4}$$

where ε is the elasticity of substitution among goods.

Let v_{it} be value added in industry i, so $v_{it} = p_{it} y_{it}$ where p_{it} is the price of good i.

Then define the growth factor of value added G_{it} as:

$$G_{it} = v_{i,t+1}/v_{it}.$$

On the demand side, the consumer's first order conditions imply $\frac{p_{it}}{p_{jt}} = \left(\frac{y_{j,t}}{y_{i,t}}\right)^{\frac{1}{\varepsilon}} \frac{\xi_i}{\xi_j}$, so that

$$\frac{G_{it}}{G_{jt}} = \left[\frac{\frac{p_{i,t+1}}{p_{it}}}{\frac{p_{j,t+1}}{p_{jt}}}\right]^{1-\varepsilon}. \tag{2.5}$$

On the supply side, the optimal capital labor ratio is a constant across industries, so that $\frac{A_{it}}{A_{jt}} = \frac{p_{jt}}{p_{it}}$.[5] Thus, for any industries i and j, $\left(\frac{p_{i,t+1}}{p_{it}}\right) \div \left(\frac{p_{j,t+1}}{p_{jt}}\right) = \left(\frac{g_i}{g_j}\right)^{-1}$. In equilibrium (2.5) becomes:

$$\frac{G_{it}}{G_{jt}} = \left[\frac{g_i}{g_j}\right]^{\varepsilon-1}. \tag{2.6}$$

Let $s_{i,t}$ be the share of manufacturing of industry i at date t. Given shares $s_{i,t}$ for one year t, I can compute shares for the next year $t+1$ by multiplying $s_{i,t}$ by $g_i^{\varepsilon-1}$ and repeating this procedure to get predicted shares for as many years as desired[6]. Thus, given initial conditions, a value of ε, and productivity growth factors g_i, I can compute model-generated industry shares of manufacturing, and subject the resulting industry structure to the same nonparametric methodology as in IW to study whether productivity differences might be able to generate a U-shaped specialization pattern.

This might occur if "initial" industry composition is skewed towards low-tech industries. For example, suppose that $N = 2$ and that "specialization" is measured using the Gini coefficient. If s_{jt} is the share of industry j, then the Gini coefficient

[5] To see this, the conditions can be written $p_{it}\alpha y_{it}/K_{it} = r_{it}$ and $p_{it}(1-\alpha)y_{it}/n_{it} = w_{it}$. Dividing one condition by the other I get that $\frac{1-\alpha}{\alpha}\left(\frac{K_{it}}{n_{it}}\right) = \frac{w_t}{r_t}$. Then, dividing any of these conditions for industry i by that for j yields the result.

[6] Literally, this procedure would yield shares that do not add to one. To be precise, let $z_{i,t+1} = g_i^{\varepsilon-1}s_{i,t}$,Then $s_{i,t+1} = \frac{z_{i,t+1}}{\sum_{n=1}^{N} z_{n,t+1}}$.

equals $0.5 - \min\{s_{1t}, 1 - s_{1t}\}$.[7] Now suppose that $g_1 < g_2$. Then, if $\varepsilon > 1$, for a sufficiently low initial share of industry 2 the economy will start off specialized in industry 1, whereas in all periods thereafter the share of 2 will increase and that of 1 will decrease. Thus, the minimum of the two (s_{2t}) will rise until it reaches 0.5 and the Gini coefficient has dropped to 0. After this, the minimum of the two becomes s_{1t} and, as its share continues to decrease, the Gini coefficient rises again. Thus, for a time, specialization decreases, until s_{1t} drops below half – after which specialization will begin increasing again. Alternatively, if $\varepsilon < 1$, for sufficiently low initial share in 1 the economy will start off specialized in industry 2, whereas in all periods thereafter the share of 1 will increase, and the same dynamics obtain.

I now examine whether the heuristic model presented above can generate a U-shaped specialization pattern for the 28 manufacturing industries examined in IW. I use the initial industry shares in 1963 from the UNIDO employment data, and simulate a time series of future industry shares until 1992 using equation (2.6). I then include the same country-time pairs as IW, so that I have a model-generated unbalanced panel that is of the same dimensions as that in the IW database. I simulate industry shares for the 28 manufacturing industries in the ISIC revision 2 industry classification used by the UNIDO INDSTAT3 database, from 1964 until 1992 given the initial share in 1963 drawn from the UNIDO employment data. To perform this simulation I adopt the value $\varepsilon = 3.75$, which is estimated in Ilyina and

[7] To see this, note that the Lorenz curve of industry composition when $N = 2$ is a line joining $(0, 0)$ to $(0.5, \min\{s_1, s_2\})$ and another line joining $(0.5, \min\{s_1, s_2\})$ to $(1, 1)$. The Gini coefficient is defined as the integral of the area above this line.

Samaniego (2012) by observing that the logarithm of (2.6) indicates that regressing value-added growth rates (or employment growth rates) on TFP growth rates yields a coefficient equal to $\varepsilon - 1$.[8] Finally, TFP growth data are computed using the NBER manufacturing productivity database. Note that the NBER industry classification is 4-digit SIC. I use Domar weights to convert NBER SIC industry TFP growth data into ISIC revision2 data (see Table 16 in the Appendix for values). The value of g_i is the industry average over time. GDP per-capita data are drawn directly from the data for each country-year combination.[9]

2.2.3 Basic Model: Results

I regress Gini coefficients generated from my TFP growth simulation on income per capita for countries and periods, following the IW methodology. The results display a similar U-shaped relation between industry concentration and income levels: see Figure 2.2. In addition, the turning point is roughly $\$9,000$, as found by IW, something that lends weight to the empirical relevance of the productivity mechanism.

As a robustness check, I use an alternative way of measuring TFP growth rates. Using the UNIDO data set, I compute the TFP growth rates for the 28 UNIDO

[8]To see this, consider that (2.6) is equivalent to $\log G_i = a + (\varepsilon - 1) \log g_i + \epsilon_i$ where $a = \log G_j - \log g_j$ for some arbitrary industry j and ϵ_i is any unmodeled noise in the relationship. Ilyina and Samaniego (2012) estimate this coefficient using the industry TFP and value-added data reported in Jorgenson et al (2007).

[9]It is worth mentioning that the correlation between the NBER productivity values and US industry employment growth in the UNIDO database is 0.46**. In what remains of the paper, one, two and three asterisks represent standard statistical significance at the 10, 5 and 1 percent levels respectively.

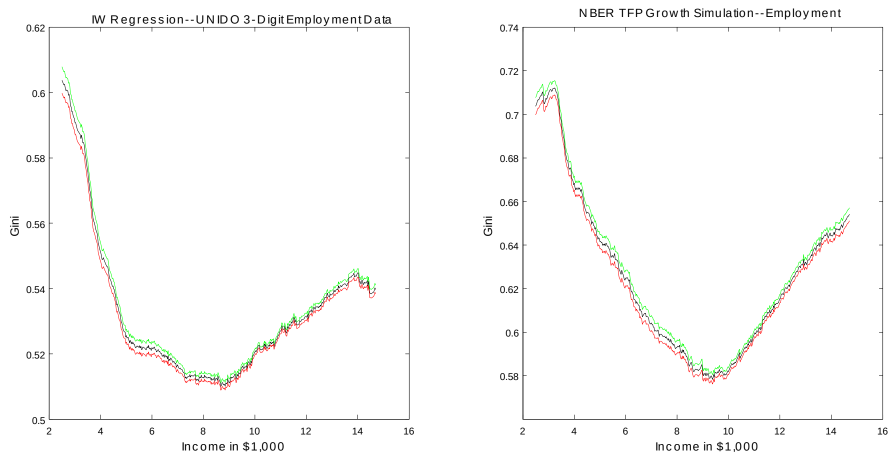

Figure 2.2: Industry structure along the development path in the simple model–employment data.

manufacturing industries in the United States using the following equation:[10]

$$\ln(TFP_{it}) = \ln(Y_{it}) - (1-\alpha)\ln(L_{it}) - \alpha \ln(K_{it}) \tag{2.7}$$

where Y_{it} is the production index, L_{it} is the total amount of labor and K_{it} is capital used in industry i at time t. See the Appendix for details.

Also I compute industry price growth rates as a robustness check, so that equation (2.5) rather than (2.6) dictates industry dynamics. The price index is computed using value added divided by the production index from the UNIDO data set.[11]

Both TFP and price growth rates (in Table 17, see Appendix) are averages over the

[10]It is an important part of the experiment that industry TFP growth rates be the same across countries: all that varies are initial conditions. When I used this procedure to measure industry TFP growth rates in different countries I found that the estimated values in some countries were sometimes absurdly high. I interpret this as indicating that the input data in those countries are likely mismeasured. This implies that I cannot reliably estimate country-specific industry growth rates using the UNIDO data: however, this does not affect the usefulness of the reported initial conditions, which do not depend on input data.

[11]Recall that value added $v_{it} = p_{it} y_{it}$. The assumption is that growth in the UNIDO industrial production index proxies for growth in y_{it}.

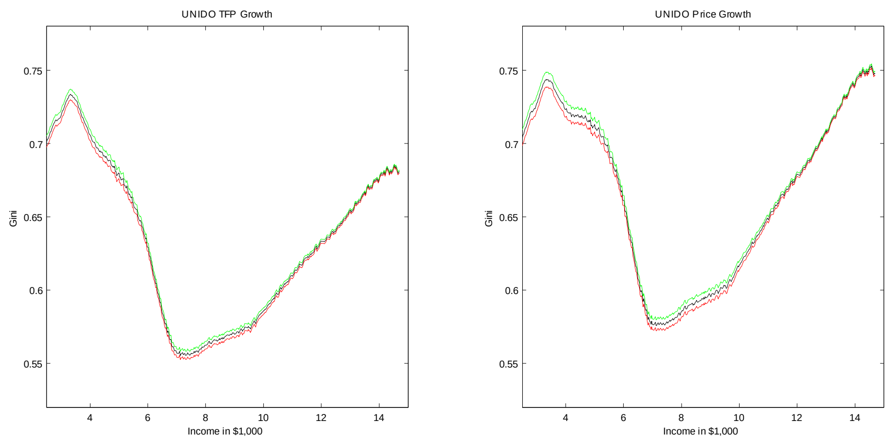

Figure 2.3: IW nonparametric regression using UNIDO TFP and price growth rates

period $1963-1992$ and assumed to be the same for all countries. TFP growth rates computed this way are highly correlated with those derived from the NBER data, with a correlation coefficient of 0.6 (significant at the 5 percent level). The TFP growth and price growth series based on UNIDO data are highly negatively correlated with a coefficient of -0.9 (significant at the 5 percent level). All of this is encouraging as to the robustness of the productivity measures.

I simulate industry shares following equation (2.5) for UNIDO price growth and (2.6) for TFP growth and apply nonparametric methodology to model simulated Gini coefficients on income. Again, I obtain a U-shape in both cases, see Figure 2.3. So far, I only show the results of employment shares of manufacturing industries. IW show that the stages of diversification also hold for value added data. Notice that, in the model, the relative employment share is in fact equal to the relative value added share. While I defined $G_{it} = v_{i,t+1}/v_{it}$, (2.6) would also hold if

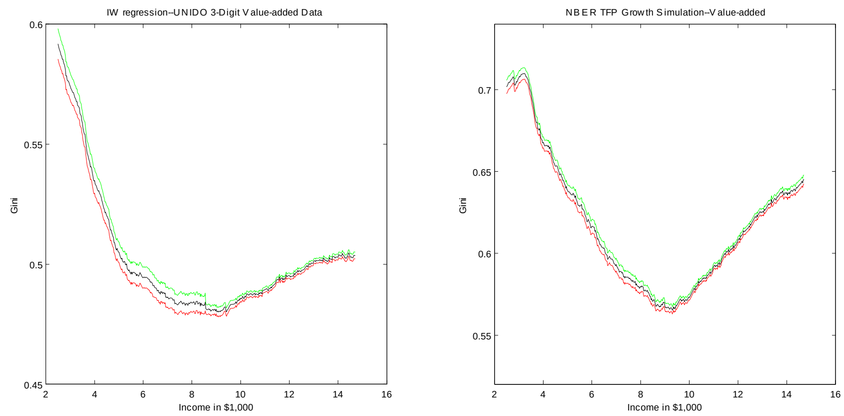

Figure 2.4: Industry structure along the development path in the simple model–value-added data.

$G_{it} = n_{i,t+1}/n_{it}$. To see this, remember the household's first order conditions imply that $\frac{p_{it}}{p_{jt}} = \left(\frac{y_{j,t}}{y_{i,t}}\right)^{\frac{1}{\varepsilon}} \frac{\xi_i}{\xi_j}$. Plugging in the production functions and recalling that capital labor ratios are constant across industries yields $\frac{p_{it}}{p_{jt}} = \left(\frac{A_{jt}n_{jt}}{A_{it}n_{it}^{1-\alpha}}\right)^{\frac{1}{\varepsilon}} \frac{\xi_i}{\xi_j}$. Rearranging, I have that $\frac{n_{it}}{n_{jt}} = \frac{p_{it}y_{it}}{p_{jt}y_{jt}}$. I then repeat the simulation procedure using industry value added shares and NBER TFP growth factors. The results from Gini coefficients with the initial conditions chosen to match value added shares still generate the U-shaped stages of diversification (see Figure 2.4). In the discussion below, I will focus on the employment shares of manufacturing industries.

2.2.4 Productivity and structural change

In the model, the value of ε, elasticity of substitution, is very important. $\varepsilon > 1$ is relevant for manufacturing, so that, within manufacturing, as countries develop they shift resources towards high-TFP growth industries.

To test whether the data support this prediction, I compute a time series for the

weighted average of the measure of industry TFP growth rates in manufacturing for each country and at each date. First, I take the NBER productivity numbers g_i, and normalize them so that the mean measure is zero and the standard deviation is one. Then, for each country at each date, I compute the weighted average TFP growth measure, where the weights are the value added shares of each industry in total manufacturing, computed using UNIDO data. Finally, I apply the nonparametric method in IW to this measure, examining its relationship to real GDP per capita. TFP growth rates are assumed constant in each industry across time and across countries, so any patterns are solely due to patterns of specialization among industries with different average rates of TFP growth.
Figure 2.5 shows the estimated curve (nonparametric) weighted average TFP growth rate for manufacturing sector. There is a mostly positive relationship with income, indicating that, behind the "stages of diversification", economic structure shifts towards manufacturing industries with rapid TFP growth. These results clearly support the assumption that TFP growth differences can be a driving force behind structural change along the development path.

2.2.5 Other factors of structural change

In the paper I focus on productivity differences as the mechanism that drives structural change. However, there are other theories of long-run structural change that imply a shift in resources towards particular industries in the long run. As long as countries begin specialized in industries other than those that dominate in the

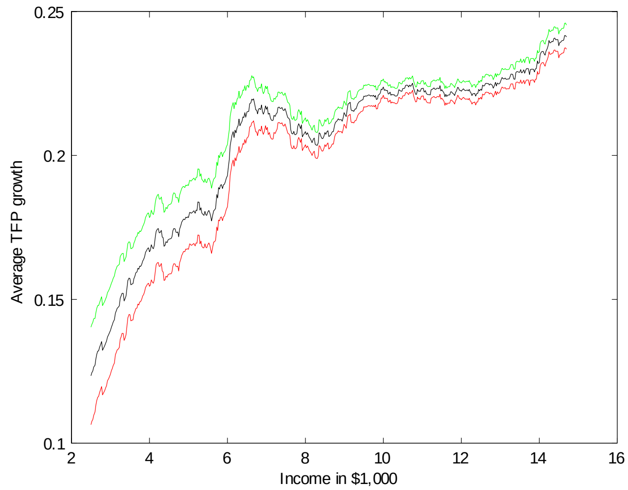

Figure 2.5: Trends in average TFP growth within manufacturing

long run, those models too might display stages of diversification.

At least four general equilibrium frameworks have recently been developed to think about long-term structural change:

1. Ngai and Pissarides (2007, NP) emphasize persistent productivity differences across industries, as I do.

2. Ilyina and Samaniego (2012) emphasize productivity differences driven by differences in desired R&D intensity. This theory is not at odds with that of NP, but digs deeper as to the underlying causes of TFP growth differences.

3. Acemoglu and Guerrieri (2008) consider both productivity differences and differences in capital shares. Specifically they predict that TFP growth rates divided by labor shares determine which industries tend to dominate in the long run.

4. Buera et al. (2011) argue that structural change is affected by industry differences in firm size, with poorer countries less able to finance large-scale technologies.

To see whether structural change appears related to any of the factors of structural change other than TFP growth rates (R&D intensity, labor intensity, firm size), I repeat the experiment illustrated in Figure 2.5 and compute series for the weighted average of each of these measures (R&D intensity, etc.) for each country over time. Industry R&D intensity and labor intensity measurements are 3-decade averages of the measures RND and LAB drawn from Ilyina and Samaniego (2011). The industry firm size is the average number of employees per establishment in the US over the period 1963-1992, as reported by UNIDO in INDSTAT3. Again, each measure is normalized so that the mean measure is zero and the standard deviation is one. Then, as before, weighted averages are computed for each country-year, where the weights are value added shares of each industry in total manufacturing, computed using UNIDO data. Finally, I apply the same nonparametric method to these measures, examining their relationship to real GDP per capita.

Figure 2.6 shows the estimated curve (nonparametric) for each of these measures. Average R&D displays a positive relationship with income within manufacturing, indicating that, behind the "stages of diversification", economic structure shifts towards industries with rapid TFP growth, and industries with high R&D intensity. These results support the assumption that TFP growth differences can be a driving force behind structural change along the development path, and that TFP growth is related to R&D intensity.

Regarding the other measures, Acemoglu and Guerrieri (2008) argue that differences in labor shares could also be a driving force behind structural change. I also report the estimated curve (nonparametric) of the weighted average labor intensity in the manufacturing sector. We can see that labor intensity shows a hump-shaped relationship with income. In particular, labor intensity declines beyond the income level of $10,000. Thus, structural change seems more closely linked to productivity differences than to differences in labor shares.[12] This justifies my focus on a model with productivity differences, abstracting from differences in labor shares. As for firm size, average firm size declines along the development path, which contradicts the idea that countries are more able to overcome large optimal scales of production as they develop.[13]

2.3 Model Economy

There are several reasons why the above results might not extend to the "full" growth model. First, manufacturing can be separated into capital goods and non-capital goods, which serve different purposes and which may hence have different elasticities of substitution. Second, the share of capital goods within

[12] More specifically, Acemoglu and Guerrieri (2008) argue that the relevant variable is the productivity growth rate divided by the labor share. The weighted average of this variable across manufacturing industries is a hump shape with an upturn towards the right tail.

[13] This result, however, is consistent with high TFP growth industries having a relatively small firm size, as found by Mitchell (2002).

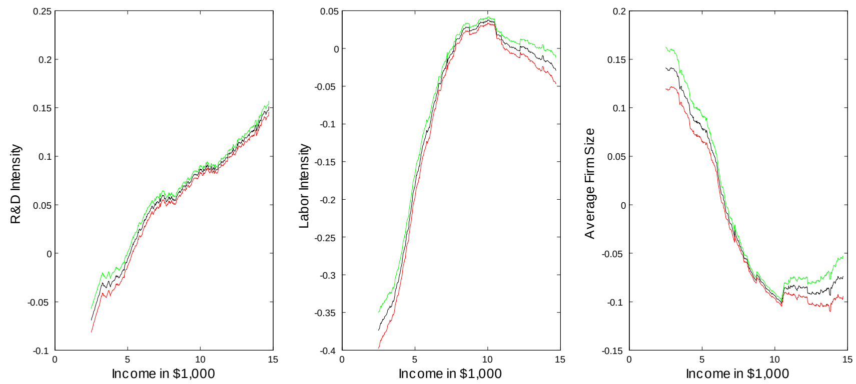

Figure 2.6: Trends in R&D intensity, labor intensity and average firm size within manufacturing

manufacturing will be determined by agents' investment behavior, whereas the share of non-capital goods will be determined by their consumption behavior. Third, capital also includes structures, which are built by the construction sector but which is not part of manufacturing. Fourth, the basic model does not generate a series for income per capita: I simply took the data values as given. The general equilibrium model addresses all of these issues to see whether productivity differences can account for the observed evolution of economic structure along the development path within an integrated theoretical framework.

I now develop a general equilibrium multi-industry growth model to test whether the mechanisms described above can generate "stages of diversification" in a "full" growth model.

2.3.1 Preferences and Technology

Time is discrete and there is a $[0,1]$ continuum of agents. In the baseline economy, there are S sectors, each of which produces an aggregate of I industries. Let I_s be the set of industries that supplies sector s. I focus on the case in which each industry supplies only one sector, so that $I_s \cap I_{s'} = \varnothing$, $\forall s \neq s'$. Note that this is without loss of generality, as one could have two industries identical in all ways that are distinguished by the fact that they provide a given good to two different sectors. I assume that sectors $s \in \{1, ..., S-1\}$ produce consumption goods. Only one sector, S, produces capital goods. Now for each sector $s \in \{1, ...S\}$, the production function has the CES form:

$$y_{st} = \left[\sum_{i \in I_s} \xi_{s,i} \times u_{s,i,t}^{\frac{\varepsilon_s - 1}{\varepsilon_s}} \right]^{\frac{\varepsilon_s}{\varepsilon_s - 1}}, \ \sum_{i \in I_s} \xi_{s,i} = 1, \qquad s = 1, ..., S \tag{2.8}$$

where u_{sit} is use of good i by sector s, $\xi_{s,i}$ is the weight on good i, and ε_s is the elasticity of substitution among goods within sector s.

Agents consume a CES aggregate c_t of the output of the different consumption sectors:

$$c_t = \left[\sum_{s=1}^{S-1} \zeta_s y_{st}^{\frac{\varepsilon - 1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon - 1}}.$$

Finally, agents have isoelastic preferences over c_t and discount the future using a factor $\beta < 1$, so that:

$$\sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\theta} - 1}{1 - \theta}. \tag{2.9}$$

They are endowed with one unit of labor every period which they supply inelastically, and start at period zero with capital K_0. Let q_{st} be the price of the sector aggregate s, with r_t as the interest rate and w_t as the wage. Agents choose expenditure on each good so as to maximize (2.9) subject to the budget constraint

$$\sum_{s=1}^{S} q_{st} y_{st} \leq \sum_{s=1}^{S} \sum_{i \in I_s} r_t K_{it} + \sum_{s=1}^{S} \sum_{i \in I_s} w_t n_{it} \tag{2.10}$$

and the capital accumulation equation

$$K_{t+1} = y_{St} + (1-\delta) K_t. \tag{2.11}$$

On the supply side, each industry features a Cobb-Douglas production function:

$$y_{it} = A_{it} K_{it}^{\alpha} n_{it}^{1-\alpha}, \ A_{it} = A_{i0} g_i^t \tag{2.12}$$

where $g_i = A_{i,t+1}/A_{it}$ is the TFP growth factor of industry i and A_{i0} is given. Producers maximize profits

$$\max_{n_{it}, K_{it}} \{p_{it} y_{it} - w_t n_{it} - r_t K_{it}\} \tag{2.13}$$

subject to (2.12), where p_{it} is the output price of industry i at time t. Capital and labor are freely mobile across sectors.

2.3.2 Equilibrium

The producers' first order conditions imply that the capital labor ratio is constant across industries, which implies that $A_{it} p_{it} = A_{jt} p_{jt}$. Thus, as in related models, goods that experience rapid productivity growth display a decline in their relative price. This result, combined with the consumer's first order conditions implies that the ratio of value added $p_{it}y_{it}$ in any two industries in the same sector s depends on preference parameters and on the productivity terms.

$$\frac{p_{it}y_{it}}{p_{jt}y_{jt}} = \left(\frac{\xi_{s,i}}{\xi_{s,j}}\right)^{\varepsilon_s} \left(\frac{A_{it}}{A_{jt}}\right)^{\varepsilon_s - 1} = \frac{n_{it}}{n_{jt}} \qquad \forall s \tag{2.14}$$

Notice that the same relationship holds for the ratio of employment – just as with the basic model – except that it only holds comparing industries that are in the same sector.

Define the growth factor of employment (or value added) in industry i as

$$G_{it} \equiv \frac{n_{i,t+1}}{n_{i,t}} = \frac{p_{i,t+1}y_{i,t+1}}{p_{it}y_{it}}. \tag{2.15}$$

Then, the expression G_{it}/G_{jt} then denotes the growth of employment (or value added) in industry i relative to industry j. Using (2.14) I have that

$$\frac{G_{it}}{G_{j,t}} = \left(\frac{g_i}{g_j}\right)^{\varepsilon_s - 1} \qquad \forall s. \tag{2.16}$$

Consequently, within sectors, structural change depends on relative TFP growth factors $\frac{g_i}{g_j}$ and on the elasticity of substitution ε_s. For comparing industries across sectors requires characterizing shifts in expenditure across sectors, as well as investment behavior.

2.3.3 Sectoral and Aggregate Growth

Notice that in equilibrium I can aggregate the industries in a given sector into a sectoral production function. To see this, define q_{st} as the price index for final goods in sector s, so that

$$q_{st}y_{st} = \sum_{i\in I_S} p_{it}A_{it}k_t^{\alpha}n_{it}$$

where k_t is the equilibrium capital-labor ratio, which is common across industries. Define input use in sector s as $K_{st} = \sum_{i\in I_s} K_{it}$ and $n_{st} = \sum_{i\in I_s} n_{it}$. Then, define a sectoral production function:

$$y_{st} = A_{st}K_{st}^{\alpha}n_{st}^{1-\alpha}, \;\; A_{st} = A_{s0}\bar{g}_s^t \tag{2.17}$$

The problem of the sector firm and the industry firms can be combined as

$$\max_{n_{it}} q_{st}\left[\sum_{i\in I_s}\xi_{s,i}\times\left(A_{it}k_t^{\alpha}n_{it}\right)^{\frac{\varepsilon_s-1}{\varepsilon_s}}\right]^{\frac{\varepsilon_s}{\varepsilon_s-1}} - r_tk_t\sum n_{it} - w_t\sum n_{it} \tag{2.18}$$

The first order conditions imply that:

$$\frac{n_j}{n_i} = \left(\frac{\xi_{s,j}}{\xi_{s,i}}\right)^{\varepsilon_s}\left(\frac{A_i}{A_j}\right)^{1-\varepsilon} \tag{2.19}$$

We also have that $\sum_i n_i = n_s$ by definition, so we can use (2.19) to write n_i in terms of n_s. Substituting this back into the problem (2.18), we have

$$\max_{n_{it}} q_{st}A_{st}k_t^{\alpha}n_{st} - r_{st}k_{st}n_{st} - w_{st}n_{st}$$

where

$$A_{st} = \left[\sum_{i\in I_s}\xi_{s,i}^{\varepsilon_s}\times A_{it}^{\varepsilon_s-1}\right]^{\frac{1}{\varepsilon_s-1}} = \left[\sum_{i\in I_s}\xi_{s,i}^{\varepsilon_s}\times A_{i0}^{\varepsilon_s-1}g_i^{t(\varepsilon_s-1)}\right]^{\frac{1}{\varepsilon_s-1}} \tag{2.20}$$

and

$$\bar{g}_s = \prod_{i\in I_s} g_i^{x_{it}/X_{st}} \tag{2.21}$$

where

$$x_{it}=\xi_{s,i}^{\varepsilon_s}A_{it}^{\varepsilon_s-1},\ X_{st}=\sum_{i\in I_s}x_{it}.$$

Since the total production of the consumption sectors $c_t=\left[\sum_{s=1}^{S-1}\zeta_s y_{st}^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}$, we can also aggregate all the consumption goods production sectors. Then we have that

$$c_t=A_{c_t}K_{ct}^{\alpha}n_{ct}^{1-\alpha},\ A_{c_t}=\left[\sum_{s=1}^{S-1}\zeta_s^{\varepsilon}\times A_{st}^{\varepsilon-1}\right]^{\frac{1}{\varepsilon-1}} \tag{2.22}$$

As a result, the aggregate behavior of the model economy with many sectors is the same as that of a 2-sector economy that produces c_t using technology (2.22) and produces capital goods using technology (2.17). In the consumption goods sector, firms maximize

$$\max_{K_{c_t},n_{c_t}}\left\{p_{c_t}A_{c_t}K_{c_t}^{\alpha}n_{c_t}^{1-\alpha}-r_tK_{c_t}-w_tn_{c_t}\right\}$$

$$\text{where}\qquad A_{c_t}=\left[\sum_{s=1}^{S-1}\zeta_s^{\varepsilon}\times A_{st}^{\varepsilon-1}\right]^{\frac{1}{\varepsilon-1}}$$

whereas in the capital goods sector:

$$\max_{K_{S_t},n_{S_t}}\left\{p_{S_t}A_{S_t}K_{S_t}^{\alpha}n_{S_t}^{1-\alpha}-r_tK_{S_t}-w_tn_{S_t}\right\}$$

$$\text{where}\qquad A_{S_t}=\left[\sum_{i\in I_S}\xi_i^{\varepsilon_S}\times A_{it}^{\varepsilon_S-1}\right]^{\frac{1}{\varepsilon_S-1}}$$

Consumers choose consumption c_t and investment S_t to solve:

$$\max_{c_t,S_t}\left\{\sum_{t=0}^{\infty}\beta^t\frac{c_t^{1-\theta}-1}{1-\theta}\right\} \tag{2.23}$$

$$s.t.\qquad p_{c_t}c_t+p_{S_t}S_t\ \leq\ r_tK_t+w_t \tag{2.24}$$

$$K_{t+1}\ =\ K_t(1-\delta)+S_t \tag{2.25}$$

$$K_0 \text{ given.} \tag{2.26}$$

In equilibrium, capital and labor markets must clear at all dates, so

$$\begin{aligned} c_t &= A_{c_t} K_{c_t}^{\alpha} n_{c_t}^{1-\alpha} && (2.27) \\ S_t &= A_{S_t} K_{S_t}^{\alpha} n_{S_t}^{1-\alpha} \\ K_t &= K_{S_t} + K_{c_t} && (2.28) \\ n_{c_t} + n_{S_t} &= 1 && (2.29) \end{aligned}$$

It will be convenient to set $p_{S_t} = 1 \forall t$, so that consumption goods prices p_{c_t} are expressed relative price to the price of capital goods.

Solving the 2-sector problem and using the equilibrium conditions, I obtain expressions for labor shares in the capital goods sector n_{St} and the consumption goods' sector $n_{ct} = 1 - n_{St}$ along an unbalanced growth path[14]. These turn out to be functions only of the productivity growth rates g_i, parameters, and of the equilibrium growth rate of aggregate consumption $g_{c_t} = \frac{p_{c,t+1}c_{t+1}}{p_{ct}c_t}$ which is endogenous. This will be true at all dates except possibly date zero, where n_{St} is determined by the initial condition K_0.

Define real GDP as $y_t = S_t + p_{ct}c_t$. Notice it is measured in units of capital.

[14] I do not focus on the balanced growth path (BGP), because BGP results understate the impact of productivity differences on the stages of diversification. One reason is that I ruled out stages of diversification among capital producing industries when assuming Cobb-Douglas production (which leads to constant growth rate and is required for the existence of BGP) in the capital sector. Moreover, from my estimations of the elasticity of substitution for both capital and non-capital manufacturing sectors, I find that the elasticities of substitution in both sectors are not statistically different from each other, and that the elasticity of substitution of the capital sector is statistically different from one. So I abandon the Cobb-Douglas production function in the capital sector. Instead, I use CES function for the capital sector and focus on an unbalanced growth path in this paper.

Proposition 1 *In equilibrium, the growth factors of total capital K,capital per capita k, and total output y depend on the growth factors of TFP in the consumption and capital sectors and on the growth factor of consumption sector (as well as parameters):*

$$g_{k_t} = \frac{k_{t+1}}{k_t} = \frac{K_{t+1}}{K_t} = \overline{g}_{A_{St}}^{\frac{1}{1-\alpha}} \left(\frac{r_t}{r_{t+1}} \right)^{\frac{1}{1-\alpha}} \tag{2.30}$$

and

$$g_{yt} = \frac{y_{t+1}}{y_t} = \overline{g}_{A_{St}}^{\frac{1}{1-\alpha}} \left(\frac{r_t}{r_{t+1}} \right)^{\frac{\alpha}{1-\alpha}} \tag{2.31}$$

where GDP is defined as $y_t = S_t + p_{ct} c_t$ and the equilibrium interest rate is $r_t = \frac{\left(\frac{\overline{g}_{A_{St-1}}}{\overline{g}_{A_{ct-1}}} \right)^{1-\theta} g_{c_{t-1}}^{\theta}}{\beta} - 1 + \delta$ for $t > 0$. At date zero, r_0 is determined by market clearing given K_0.

Proposition 2 *The model economy converges to a balanced growth path where in each sector*

$$\lim_{t \to \infty} A_{st} = A_{jt} \text{ where } j = \begin{cases} \arg\max_{i \in I_s} \{g_i\} & \text{if } \varepsilon_s > 1 \\ \arg\min_{i \in I_s} \{g_i\} & \text{if } \varepsilon_s < 1 \end{cases},$$

and in the consumption goods sector

$$\lim_{t \to \infty} A_{ct} = A_{st} \text{ where } s = \begin{cases} \arg\max_{s < S} \{g_s\} & \text{if } \varepsilon > 1 \\ \arg\min_{s < S} \{g_s\} & \text{if } \varepsilon < 1 \end{cases}.$$

Proposition 2 predicts that for each sector, the sector productivity will asymptotically converge to the productivity of industry with highest (lowest) TFP growth rate if the sector elasticity of substitution is greater (smaller) than one. The aggregate TFP of the consumption goods sector will asymptotically converge to the productivity of the sector with highest (lowest) TFP growth rate if the elasticity of substitution of the consumption sector is greater (smaller) than one. The prediction is confirmed by the evidence in the manufacturing industries in Figure 2.5. Within manufacturing, as countries develop they shift resources towards high-TFP growth industries, since $\varepsilon_s > 1$ is relevant for manufacturing.

Recalling that the only endogenous variable that affects r_t for $t > 0$ is g_{ct},[15] Proposition 1 implies that I can compute the equilibrium for the multi-industry model economy in transition, provided I can derive the series for g_{ct}. The economy with many consumption goods sectors will asymptotically converge to an economy with one consumption sector which has either the highest or lowest TFP growth rate depending on the elasticity of substitution. The same occurs within the capital goods sector. As a result, the expression r_t converges to some constant r and, although in general the model does not possess a balanced growth path (see Ngai and Pissarides (2007)), it converges to one. This suggests that the equilibrium may be computed by finding a sufficiently good approximation to the series for g_{ct}. In the limit, since by assumption $\varepsilon_s \neq 1$ for all $s \leq S$, one industry will end up dominating each sector. However, I wish to study the behavior of the model economy in transition, where sectors are relatively diversified.

[15] In general, at $t = 0$, the value of r_0 is determined by market clearing and the value of K_0.

2.4 Calibration

In the remainder of the paper I focus on a particular type of equilibrium. Observe that the capital stock will be set to satisfy the Euler equation (2.30) at all dates except date zero. In other words, the investment share of the model economy will in general be smooth over time, except between dates zero and one. The model will be calibrated to the available data and, since the initial year in which data for a given country become available has no economic content, it is difficult to justify why the first year I have data for (generally 1963) happens to be the only date when the intertemporal optimization condition (2.30) is not satisfied. For this reason, I focus on an equilibrium where this does not occur.

Definition 3 *An Euler Growth Path (EGP) is an equilibrium and an initial condition K_0 such that equation* (2.30) *holds at date zero.*

The Euler growth path is a generalization of a balanced growth path which may exist in models that do not exhibit balanced growth. For the benchmark results, I calibrate the model to match an Euler growth path by matching the composition of manufacturing but not necessarily its size. Details are in the Appendix. Nonetheless, it is important to underline that the results concerning the structure of the economy turn out not to hinge on whether I focus on an Euler growth path: results on the equilibrium calibrated to match the initial conditions in the data are almost indistinguishable.

In this section, I calibrate the model so as to focus on the "stages" in manufacturing in the UNIDO data. The simulation requires computing transition dynamics in a model without a balanced growth path, and the procedure is described in the Appendix for the interested reader.

Calibrating the model economy requires a choice of industries, and values of the following parameters and variables.

1. Technological parameters α, δ.
2. Preference coefficients $\xi_{s,i}, \zeta_s, \beta$.
3. Elasticities of substitution ε_s for $s \leq S$, and ε, the elasticity across consumption sectors
4. The intertemporal elasticity parameter θ.
5. Productivity growth values g_i.
6. Productivity initial conditions $A_{i0.}$

For calibration, I group all industries into four sectors: Agriculture, Services, Capital and Non-capital manufacturing. Agriculture, services and non-capital manufacturing sectors produce consumption goods, and the capital sector only produces capital goods. Industries include agriculture, services, the 28 UNIDO manufacturing industries, and construction (see Table 2.1). Thus, the agriculture and services industries only contain one industry. The UNIDO industries serve

Table 2.1: Sectors and Industries in the model economy

Sector	Industries Services, etc.	Agriculture	ISIC Manuf.	Construction
Services, etc.	X	-	-	-
Agriculture	-	X	-	-
Capital Manufacturing	-	-	X	X
Non-Cap Manufacturing	-	-	X	-

Table 2.2: Capital good-producing manufacturing industries

Industry	ISIC code
Wood products	331
Furniture, except metal	332
Fabricated metal products	381
Machinery, except electrical	382
Machinery, electric	383
Transport equipment	384
Prof. & sci. equip.	385
Other manufactured prod.	390

either the capital or the non-capital manufacturing sectors. I assigned an industry to the capital sector if the US NIPA tables count it in their "fixed asset" tables (see Table 2.2). Construction serves the capital sector too. The initial shares of agriculture, services, manufacturing and construction sectors out of GDP are derived from World Development Indicators data (WDI).[16]

1. I assume that $\delta = 0.06$ as in Greenwood et al. (1997): this is a standard values

[16] For countries with missing data, I use predicted values computed by regressing sector shares on income, income squared and UNIDO industry shares in the manufacturing sector for all countries and years in my sample.

in models in which the productivity of the investment technology exceeds that in the consumption sector. I use a standard value for the capital share, $\alpha = 0.3$.

2. To calibrate the utility weights $\xi_{s,i}$, it should be noted that in a sense these weights are arbitrary, as they depend on the exact unit of measurement for good i.[17] Thus, without loss of generality, I set $\xi_{s,i} = \frac{1}{I_s}$, where I_s is the number of industries in sector s. The same applies to ζ_s, so $\zeta_s = \frac{1}{S-1}$. I set $\beta = 0.95$, a standard value.

3. For each sector, equation (2.16) is equivalent to $\log G_i = a + (\varepsilon - 1)\log g_i + \epsilon_i$ where $a = \log G_j - \log g_j$ for some arbitrary industry j and ϵ_i is any unmodeled noise in the relationship. I regress U.S. value added growth rates on TFP growth rates[18] for capital and non-capital manufacturing goods respectively, finding that they were not statistically significantly different: $\varepsilon_{noncapmanuf} = \varepsilon_{capital}$. Pooling the data, I estimate that $\varepsilon_{noncapmanuf} = \varepsilon_{capital} = 3.73$. Across consumption sectors, I use the value $\varepsilon = 0.3$[19], which is the estimate in Ngai and Pissarides (2004).

4. The preference parameter θ is calibrated so that in the long run the

[17] For example, if I measure apples and get $\xi_{s,apples} = 2$ (and $A_{apples,0} = 3$), I could choose to measure apples in units of "half an apple" and then $\xi_{s,apples} = 1$ (and $A_{apples,0} = 1.5$).

[18] I use data from Jorgenson et al (2007): although they are a little more disaggregated, I want a value estimated at roughly the same level of aggregation as the UNIDO data. The UNIDO data themselves are too few so I was unable to obtain a good estimate from them directly.

[19] I examine other values of $\varepsilon \in [0.1, 0.9]$ and find results to be visually indistinguishable, as the value of ε has negligible impact on what occurs within the manufacturing sector.

investment share of GDP converges to 12 percent, which is roughly the share in the US: investment shares in transition turn out not to be very different. This implies that $\theta = 3$: typical values used in calibration fall in the range $\theta \in [1, 5]$,[20] so it is encouraging that my value falls in the middle.

5. Productivity growth values g_i are drawn from the NBER productivity database, as described in Section 2.2. I use the average value over the period 1963-1992 (See Table 16). To calibrate the growth factors of the consumption goods sectors, first I use equation (2.20) to compute TFP growth in the capital sector (excluding construction) over the period 1963-1992, and get the average value $\widetilde{g}_S = 1.0241$. According to NIPA, the relative price of construction has risen at a rate of 0.0109 each year relative to other capital. This means the growth factor of construction sector $g_{construction} = \tilde{g}_S / e^{0.0109} = 1.0130$. For the services sector, the relative price of services has risen at a rate of 0.0103 each year relative to other capital. This means the growth factor of services sector $g_{services}$ is then $\tilde{g}_S / e^{0.0103} = 1.0136$. For agriculture, I have that the relative price of agriculture has dropped at a rate of 0.004 each year relative to other capital. So the growth factor of the agricultural sector is $g_{agriculture} = \tilde{g}_S / e^{-0.004} = 1.0282$.

6. For the initial productivities of the capital and consumption sectors, I initially

[20] Growth models tend to use $\theta = 1$, whereas asset pricing studies tend to use larger values. For an example with $\theta = 5$, see for example Jermann (1998).

Table 2.3: Calibrated Parameters: Baseline Model

$g_{construction}$	$g_{services}$	$g_{agriculture}$	$\varepsilon_{capital}$	$\varepsilon_{consumption}$
1.0130	1.0136	1.0282	3.73	0.3

$\varepsilon_{noncapmanuf}$	θ	δ	α	β
3.73	3	0.06	0.3	0.95

set $A_{capital,0} = 1$ and $A_{consumption,0} = 1$. The former is a normalization, and the latter is without loss of generality because the size of the non-investment sectors is independent of the level of $A_{consumption,0} = 1$.[21] Then, using (2.14) and (2.20), for the capital sector industries $i \in I_S$, I set initial TFP to equal $A_{i0} = \left[\frac{n_{i0}}{\sum \xi_{S,i}^{\varepsilon_S} n_{i0}}\right]^{\frac{1}{\varepsilon_S - 1}}$, thus matching the initial share of capital industries in each country. For the consumption sectors, set A_{s0} (where $s \in \{$services, agriculture and non-capital manufacturing$\}$) so as to match the initial share of that sector in each country: $A_{s0} = \left[\frac{n_{s0}}{\sum \zeta^{\varepsilon} n_{s0}}\right]^{\frac{1}{\varepsilon - 1}}$. Finally, for industry productivity in non-capital manufacturing, I have again that $A_{i0} = \left[\frac{n_{i0} A_{s0}}{\sum \xi_{s,i}^{\varepsilon_s} n_i}\right]^{\frac{1}{\varepsilon_s - 1}}$. Industry shares are drawn from UNIDO and sector shares are based on the WDI.[22] Finally, I multiply A_{i0} in all industries and sectors by a country-specific constant so that the country GDP per head relative to US GDP per head in the initial year is the same as in the data.

[21] Proof available upon request.

[22] As mentioned, an adjustment to industry shares is required due to my focus on an EGP: see the Appendix for details.

For each country I use initial conditions from 1963[23] as starting points, and simulate the share of GDP n_{it} of any industry or sector along unbalanced growth path.[24] Figure 2.7 shows the estimated curve of Gini coefficients using industry shares simulated in the baseline model. We can see that the baseline model is able to capture the U-shape of the stages of diversification very well. Again, the turning point is around $\$9,000$, as found by IW. Thus, the results derived using the simple model are robust to allowing the composition and size of the capital sector to evolve independently of the non-capital manufacturing sector, and to allowing the model to generate the GDP series as well as just industry structure. It is notable that, in the full growth model, the re-specialization process after the turning point is slower than the initial specialization, just as in IW.[25]

For robustness, I also repeat my calibration using the TFP measures in table 17 which were derived from the UNIDO data instead of the NBER data. The simulated Gini displays similar U-shape as the baseline model, and the turning point appears between $8,000 and $10,000. See the Appendix.

[23] For some countries initial data in 1963 are not available: then I use the earliest available year.

[24] In my derivations, the model measures GDP in terms of capital goods (remember I normalize capital goods price to 1 and consumption goods prices are expressed as relative to capital goods price). In the data, however, GDP is measured in terms of consumption goods, see Greenwood et al (1997). Since in the model, $A_{h_t} = p_{c_t} A_{c_t}$, I can express the GDP growth factor measured in units of consumption using the formula $\widetilde{g}_{yt} = g_{yt} \frac{g_{Ah}}{g_{Ac}}$. This is the notion of GDP I use in the graphs below. The model simulated using GDP defined in terms of capital goods yields very similar results. An issue here is that the values of A_{h_0} and A_{c_0} are arbitrary in the calibration, but not when I wish to express cross-country GDP in common units. I handle this by assuming that the real GDP data are measured in units of consumption and are internationally comparable, and then use the model to compute growth rates (which do not depend on GDP levels) extrapolating from initial GDP in the data.

[25] If I extend the simulated curve from $15,000 to $20,000, the rising right hand side of the curve continues to increase linearly.

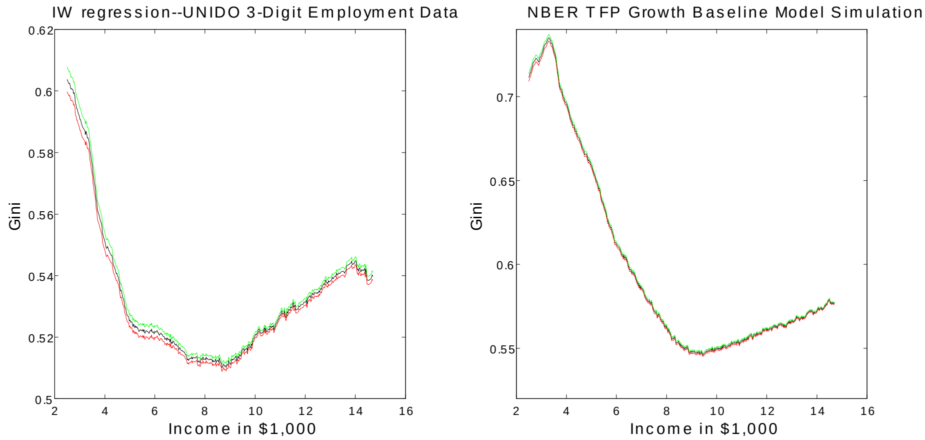

Figure 2.7: Industry structure along the development path in the full model.

In the model economy, the concept of capital includes any goods that are durable. Some items that are not classified in the fixed asset tables may be thought of as durable goods. As a result I redefined capital in broader terms to include things that could be durable but are not classified as such (e.g., pottery, iron products, and so on). This raises the number of capital goods to 15, plus construction. The calibrated parameters using the alternative classification of capital industry is listed in Table 18 in the Appendix. The simulated industry shares display similar stages of diversification to the baseline model (see Appendix).

For robustness, I also check other measures of industry concentration: the log-variance, Herfindahl index, coefficient of variation and the max-min coefficient. All these measures display a similar U-shape, of which the log-variance measurement shows the most obvious U-shape. Results are available upon request.

2.5 Discussion and extensions

2.5.1 Country-Specific Productivity Growth

There are many country factors the literature has related to growth which are not featured in the model (see for example Barro (1991) or Sala-i-Martin (1997)). Thus, I would not expect the model to match per capita GDP growth rates around the world.[26] Still, one might ask whether modifying the model so as to match country GDP growth rates might affect the results regarding economic structure. To check, I add country-specific productivity growth factor that affects all industries, and calibrate it to match average GDP growth rates in each country over the sample period. This factor could be interpreted as capturing policies that affect technological diffusion, trends in policy, or any of the factors commonly included in growth regressions. When I do this to the full model, I find that results are almost identical, just that the curve appears slightly stretched to the left (see Figure 2.8). From all the experiments discussed in my paper, I can conclude that the U-shape generated in my TFP growth differences driven model is robust.

2.5.2 Variation in TFP growth rates across countries

So far I have assumed that industry TFP growth rates are similar across countries. This assumption seems reasonable in view of the results of Rodrik (2012), which reports unconditional convergence in labor productivity at the industry level within

[26] In general I do not find a robust statistically significant correlation between model GDP growth rates and those in the data, even though in the manufacturing calibration the correlation is generally positive. Still, it is worth noting that the mean annual growth rate in the model is 1.9%, compared to 2.0% in the data.

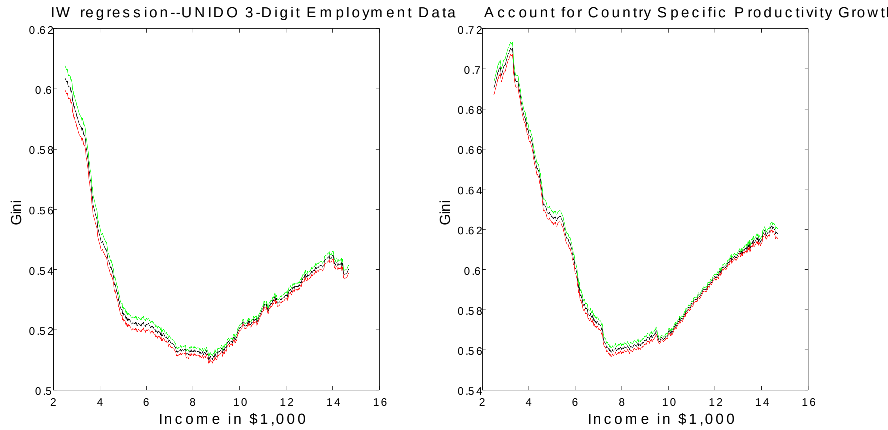

Figure 2.8: Account for Country Specific Productivity Growth.

manufacturing.[27] Still, the fact is that comprehensive internationally comparable TFP data are lacking. Hence, it is important to check the robustness of the results to variation in industry productivity growth rates across countries. For simplicity in what follows I focus on the basic model, so that all manufacturing industries are substitutes with a common elasticity of substitution.

First, suppose that all countries differ by some country specific productivity factor – which could be time-varying (as, for example, along a productivity convergence path). Notice that equation (2.6) dictates patterns of structural change, and that any country-specific productivity factor would appear in both the numerator and the denominator, dropping out and not affecting economic structure. Thus, the only way in which country variation in TFP growth rates might affect the results is if there is a systematic pattern of variation across countries in TFP growth rates at

[27] This finding does not extend to the service sector but difficulties measuring productivity in the service sector suggest that this result should be taken with some caution.

the industry level that offsets the findings in this paper, or if there is so much noise in productivity growth rates across countries that the U-shaped pattern washes out. There are two possibilities here. One is that less developed countries experience catch-up particularly fast in industries that have relatively rapid TFP growth. This is as in the model of Ilyina and Samaniego (2012), where productivity convergence is more rapid in high-tech industries. Another possibility raised in Ilyina and Samaniego (2012) is that developing countries are poor precisely because of institutional barriers (e.g., financial development) and that these disproportionately inhibit convergence in high-tech industries (since they need external finance to fund R&D).[28]

I further conduct an experiment to see what kind of variation in productivity growth rates preserves the results. The point of the experiment is not to generate "realistic" cross-country variation in industry TFP growth rates. Rather, I will generate a large space of potential country-industry variation, and explore under what circumstances the results continue to hold – particularly, the results that the Gini-earnings relationship is U-shaped, and that the trough is around $9,000.

I repeat the experiment above, except that in each country industry TFP growth rates may be different

$$\log g_{i,c} = \log g_{i,US} + \epsilon_{i,c},\ \epsilon_{i,c} \sim N\left(0, \sigma_\epsilon^2\right)$$

[28] Although it does not address structural change, Samaniego (2006) finds that labor market regulation may skew the composition of the economy away from high-tech industries. Messina (2006) also finds that entry costs can affect structural change. Thus, there are other barries that might disproportionately slow convergence in high-tech industries.

where $g_{i,US}$ is the calibrated value of g_i, and $g_{i,c}$ is the value of g_i in country c. Thus, there is random variation in industry TFP growth rates across countries. I set σ_ϵ^2 to equal the cross-sectional variance of industry TFP growth rates. This allows for large variation across countries in industry TFP growth rates – so I can see if a high variance per se matters for the results. Then I see if the model generates a U shaped specialization profile, as reflected in a regression of the fitted IW Gini curve on income and income squared, as well as a constant. Success requires a positive and statistically significant coefficient on income squared. I also check whether the trough is between \$8,500 and \$9,500, so that it is close to the IW results. I run the model 1000 times (so there are 1000 draws of the $I \times C$ vector $\epsilon_{i,c}$), and study the circumstances under which the results satisfy these criteria.

Specifically, I pool all the $\epsilon_{i,c}$ vectors from all 1000 runs, and estimate the following regression:

$$\begin{aligned}\varepsilon_{icr} &= \alpha_{c,r} + \gamma_{no} \log(initialGDP) \times \log(g_{i,US}) \\ &\quad + \gamma_{yes} \log(initialGDP) \times \log(g_{i,US}) \times I(r) + v_{icr}\end{aligned}$$

where $r \in \{1, 1000\}$ indexes the simulation run, and $I(r)$ is an indicator variable that equals one iff the run r satisfies the success criteria (that the Gini profile is U-shaped and lies in the desired bounds). We are interested in seeing whether there is a statistically significant difference between γ_{no} and γ_{yes}, and also in the sign.

First, I find that only 61 of the runs satisfy the success criteria. At the same time, both γ_{no} and γ_{yes} are statistically significant. γ_{no} is small in magnitude and positive

(.003***), whereas γ_{yes} is larger in magnitude and negative (-.017**). This indicates that a successful simulation requires high GDP countries to have relatively low $g_{i,c}$ in industries with high g_i in the US. In other words, convergence must be relatively fast in high TFP-growth industries.

Interestingly, I also find that the variance of ϵ in the successful and unsuccessful samples is the same. This indicates that a small variance is not the issue, rather it is the systematic relationship between initial GDP and ϵ that is required for success (or failure).

2.5.3 Concluding Remarks

I develop a multi-sector model in which differential TFP growth rates across manufacturing industries lead to structural change along an unbalanced growth path. The model accounts for the pattern of diversification followed by specialization that is well-known in the literature. The results are robust to a variety of extensions and modifications. The results suggest that a productivity driven theory can account for both income levels and economic structure. This lends further emphasis to the question of the ultimate determinants of productivity growth rates. Ngai and Samaniego (2011) relate productivity growth rates to the technological determinants of R&D intensity and Ilyina and Samaniego (2012) are able to account for country differences in industry productivity growth rates based on an interaction of research intensity and institutional frictions, suggesting fruitful avenues for future research. I do not exclude other possible factors, such as differences in factor shares (as in

Acemoglu and Guerrieri (2008)) or international trade (as in IW). However, the paper provides quantitative evidence that productivity differences on their own can account for the dynamics of industrial structure along the development path. It would be interesting in future work to develop a theoretical or empirical model that nests all the various possibilities, and estimate the contribution of different factors to the evolution of economic structure. At the same time, it is useful to understand how economic structure evolves under autarky, and compare that to the stylized facts about how economic structure varies along the development path.

In the paper I take initial conditions as a given for my quantitative experiments. The results suggest that poorer countries tend to begin specialized in industries where TFP growth is low. Although it is beyond the scope of this paper, it is interesting to think about why initial conditions might be biased in this way. One possibility is that there are non-homothetic preferences (see Kongsamut et al. (2000)), so that consumption patterns in poor countries are dominated by subsistence considerations that wear off later. If manufacturing industries that produce the goods necessary for subsistence (e.g., food products) happen to have slow TFP growth, then I would observe these initial conditions. This explanation, however, relies on coincidence. Another possibility that does not require non-homothetic preferences involves the transition from a "traditional" technology with low productivity growth to a "modern" technology with more rapid productivity growth. Ngai (2004) shows that small differences across countries in barriers to technology adoption can lead to very large differences in income by delaying the transition from the "traditional" to the "modern" technologies. Initial conditions would be determined by the traditional technology and the date of transition between technologies. The idea that the transition between the "traditional" and "modern" technologies could explain historical economic structure as well as income levels is an interesting topic for future research.

Chapter 3

Structural change in the short run: technological factors and financing constraints

3.1 Introduction

Theory suggests several technological (real) factors that underlie financing constraints. For example, Hart and Moore (1994, hereafter HM) argue that fixed assets help raise external finance, as they are more liquid and hence more effectively used as collateral than assets that are intangible. The same is true of productive assets that are durable, or that are non-specific. On the other hand, Myers and Rajan (1998, hereafter MR) argue that the liquidity of assets could make them <u>less</u> suitable as collateral, as they could be more easily disposed of against the interests of creditors. Thus, a variety of technological factors could affect the ability to borrow – yet it is not known which are the empirically relevant ones, nor what is the sign of the relationship.

One way to determine the interaction of different technological factors with financing constraints is by looking at the <u>industry sensitivity to recessions</u>. Recessions have been found to have a financial component: for example, Braun and Larrain (2005, henceforth BL) find that growth in industries that tend to rely heavily on external finance is disproportionately hit in recessions.[1] They also find that the disproportionate impact of recessions on high external finance dependence (EFD) industries is less severe if firms have more tangible assets that can be used as collateral, or if they are located in economies with high financial development: thus, both the need for external finance and the ability to raise it seem to affect the impact of recessions. In addition, there may be technological factors that lead to difficulty in recessions that do not obviously occur through financial channels that are of independent interest.

This paper explores the technological factors that lead certain industries to be more sensitive to recessions. The aim is to narrow down the most empirically relevant technological determinants of credit constraints with regards to short run fluctuations, as well as to identify other technological factors that might interact with recessions.

First, I set up a two-period multi-industry model with borrowing constraints. The production function relies on two types of inputs/assets: type 1 has properties that make it easier for firms to raise external funds, and type 2 assets make it more difficult to raise external funds. The investment level of each industry is determined by the borrowing constraint, which relies on the share of type 1 assets in the production function, a technology shock, and the quantity of inputs used. The

[1] The assumption is that industry external finance dependence (EFD) represents some technological characteristic that affects firms in a given industry regardless of where they are located: see Rajan and Zingales (1998). Ilyina and Samaniego (2011) find that EFD is closely linked to R&D intensity.

model shows that the growth rate of a given industry can be written as a function of the borrowing constraint. It predicts that industries that rely more heavily on type 2 assets are disproportionately affected in recessions. I further decompose the equilibrium industry growth function into a difference-in-differences regression specification, which allows me to test this prediction. This also provides a theoretical basis for the empirical exercise in Braun and Larrain (2005).

In the empirical sections, I investigate the industry vulnerability to recessions by using an interaction term between a recession dummy variable and industry characteristics based on the difference-in-differences equation derived from the model. In addition to external finance dependence and capital intangibility as in Braun and Larrain (2005), I also study extensively other industry technological determinants that are associated with the ability and/or need to raise finance and which may hence lead to financial difficulty in recessions. Specifically, I use industry indicators that are linked to the structure of the industry production function, to reflect technological characteristics of each industry. Most are drawn from Ilyina and Samaniego (2011, hereafter IS), including measurements of asset fixity, durability, investment lumpiness, R&D intensity, human capital and labor intensity, as well as embodied technical change. I also look into the specialization of capital used in each industry, measured using the extent to which inputs rely on relationship-specific investments (see Nunn (2007)). Based on Hart and Moore (1994), I expect that recessions will have disproportionate effects on industries that are more dependent on external finance but have a lower ability to raise funds – whereas Myers and Rajan (1998) indicate that the opposite could be the case.

My results are largely in line with the hypotheses of Hart and Moore (1994). I find that compared to normal times, industries that are highly dependent on external finance, labor, or relationship-specific investments, that experience rapid embodied technical change, rapid depreciation and high lumpiness in investment, shrink disproportionately during recession years. This difference appears not to be due to disproportionate decreases in investment or productivity, but is due to differences in labor usage, again consistent with the theory of Hart and Moore (1994) that labor is inalienable and hence cannot be used to raise funds in hard times, unlike physical or even some intangible assets. Moreover, when I check whether these sensitivities depend on country characteristics, the disproportionate negative effects are more significant if industries are located in less financially developed economies. In other words, one new function of financial development appears to be that it is able to ameliorate technologically-determined financing frictions during recessions.

Rajan and Zingales (1998) find that industry growth in high-EFD industries is disproportionately sensitive to financial development at a 10 year frequency, and Ilyina and Samaniego (2011) examine the "real" determinants of the sensitivity of industry growth to financial development in that time frame, finding that industries with greater R&D intensity and investment lumpiness grow faster in more financially developed economies, as well as being correlated with financial development. They provide evidence that finance promotes growth by directing resources towards R&D activities. However, the sensitivity to recessions is different, and does not necessarily have the same determinants. For example, factors that are important in the long run may not be important in the short run if agents' adjustment to long run conditions involves protecting themselves from short-run financial vulnerability. Alternatively, R&D investments may simply mature over a longer time frame than the business cycle, or may be a factor of medium-term or long-run growth in ways that other investments are not. In addition, the impact of financing constraints depends on the ability, not just the need, to raise external funds. Thus, the technological factors that lead certain industries to suffer more in recessions may be unrelated to external finance dependence and R&D intensity, even if they relate to financing constraints. To my knowledge, this is the first effort to extensively investigate the technological determinants of industry sensitivity to business cycles, and I do indeed find that the technological factors that affect financing constraints in high frequency data (labor intensity, depreciation rates, embodied technical change, investment specificity) are different from those that Ilyina and Samaniego (2011) find to be important in the long run (i.e. R&D intensity).

The paper is organized as follows. Section 3.2 describes the model. Section 3.3 introduces data and empirical methodology. Section 3.4 reports empirical results. Section 3.5 provides robustness check and Section 3.6 concludes.

3.2 Model

3.2.1 Intermediate Goods Sector

In this economy, there are I industries, each of which produces an intermediate good. Industry i faces the production function:

$$y_{it} = z_t k_{i1t}^{\alpha_i} k_{i2t}^{1-\alpha_i} \qquad 0 < \alpha_i < 1 \tag{3.1}$$

y_{it} is the production of industry i at time t. z_t is the aggregate technology shock. Let k_{ijt} stand for capital type $j \quad (j = 1, 2)$ at time t in industry i. k_{i1t} and k_{i2t} are two types of assets. Type 1 assets , k_{i1t}, help firms raise external funds, for example, tangible, durable, alienable or nonspecific assets, according to (Hart and Moore (1993)). Type 2 assets k_{i2t} are intangible, nondurable, inalienable or specific assets. I assume that labor is a form of k_{i2t}.

In an economy with imperfect financial markets, where internal and external funds are not perfect substitutes, firms may need to borrow to fund their investment. However, their ability to obtain external finance is limited by the quantity and nature of the inputs at their disposal (Hart and Moore (1993)). The input level is bounded above by :

$$r_{1t} k_{i1t} + r_{2t} k_{i2t} \leq F(\alpha_i, z_t) k_{i1t}^{\eta_1} k_{i2t}^{\eta_2}$$

The investment constraint $F(\alpha_i, z_t)$ is a function of the share of type 1 assets in the production function, α_i, and aggregate technology shock, z_t. Based on the findings of Hart and Moore (1994) and Braun and Larrain (2005), I assume the investment constraint satisfies the following properties:

- $F_z > 0$: business cycle upswings make it easier to raise external funds, while negative shocks makes borrowing more difficult;

- $F_\alpha > 0$: more dependence on k_{i1t} makes it easier to raise external funds; alternatively, more dependence on k_{i2t} makes it harder to borrow;

- $F_{z\alpha} > 0$: industries with more type 1 assets have less difficulty raising funds during bad times.

I further assume $\eta_1 + \eta_2 < 1$, so that industries display decreasing returns to scale in terms of borrowing ability, i.e. any form of collateral becames less effective as it accumulates. Moreover, k_{i1t} and k_{i2t} are neither substitutes nor complements in the borrowing constraint, because having more k_{i1t}, for example tangible assets, does not increase or decrease k_{i2t}'s ability to raise external funds.

Firms live two periods, and z_t follows the process:

$$\text{At time } 1, z_1 = 1;$$

$$\text{At time } 2, z_2 = \begin{cases} z_{low} = 1 - \sigma, \text{with probability} \quad \mu \\ z_{high} = 1 + \sigma, \text{with probability} \quad 1 - \mu \end{cases}, \qquad (0 < \mu, \sigma < 1) \tag{3.2}$$

3.2.2 Final Good Sector

There exists a final good sector, which combines the I types of intermediate goods into one final good using the technology:

$$y_t = (\sum_{i=1}^{I} \phi_i y_{it}^{\frac{\varepsilon-1}{\varepsilon}})^{\frac{\varepsilon}{\varepsilon-1}}, \qquad \sum_{i=1}^{I} \phi_i = 1, \quad t = 1, 2$$

The final good sector earns zero profit. It maximizes the following problem:

$$\max_{y_{it}} \{y_t - \sum_{i=1}^{I} p_{it} y_{it}\}$$

where the price of the final good y_t is normalized to one; the price of intermediate good i at time t is p_{it}.

3.2.3 Agents

Agents live for two periods: they are born at time 1 and die at period 2. They maximize their life-time utility:

$$\max_{k_{12}^s, k_{22}^s} \{u(c_1) + \rho E u(c_2)\}$$

subject to the budget constraints at time 1 and 2.

$$c_1 + k_{12}^s + k_{22}^s = r_{11} k_{11}^s + r_{21} k_{21}^s \qquad \text{at time 1}$$

$$c_2 = r_{12} k_{12}^s + r_{22} k_{22}^s \qquad \text{at time 2}$$

At time 1, the initial capital is given ($k_{11}^s = \sum_{i=1}^{I} k_{i11}$ and $k_{21}^s = \sum_{i=1}^{I} k_{i21}$ are fixed). Agents decide to save capital, k_{12}^s and k_{22}^s to produce i types of intermediate goods in period 2. For simplicity, the depreciation rate of capital is 100%.

3.2.4 Equilibrium

Since the initial capital is given ($\sum_{i=1}^{I} k_{i11}$ and $\sum_{i=1}^{I} k_{i21}$ are fixed), interest rates at time 1, $r_{11} = \overline{r_{11}}$ and $r_{21} = \overline{r_{21}}$ are given by the marginal product of each type of capital. An equilibrium sequence of values for prices $p_{it} \quad (t = 1, 2)$, r_{12} and r_{22} satisfy resource constraints, solve consumers and producers' problems and clear the following markets:

Goods market:

$$c_1 + k_{11} + k_{21} = y_1 \quad \text{at time 1} \tag{3.3}$$

$$c_2 = y_2 \quad \text{at time 2}$$

Capital market:

$$k_{1t}^s = \sum_{i=1}^{I} k_{i1t}^s = \sum_{i=1}^{I} k_{i1t} = k_{1t}^d, \qquad t = 2$$

$$k_{2t}^s = \sum_{i=1}^{I} k_{i2t}^s = \sum_{i=1}^{I} k_{i2t} = k_{2t}^d, \qquad t = 2$$

3.2.5 Industry growth

I am interested in differences in industry growth in the presence of financing constraint. First I define growth rate of industry i as[2]:

$$\Psi_i = \frac{y_{i2}}{y_{i1}}$$

Then the relative growth rate of industry i to industry j is:

$$\frac{\Psi_i}{\Psi_j} = \frac{\frac{y_{i2}}{y_{i1}}}{\frac{y_{j2}}{y_{j1}}} \tag{3.4}$$

Let $\Omega_{ij}(z) \equiv \frac{\Psi_i}{\Psi_j}$ be the difference in industry growth factors at time t. Whether the limit of the difference in growth rates in recessions relative to booms $\frac{\Omega_{ij}^{recession}}{\Omega_{ij}^{boom}} \gtrless 1$ depends on the degree of the borrowing constraint response to technological shock, z, the share of type 1 assets, α, relative to cross response to z and α and F.

Proposition 4 *The difference in industry growth rates in recessions relative to booms is a function of the borrowing constraint $F(\alpha_i, z_t)$ when the constraint is binding.*

$$\frac{\Omega_{ij}(z_{low})}{\Omega_{ij}(z_{high})} = \left(\frac{\frac{F(\alpha_i, z_{low})}{F(\alpha_j, z_{low})}}{\frac{F(\alpha_i, z_{high})}{F(\alpha_j, z_{high})}}\right)^{\frac{1}{1-\eta_1-\eta_2}}$$

$$\lim_{\triangle_\alpha \to 0} \lim_{\triangle_z \to 0} \frac{\Omega_{ij}(z_{low})}{\Omega_{ij}(z_{high})} = \left(\frac{F_\alpha F_z}{F_{\alpha z} F}\right)^{\frac{1}{1-\eta_1-\eta_2}}$$

where $\alpha_i = \alpha_j + \triangle_\alpha, z_{high} = z_{low} + \triangle_z$.

[2] Some research use value added growth as an industry growth measure, e.g., Rajan and Zingales (1998), Ilyina and Samaniego (2011, hereafter IS), Fisman and Love (2004). I show in the appendix that the same results hold for value added growth definition under the assumption that $\varepsilon > 1$.Ilyina and Samaniego (2012) find that this is a reasonable assumption for manufacturing sectors. Also, in Section 3.5, I show that results are robust to measuring industry performance using value added growth instead of an output index.

There are two possibilities given the assumption $\eta_1 + \eta_2 < 1$:

1. If $\frac{F_\alpha F_z}{F_{\alpha z} F} > 1$, then $\lim\limits_{\triangle_\alpha \to 0} \lim\limits_{\triangle_z \to 0} \frac{\Omega_{ij}^{recession}}{\Omega_{ij}^{boom}} > 1$. In this case, the difference in growth rates between industries with high and low α in recessions is larger relative to booms.

2. If $\frac{F_\alpha F_z}{F_{\alpha z} F} < 1$,then $\lim\limits_{\triangle_\alpha \to 0} \lim\limits_{\triangle_z \to 0} \frac{\Omega_{ij}^{recession}}{\Omega_{ij}^{boom}} < 1$. In this case, the difference in growth rates between industries with high and low α in recessions is smaller relative to booms.

To obtain an analytical solution, I further assume F takes the CES form:

$$F(\alpha, z) = [\lambda \alpha^\rho + (1-\lambda) z^\rho]^{\frac{1}{\rho}}$$

where $0 < \lambda < 1$ so that the assumptions $F_\alpha > 0, F_z > 0$ and $F_{\alpha z} > 0$ are satisfied. Then proposition 3 tells us that:

$$\begin{aligned}
\lim_{\triangle_\alpha \to 0} \lim_{\triangle_z \to 0} \frac{\Omega_{ij}^{recession}}{\Omega_{ij}^{boom}} &= \left(\frac{F_\alpha F_z}{F_{\alpha z} F} \right)^{\frac{1}{1-\eta_1-\eta_2}} \\
&= \left\{ \frac{1}{1-\rho} \right\}^{\frac{1}{1-\eta_1-\eta_2}} \qquad (3.5)
\end{aligned}$$

Since $1 - \eta_1 - \eta_2 > 0$, then $\lim\limits_{\triangle_\alpha \to 0} \lim\limits_{\triangle_z \to 0} \frac{\Omega_{ij}^{recession}}{\Omega_{ij}^{boom}} \gtrless 1$ depends on $\frac{1}{1-\rho}$, the elasticity of substitution between α and z. If $\frac{1}{1-\rho} > 1$, then α and z are more like "substitutes". According to Hart and Moore (1994) and Braun and Larrain (2005), with more tangible assets, the effects from a negative shock should be less serious. In this sense, I can regard α and z as "substitutes"$\left(\frac{1}{1-\rho} > 1 \right)$. During recessions ($z$ is low), firms need more tangible assets as collateral than when z is high to raise a given amount of funds. So I predict that $\lim_{\triangle_\alpha \to 0} \lim_{\triangle_z \to 0} \frac{\Omega_{ij}^{recession}}{\Omega_{ij}^{boom}} > 1$ is more likely to happen, i.e. the difference in growth rates between industries with more type 1 (e.g., tangible) assets relative to industries with low type 1 (i.e., more type 2, intangible) assets is even larger in recessions. If $\frac{1}{1-\rho} < 1$, then α and z are more like "complements". In this sense, with more tangible assets, the effects from a negative shock should be more serious, which is in line with Myers and Rajan (1998).

From (29), I can see that the differences in industry growth rates $\Omega_{ij}(z_t)$ can be rewritten as: $\Omega_{ij}(z_t) = \Omega(\alpha_i, z_t)$, assuming η_1, η_2, α_j and $\overline{r_1}$ are given. Thus, the relative industry growth rate $\Omega(\alpha_i, z_t)$ can be decomposed into 2 parts, the share of tangible assets α_i, and the aggregate technological shock z_t. Using a Taylor approximation, in the Appendix I show that the log of the growth rate of industry i can be written as:

$$\ln(\Psi_i) = \beta_i + \beta_z + \beta_{iz}\alpha_i z_t + \epsilon_{it} \tag{3.6}$$

where ϵ_{it} is small. In other words, the model suggests a difference-in-differences regression specification, including an interaction between the state of the macroeconomy z_t and the technological measure of "finance enabling" input intensity α_i. If input i helps raise external funds in recessions, then $\beta_{iz} > 0$. If it does not, then $\beta_{iz} < 0$.

3.2.6 Empirical implementation

To empirically implement this equation (3.6) in a dynamic context, I estimate the industry growth rate in recessions relative to booms using:

$$\begin{aligned} \text{Growth}_{c,i,t} &= \beta_1 \text{Share}_{c,i,t-1} + \beta_2 \text{Recession}_{c,t} + \beta_3 (\text{Recession}_{c,t} * X_i) \quad (3.7) \\ &\quad + \beta_4 \text{Dummy}_{i,c,t} + \epsilon_{c,i,t} \quad (3.8) \end{aligned}$$

Here $Growth_{c,i,t}$ is growth in industry i in country c at date t, and X_i is an industry characteristic such as asset tangibility that is hypothesed to help raise external funds, to capture α_i. $Recession_{c,t}$ is an indicator that $z_t = z_{low}$. Empirically, $Recession_{c,t}$ is a country- and year-specific dummy variable, which takes the value of 1 if country c is in recession in year t, and 0 if otherwise. Thus β_3 is the derivative of growth with respect to z_t and industry characteristic X_i – the empirical counterpart to β_{iz}. $Dummy_{i,c,t}$ is a vector of dummy variables that includes country, time (β_z), industry(β_i), industry-country, and industry-time specific effects, so that β_3 captures only the differential effect of X_i in recessions, net of any conditions that affect particular industries in a given environment or on a given date. Other remaining industry effects are captured by the initial size of industry i, $Share_{c,i,t-1}$, which reflects the possibility that large and small industries may react differently to recessions. Since β_3 captures the difference in industry growth in recessions relative to booms for industries with different levels of X_i, I expect $\beta_3 > 0$ ($\beta_3 < 0$) to indicate that industries with high X_i are less (more) seriously affected in recessions. For example, if X_i measures high asset tangibility (intangibility), high durability (non-durability) or high non-specificity (specificity), then $\beta_3 > 0$ ($\beta_3 < 0$) would be consistent with the Hart and Moore (1994)-inspired hypothesis that these features help ease credit constraints in recessions. On the other hand, $\beta_3 < 0$ ($\beta_3 > 0$) for measures of high asset tangibility (intangibility), high durability (non-durability) or high non-specificity (specificity) would support the Myers and Rajan (1998)- inspired hypothesis that these features actually worsen credit constraints in recessions. I allow the error term $\epsilon_{c,i,t}$ to be serially correlated and follow an AR(1) process.

Notice that the model generates essentially the same regression specification as in Braun and Larrain (2005). My model shows that the difference-in-differences regression in Braun and Larrain (2005) can be thought of in terms of a multi-industry growth model with borrowing constraints.

3.3 Data and Empirical Methodology

I investigate a variety of industry performance indicators in recessions to check my hypothesis of whether recessions have a disproportionate effect on industries with higher dependence on external finance, or a lower ability to raise it. Industry data are taken from the INDSTAT3 and INDSTAT4 databases, distributed by UNIDO. I focus on the production index (it is a Laspeyres quantity index) growth of 28 manufacturing industries (based on the ISIC-revision 2 classification in INDSTAT3) in 149 countries from 1970 to 2007, leading to over 50,000 observations. Table 3.1

lists the country sample and number of observations for each country.[3] Data from 1970 to 2004 are from INDSTAT3, while data from 2005 and forward are from the successor dataset INDSTAT4. To identify the channels through which recessions affect industry value-added growth, I also investigate other indicators of industry performance: number of employees, number of establishments, wages and salaries, gross fixed capital formation, and the average firm size (value added per establishment). Wages and salaries and gross fixed capital formation are deflated using the CPI of the local currency (from World Development Indicators). The average firm size is defined as the ratio of industry value added over the number of establishments, following the definition of Fisman and Sarria-Allende (2010). I use sector shares of manufacturing value added in the previous period as a control for industry size before recessions, assuming that there may exist different effects of recessions on large and small industries. Certain outlier rules are applied: the 1st and 99th percentiles of the distributions of the industry variables are eliminated. The panel is unbalanced, and the sample sizes vary across countries and industries, due to data availability.

The benchmark regression is (3.7):

$$\text{Growth}_{c,i,t} = \beta_1 \text{Share}_{c,i,t-1} + \beta_2 \text{Recession}_{c,t} + \beta_3 (\text{Recession}_{c,t} * X_i)$$

[3] The number of observations may be lower in some regressions depending on the availability of each variable.

$$+\beta_4 \text{Dummy} + \epsilon_{c,i,t}$$

3.3.1 Industry Technological Measures

Ilyina and Samaniego (2011) measure the characteristics of the industry production technology using several input factor intensities and factor attributes, and relate them to the industry need and ability to raise external finance. The technological measures are:

- Fixity of assets (FIX) is the ratio of fixed assets to total assets, computed using Compustat data[4] as in Braun and Larrain (2005);
- R&D intensity (RND) is R&D expenditures over total capital expenditures, computed using Compustat data;
- Depreciation (DEP) is the industry rate of depreciation, computed using the BEA capital flow tables;
- Embodied technical change (ETC) is the rate of decline in the price of capital goods used by each industry, relative to consumption, computed using the BEA capital flow tables;
- Labor intensity (LAB) is measured as the ratio of the total wages and salaries over the total value added, using UNIDO data;

[4] All industry measures computed from Compustat database are the median firm values.

- Human capital intensity (HC) is measured as the ratio of the total wages and salaries over the number of employees, using UNIDO data;

- Investment lumpiness (LMP) is defined as the average number of investment spikes[5] of an industry in a decade, computed using Compustat data.

- Relationship-specificity (RS) is defined below, as in Nunn (2007).

They measure these variables for 1970-1999 and for each decade separately. Since these measures are highly correlated over decades and the industry rankings of them are stable, I take the average value over three decades for each measure (see Table 3.2).

Based on the Ilyina and Samaniego (2011) survey of the literature, higher values of depreciation, embodied technical change, R&D intensity, investment lumpiness, labor intensity and human capital intensity are correlated with less ability to access external finance because of the low alienability and tangibility of their assets (i.e., type 2 asset in my model), while fixity of assets provides a higher ability to access external finance because such assets (i.e., type 1 asset in my model) are more tangible (also see Hart and Moore (1994)). Regarding the financial need, industry rates of depreciation, embodied technical change, R&D intensity, investment lumpiness and human capital intensity may all reflect a higher need for external funds because of their higher need for follow-up investment, or longer gestation

[5] A spike is defined as an annual capital expenditure exceeding 30% of the firm's stock of fixed assets, as in Doms and Dunne (1998).

period, high startup costs, while fixity of assets and labor intensity need less. Industries benefit disproportionately from financial development because of their different needs and abilities to raise external funds, which is not a perfect substitute of internal funds due to asymmetric information, moral hazard problem and other financial market frictions. Based on my model and on the related literature, under the Hart and Moore (1994) inspired hypothesis I expect negative β_3 for all the above measures except for the fixity of assets, i.e., industries that depend highly on non-durable or intangible or inalienable assets are disproportionately affected in recessions. Under the Myers and Rajan (1998) inspired hypothesis, the opposite would be the case.

In addition to these variables, I include one more: relationship specificity. According to Hart and Moore (1994), if assets are firm-specific, it is difficult for firms to raise debt because these assets are hard to liquidate, so they are not useful as collateral. Nunn (2007) constructs a relationship specificity (or contract intensity) index (see table 3.2) to measure the extent to which inputs are dependent on relationship-specific investment between the supplier and the buyer. He measures, for each good, the proportion of inputs that are neither sold on an organized exchange nor reference priced in a trade publication. If inputs are sold on an organized exchange or priced in a trade publication, there must exist a large number of buyers and sellers, indicating this good is not dependent on relationship-specific investments. I use this index as a measure of industry-technological characteristics because I believe some industries may require relationship-specific inputs for technologically-determined needs. I focus on the strict relationship specificity measure[6] from Nunn (2007), i.e., the proportion of inputs that are neither sold on an organized exchange nor reference priced in a trade publication.

Table 3.3 shows the correlation matrix of industry measures discussed above. I find that the relationship-specificity variable is strongly positively related with investment lumpiness, which according to Ilyina and Samaniego (2011) also reflects asset specificity. Relationship-specificity is also positively correlated with the industry rate of depreciation, but negatively related with fixity of assets.[7] I therefore expect a negative coefficient for the interaction term of recession and the relationship specificity index.

3.3.2 External Finance Dependence

Rajan and Zingales (1998) introduce an external finance dependence (EFD) index (see table 3.2), defined as the share of capital expenditure that is not financed by cash flow from operations. The industry value is that of the median firm value in COMPUSTAT. Ilyina and Samaniego (2011) compute this index for my industry classification over the 70s, 80s and 90s, separately.[8] I use the average value of the three decades from Ilyina and Samaniego (2011) as my external finance dependence

[6] Nunn (2007) also has a second measure (i.e., the proportion of inputs not being sold on an exchange but reference priced). This moderate measure of relationship specificity is strongly correlated with the strict one, and my regression results of these two measures are close. So I only report the results for the strict definition.

[7] Thus, interestingly, all the technological features that HM argue are related to the severity of financing constraints turn out to be positively correlated.

[8] They find that cross-decade correlations are mostly very high.

index. External finance dependence measures financial constraints at the firm level and has been identified as an important factor linking finance to growth and business cycles (see RZ, IS, BL and others). Rajan and Zingales (1998) assume some industries are more dependent on external finance than others for technological reasons like the initial project scale, gestation period, cash harvest period and the requirement for continuing investment.

External finance dependence and the other technological measures are calculated using U.S. data and are assumed to represent the real industry technological characteristics in a financially frictionless economy. The technological differences among industries are assumed to be persistent across countries, meaning that the rankings of these indices are stable across countries, even if the index values of each country may not be the same. Similarly, I also apply this assumption to other technological measures discussed above. The United States is not included in my regressions because it is a benchmark economy. The coefficient β_3 is expected to be negative, i.e., industries that are more dependent on external finance are disproportionately affected in recessions.

3.3.3 Recession and Crisis

Following the definition of Braun and Larrain (2005), I identify recessions using a peak-to-trough criterion. Troughs are identified as years when the logarithm of annual real GDP (data are from World Development Indicators) falls one standard deviation of the cyclical GDP below its trend using the Hodrick-Prescott filter[9]. The peak year is identified as the nearest year preceding the trough that features a cyclical GDP value that is higher than that of its previous and posterior years. Periods between the peak and the trough are defined as recession periods. The dummy variable $recession_{c,t}$ is equal to 1 if the year is a recession, and 0 if otherwise. While there are more sophisticated methods for identifying recessions, given that I am using annual data in this paper, this method seems to be appropriate and its simplicity means that I can apply it to a large set of countries.[10] As a robustness check, I also compare the impact of recessions and credit crunch. Credit crunches reflect periods of severe financial stress, which may or may not be subsets of economic recessions. Systematic credit crises are disruptive to financial systems and sometimes even to the whole economy, depending on their severity. Although not all credit crunches lead to recessions, I am still interested in the industry vulnerability to bank credit crunches since bank credit is an important source of external finance, and I wish to see if bank credit crises and recessions behave differently. As with recession periods, the definition of a credit crunch periods follows Braun and Larrain (2005), and is based on the cyclicality of bank credit to the private sector as a share of GDP (from World Bank Financial Development and Structure dataset 2012). Troughs are identified as years when the bank credit to GDP ratio falls one standard deviation below its trend computed

[9] Countries with interruption in the GDP data are eliminated from the sample, e.g Kuwait.

[10] The recession periods identified for the US are mostly consistent with other studies, for example, the business cycle chronologies by Economic Cycle Research Institute.

using the Hodrick-Prescott filter. The peak year is identified as the nearest year preceding the trough that features a cyclical bank credit over GDP value that is higher than that of its previous and posterior years. Periods between the peak and the trough are defined as bank credit crisis periods. I set a crisis dummy equal to 1 if the country is in a bank credit crisis, and 0 otherwise.

3.3.4 Financial Development

The financial development level is measured using total credit to the private sector as a percentage of GDP, since the channeling of savings to investors is regarded as a key function of financial intermediaries. Data are from the World Development Indicators (WDI) and are averaged over 1970-2007 for each country.[11] I do not use the value in each year as the credit-to-GDP ratio is viewed as a proxy for the institutions that underlie credit growth and financial development – which change rarely over time – whereas credit in the short run may change for all sorts of reasons (see Ilyina and Samaniego (2011)). As a robustness check, I also use the accounting standards index from La Porta et al (1998) as a measure of financial development. This is a commonly used measure of financial development, because it reflects the cost of monitoring and screening potential borrowers.

[11] Ilyina and Samaniego (2011 report that cross-decade correlations are high (over 70% in their sample of 42 countries). Thus it appears that financial development in general changes little over time.

3.3.5 US Growth Opportunities

Fisman and Love (2004, hereafter FL) argue that the short-run impact of financial development on industry growth is determined by potential growth opportunities, while in the long run industry growth is a function of inherent industry characteristics interacting with financial development. As a further robustness check, I control for industry growth opportunity following FL. They use the U.S. growth rate change as the proxy for global shocks to growth opportunities for the same industry in other countries. It is based on the same assumption as in Rajan and Zingales (1998) that actual industry growth in the U.S. reflects global shocks (demand or productivity shocks) because the financial market in the U.S. is well developed and its market is large. To control for industry growth opportunity shocks, I add an interaction term of a country-specific financial development indicator and the U.S. growth rate of real sales, following Fisman and Love (2004). The country specific financial development indicator is the average of total credit to the private sector as a percentage of GDP for each country, using the WDI database. Industry growth opportunities are computed as the median growth rate of real sales of firms in the U.S. in each year from 1970 to 2005, using the COMPUSTAT database.

3.4 Empirical Results

3.4.1 Basic Results

First, I estimate the basic regression using the industry production index growth rate for the entire sample as the dependent variable (see table 3.4). The results suggest that, compared to normal times, during recession years industries that are highly dependent on external finance (EFD), labor (LAB) or relationship-specific investment (RS), and that experience high depreciation rate (DEP), embodied technical change (ETC) and lumpiness in investment (LMP) are disproportionately affected in the growth rate. The growth rate of the median industry in terms of the external finance dependence falls 3.45%. For industries that are highly dependent on external finance (75th percentile in the index, i.e., the apparel industry), their value added growth rate falls 3.5%, in contrast to a 3.4% decrease in the growth rate for less-dependent industries (25th percentile, i.e., the paper and paper products industry) in recessions . The difference is 0.1 percentage points, representing 3% of the decrease in the growth rate during recessions for a typical industry. The results confirm my prediction that industries highly dependent on external finance are disproportionately affected in recessions, and are consistent with Braun and Larrain (2005)'s evidence for the credit channel of business cycles. It provides evidence that recessions are indeed times when credit is scarce. Similarly, for industries with a high capital depreciation rate (75th percentile), the growth rate falls 3.9% in recessions, compared with a 3.0% fall for industries with a lower depreciation rate (25th percentile). The differential effect is 0.9 percentage points, which represents 26% of the decrease in the growth rate (3.5%) for an industry with the median depreciation rate. For industries with high technical change rate (75th percentile), the growth rate declines 3.7%, compared with a 3.2% decrease for industries with a lower technical change rate (25th percentile). The implied differential effect is 0.5%, accounting for 14% of the fall in the growth (3.5%) for the median level industry. Labor-intensive industries (75th percentile) experience a 4% fall in value-added growth rate, while the decline in industries that use less labor is only 3.4%. The 0.6-percentage-point difference effect accounts for 16% of the fall in the growth (3.8%) for the median labor-intensive industry. Industries with high-capital investment lumpiness suffer 3.7% loss in recessions, compared to a 3.2% fall in low-lumpiness industries. The 0.5-percentage-point differential effect accounts for 15% of the decrease (3.4%) of a median industry. Industries that are highly dependent on relationship-specific inputs experience a 3.8% fall in growth, compared to a 3.1% decrease for industries less dependent on relationship-specific inputs. The 0.7 percentage point represents a 20% loss of growth (3.4%) for a typical industry.

The results confirm the predictions of the theory of Hart and Moore (1994) as it pertains to recessions, and the disproportionate effects of external finance dependence, the industry rate of depreciation, embodied technical change, labor intensity, investment lumpiness and relationship-specificity are statistically and economically significant. Industries with more non-durable (higher physical depreciation rate, or technological obsolescence), more intangible (e.g., labor) or investment-specific assets (recall that both relationship-specificity and investment lumpiness are associated with asset specificity) are less able to raise debt and disproportionately are therefore hit harder in recessions when external finance is more scarce, because their assets have lower liquidation value and are difficult to be used as collateral to creditors in recessions. It is also obvious that the differential effects of the industry rate of depreciation, embodied technical change, labor intensity, investment lumpiness and relationship-specificity are much higher than that of external finance dependence, indicating that the "need" channel is less important than "ability".

I further investigate the channels that may affect the growth rate by examining a series of industry performance measures: the number of employees in the industry, the number of establishments, wages and salaries, gross fixed capital formation and average firm size (see table 3.5-3.7). External finance dependence, the industry rate of depreciation, labor intensity and investment lumpiness intensive industries usually lay off more of their employees and shut down more firms in recessions. Moreover, industries that are dependent on labor, experience a significant cut in the wage growth in face of recessions. Industries with high depreciation experience a loss in wage growth, too, but at less significant levels. industries with rapid embodied technical change suffer loss in output by laying off more employees.

Industries dependent on relationship-specific investment are most affected in the number of establishments. However, in general no significant disproportionate effects are detected in the capital formation growth and average firm size growth (results are not reported for conciseness). These results indicate that recessions affect capital investment growth and firm size to the same extent across industries, but affect labor investment differently. Thus, it appears that firms in industries where credit constraints become more severe in recessions respond by firing workers to reduce the wage bill and raise funds that way, underlining the inalienability of labor and the difficulty of using it as collateral.

Also, from the results above, I can see that labor-intensive industries are affected in almost all industry performance regressions, suggesting that labor-intensive industries seem to be the most vulnerable to recessions. To find out whether this is true, I include all the technological variables that significantly interact with recessions into one regression to see which of these interactions is still significant (see table 3.8). Since my industry measurements are correlated (see table 3.3), to remove any collinearity I first orthogonalize industry variables and then run the basic regression using the orthogonal variables[12]. The estimations with all six interaction terms indicate that labor intensity wins the "competition": the labor intensity

[12] I orthogonalizes these six variables, creating a new set of orthogonal variables, using a modified Gram-Schmidt procedure (Golub and Van Loan 1996). The order of the variables determines the orthogonalization; hence, the "most important" variables should be listed first. I determine the order of the variables according to the significance levels in their individual regressions. Thus the order is: LAB, EFD, RS, DEP, LMP and ETC. In fact, for different orders, orthogonalized LAB interaction terms are always the most significant one among all variables and significant at 1%.

interaction term is most statistically significant. External finance dependence and embodied technical change interaction terms are significant at the 5% level, however other interaction terms are either not significant or very weakly significant. The "horse race" results indicate that the disproportionate effects of the industry rate of depreciation, investment lumpiness and relationship-specificity are through labor intensity (and possibly external finance dependence and embodied technical change). All the evidence points to the finding that industries highly dependent on external finance and labor, especially labor, are the hardest-hit in recessions.

3.4.2 Country Financial Development

The fact that recessions have a financial component and that labor-intensive industries suffer more in recessions doesn't necessarily mean that the interaction of recession dummy with labor intensity is due to financing frictions. Supporting evidence comes from the fact that many types of industries that are vulnerable to financing frictions respond to recessions disproportionately by firing and by reducing the wage bill. Here I provide further evidence.

In this section, I analyze samples according to country financial development levels, which may affect an industry's ability to raise external finance as discussed above. I add a country dummy variable in the basic regression to check the disproportionate effects in high- or low-financial development groups [13]:

[13] I also run the regressions for two sub-groups separately and the results are close to the regression using dummy variable.

$$\begin{aligned}\text{Growth}_{c,i,t} = {} & \beta_1 \text{Share}_{c,i,t-1} + \beta_2 \text{Recession}_{c,t} + \beta_3(\text{Recession}_{c,t} * X_i) \\ & + \beta_4(\text{Recession}_{c,t} * X_i * I_c) + \beta_5(\text{Recession}_{c,t} * I_c) \\ & + \beta_6 \text{Dummy} + \varepsilon_{c,i,t}\end{aligned}$$

where I_c is the country dummy variable, which takes the value of 1 if sample is in the high value group, or 0 if in the low value group. Therefore, the country-industry-year effect in the variation in growth rates for the low value group is β_3, and $\beta_3 + \beta_4$ for the high value group. In this subsection, I only report β_3, and $\beta_3 + \beta_4$ results and focus on production index growth regression only.

I separate the data into groups depending on whether, by a given criterion, they fall into the category "high" or "low". For example, if my criterion is financial development, I separate countries into groups with financial development that is high or low.

First, I investigate whether financial development would ameliorate the negative effects of recessions on industry growth. Braun and Larrain (2005) and Raddatz (2003) show that the volatility of growth is dampened with higher financial development or in industries with higher asset tangibility. For the top 50 countries, the dummy variable is equal to 1; for the bottom 50 countries, the dummy variable is 0. Table 3.9 shows that in countries with a low private debt to GDP ratio, all interactions of the recession dummy and industry measures are significant, indicating that those industries lose more if they are located in a financially under-developed country. For industries with high depreciation rate and labor intensity, they are disproportionately affected in both low and high credit countries. When I split countries according to the accounting standards measure, industries that experience high depreciation and rely on relationship-specific investment suffer more in recessions in a shallower financial system. Labor intensive industries experience disproportionate losses in countries with different accounting standard levels. My results are largely consistent with Braun and Larrain (2005) and Raddatz (2003), indicating that financial development especially benefit industries that are constrained in external funding in hard times.

3.5 Robustness

Fisman and Love (2004) argue that short-run industry growth is determined by potential growth opportunities, instead of inherent industry characteristics. To control for short-run industry-specific growth opportunities, I add an interaction term of financial development and U.S. growth opportunity as defined in Fisman and Love (2004) in my benchmark regression equation (3.7):

$$\begin{aligned} Growth_{c,i,t} = \beta_1 Share_{c,i,t-1} + \beta_2 Recession_{c,t} + \beta_3 (Recession_{c,t} * X_i) + \\ \beta_4 CRED_c * \text{US}Growth_{i,t} + \beta_5 Dummy_{i,c,t} + \epsilon_{c,i,t} \end{aligned} \tag{3.9}$$

$CRED_c$ is country specific indicator of financial development, and $\text{USGrowth}_{i,t}$ is industry growth rate in time t for industry i in the U.S.

Table (3.10) presents the results controlling for U.S. short-term growth opportunities. We can see that even after controlling for growth opportunities and the financial development interaction term, my industry characteristics interaction terms are still significant for external finance dependence, the industry rate of depreciation, embodied technical change, labor intensity, investment lumpiness and relationship-specificity. My results show that financial development does have disproportionate impacts on industry performance due to some industry inherent characteristics during recessions, even though financial development also affects industry growth rates through growth opportunities.

Since credit crunches reflect periods of severe financial stress, which may or may not be subsets of economic recessions, I ask whether recessions and bank credit crises interact differently with industry characteristics (see table 3.11). The bank crisis dummy is equal to 1 if the country is in a bank credit crunch period, and 0 if otherwise. Then, I include the interaction terms of a credit crisis with industry variables in the recession regressions (equation (3.7)). The results show that after controlling for the bank crisis effect, the coefficients of the interactions of a recession dummy with industry variables are still significant and consistent with my previous results, while the bank crisis interaction coefficients are only significant for the industry rate of depreciation, labor intensity and relationship-specificity. Banking crises may not necessarily coincide with recession periods. In fact, out of my 23,370 recession identifications, only 8,699 coincide with banking crises. This suggests that the results have to do with recessions specifically, whereas bank credit crunches on their own only appear to disproportionately affect a few types of industry (or maybe they hit everyone hard).

Some studies use value added growth as a measure of industry growth. The model in Section 3.2 suggests a value added growth difference-in-difference regression equation similar to equation (3.6) (see Appendix for proofs). Table 3.12 shows that industries that are highly dependent on external finance (EFD), labor (LAB) or relationship-specific investment (RS), and that experience high depreciation rates (DEP) or investment lumpiness are disproportionately affected in the production index growth rate. Similar to my basic results, R&D intensity, human capital intensity and fixity of assets industries do not interact with recessions. Thus, the results are robust to measuring industry growth using the growth in the industrial production index or using value added growth.

3.6 Conclusion

There exists a large body of literature on the link between finance and growth or the business cycle. However, no systematic effort has been made to identify the real factors that lie behind financial difficulty in recessions. I find that growth in industries that are highly dependent on external finance, labor or relationship-specific investments, and which experience high depreciation rates, embodied technical change and lumpiness in investment, is disproportionately reduced in recessions. My findings are consistent with the industry characteristics that Hart and Moore (1994) suggest as mattering for credit constraints, who claim that more durable, fix, tangible and nonspecific assets are better for raising debt because they provide higher liquidation value and more security to creditors.

Among all industries, labor intensive industries are hit hardest in recessions. Also, other industries that suffer from financing constraints shrink in recessions by disproportionately shedding labor rather than lowering investment or losing productivity, underlying the financial channel behind the results. Furthermore, when I group samples according to country financial development, the growth rates of industries which are identified to have less ability to raise external finance or higher need for external funds decline more if they are located in less-developed financial system. The results are robust to controlling for potential growth opportunities, and to adding a banking crisis interaction.

The paper indicates that financial development could ease recessions particularly in certain industries. Thus, policies that are aimed to promote national financial development and/or provide the vulnerable industries better access to finance in recessions could potentially ease losses in growth and employment in the presence of bad shocks. This interesting possibility is left for future research.

Table 3.1: Country Coverage and Number of Observations

Country	No. of observations	Country	No. of observations
Albania	23	Kenya	873
Algeria	502	Korea, Rep.	977
Argentina	377	Kyrgyz Republic	19
Australia	756	Latvia	295
Austria	876	Lithuania	158
Azerbaijan	54	Luxembourg	372
Bahamas, The	93	Macao SAR, China	329
Bangladesh	190	Macedonia, FYR	81
Barbados	387	Madagascar	434
Belgium	809	Malawi	271
Belize	45	Malaysia	892
Benin	24	Malta	802
Bolivia	795	Mauritius	550
Botswana	125	Mexico	673
Brazil	80	Mongolia	45
Bulgaria	260	Morocco	533
Burkina Faso	299	Myanmar	135
Burundi	215	Nepal	114
Cameroon	546	Netherlands	661
Canada	916	New Zealand	649
Cape Verde	25	Niger	71
Central African Republic	112	Nigeria	452
China	439	Norway	846
Colombia	892	Oman	150
Costa Rica	906	Pakistan	616
Cote d'Ivoire	427	Panama	695
Croatia	80	Papua New Guinea	345
Cyprus	788	Paraguay	312
Czech Republic	72	Peru	629
Denmark	639	Philippines	784
Dominican Republic	419	Poland	353
Ecuador	994	Portugal	959
Egypt, Arab Rep.	798	Qatar	115
El Salvador	545	Romania	253
Estonia	132	Russian Federation	324
Ethiopia	299	Rwanda	50
Fiji	410	Senegal	411
Finland	924	Seychelles	68
France	949	Singapore	938
Gabon	261	Slovak Republic	195
Gambia, The	70	Slovenia	235
Georgia	49	South Africa	654
Germany	176	Spain	981
Ghana	520	Sri Lanka	626
Greece	788	Sudan	54
Guatemala	476	Swaziland	190
Haiti	39	Sweden	893
Honduras	527	Switzerland	143
Hong Kong SAR, China	541	Syrian Arab Republic	422
Hungary	805	Tanzania	157
Iceland	635	Thailand	210
India	924	Togo	100
Indonesia	863	Trinidad and Tobago	668
Iran, Islamic Rep.	950	Tunisia	306

Table 3.2: Industry Technological Measures

Industry	ISIC	EFD	DEP	ETC	RND	HC	LAB	FIX	LMP	RS
Food products	311	-0.039	7.09	3.948	0.073	1.78	0.281	0.373	1.195	0.331
Beverages	313	-0.048	7.09	3.975	0.039	2.378	0.248	0.372	1.29	0.713
Tobacco	314	-0.801	5.248	3.975	0.222	2.648	0.117	0.189	0.815	0.317
Textiles	321	0.029	7.665	3.914	0.144	1.463	0.458	0.345	1.232	0.376
Apparel	322	0.075	6.437	4.369	0.02	1.084	0.447	0.134	1.998	0.745
Leather	323	-0.959	9.266	4.008	0.198	1.439	0.444	0.135	1.927	0.571
Footwear	324	-0.45	8.325	4.056	0.153	1.156	0.446	0.16	2.239	0.650
Wood products	331	0.052	9.525	3.926	0.032	1.624	0.467	0.305	1.72	0.516
Furniture, except metal	332	0.015	8.312	4.045	0.155	1.555	0.488	0.28	1.381	0.568
Paper and products	341	-0.062	8.632	3.25	0.083	2.406	0.363	0.472	0.902	0.348
Printing and publishing	342	-0.222	9.745	4.41	0.1	1.969	0.407	0.261	1.67	0.713
Industrial chemicals	351	0.028	9.646	4.595	0.269	2.921	0.241	0.381	1.34	0.240
Other chemicals	352	1.654	6.888	4.683	1.951	2.568	0.218	0.207	2.13	0.490
Petroleum refineries	353	-0.055	6.776	3.923	0.057	3.45	0.173	0.591	0.763	0.058
Misc. pet. and coal products	354	-0.059	6.776	3.996	0.186	2.395	0.3	0.372	1.042	0.395
Rubber products	355	-0.064	10.072	3.144	0.187	2.139	0.423	0.322	1.098	0.407
Plastic products	356	0.088	10.072	3.204	0.171	1.808	0.402	0.374	1.557	0.408
Pottery, china, earthenware	361	-0.107	8.234	4.603	0.503	1.733	0.475	0.4	1.292	0.329
Glass and products	362	0.289	7.554	4.379	0.115	2.189	0.399	0.4	1.755	0.557
Other non-metallic mineral prod.	369	0.021	8.234	4.754	0.095	2.072	0.385	0.48	0.99	0.377
Iron and steel	371	-0.004	6.578	3.442	0.066	2.691	0.477	0.427	0.951	0.242
Non-ferrous metals	372	0.037	5.393	3.431	0.101	2.373	0.424	0.364	1.245	0.160
Fabricated metal products	381	-0.052	7.043	3.421	0.147	2.025	0.455	0.274	1.365	0.435
Machinery, except electrical	382	0.542	8.832	5.149	0.933	2.389	0.433	0.195	2.694	0.764
Machinery, electric	383	0.543	9.381	4.313	0.814	2.268	0.407	0.208	2.704	0.740
Transport equipment	384	0.041	10.559	3.847	0.316	2.815	0.44	0.264	1.614	0.859
Prof. & sci. equip.	385	0.942	9.21	4.456	1.194	2.55	0.382	0.181	2.79	0.785
Other manufactured prod.	390	0.404	10.07	2.996	0.302	1.64	0.414	0.186	2.006	0.547

Table 3.3: Correlation Matrix of Major Variables

	EFD	DEP	ETC	RND	HC	LAB	FIX	LMP	RS
EFD	1								
DEP	0.0855	1							
ETC	0.2838	-0.0433	1						
RND	0.7896*	0.0868	0.4605*	1					
HC	0.2391	-0.148	0.0662	0.2394	1				
LAB	-0.0484	0.3895*	-0.138	-0.1732	-0.6013*	1			
FIX	-0.0895	-0.1805	-0.1689	-0.3895*	0.4503*	-0.2217	1		
LMP	0.4980*	0.3931*	0.4077*	0.6058*	-0.2589	0.3065	-0.7232*	1	
RS	0.2303	0.4433*	0.3204	0.2933	-0.3129	0.3436	-0.6875*	0.7524*	1

* significance level 5%

Note: EFD (external finance dependence), DEP (depreciation), ETC (Embodied technical change), RND (R&D intensity), HC (human capital intensity), LAB (labor intensity), FIX (fixity), LMP (investment lumpiness) are the average of 70s, 80s and 90s from Ilyina and Samaniego (2011); RS (relationship-specific investment) is taken from Nunn (2007).

Table 3.4: Production Index Growth Regression

This table represents results from the following regression:

$$\text{Growth}_{c,i,t} = \beta_1 \text{Share}_{c,i,t-1} + \beta_2 \text{Recession}_{c,t} + \beta_3 (\text{Recession}_{c,t} * X_i) + \beta_4 \text{Dummy} + \varepsilon_{c,i,t}$$

Coefficients of constant variables are not reported. The dependent variable is production index growth rate. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Variables	Production Index Growth regression									change in growth rate for 75th percentile industry index	change in growth rate for 25th percentile industry index	implied differential effect
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)			
share(t-1)	-0.252***	-0.253***	-0.252***	-0.252***	-0.252***	-0.252***	-0.252***	-0.252***	-0.252***			
	(0.0370)	(0.0370)	(0.0370)	(0.0370)	(0.0370)	(0.0370)	(0.0370)	(0.0370)	(0.0370)			
recession	-0.0343***	-0.00387	-0.0116	-0.0340***	-0.0296***	-0.00495	-0.0306***	-0.0254***	-0.0241***			
	(0.00179)	(0.0103)	(0.0137)	(0.00218)	(0.00712)	(0.00696)	(0.00519)	(0.00529)	(0.00471)			
EFD*recession	-0.00848**									-3.50%	-3.40%	-0.10%
	(0.00375)											
DEP*recession		-0.00379***								-3.9%	-3.00%	-0.90%
		(0.00124)										
ETC*recession			-0.00580*							-3.70%	-3.20%	-0.50%
			(0.00338)									
RND*recession				-0.00279								
				(0.00415)								
HC*recession					-0.00248							
					(0.00326)							
LAB*recession						-0.0794***				-4%	-3.40%	-0.60%
						(0.0179)						
FIX*recession							-0.0137					
							(0.0158)					
LMP*recession								-0.00608*		-3.70%	-3.20%	-0.50%
								(0.00321)				
RS*recession									-0.022**	-3.80%	-3.10%	-0.70%
									(0.00891)			
Observations	43,489											

Table 3.5: Employment Growth Regression

This table represents results from the following regression:

$$\text{Growth}_{c,i,t} = \beta_1 \text{Share}_{c,i,t-1} + \beta_2 \text{Recession}_{c,t} + \beta_3 (\text{Recession}_{c,t} * X_i) + \beta_4 \text{Dummy} + \varepsilon_{c,i,t}$$

Coefficients of constant variables are not reported. The dependent variable is industry employment growth rate. EFD (external finance dependence), DEP (depreciation), ETC (Embodied technical change), LAB (labor intensity), and LMP (investment lumpiness) are the average of 70s, 80s and 90s from Ilyina and Samaniego (2011); RS (relationship-specific investment) is taken from Nunn (2007). Share is the share of industry value added out of the manufacturing industry. I identify a recession using a peak-to-trough criterion. The dummy variable recession is equal to 1 if the year is in recession periods, and 0 if otherwise. Dummy variables include country, industry, year, country-industry and industry-year dummies.

Variables	employment growth rate regression					
share(t-1)	-0.685***	-0.685***	-0.684***	-0.683***	-0.685***	-0.685***
	(0.0515)	(0.0515)	(0.0515)	(0.0515)	(0.0515)	(0.0515)
recession	-0.0214***	0.00958	0.0106	0.0127	-0.00620	-0.0142**
	(0.00268)	(0.0154)	(0.0202)	(0.0108)	(0.00796)	(0.00711)
EFD*recession	-0.0132**					
	(0.00567)					
DEP*recession		-0.00387**				
		(0.00185)				
ETC*recession			-0.00821*			
			(0.00499)			
LAB*recession				-0.0918***		
				(0.0274)		
LMP*recession					-0.0102**	
					(0.00478)	
RS*recession						-0.0162
						(0.0134)
Observations	50,506					

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Establishment Growth Regression

This table represents results from the following regression:

$$\text{Growth}_{c,i,t} = \beta_1 \text{Share}_{c,i,t-1} + \beta_2 \text{Recession}_{c,t} + \beta_3 (\text{Recession}_{c,t} * X_i) + \beta_4 \text{Dummy} + \varepsilon_{c,i,t}$$

Coefficients of constant variables are not reported. The dependent variable is industry number of establishment growth rate. EFD (external finance dependence), DEP (depreciation), ETC (Embodied technical change), LAB (labor intensity), and LMP (investment lumpiness) are the average of 70s, 80s and 90s from Ilyina and Samaniego (2011); RS (relationship-specific investment) is taken from Nunn (2007). Share is the share of industry value added out of the manufacturing industry. I identify a recession using a peak-to-trough criterion. The dummy variable recession is equal to 1 if the year is in recession periods, and 0 if otherwise. Dummy variables include country, industry, year, country-industry and industry-year dummies.

Variables	establishment growth regression					
share(t-1)	-0.312***	-0.314***	-0.311***	-0.309***	-0.311***	-1.636***
	(0.0984)	(0.0984)	-0.0984	(0.0984)	(0.0984)	(0.0693)
recession	-0.00648	0.0823***	-0.00307	0.0478**	0.0279*	-0.0223**
	(0.00549)	(0.0318)	(0.0411)	(0.0225)	(0.0164)	(0.00930)
EFD*recession	-0.0213*					
	(0.0118)					
DEP*recession		-0.0109***				
		(0.00380)				
ETC*recession			-0.00118			
			(0.0102)			
LAB*recession				-0.145**		
				(0.0570)		
LMP*recession					-0.0227**	
					(0.00983)	
RS*recession						-0.0416**
						(0.0175)
Observations	28,612					

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Wages and Salaries growth regression

This table represents results from the following regression:

$$\text{Growth}_{c,i,t} = \beta_1 \text{Share}_{c,i,t-1} + \beta_2 \text{Recession}_{c,t} + \beta_3 (\text{Recession}_{c,t} * X_i) + \beta_4 \text{Dummy} + \varepsilon_{c,i,t}$$

Coefficients of constant variables are not reported. The dependent variable is industry wage and salaries growth rate. EFD (external finance dependence), DEP (depreciation), ETC (Embodied technical change), LAB (labor intensity), and LMP (investment lumpiness) are the average of 70s, 80s and 90s from Ilyina and Samaniego (2011); RS (relationship-specific investment) is taken from Nunn (2007). Share is the share of industry value added out of the manufacturing industry. I identify a recession using a peak-to-trough criterion.. The dummy variable recession is equal to 1 if the year is in recession periods, and 0 if otherwise. Dummy variables include country, industry, year, country-industry and industry-year dummies.

Variables	wage growth rate regression					
share(t-1)	-0.755***	-0.755***	-0.755***	-0.753***	-0.755***	-0.755***
	(0.0641)	(0.0641)	(0.0641)	(0.0641)	(0.0641)	(0.0641)
recession	-0.0377***	0.000110	-0.0159	0.00287	-0.0239**	-0.0276***
	(0.00328)	(0.0189)	(0.0247)	(0.0132)	(0.00976)	(0.00870)
EFD*recession	-0.00672					
	(0.00696)					
DEP*recession		-0.00465**				
		(0.00226)				
ETC*recession			-0.00556			
			(0.00611)			
LAB*recession				-0.108***		
				(0.0336)		
LMP*recession					-0.00907	
					(0.00587)	
RS*recession						-0.0214
						(0.0164)
Observations	49,297					

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Horse Race Regression

This table represents results from the following regression:

$$\text{Growth}_{c,i,t}=\beta_1\text{Share}_{c,i,t-1}+\beta_2\text{Recession}_{c,t}+\beta_{31}\left(\text{Recession}_{c,t}*\widehat{\text{EFD}}_i\right)+\beta_{32}\left(\text{Recession}_{c,t}*\widehat{\text{DEP}}_i\right)+\beta_{33}\left(\text{Recession}_{c,t}*\widehat{\text{ETC}}_i\right)+\beta_{34}\left(\text{Recession}_{c,t}*\widehat{\text{LAB}}_i\right)+\beta_{35}\left(\text{Recession}_{c,t}*\widehat{\text{LMP}}_i\right)+\beta_{36}\left(\text{Recession}_{c,t}*\widehat{\text{RS}}_i\right)+\beta_4\text{Dummy}+\varepsilon_{c,i,t}$$

Coefficients of constant variables are not reported. The dependent variable is industry production index growth rate. EFD (external finance dependence), DEP (depreciation), ETC (Embodied technical change), LAB (labor intensity), and LMP (investment lumpiness) are the average of 70s, 80s and 90s from Ilyina and Samaniego (2011); RS (relationship-specific investment) is taken from Nunn (2007). $\widehat{\text{X}}_i$ is orthogonalized X_i. Share is the share of industry value added out of the manufacturing industry. I identify a recession using a peak-to-trough criterion. The dummy variable recession is equal to 1 if the year is in recession periods, and 0 if otherwise. Dummy variables include country, industry, year, country-industry and industry-year dummies.

Variable	Output Index growth regression
share(t-1)	-0.253***
	(0.0370)
recession	-0.0325***
	(0.00513)
$\widehat{EFD}$*recession	-0.00413**
	(0.00182)
$\widehat{DEP}$*recession	-0.00186
	(0.00177)
$\widehat{ETC}$*recession	-0.00427**
	(0.00177)
$\widehat{LAB}$*recession	-0.00735***
	(0.00186)
$\widehat{LMP}$*recession	0.00330*
	(0.00177)
$\widehat{RS}$*recession	-0.00493
	(0.00979)
Observations	43,489

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.9: Interaction of country/industry characteristics

Each cell in this table represents results from the following regression:

$$\text{Growth}_{c,i,t} = \beta_1\text{Share}_{c,i,t-1} + \beta_2\text{Recession}_{c,t} + \beta_3(\text{Recession}_{c,t}{*}X_i) + \beta_4(\text{Recession}_{c,t}{*}X_i{*}I_c) + \beta_5(\text{Recession}_{c,t}{*}I_c) + \beta_6\text{Dummy}+\varepsilon$$

where I_c is dummy indicator of country/industry characteristics. The coefficients for the low subsample is β_3, for high subsample $\beta_3+\beta_4$. This table only reports β_3 and $\beta_3+\beta_4$. Other coefficients are not reported here. The high/low subsample cells for each interaction term represent one regression. The dependent variable is industry production index growth rate.

	countries w/ low private credit to GDP ratio	countries w/ high private credit to GDP ratio	countries w/ low accunting standard	countries w/ high accounting standard
EFD*recession	-0.0223***	-0.00261	-0.00991	-0.00328
	(0.00685)	0.00447	(0.00663)	(0.00506)
DEP*recession	-0.00511**	-0.00323**	-0.00413*	-0.00167
	(0.00228)	0.00147	(0.00218)	(0.00164)
ETC*recession	-0.0132**	-0.00274	-0.00453	-0.00464
	(0.00627)	0.00401	(0.00596)	(0.00447)
LAB*recession	-0.0582*	-0.0892***	-0.0664**	-0.0985***
	(0.0322)	0.0215	(0.0323)	(0.0244)
LMP*recession	-0.0212***	-7.31e-05	-0.00557	0.00183
	(0.00600)	0.00379	(0.00561)	(0.00422)
RS*recession	-0.0575***	-0.00736	-0.0360**	0.00212
	(0.0165)	0.0106	(0.0157)	(0.0117)

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.10: Account for Growth Opportunity

This table represents results from the following regression:

$$\begin{aligned}\text{Growth}_{c,i,t} &= \beta_1\text{Share}_{c,i,t-1}+\beta_2\text{Recession}_{c,t}+\beta_3(\text{Recession}_{c,t}*X_i)\\ &+\beta_4\text{CRED}_c\text{*USGrowth}_{i,t}+\beta_5\text{Dummy}+\varepsilon_{c,i,t}\end{aligned}$$

Coefficients of constant variables are not reported. The dependent variable is industry production index growth rate. USGrowth is computed as the median growth rate of real sales of firms in the U.S. from 1970 to 2005, using COMPUSTAT. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

	Production index growth index								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
share(t-1)	-0.227***	-0.228***	-0.227***	-0.227***	-0.227***	-0.227***	-0.227***	-0.227***	-0.227***
	(0.0443)	(0.0442)	(0.0442)	(0.0443)	(0.0443)	(0.0444)	(0.0443)	(0.0443)	(0.0443)
recession	-0.0354***	-0.000720	-0.0100	-0.0350***	-0.0336***	-0.00565	-0.0349***	-0.0242***	-0.0218***
	(0.00180)	(0.00977)	(0.0140)	(0.00203)	(0.00746)	(0.00543)	(0.00567)	(0.00540)	(0.00469)
CRED*USGrowth	0.000140***	0.000140***	0.000140***	0.000140***	0.000140***	0.000136***	0.000140***	0.000140***	0.000141***
	(3.57e-05)	(3.61e-05)	(3.61e-05)	(3.58e-05)	(3.58e-05)	(3.55e-05)	(3.58e-05)	(3.59e-05)	(3.62e-05)
EFD*recession	-0.00695*								
	(0.00377)								
DEP*recession		-0.00429***							
		(0.00123)							
ETC*recession			-0.00642*						
			(0.00349)						
RND*recession				-0.00273					
				(0.00395)					
HC*recession					-0.00106				
					(0.00344)				
LAB*recession						-0.0801***			
						(0.0153)			
FIX*recession							-0.00282		
							(0.0163)		
LMP*recession								-0.00748**	
								(0.00360)	
RS*recession									-0.0287***
									(0.00987)
Observations	47,455								

Table 3.11: Account for Credit Crunch

This table represents results from the following regression:

$$\text{Growth}_{c,i,t} = \beta_1 \text{Share}_{c,i,t-1} + \beta_2 \text{Recession}_{c,t} + \beta_3 (\text{Recession}_{c,t} * \text{X}_i) + \beta_4 \text{Crisis}_{c,t} + \beta_5 (\text{Crisis}_{c,t} * \text{X}_i) + \beta_6 \text{Dummy} + \varepsilon_{c,i,t}$$

Coefficients of constant variables are not reported. The dependent variable is industry production index growth rate. Crisis dummy is computed in the same way as Recession, using bank credit over GDP time series. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Variables	Production index growth regression					
share(t-1)	-0.295***	-0.295***	-0.294***	-0.295***	-0.294***	-0.292***
	(0.0488)	(0.0488)	(0.0488)	(0.0488)	(0.0488)	(0.0488)
recession	-0.0348***	-0.00849	-0.00583	-0.00352	-0.0240***	-0.0212***
	(0.00230)	(0.0131)	(0.0176)	(0.00887)	(0.00679)	(0.00604)
crisis	-0.000618	0.0272**	0.0214	0.0168*	0.00617	0.0147**
	-0.00239	(0.0137)	(0.0182)	(0.00925)	(0.00707)	(0.00626)
EFD*recession	-0.0113**					
	(0.00483)					
EFD*crisis	-0.00435					
	(0.00507)					
DEP*recession		-0.00330**				
		(0.00158)				
DEP*crisis		-0.00342**				
		(0.00165)				
ETC*recession			-0.00738*			
			(0.00435)			
ETC*crisis			-0.00554			
			(0.00450)			
LAB*recession				-0.0850***		
				(0.0228)		
LAB*crisis				-0.0470**		
				(0.0238)		
LMP*recession					-0.00739*	
					(0.00413)	
LMP*crisis					-0.00456	
					(0.00430)	
RS*recession						-0.0291**
						(0.0115)
RS*crisis						-0.0318***
						(0.0119)

Table 3.12: Value Added Growth Regression

This table represents results from the following regression:

$$\text{Growth}_{c,i,t} = \beta_1 \text{Share}_{c,i,t-1} + \beta_2 \text{Recession}_{c,t} + \beta_3 (\text{Recession}_{c,t} * X_i) + \beta_4 \text{Dummy} + \varepsilon_{c,i,t}$$

Coefficients of constant variables are not reported. The dependent variable is industry value added growth rate.

Variables	Value added growth regression								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
share(t-1)	-3.049***	-3.048***	-3.047***	-3.047***	-3.048***	-3.048***	-3.048***	-3.049***	-3.049***
	(0.0795)	(0.0795)	(0.0795)	(0.0795)	(0.0795)	(0.0795)	(0.0795)	(0.0795)	(0.0795)
recession	- 0.0403***	0.00863	-0.000488	- 0.0383***	- 0.0441***	0.0163	- 0.0499***	-0.0120	-0.0168
	(0.00400)	(0.0231)	(0.0301)	(0.00489)	(0.0159)	(0.0160)	(0.0116)	(0.0119)	(0.0106)
EFD*recession	-0.0187**								
	(0.00842)								
DEP*recession		- 0.00610**							
		(0.00276)							
ETC*recession			-0.0103						
			(0.00745)						
RND*recession				-0.0106					
				(0.00939)					
HC*recession					0.00122				
					(0.00731)				
LAB*recession						-0.152***			
						(0.0409)			
FIX*recession							0.0274		
							(0.0355)		
LMP*recession								- 0.0188***	
								(0.00716)	
RS*recession									-0.0503**
									(0.0200)
Observations	52,023								

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Chapter 4

Structural change and financial institutions

4.1 Introduction

This paper revisits the issue whether the introduction of the European Economic and Monetary Union (EMU) and the euro has had any impact on bank competition in the euro area, the U.S. and the U.K. In addition, I evaluate the degree of bank competition before and after the financial crisis and study the impact of bank competition on growth and employment.

Bank competition has been studied extensively over the past years. Theory suggests that increased competition in the financial sector could lower transaction costs, improve the efficiency of financial intermediation and the quality of financial services, promote innovation and, more importantly, increase access to finance by nonfinancial sectors and households. However fierce competition may undermine financial stability if banks take excessive risk and invest too little in information collection and establishing long-term relationships with their customers (Claessens, 2009). Decressin and Kudela (2007) compare the efficiency and competition among EU and U.S. banks, and find that small European banks tend to be less efficient and competitive than their U.S. counterparts. Shaffer (2001) compares banking sectors across a number of industrialized countries and shows that markets for banking services are either contestable or resemble a Cournot oligopoly in most countries. Bikker and Spierdijk (2008) study development in bank competition worldwide over time and find that the euro area faced a significant decline in bank competition in recent years, while emerging markets became more competitive. They attribute the decline in competition to increases in concentration, bank size and off-balance sheet activities. Claessens and Laeven (henceforth CL, 2004, 2005,) further investigate the factors that drive bank competition and its impact on economic growth. Their findings suggest that bank competition is strongly correlated with foreign entry, and that fewer entry and activity restrictions and that a competitive financial sector especially benefits sectors or industries that are highly dependent on external financing (see, Rajan and Zingales, 1998).

There are several approaches to measuring bank competition, including financial market concentration, the number of banks per capita, and the size of banks' net interest margins. This paper uses the H-statistic, developed by Panzar and Rosse (1987, henceforth PR) which has been widely used to measure competition in the banking system by investigating the relationship between a bank's costs and its revenues. H-statistics are estimated for all euro area countries, a euro area aggregate, the U.K. and the U.S. over the period 1995–2009. For countries where sufficient data are available, this paper analyzes the evolution of the competition environment over time, and compares the differences between groups of banks distinguished by size, business model and ownership.

The estimation results suggest that the euro area experienced a decline in bank competition after EMU; however competition levels in euro countries seem to have converged in the wake of EMU. Following the global financial crisis, bank competition declined further in several euro-area countries, especially where large credit and housing booms took place (including the U.S. and Spain).

Across countries, there is no strong pattern suggesting that large or small banks compete harder. In most countries, commercial banks and foreign banks compete somewhat more intensively than savings banks and domestic banks before EMU. However, the differences in the competition levels of different bank types and ownership are not significant after EMU.

Since bank competition has significant growth implications by promoting access to finance, this paper further investigates the relationship between bank competition and growth in the euro countries. By looking into the value added growth rates of manufacturing industries before and after EMU, I find that better bank competition encourages growth by disproportionately benefiting industries that are more dependent on external finance. I also explore the channels through which bank competition promotes growth by investigating a set of industry performance indicators. My findings suggest that higher bank competition allows industries to grow faster by investing more in labor, rather than in capital or productivity improvement. These results are consistent with the theory of Hart and Moore

(1994). Due to the inalienability and intangibility of human capital, labor cannot be used as collateral to provide security to creditors. My results therefore provide new evidence that bank competition helps to ameliorate the financial frictions which are caused by the inalienability and intangibility of human capital. This paper also suggests that the decline in bank competition in the euro area after the financial crisis has discouraged employment growth.

This paper is organized in the following manner. Section 4.1 provides a review of measures of bank competition, the factors that drive competition and its effects. Section 4.2 discusses the empirical model and methodology to estimate the competition indicator. Section 4.3 presents the data and empirical results. Section 4.4 concludes.

4.1.1 Bank Competition: Measurement

Traditional performance measures and market structure indicators of the financial sector- for example, the net interest margin to total assets ratio, the Lerner index, net income to total assets ratio, the concentration index and the number of institutions per million people- do not necessarily measure competition accurately and often send conflicting signals. Carbo et al (2009) compare the rankings of existing competition indicators for a number of European countries, and find that these indicators give conflicting results because they measure different aspects of bank activities. The net interest margin is most appropriate for analyzing traditional banking loan and deposit services, while the return on assets and the

Lerner index are appropriate for both traditional financial services and off-balance sheet activities. Moreover, these indicators are also influenced by the country-specific macroeconomic environment, rule of law, and taxation system as well as bank specific characteristics such as leverage and risk preferences (Claessens, 2009).

Another approach to measuring the degree of competition is to study the actual behavior of banks based on empirical industrial organization models. Based on this approach, the PR methodology provides a reduced form model to measure the change of marginal revenue in response to changes in factor prices which has been widely adopted in various empirical studies. CL and Bikker and Spierdijk (2008) apply this method to a large sample of countries, finding evidence of monopolistic bank competition with varying degrees fo market power across countries.

4.1.2 Determinants of Competition

One popular indicator used in empirical research is market structure, mainly defined as the degree of concentration in the market. Low concentration tends to promote competition. However, market structure could be endogenous since firms' behavior affects market structure. CL find that the degree of contestability determines effective competition by removing bank entry and exit barriers. Under the assumption of no entry and exit barriers, the existence of abnormal profit opportunities will attract new entrants until firms lower prices and the opportunities are extinguished. So a concentrated market may still be very competitive if banks can easily enter in case of excessive profits. To evaluate the degree of contestability, one needs to look into the entry requirement, the entry barriers for foreign banks and other factors (Claessens, 2009). CL find that greater foreign entry and fewer activity restrictions are important determinants of competition. Nathan and Neave (1989) assess competition in the Canadian banking system and conclude that the potential entry of competitors forces banks to price competitively.

Besides contestability, other factors, such as the development of new technologies, network effects and economies of scale, moral hazard problems, and preferences of risk are also important in determining the degree of bank competition (Bikker and Spierdijk, 2008).

4.1.3 Effects of Competition

Similar to other industries, increased competition in the financial sector could result in lower costs, higher efficiency across banks, better quality of financial services and therefore greater access to finance by nonfinancial firms and households. Better access to finance and lower costs of capital promote growth of other industries, especially those dependent on external finance (Besanko and Thakor (1992), Rajan and Zingales (1998), Ilyina and Samaniego (2011)). Some research investigates the linkage between bank competition and the growth of industries, and shows that financially dependent industries grow faster in countries with strong bank competition (CL, 2005).

However, theory shows that the effects of competition are complex. Advances in technology can promote financial system consolidation, which in turn leads to greater distance between intermediaries and their clients and less lending to small and medium enterprises (Bekaert, Harvey, and Lundblad, 2005). Intensive competition can also undermine the incentives of banks to invest in information collection and long-term relationship lending to avoid costs. Increased competition may also encourage banks to engage in more risky activities and therefore undermine the stability in the financial sector. However, competition is not a necessary condition of fragility. A bank run could happen to a monopolist too and one needs to take into account the macroeconomic environment and the quality of supervision, regulation and legal institutions when evaluating a possible trade-off between stability and competition. Boyd, De Nicolo, and Jalal, (2009)and De Nicolo and Turk Ariss (2010) do not find much evidence for this trade-off.

4.2 The Empirical Model

4.2.1 The Panzar-Rosse Methodology

PR developed a general test for market structure using a reduced form revenue equation, which is regarded as a key method of measuring the degree of competition in the empirical industrial organization literature. Based on the profit-maximization equilibrium condition, the PR methodology evaluates the relation between costs and revenues to determine different market structures: monopoly, monopolistic competition and perfect competition. The sum of the factor price elasticities in the PR model is:

$$\psi \equiv \sum w_i \left(\frac{\partial R}{\partial w_i} \right) / R$$

where R(.) is the revenue function, w_i is the spending on input factor i, so ψ is the sum of the factor price elasticities.

PR show that in a monopoly market, $\psi \leq 0$. Since an increase in costs leads to a cut in output, and since marginal revenue (which is equal to marginal cost) is always positive, an increase in input prices results in a fall in total revenue[1]. With monopolistic competition, $0 < \psi < 1$, because firms raise output prices in response to increase in factor prices, but the rise in the output price and the input price is not one to one, depending on the demand elasticity. The higher the demand elasticity, the lower the market power and the higher the degree of competition. With perfect competition, $\psi = 1$, because in the long run entry and exit will force firms to set output prices to equal the minimum average cost, so output prices change in the same direction and the extent as the factor prices. Then, the relation between the rise in cost and in revenue is one to one.

4.2.2 The Model and H-statistic

PR's empirical model for testing market structure has been widely used to study the banking system. This paper uses the following reduced-form bank revenue equation to test the competition environment in the banking system for each country

[1]PR assume demand elasticity is larger than 1. Samaniego and Sun (2013) and Sun (2013) show this is true among manufacturing industries studied in this paper.

independently:

$$
\begin{aligned}
\ln(P_{it}) \quad = \quad & \alpha_0 + \beta_1 \ln(W_{1,it}) + \beta_2 \ln(W_{2,it}) + \beta_3 \ln(W_{3,it}) \\
& + \gamma_1 \ln(Y_{1,it}) + \gamma_2 \ln(Y_{2,it}) + \gamma_3 \ln(Y_{3,it}) \\
& + T_1 \left[\begin{array}{c} \alpha_1 + \beta_4 \ln(W_{1,it}) + \beta_5 \ln(W_{2,it}) + \beta_6 \ln(W_{3,it}) \\ + \gamma_4 \ln(Y_{1,it}) + \gamma_5 \ln(Y_{2,it}) + \gamma_6 \ln(Y_{3,it}) \end{array} \right] \\
& + T_2 \left[\begin{array}{c} \alpha_2 + \beta_7 \ln(W_{1,it}) + \beta_8 \ln(W_{2,it}) + \beta_9 \ln(W_{3,it}) \\ + \gamma_7 \ln(Y_{1,it}) + \gamma_8 \ln(Y_{2,it}) + \gamma_9 \ln(Y_{3,it}) \end{array} \right] \\
& + \varepsilon_{it}
\end{aligned}
\tag{4.1}
$$

where i is bank i, and t is year t. In order to compare competition levels before and after the EMU and the recent financial crisis, this equation introduces two time dummies: $T_1 = 1$ for the period of EMU (2001-07) ($T_1 = 0$ otherwise) and $T_2 = 1$ for period of the financial crisis (2008-09) ($T_2 = 0$ otherwise)[2]. For sample splits by size, business model and ownership and comparisons pre and post EMU, only time dummy $T1$ is included in the equation. Following CL (2004), P_{it} is the ratio of gross interest income over total assets as a measure for output price of loans. For robustness, this paper also uses the ratio of gross interest income and other operating income over total assets as the dependent variable P_{it} to cover noninterest income. $W_{1,it}$ is calculated as the ratio of total interest expenses to total deposits and money market funding, as a proxy for input price of deposits; $W_{2,it}$ is the ratio of personnel expenses over total assets, as a proxy for labor costs; $W_{3,it}$ is the ratio

[2]Bikker and Groeneveld (2000), De Bandt and Davis (2000) and Bikker (2004) estimate H-statistics recursively over time. A possible complication of such an approach is that H-Statistics are only valid under the assumption that markets are in long-run equilibrium which could be at odds with frequent variations in the level of competition in banking.

of other operating expenses over total assets, as a proxy for input prices of equipment and other fixed capital. $Y_{1,it}$, $Y_{2,it}$, and $Y_{3,it}$ are the ratio of equity over total assets, the ratio of net loans to total assets and the total assets respectively, which are used as control variables for bank-specific effects. Bikker, et al (2008) point out that the scaled revenue function (including total assets as a control variable) can lead to overestimation of the degree of competition in the banking industry. Estimation with an un-scaled revenue function did not change the results qualitatively but significance levels were low. To facilitate comparison with previous studies, only scaled results are reported in this paper.

The H-statistic, defined in PR's model as the sum of factor price elasticities, is:

$$
\begin{aligned}
H &= \beta_1 + \beta_2 + \beta_3 \text{ for pre EMU } (1995 - 2000) \\
H &= \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 \text{ for EMU } (2001 - 07) \\
H &= \beta_1 + \beta_2 + \beta_3 + \beta_7 + \beta_8 + \beta_9 \text{ for the financial crisis } (2008 - 09)
\end{aligned}
$$

The interpretation of the H-statistic is the following: under perfect competition, the total revenue and total cost rise by the same amount when the input prices increase, while under monopoly, the total revenue falls and the marginal cost increases. Therefore, the H-statistic should be: $H < 0$ under monopoly, $H = 1$ under perfect competition, and $0 < H < 1$ under monopolistic competition.

This paper estimates the H-statistic based on the reduced-form bank revenue equation (4.1) using pooled OLS[3] for two models: one is estimated with the

[3] Due to the limited observations for some countries, the fixed effect panel estimation could be

dependent variable of gross interest revenue ratio, and the other one is estimated using gross interest revenue and other revenue ratio as the dependent variable. These two models generate close estimates of H-statistics. The H-statistics used as the indicator of competition of banking system are the average of the H-statistics estimated using these two models.

4.2.3 Equilibrium Test

Since PR's model for perfect competition and monopolistic competition is based on the assumption of long-run equilibrium, I test it, following CL by estimating the equation:

$$\begin{aligned}
\ln(ROA_{it}) = {} & \alpha_0 + \beta_1 \ln(W_{1,it}) + \beta_2 \ln(W_{2,it}) + \beta_3 \ln(W_{3,it}) \\
& + \gamma_1 \ln(Y_{1,it}) + \gamma_2 \ln(Y_{2,it}) + \gamma_3 \ln(Y_{3,it}) \\
& + T_1 \left[\begin{array}{c} \alpha_1 + \beta_4 \ln(W_{1,it}) + \beta_5 \ln(W_{2,it}) + \beta_6 \ln(W_{3,it}) \\ + \gamma_4 \ln(Y_{1,it}) + \gamma_5 \ln(Y_{2,it}) + \gamma_6 \ln(Y_{3,it}) \end{array} \right] \\
& + T_2 \left[\begin{array}{c} \alpha_2 + \beta_7 \ln(W_{1,it}) + \beta_8 \ln(W_{2,it}) + \beta_9 \ln(W_{3,it}) \\ + \gamma_7 \ln(Y_{1,it}) + \gamma_8 \ln(Y_{2,it}) + \gamma_9 \ln(Y_{3,it}) \end{array} \right] \\
& + \varepsilon_{it}
\end{aligned} \tag{4.2}$$

where ROA is the ratio of pre-tax profits to total assets, as the proxy for returns on bank assets. To avoid negative values of returns on assets, the independent variable is calculated as $\ln(1 + ROA_{it})$. In equilibrium, input prices should not affect returns on total assets. Thus this paper tests whether the E-statistics=0 using F-test:

inefficient (the average number of observations for each bank is very low, e.g. in some cases less than 2, especially when the full sample is split into sub-samples. And the Hausman test rejects fixed effects in these cases.). To be consistent in the full sample and sub-sample analysis, OLS is preferred.

$$
\begin{aligned}
E &= \beta_1 + \beta_2 + \beta_3 \text{ for pre EMU } (1995 - 2000) \\
E &= \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 \text{ for EMU } (2001 - 07) \\
E &= \beta_1 + \beta_2 + \beta_3 + \beta_7 + \beta_8 + \beta_9 \text{ for the financial crisis } (2008 - 09)
\end{aligned}
$$

If the F-test can not reject the null $E = 0$, then the market is in long run equilibrium. The tests suggest that for most countries this condition is not violated.[4]

4.2.4 Growth Equation

Bank competition has been found to have a significant growth effect through better access to finance and lower financing costs faced by households and non-financial sectors. CL (2005) investigates the effect of bank competition on industrial growth for over forty countries using an interaction term between the H-statistic and the external finance dependence index. Rajan and Zingales (1998, hereafter RZ) define external finance dependence (EFD) as the share of capital expenditure which is not from cash flow from operations. EFD measures financial constraint at firm level and has been identified as an important channel between finance and growth and business cycles. RZ assume that some industries are more dependent on external finance than others for technological reasons such as the initial project scale, gestation period, cash harvest period and the requirement for continuing investment. They use USA manufacturing industry data among publicly traded firms as a global benchmark to calculate EFD because it represents the real

[4]Equilibrium test results are not reported, but are available upon request.

industry technological characteristics in a financially frictionless economy. Technological differences among industries are assumed to be persistent across countries, meaning that the rankings of these indices are stable across countries. RZ apply an interaction term of country financial development and EFD to investigate the marginal effect of financial development on the growth of industries that highly depend on external finance. They find that the sign of the coefficient of the interaction term is positive, indicating that financial development particularly benefits sectors or industries that are highly dependent on external financing. CL (2005) applies RZ's approach to determine the effects of bank competition on growth. I use CL's growth regression equation:

$$\begin{aligned}\text{Growth}_{ic} &= \text{constant} + \theta_1 \text{Dummy} + \theta_2 \text{share}_{ic} + \theta_3 \text{EFD}_i \times \text{Financial Development}_c \\ &\quad + \theta_4 \text{EFD}_i \times \text{Bank Competition}_c + \varepsilon_{ic}\end{aligned}$$

where Growth_{ic} is the average value added growth rate of industry i in country c. Dummy variables include country c and industry i dummies to control for country and industry specific effects. Shareic is the share of value added of industry i in total manufacturing industry in country c, to control for the scale effect on growth because larger industries may experience lower growth rate due to the decreasing returns to scale. EFDi is the external finance dependence index using US industry as a benchmark industry measure for all countries. Financial development measure is a country-specific indicator. The bank competition index is the H-statistic estimated using equation (4.1). Then the coefficient θ_4 captures the marginal effect of bank competition on growth through its disproportionate effect on financially dependent industries. CL find that θ_4 is positive, indicating that greater bank competition allows financially dependent industries to grow faster.

4.3 Data and empirical results

4.3.1 Data

The sample includes ten euro area countries. The United Kingdom and the United States are included too so we can compare the euro area results to those of other large econmies that were also affected by the crisis[5]. For the variables in the competition and equilibrium tests, this paper uses bank-level annual data from BANKSCOPE for the years 1995–2009 and focuses on commercial banks, savings banks, and cooperative banks. Other types of financial institutions, including investment banks, real estate/mortgage banks, other nonbanking credit institutions, government banks, securities firms, bank holding companies and so on, are not included in the sample, because their structures and functions are usually different from those of traditional financial intermediation. Data from consolidated accounts are used if available, otherwise unconsolidated accounts are used.

As discussed in the previous section, the dependent variable is the ratio of gross interest revenue to total assets or gross interest revenue and other revenue to total assets. The independent variables are: the ratio of interest expenses to total deposits and money market funding, personnel expense to total assets, other

[5] The euro area countries in the sample include members since the start in 1999: Austria, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal and Spain, and Greece which joined in 2001.

operating expense to total assets, equity to total assets, net loans to total assets and total assets. All variables[6] are included as natural logarithms in the estimation models. Banks for which all major variables are available are kept in the sample. Certain outlier rules are applied: the 1st and 99th percentiles of the distributions of main variables are eliminated. To obtain an accurate estimation of H-statistic, this paper only reports results for countries with more than 50 bank-year observations. This rule applies particularly to estimations breaking up national banking sectors by size, domestic and foreign ownership and commercial versus savings banks. In the full sample regression, the largest number of observations is available for the United States, followed by Germany, Italy and France, with over 2000 bank-year observations. Table 4.1 and 4.2 show the median statistics for each country, and the correlation matrix of major variables for all observations in all countries for the period of 1995–2009.

For the industry growth regressions, data are taken from UNIDO INDSTAT3 (2006 ISIC Rev.2) and INDSTAT4 (2010 ISIC Rev3) for 28 manufacturing industries. Because of the short period coverage of INDSTAT4, data from 1970 to 2004 are from INDSTAT3, while from 2005 and forward are from INDSTAT4 and converted from the ISIC revision3 classification system to the ISIC revision2 system. To

[6] We need to be aware that accounting differences across countries (especially with the U.S.) and over time may affect the comparability of the accounting data. For example, the Continental model focuses on debt holders, while the Anglo-Saxon model favors share holders, which may leads to different emphases on losses/costs or gains in their statements and therefore possible distortions of the comparisons of H-statistics which are based on factor cost elasticities. Although variables are normalized with total assets, and the effects of accounting differences on H-statistics are not specifically estimated in this paper, conclusions should be drawn with caution.

identify the channels through which bank competition affects industry growth, I investigate the value added growth rate, as well as other industry performances: output, number of employees, number of establishments, wages and salaries, gross fixed capital formation, and productivity. Value added, output, wages and salaries and gross fixed capital formation are deflated using the CPI in local currency[7]. Productivity is defined as the real value added over the number of employees (labor productivity). The industry share is the value added share of each industry in total manufacturing industry value added.

Since the H-statistic is estimated for 1995-2000, 2001-07, and 2008-09, the industry value added growth rate is averaged for 1995-2000 and 2001-07. I do not use the H-statistic after the financial crisis (2008-09) because of the lack of industry data. All industry growth data and financial development measures are the averages for 1995-2000 and 2001-07. I measure financial development using the credit to private sector as a percentage of GDP from the World Development Indicators (WDI). The external finance dependence index (EFD) is taken from Ilyina and Samaniego (2011), who compute EFD in the 70s, 80s and 90s. Since EFD is highly correlated over decades and since the industry rankings of them are stable, I take the average values of EFD for the three decades as the external finance dependence index in the growth regression (see table 4.3 and 4.4).

As a robustness check, I also use domestic credit provided by the banking sector and

[7] CPI data are drawn from World Development Indicator.

the interest rate spread from WDI and IFS respectively as alternative measures of financial development. I also control for the level of development using GDP per capita (from WDI). Since CL (2005) find that bank concentration affects the bank competition level, I include the share of the top 3 or 5 bank assets as a share of banking industry assets (concentration3 and concentration5) in the regression. The concentration measures are calculated by the author using the BANKSCOPE database. In the growth regression, I do not include the US because it is a benchmark economy in the model.

4.3.2 Bank Competition Results

The following sub-sections present estimation results for bank competition over time, as well as comparisons across banks of different sizes, types and ownership.

Before and after EMU

The effect of EMU is studied by dividing the whole period into two sub-periods: 1995–2000, and 2001–07[8]. Considering the effect of the financial crisis adds the panel 2009-2009, Table 4.5 displays the estimated average H-statistic for each country and a euro area aggregate[9] for the period of pre EMU (1995–2000), EMU (2001–07) and financial crisis (2008-09). Column (3) and (4) report the H statistics and standard errors before EMU for each country or region, column (5) and (6)

[8] EMU started in 1999 but the euro entered circulation only in 2002. Estimation results are robust if the sample is split in 1999, or 2000.

[9] This paper deletes branches of euro banks in other euro countries in the estimations for euro area aggregate to avoid double counting. For example, Deutsche is treated as one German bank, notwithstanding it having major business abroad. Since consolidated accounts are used if available, this recollection method is reasonable and less complicated given the data.

after the introduction of EMU. Column (9) displays the changes in the H-statistics from pre to post EMU period.

The overall competition level in euro area dropped slightly after EMU, from 0.699 to 0.518 while competition levels across member countries converged[10]. The finding that large and financially integrated countries or regions tend to exhibit less competitive behavior than smaller sectors is in line with others studies, including Bikker and Spierdijk (2008), who also find some deterioration in competitive behavior over time for Europe's banks. They argue that banks in large and integrated financial markets are pushed by rising capital market competition and tend to shift from traditional intermediation to more sophisticated and complex products associated with less price competition. While the small decline in the level of bank competition for the euro area is statistically significant, it is somewhat smaller than the estimates reported by Bikker et al. (2008) using an un-scaled revenue function. For Austria and Germany, a slight increase in the competition level of their banking systems is estimated; however, the increase is not statistically significant. The H-statistics in Finland, France, Greece, Italy and Netherlands dropped after EMU. At the same time, Spain, the U.K. and the U.S. experienced some small but statistically significant improvement in the competition level of their banking systems.

[10] The standard deviation of H-statistics of euro member countries drops from 0.17 before EMU to 0.12 after EMU.

Before and after the recent financial crisis

The recent financial crisis and possibly corresponding policy changes seem to have left a strong mark on bank competition in many countries, as indicated by the competition indicators before and after the crisis for the sample. Using the reduced revenue equation (4.1), this section estimates the H-statistic for each country. The crisis period covers 2008 to 2009. Most countries show equilibrium market structure in the equilibrium test in both periods.

Column (7) and (8) of Table 4.5 show the H-statistics after the financial crisis. In the U.S., Italy, Germany, Spain and the euro area, bank competition seems to have declined following the financial crisis; however the declines in Germany, Italy and the euro area are trivial. Estimates suggest that in the U.S. and Spain, where large credit and housing booms had preceded the crisis, a significant fall in competition following the recent global financial crisis occurred. While competition in the Netherlands shows some increase, other euro countries remained broadly unchanged. Finally, these post-crisis estimates only provide preliminary evidence in view of the limited number of observations and the fact the structural change in the aftermath of the crisis may distort the long-run market equilibrium necessary for validity of the H-Statistic.

In the following sub-sections, results for bank competition comparisons across banks of different sizes, types and ownership are presented. Due to the limited observations in the post crisis period in some countries, the over time comparisons of the sample separations are made between pre and post EMU periods.

Bank competition among large and small banks

There is no strong pattern suggesting whether large (top 50) or small banks (bottom 50) compete harder (see Table 4.6 for the comparison among banks of different sizes). For some countries, like the U.S. and the U.K., small banks compete more intensively, while larger banks in Austria, France, Italy, Portugal and Spain are more competitive before EMU. In other countries, the competition indicators of larger banks are not statistically different from those of smaller banks before EMU (panel A of table 4.6). Panel B of table 4.6 compares competition among large and small banks after EMU. Interestingly, small banks show more competitive behavior in most countries, except in France and Spain. Panel C compares the changes of competition across small and large banks. The euro area, France, Greece, Italy and the Netherlands have experienced a significant drop in competition among both small and large banks, while both types of banks in the U.S. and U.K. showed a noticeable increase in competition.

Comparison across bank types

The sample countries vary in the composition of their banking systems. For some countries, including U.S, U.K., Finland, Greece and etc, commercial banks dominate, while in Germany and Italy, there are more savings banks and cooperative banks. The sample is divided into two groups: savings/cooperative banks, and commercial banks. This section investigates selected countries: U.S., France, Germany, Italy, Spain and Austria because other countries have a predominant number of one group of banks while lacking the other group (see column (17)-(20) in table 4.7 for the number of observations and banks in the sample).

Before EMU, in Germany, Italy and USA, commercial banks are more competitive than savings/corporative banks. After EMU, the differences between commercial banks and savings/corporative banks are small and not significant, in most euro countries (except Spain), which indicates that competition levels of different types of banks after EMU seem to converge. For the euro area, commercial banks display a higher level of competition after EMU. In contrast, commercial banks are consistently more competitive in the U.S. over time. Panel C in table 4.7 displays the evolution of H statistics for two groups of banks. Most euro-area countries and the euro area as a whole have seen drops in competition for both types of banks, in contrast with improvements in the U.S.

However, there is no sign that whole banking systems with more diversified bank types compete harder: indeed the opposit seems the case. After comparing the H-statistics of the U.S., France, Germany, Italy, Spain and Austria with those of other countries in both sub-sample periods for all types of intermediaries (see table 4.7), the average H-statistic of the former group, which has a more diversified banking system, is lower than that of the later one, and the difference is statistically significant at 5% level[11].

[11] The t-test is not reported, but can be easily computed.

Foreign vs. Domestic banks

Some research indicates that competition from foreign banks promotes competition in local financial markets. This paper finds mixed patterns: some domestic markets become more competitive over time as they open to foreign competition, while some do not. Foreign banks here are defined as having over 51% of foreign ownership. Due to the limited information in the database, not all banks report their global ultimate ownership. In this section, the sample only includes banks which report their global ultimate owners, and also countries with more than 50 bank-year observations in each (foreign/domestic) group (see panel C in table 4.8 for the number of observations and banks). Therefore, countries in this section are reduced to: U.S., U.K., France, Italy and Portugal.

Panels A and B in Table 4.8 display the results for both foreign and domestic banks before and after EMU. In France and U.S., foreign banks compete harder before EMU, but the differences between foreign and domestic banks are smaller and not significant after EMU. For Italy and Portugal, competition among foreign banks and domestic banks is not significantly different in both periods. From the results in panel B, I could see that after EMU, the difference in competition levels between foreign and domestic banks tend be less obvious in both Europe and the U.S.

Finally, Panel C of table 4.8 shows the evolution of H statistics among foreign and domestic banks. In France and Italy, competition among both foreign and domestic banks deteriorated (although the fall in domestic banks in Italy is not significant), while foreign banks in the U.K. and domestic banks in the U.S. improved over time.

4.3.3 Growth Results

The bank competition tests show that euro countries experienced a decline in the degree of competition in their banking sectors. Now I apply the H-statistics obtained in the sections above to the industry growth regression to check whether bank competition has any effect on industry growth. In this section, I only use H-statistics for the full sample before and after EMU (see the results in Table 4.5. H-Statistics Over Time).

The growth regression results suggest that bank competition does promote growth in financially dependent industries (see column (1) in Table 4.9. Bank Competition and Growth). The coefficient of the interaction term of EFD and bank competition is positive and significant after controlling for country, time and industry specific effects, as well as the interaction between EFD and financial development. This result is consistent with CL (2005), although the coefficient is higher than the findings in CL.

In general, the time period of study has seen numerous financial innovations, including a rise in the sources of non-bank financing that firms might access and in non-traditional business activities within the banking sector. One could ask whether the results are perhaps due to changes in competition from outside the banking sector rather than by developments in competition among banks. In the euro area, unlike the U.S., non-banking financial institutions (like the equity markets) are not as important as the banking sector as a source of external finance. For robustness, I use alternative measures of financial development including interest rate spreads and bank credit to the private sector (columns (2) and (3)). The financial development level reflects credit from all domestic sources. Credit from the banking sector also reflects the structure of domestic financial markets. Interest rate spreads indicate the efficiency of banking sector and also the intensity of competition with non-banking financial institutions. We can see from column (1)-(3) that the effects of bank competition on growth are not affected by competition from other financial institutions, the structure of domestic financial markets and their changes over time (since all measures are averaged over two periods, i.e. 1995-2000 and 2001-07). Moreover, the change in H-statistic level already reflects competition from non-traditional business activities in the banking sector (Bikker and Spierdijk (2008)). Thus, my results are not affected when taking into account competition from other financial institutions and non-traditional business activities within the banking sector.

In addition, I include GDP per capita (column (4)) in the regression to control for economy size. The result indicates that the disproportionate effect of bank competition is basically the same. I also control for bank concentration measures: the share of top 3 and 5 bank assets. The coefficients of the interaction term between EFD and bank competition is lower, but still significant.

I further explore the channels through which bank competition may affect industry growth by running regression for the growth rates of fixed capital formation, number of employees, number of establishments, output, wage rates, and productivity (see table 4.10-4.15). The capital growth regression (table 4.10) shows that bank competition does not have disproportionate effect on capital investment. However the employment regression (table 4.11) tells us that more bank competition enables firms to hire more labor. It is probably because more competition increases the supply of short-term loans, which are more useful for firms to invest in labor inputs rather than for capital. The effect of competition on labor can also been seen in the wage growth regression (table 4.15). Easier access to external funds enables firms to pay higher salaries to employees. These findings support the theory of Hart and Moore (1994). They show that due to the inalienability and intangibility of human capital, labor cannot be used as collateral and provide security to creditors so that intangible assets are hard to raise debts. My results provide evidence that bank competition helps to ameliorate financial friction which is caused by the inalienability and intangibility of human capital. It is also not surprising to see that bank competition encourages output growth (table 4.13). The results for growth regression using the number of establishments (table 4.12) show that bank competition also encourages more entry. Still, when I control for interest rate spreads and bank concentration, the effect of bank competition is not significant. In the productivity regression, none of the coefficients of the interaction term of competition is significant, indicating that better access to finance does not lead to productivity improvements.

To conclude, the industry growth regressions confirm that bank competition disproportionately promotes growth in industries that need external finance the most. Furthermore, I find that bank competition especially benefits increases in employment and wage payments. However, bank competition does not significantly encourage capital investment and productivity growth. Since the degree of bank competition in euro countries declined since the introduction of EMU, my results indicate that this decline of competition has had negative effects on growth of these countries, especially on employment and labor income.

4.4 Conclusion

Estimates of bank competition for the euro-area countries, as well as the U.K. and the U.S., suggest that neither the introduction of the euro nor the recent financial crisis has had a common impact across countries. The euro area experienced a significant but small decline in bank competition after EMU and the financial crisis. Some studies with similar findings have attributed the decline in competition to the process of consolidation, and the movement of bank activities from traditional financial business to off-balance sheet activities. More importantly, competition levels in euro countries seem to have converged after EMU, not just at the average national market level, but also between different bank types and ownership. Finally, following the financial crisis, competition fell in many countries, especially in some countries where large credit and housing booms took place. Moreover, I find a

Table 4.1: Summary Statistics of Competition Regression Variables

Country	Gross interest income over total assets	Total income over total assets	Total interest expenses to total deposits and money market funding	Personnel expense over total assets	Other operating expenses over total assets	Equity over total assets	Net loans to total assets	Total assets ('000,000 USD)
Austria	0.045	0.077	0.029	0.012	0.008	6.15	57.70	471.09
Finland	0.042	0.072	0.032	0.008	0.010	5.52	56.96	22900.00
France	0.054	0.092	0.037	0.014	0.011	6.39	63.74	3942.03
Germany	0.052	0.088	0.031	0.015	0.010	5.10	62.59	567.64
Greece	0.056	0.100	0.036	0.014	0.012	7.47	59.53	5039.09
Ireland	0.040	0.056	0.042	0.001	0.002	4.86	53.83	15600.00
Italy	0.051	0.092	0.035	0.015	0.013	10.34	63.21	564.45
Netherlands	0.050	0.075	0.049	0.008	0.007	5.28	59.92	16200.00
Portugal	0.059	0.091	0.049	0.010	0.010	5.80	55.54	5915.19
Spain	0.048	0.081	0.029	0.011	0.008	6.97	67.73	6200.13
U.K.	0.056	0.086	0.047	0.009	0.009	7.42	48.43	4854.15
U.S.	0.059	0.103	0.027	0.015	0.013	9.58	65.85	113.53

Note: This table reports the median of major variables for each country. The sample covers the years 1995-2009. Data source: BankScope

significant effect of bank competition on growth in the euro countries: bank competition disproportionately promotes growth of industries that are highly dependent on external finance. The disproportionate positive effects are related to increases in employment and labor payments, which indicates that bank competition helps to ameliorate financial frictions which are caused by the inalienability and intangibility of human capital.

Table 4.2: Correlation Matrix Between Major Variables

	Gross interest income over total assets	Total income over total assets	Total interest expenses to total deposits and money market funding	Personnel expense over total assets	Other operating expenses over total assets	Equity over total assets	Net loans to total assets	Total assets ('000,000 USD)
Gross interest income over total assets	1							
Total income over total assets	0.8605*	1						
Total interest expenses to total deposits and money market funding	0.5692*	0.2216*	1					
Personnel expense over total assets	0.1871*	0.4637*	-0.2253*	1				
Other operating expenses over total assets	0.1905*	0.4407*	-0.1652*	0.5734*	1			
Equity over total assets	-0.0273*	0.0489*	-0.1176*	0.0772*	0.0229*	1		
Net loans to total assets	0.2113*	0.2147*	0.0495*	0.0814*	0.0862*	-0.1219*	1	
Total assets ('000,000 USD)	-0.0816*	-0.1182*	0.0975*	-0.1125*	-0.0898*	-0.1022*	-0.0529*	1

Note: This table reports the correlation matrix between major variables for all observations including all countries in the sample for 1995-2009. * significant at 5% level

Table 4.3: Summary Statistics of Growth Regression Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Value added growth	515	0.032	0.171	-1.970	2.025
Fixed capital formation growth	420	0.010	0.182	-0.743	1.399
Output growth	609	0.006	0.056	-0.255	0.239
Productivity	545	63964.430	69088.590	0.000	897413.900
Number of employees growth	520	0.017	0.146	-2.113	1.493
Number of establishments growth	561	0.084	0.179	-1.447	0.765
Wage growth	516	0.027	0.152	-1.816	1.651
Share	551	0.039	0.043	0.000	0.358
Private credit	616	100.925	32.307	35.916	157.747
Bank credit	616	116.735	28.024	58.410	169.161
Interest spread	532	4.073	1.699	0.821	7.318
GDP per capita	616	27722.750	4744.887	18687.940	37333.320
EFD	616	0.082	0.481	-0.839	1.670
Concentraton of top 3	616	0.597	0.207	0.276	0.964
Concentraton of top 5	616	0.722	0.186	0.404	0.994

Table 4.4: External Finance Dependence Indicator

Industry	ISIC	EFD
Food products	311	-0.039
Beverages	313	-0.048
Tobacco	314	-0.801
Textiles	321	0.029
Apparel	322	0.075
Leather	323	-0.959
Footwear	324	-0.45
Wood products	331	0.052
Furniture, except metal	332	0.015
Paper and products	341	-0.062
Printing and publishing	342	-0.222
Industrial chemicals	351	0.028
Other chemicals	352	1.654
Petroleum refineries	353	-0.055
Misc. pet. and coal products	354	-0.059
Rubber products	355	-0.064
Plastic products	356	0.088
Pottery, china, earthenware	361	-0.107
Glass and products	362	0.289
Other non-metallic mineral prod.	369	0.021
Iron and steel	371	-0.004
Non-ferrous metals	372	0.037
Fabricated metal products	381	-0.052
Machinery, except electrical	382	0.542
Machinery, electric	383	0.543
Transport equipment	384	0.041
Prof. & sci. equip.	385	0.942
Other manufactured prod.	390	0.404

Source: average of EFD in 70s, 80s and 90s fromIlyina and Samaniego (2011).

Table 4.5: H-Statistics Over Time

	# obs.	# banks	Before EMU		After EMU		After Crisis		compare pre and post EMU		compare pre and post Crisis	
			H-Statistic	S.E	H-Statistic	S.E	H-Statistic	S.E	ΔH	S.E	ΔH	S.E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)=(5)-(3)	(10)	(11)=(7)-(5)	(12)
Austria	751	114	0.583***	0.0355	0.604***	0.0273	0.707***	0.104	0.0209	0.0437	0.103	0.107
Finland	94	15	0.797***	0.0966	0.550***	0.0628	0.647***	0.0528	-0.247**	0.116	0.0964	0.0793
France	2,921	359	0.638***	0.0139	0.584***	0.0162	0.625***	0.0504	-0.0544***	0.0212	0.0414	0.0529
Germany	6,625	1558	0.432***	0.0141	0.449***	0.00956	0.364***	0.0211	0.0171	0.0166	-0.0849***	0.0229
Greece	199	28	0.816***	0.0780	0.518***	0.0599	0.385***	0.0992	-0.298***	0.0966	-0.133	0.113
Ireland	144	28	1.020***	0.161	0.754***	0.0705	0.589***	0.125	-0.266	0.172	-0.165	0.144
Italy	4,776	689	0.878***	0.0144	0.588***	0.0130	0.496***	0.0310	-0.290***	0.0194	-0.0917***	0.0334
Netherlands	169	29	0.896***	0.155	0.407***	0.0611	0.611***	0.0833	-0.488***	0.162	0.204**	0.0976
Portugal	255	37	0.705***	0.0401	0.679***	0.0525	0.849***	0.170	-0.0254	0.0660	0.170	0.178
Spain	1,120	164	0.704***	0.0261	0.795***	0.0282	0.505***	0.0509	0.0908**	0.0380	-0.290***	0.0579
U.K.	813	137	0.506***	0.0371	0.647***	0.0270	0.618***	0.0467	0.141***	0.0443	-0.0289	0.0531
U.S.	82,566	9338	0.309***	0.00691	0.425***	0.00258	0.270***	0.00529	0.116***	0.00725	-0.155***	0.00578
euro area	16,706	2969	0.699***	0.00645	0.518***	0.00609	0.444***	0.0123	-0.182***	0.00879	-0.0737***	0.0136

Note: The table displays the estimated average H-statistics of two reduced-form bank revenue equations using pooled OLS for each country and euro area aggregate independently: $\ln P=\alpha 0+\beta 1\ln W1+\beta 2\ln W2+\beta 3\ln W3+\gamma 1\ln Y1+\gamma 2\ln Y2+\gamma 3\ln Y3+T1*(\alpha 1+\beta 4\ln W1+\beta 5\ln W2+\beta 6\ln W3+\gamma 4\ln Y1+\gamma 5\ln Y2+\gamma 6\ln Y3)+T2*(\alpha 2+\beta 7\ln W1+\beta 8\ln W2+\beta 9\ln W3+\gamma 7\ln Y1+\gamma 8\ln Y2+\gamma 9\ln Y3)+\varepsilon$. One is estimated using gross interest revenue over total assets as dependent variable, the other one using gross revenue (interest and other revenue) over total assets. The sample covers years 1995-2009. The pre EMU period is from 1995-2000, post EMU from 2001-07, and post financial crisis from 2008-09. T1,2 are the time dummies for EMU and financial crisis respectively: T1=1 for for 2001-2007, T1=0, otherwise; T2=1 for 2008-09, T2=0, otherwise. H= β1+β2+β3 for pre EMU period, H= β1+β2+β3+β4+β5+β6 for post EMU, H= β1+β2+β3+β7+β8+β9 for post financial crisis period. Column (9) and (11) display the difference in the H-statistic pre and post EMU, i.e. (9)=(5)-(3), and the H-statistic pre and post financial crisis, i.e. (11)=(7)-(5) . All variables in the estimations are annual data from BankScope. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.6: H-Statistics of Banking System by Size

Panel A: Before EMU

	SMALL		LARGE		Diff	
	H-Statistic	S.E	H-Statistic	S.E	ΔH	S.E
	(1)	(2)	(3)	(4)	(5)=(3)-(1)	(6)
Austria	0.459***	0.0523	0.714***	0.0471	0.255***	0.0698
Finland	0.840***	0.0919	0.783***	0.175	-0.0572	0.196
France	0.616***	0.0184	0.675***	0.0202	0.0582**	0.0271
Germany	0.447***	0.0204	0.415***	0.0210	-0.0319	0.0290
Greece	0.789***	0.0960	0.829***	0.169	0.0399	0.194
Italy	0.803***	0.0232	0.929***	0.0182	0.126***	0.0295
Netherlands	1.153***	0.176	0.837***	0.287	-0.316	0.337
Portugal	0.677***	0.0437	0.858***	0.0839	0.182*	0.0936
Spain	0.659***	0.0319	0.804***	0.0503	0.145**	0.0593
U.K.	0.534***	0.0419	0.406***	0.0612	-0.128*	0.0730
U.S.	0.375***	0.00935	0.245***	0.00989	-0.130***	0.0135
euro area	0.667***	0.0109	0.706***	0.00817	0.0394***	0.0134

Panel B: After EMU

	SMALL		LARGE		Diff	
	H-Statistic	S.E	H-Statistic	S.E	ΔH	S.E
	(7)	(8)	(9)	(10)	(11)=(9)-(7)	(12)
Austria	0.665***	0.0345	0.543***	0.0422	-0.122**	0.0535
Finland	0.709***	0.134	0.735***	0.0747	0.0265	0.160
France	0.534***	0.0258	0.612***	0.0207	0.0783**	0.0332
Germany	0.455***	0.0151	0.441***	0.0133	-0.0145	0.0199
Greece	0.483***	0.104	0.481***	0.0811	-0.00129	0.135
Italy	0.601***	0.0178	0.587***	0.0185	-0.0149	0.0256
Netherlands	0.579***	0.0766	0.333***	0.0724	-0.246**	0.100
Portugal	0.810***	0.0671	0.455***	0.0760	-0.354***	0.102
Spain	0.739***	0.0417	0.852***	0.0405	0.113*	0.0580
U.K.	0.645***	0.0364	0.601***	0.0382	-0.0440	0.0517
U.S.	0.432***	0.00367	0.423***	0.00349	-0.00905*	0.00497
euro area	0.495***	0.0110	0.553***	0.00760	0.0579***	0.0133

Panel C: Compare pre and post EMU

	SMALL		LARGE	
	ΔH	S.E	ΔH	S.E
	(13)=(7)-(1)	(14)	(15)=(9)-(3)	(16)
Austria	0.206***	0.0616	-0.170***	0.0626
Finland	-0.131	0.158	-0.0473	0.190
France	-0.0826***	0.0317	-0.0625**	0.0283
Germany	0.00799	0.0251	0.0253	0.0244
Greece	-0.306**	0.144	-0.348*	0.190
Italy	-0.202***	0.0292	-0.342***	0.0259
Netherlands	-0.574***	0.188	-0.504*	0.296
Portugal	0.133*	0.0806	-0.403***	0.113
Spain	0.0803	0.0524	0.0481	0.0642
U.K.	0.112**	0.0546	0.195***	0.0698
U.S.	0.0567***	0.00992	0.178***	0.0104
euro area	-0.172***	0.0155	-0.154***	0.0112

Note: The table displays the estimated average H-statistics of two reduced-form bank revenue equations using pooled OLS for each country and euro area independently: $\ln P=\alpha 0+\beta 1\ln W1+\beta 2\ln W2+\beta 3\ln W3+\gamma 1\ln Y1+\gamma 2\ln Y2+\gamma 3\ln Y3+T1*(\alpha 1+\beta 4\ln W1+\beta 5\ln W2+\beta 6\ln W3+\gamma 4\ln Y1+\gamma 5\ln Y2+\gamma 6\ln Y3)+\varepsilon$. One is estimated using gross interest revenue over total assets as dependent variable, the other one using gross revenue (interest and other revenue) over total assets. T1 is the time dummy for EMU, T1=0 for 1995-2000, T1=1 for 2001-2007. Column (5) and (11) display the difference in the H-statistic between small and large banks before and after EMU respectively, i.e. (5)=(3)-(1), (11)=(9)-(7). Column (13) and (15) reports the change in H-statistic before and after EMU for small and large banks respectively, i.e. (13)=(7)-(1), (15)=(9)-(3). All variables in the estimations are annual data from BankScope. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.7: H-Statistics of Banking System by Bank Types

Panel A: Before EMU						
	Commercial		Savings/Corporative		Diff	
	H-Statistic	S.E	H-Statistic	S.E	ΔH	S.E
	(1)	(2)	(3)	(4)	(5)=(1)-(3)	(6)
Austria	0.594***	0.0400	0.741***	0.0966	-0.147	0.105
France	0.632***	0.0158	0.693***	0.0288	-0.0610*	0.0324
Germany	0.609***	0.0475	0.419***	0.0148	0.190***	0.0495
Italy	0.922***	0.0248	0.865***	0.0172	0.0571*	0.0302
Spain	0.640***	0.0443	0.859***	0.0334	-0.219***	0.0550
U.S.	0.359***	0.00722	0.239***	0.0192	0.120***	0.0204
euro area	0.682***	0.00974	0.721***	0.00904	-0.0388***	0.0132

Panel B: After EMU						
	Commercial		Savings/Corporative		Diff	
	H-Statistic	S.E	H-Statistic	S.E	ΔH	S.E
	(7)	(8)	(9)	(10)	(11)=(7)-(9)	(12)
Austria	0.608***	0.0379	0.642***	0.0456	-0.0342	0.0592
France	0.572***	0.0189	0.616***	0.0336	-0.0436	0.0385
Germany	0.454***	0.0325	0.452***	0.0101	0.00212	0.0340
Italy	0.587***	0.0262	0.606***	0.0149	-0.0195	0.0301
Spain	0.678***	0.0400	0.956***	0.0383	-0.277***	0.0555
U.S.	0.437***	0.00260	0.395***	0.00799	0.0422***	0.00833
euro area	0.584***	0.0112	0.533***	0.00833	0.0510***	0.0139

Panel C: Compare pre and post EMU								
	Commercial		Savings/Corporative		Commercial		Savings/Corporative	
	ΔH	S.E	ΔH	S.E	# obs.	# banks	# obs.	# banks
	(13)=(7)-(1)	(14)	(15)=(9)-(3)	(16)	(17)	(18)	(19)	(20)
Austria	0.0142	0.0538	-0.0987	0.107	359	52	392	62
France	-0.0594**	0.0245	-0.0769*	0.0436	1396	200	1525	159
Germany	-0.155***	0.0574	0.0326*	0.0174	177	67	6448	1491
Italy	-0.335***	0.0360	-0.259***	0.0228	969	149	3807	540
Spain	0.0386	0.0596	0.0968**	0.0493	291	59	829	105
U.S.	0.0780***	0.00754	0.156***	0.0207	75217	8411	7349	927
euro area	-0.0987***	0.0148	-0.189***	0.0121	3002	498	12987	2356

Note: The table displays the estimated average H-statistics of two reduced-form bank revenue equations using pooled OLS for each country and euro area independently:
$\ln P=\alpha0+\beta1\ln W1+\beta2\ln W2+\beta3\ln W3+\gamma1\ln Y1+\gamma2\ln Y2+\gamma3\ln Y3+T1*(\alpha1+\beta4\ln W1+\beta5\ln W2+\beta6\ln W3+\gamma4\ln Y1+\gamma5\ln Y2+\gamma6\ln Y3)+\varepsilon$.
One is estimated using gross interest revenue over total assets as dependent variable, the other one using gross revenue (interest and other revenue) over total assets. T1 is the time dummy for EMU, T1=0 for 1995-2000, T1=1 for 2001-2007. Column (5) and (11) display the difference in the H-statistic between commercial and savings banks before and after EMU respectively, i.e. (5)=(3)-(1), (11)=(9)-(7). Column (13) and (15) reports the change in H-statistic before and after EMU for commercial and savings banks respectively, i.e. (13)=(7)-(1), (15)=(9)-(3). All variables in the estimations are annual data from BankScope. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.8: H-Statistics of Banking System by Foreign/Domestic Ownership

Panel A: Before EMU

	Foreign		Domestic		Diff	
	H-Statistic	S.E	H-Statistic	S.E	ΔH	S.E
	(1)	(2)	(3)	(4)	(5)=(1)-(3)	(6)
France	0.765***	0.0589	0.626***	0.0399	0.138*	0.0707
Italy	0.712***	0.165	0.924***	0.0305	-0.212	0.167
Portugal	0.740***	0.0921	0.581***	0.0785	0.159	0.123
U.K.	0.421***	0.0439	0.792***	0.0729	-0.372***	0.0852
U.S.	0.431***	0.0632	0.242***	0.0279	0.189***	0.0681

Panel B: After EMU

	Foreign		Domestic		Diff	
	H-Statistic	S.E	H-Statistic	S.E	ΔH	S.E
	(7)	(8)	(9)	(10)	(11)=(7)-(9)	(12)
France	0.550***	0.0519	0.487***	0.0501	0.0637	0.0723
Italy	0.638***	0.109	0.496***	0.0295	0.142	0.113
Portugal	0.807***	0.148	0.712***	0.0687	0.0945	0.164
U.K.	0.700***	0.0351	0.556***	0.0417	0.144***	0.0540
U.S.	0.358***	0.0358	0.397***	0.0109	-0.0385	0.0373

Panel C: compare pre and post EMU

	Foreign		Domestic		Foreign		Domestic	
	ΔH	S.E	ΔH	S.E	# obs.	# banks	# obs.	# banks
	(13)=(7)-(1)	(14)	(15)=(9)-(3)	(16)	(17)	(18)	(19)	(20)
France	-0.214***	0.0782	-0.140**	0.0630	157	24	491	53
Italy	-0.0741	0.197	-0.428***	0.0417	61	7	889	100
Portugal	0.0666	0.173	0.131	0.106	50	6	80	11
U.K.	0.280***	0.0548	-0.236***	0.0816	334	59	336	47
U.S.	-0.0725	0.0720	0.155***	0.0298	406	45	4811	515

Note: The table displays the estimated average H-statistics of two reduced-form bank revenue equations using pooled OLS for each country independently: $lnP=\alpha0+\beta1lnW1+\beta2lnW2+\beta3lnW3+\gamma1lnY1+\gamma2lnY2+\gamma3lnY3+T1*(\alpha1+\beta4lnW1+\beta5lnW2+\beta6lnW3+\gamma4lnY1+\gamma5lnY2+\gamma6lnY3)+\varepsilon$. One is estimated using gross interest revenue over total assets as dependent variable, the other one using gross revenue (interest and other revenue) over total assets. T1 is the time dummy for EMU, T1=0 for 1995-2000, T1=1 for 2001-2007. Column (5) and (11) display the difference in the H-statistic between foreign and domestic banks before and after EMU respectively, i.e. (5)=(3)-(1), (11)=(9)-(7). Column (13) and (15) reports the change in H-statistic before and after EMU for foreign and domestic banks respectively, i.e. (13)=(7)-(1), (15)=(9)-(3). All variables in the estimations are annual data from BankScope. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.9: Bank Competition and Growth

	Value Added Growth					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
EFD*Competition	0.400***	0.378***	0.235**	0.400***	0.228**	0.224**
	(0.116)	(0.119)	(0.115)	(0.116)	(0.109)	(0.109)
EFD*Private Credit	0.00202***			0.00203***		
	(0.000489)			(0.000491)		
EFD*Bank Credit		0.00179***				
		(0.000562)				
EFD*Interest Spread			-0.00973			
			(0.0105)			
GDP per capita				-1.40e-06		
				(3.12e-06)		
EFD*Concentration 3					0.194**	
					(0.0772)	
EFD*Concentration 5						0.217**
						(0.0839)
Share	0.349	0.346	0.257	0.351	0.338	0.350
	(0.248)	(0.250)	(0.274)	(0.248)	(0.251)	(0.251)
Observations	515	515	438	515	515	515
R-squared	0.173	0.162	0.153	0.174	0.155	0.156

Note: This table reports results for the value added growth regression using OLS: $Growth_{i,c}=Constant+\theta_1 Dummy+\theta_2 Share+\theta_3 EFD_i \times Financial\ development_c+\theta_4 EFD_i \times Competition_c+\varepsilon_{i,c}$. Dummy variables include country, industry and year specific dummies. The coefficients for dummy and constant variables are not reported. The dependent variable is the average of value added growth rate over 1995-2000 and 20001-07 calculated by the author using UNIDO data for 28 manufacturing industries. The competition measure is taken from columns (3) and (5) from table 5. All variables are the average of 1995-2000 and 2001-07 values. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4.10: Bank Competition and Capital Growth

	Capital Growth					
VARIABLES	(1)	(2)	(3)	(4)	(7)	(8)
EFD*Competition	0.208	0.165	0.0709	0.213	0.0239	0.0225
	(0.137)	(0.139)	(0.129)	(0.138)	(0.126)	(0.127)
EFD*Private Credit	0.00195***			0.00197***		
	(0.000669)			(0.000670)		
EFD*Bank Credit		0.00156**				
		(0.000749)				
EFD*Interest Spread			-0.0260*			
			(0.0133)			
GDP per capita				-3.48e-06		
				(7.22e-06)		
EFD*Concentration 3					0.0374	
					(0.0839)	
EFD*Concentration 5						0.0389
						(0.0907)
Share	0.208	0.203	0.177	0.223	0.179	0.182
	(0.253)	(0.255)	(0.269)	(0.253)	(0.256)	(0.256)
Observations	420	420	377	420	420	420
R-squared	0.328	0.321	0.285	0.332	0.314	0.314

Note: This table reports results for the value added growth regression using OLS: $Growth_{i,c}$=Constant+θ_1Dummy+θ_2Share+$\theta_3 EFD_i$×Financial $development_c$+$\theta_4 EFD_i$×$Competition_c$+$\varepsilon_{i,c}$. Dummy variables include country, industry and year specific dummies. The coefficients for dummy and constant variables are not reported. The dependent variable is the average of capital growth rate over 1995-2000 and 20001-07 calculated by the author using UNIDO data for 28 manufacturing industries. The competition measure is taken from columns (3) and (5) from table 5. All variables are the average of 1995-2000 and 2001-07 values. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4.11: Bank Competition and Employment Growth

	Employment Growth					
VARIABLES	(1)	(2)	(3)	(4)	(7)	(8)
EFD*Competition	0.352***	0.342***	0.184**	0.346***	0.186**	0.180**
	(0.0948)	(0.0977)	(0.0927)	(0.0946)	(0.0901)	(0.0900)
EFD*Private Credit	0.00205***			0.00207***		
	(0.000411)			(0.000410)		
EFD*Bank Credit		0.00192***				
		(0.000473)				
EFD*Interest Spread			-0.0156*			
			(0.00830)			
GDP per capita				-1.28e-05**		
				(5.91e-06)		
EFD*Concentration 3					0.148**	
					(0.0649)	
EFD*Concentration 5						0.167**
						(0.0708)
Share	0.435**	0.435**	0.374	0.439**	0.421**	0.429**
	(0.209)	(0.210)	(0.228)	(0.208)	(0.213)	(0.213)
Observations	518	518	441	518	518	518
R-squared	0.198	0.185	0.163	0.206	0.166	0.166

Note: This table reports results for the value added growth regression using OLS: $Growth_{i,c}$=Constant+θ_1Dummy+θ_2Share+$\theta_3 EFD_i \times$Financial development$_c$+$\theta_4 EFD_i \times$Competition$_c$+$\varepsilon_{i,c}$. Dummy variables include country, industry and year specific dummies. The coefficients for dummy and constant variables are not reported. The dependent variable is the average of employment growth rate over 1995-2000 and 20001-07 calculated by the author using UNIDO data for 28 manufacturing industries. The competition measure is taken from columns (3) and (5) from table 5. All variables are the average of 1995-2000 and 2001-07 values. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4.12: Bank Competition and Establishment Growth

	Establishment Growth					
VARIABLES	(1)	(2)	(3)	(4)	(7)	(8)
EFD*Competition	0.264**	0.264**	0.126	0.227**	0.132	0.132
	(0.103)	(0.105)	(0.0990)	(0.0968)	(0.0968)	(0.0968)
EFD*Private Credit	0.00156***			0.00149***		
	(0.000445)			(0.000420)		
EFD*Bank Credit		0.00154***				
		(0.000510)				
EFD*Interest Spread			-0.00977			
			(0.00886)			
GDP per capita				-1.42e-05**		
				(6.05e-06)		
EFD*Concentration 3					-0.0114	
					(0.0698)	
EFD*Concentration 5						-0.00176
						(0.0762)
Share	0.147	0.149	0.136	0.132	0.124	0.125
	(0.226)	(0.227)	(0.243)	(0.213)	(0.229)	(0.229)
Observations	524	524	444	524	524	524
R-squared	0.319	0.314	0.363	0.398	0.301	0.301

Note: This table reports results for the value added growth regression using OLS: $Growth_{i,c}$=Constant+θ_1Dummy+θ_2Share+$\theta_3 EFD_i\times$Financial $development_c$+$\theta_4 EFD_i\times Competition_c+\varepsilon_{i,c}$. Dummy variables include country, industry and year specific dummies. The coefficients for dummy and constant variables are not reported. The dependent variable is the average of establishment growth rate over 1995-2000 and 20001-07 calculated by the author using UNIDO data for 28 manufacturing industries. The competition measure is taken from columns (3) and (5) from table 5. All variables are the average of 1995-2000 and 2001-07 values. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4.13: Bank Competition and Output Growth

	Output Growth					
VARIABLES	(1)	(2)	(3)	(4)	(7)	(8)
EFD*Competition	0.0717***	0.0702**	0.0614**	0.0738***	0.0702***	0.0697***
	(0.0270)	(0.0277)	(0.0255)	(0.0266)	(0.0255)	(0.0254)
EFD*Private Credit	6.89e-05			8.95e-05		
	(0.000116)			(0.000115)		
EFD*Bank Credit		4.40e-05				
		(0.000135)				
EFD*Interest Spread			0.00244			
			(0.00231)			
GDP per capita				-5.22e-06***		
				(1.52e-06)		
EFD*Concentration 3					0.0554***	
					(0.0187)	
EFD*Concentration 5						0.0633***
						(0.0202)
Share	0.432***	0.432***	0.430***	0.438***	0.438***	0.443***
	(0.0601)	(0.0601)	(0.0618)	(0.0592)	(0.0596)	(0.0596)
Observations	549	549	468	549	549	549
R-squared	0.523	0.523	0.557	0.539	0.531	0.532

Note: This table reports results for the value added growth regression using OLS: $Growth_{i,c}=Constant+\theta_1 Dummy+\theta_2 Share+\theta_3 EFD_i \times Financial\ development_c+\theta_4 EFD_i \times Competition_c+\varepsilon_{i,c}$. Dummy variables include country, industry and year specific dummies. The coefficients for dummy and constant variables are not reported. The dependent variable is the average of output growth rate over 1995-2000 and 20001-07 calculated by the author using UNIDO data for 28 manufacturing industries. The competition measure is taken from columns (3) and (5) from table 5. All variables are the average of 1995-2000 and 2001-07 values. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4.14: Bank Competition and Productivity

	Productivity					
VARIABLES	(1)	(2)	(3)	(4)	(7)	(8)
EFD*Competition	10,876	9,914	23,772	13,081	26,006	25,841
	(32,600)	(33,441)	(33,567)	(32,552)	(31,032)	(31,000)
EFD*Private Credit	-184.5			-183.0		
	(141.0)			(140.8)		
EFD*Bank Credit		-185.0				
		(163.6)				
EFD*Interest Spread			2,644			
			(3,050)			
GDP per capita				3.652**		
				(1.858)		
EFD*Concentration 3					34,039	
					(22,794)	
EFD*Concentration 5						42,126*
						(24,645)
Share	807,089***	806,191***	840,123***	807,750***	811,401***	814,838***
	(72,581)	(72,620)	(81,348)	(72,414)	(72,593)	(72,624)
Observations	545	545	467	545	545	545
R-squared	0.537	0.536	0.527	0.541	0.537	0.538

Note: This table reports results for the value added growth regression using OLS: $Growth_{i,c}=Constant+\theta_1 Dummy+\theta_2 Share+\theta_3 EFD_i\times Financial\ development_c+\theta_4 EFD_i\times Competition_c+\varepsilon_{i,c}$. Dummy variables include country, industry and year specific dummies. The coefficients for dummy and constant variables are not reported. The dependent variable is the average of productivity over 1995-2000 and 20001-07 calculated by the author using UNIDO data for 28 manufacturing industries. The competition measure is taken from columns (3) and (5) from table 5. All variables are the average of 1995-2000 and 2001-07 values. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4.15: Bank Competition and Wage Growth

	Wage Growth					
VARIABLES	(1)	(2)	(3)	(4)	(7)	(8)
EFD*Competition	0.353***	0.341***	0.209**	0.353***	0.213**	0.206**
	(0.101)	(0.104)	(0.0980)	(0.101)	(0.0954)	(0.0954)
EFD*Private Credit	0.00177***			0.00180***		
	(0.000437)			(0.000437)		
EFD*Bank Credit		0.00161***				
		(0.000502)				
EFD*Interest Spread			-0.0103			
			(0.00881)			
GDP per capita				-9.44e-06		
				(6.28e-06)		
EFD*Concentration 3					0.163**	
					(0.0687)	
EFD*Concentration 5						0.178**
						(0.0751)
Share	0.486**	0.485**	0.433*	0.493**	0.478**	0.487**
	(0.221)	(0.223)	(0.239)	(0.221)	(0.224)	(0.224)
Observations	514	514	437	514	514	514
R-squared	0.172	0.161	0.156	0.178	0.153	0.153

Note: This table reports results for the value added growth regression using OLS: $Growth_{i,c}=Constant+\theta_1 Dummy+\theta_2 Share+\theta_3 EFD_i \times Financial\ development_c+\theta_4 EFD_i \times Competition_c+\varepsilon_{i,c}$. Dummy variables include country, industry and year specific dummies. The coefficients for dummy and constant variables are not reported. The dependent variable is the average of wage growth rate over 1995-2000 and 20001-07 calculated by the author using UNIDO data for 28 manufacturing industries. The competition measure is taken from columns (3) and (5) from table 5. All variables are the average of 1995-2000 and 2001-07 values. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

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Proofs

Proof of decentralized economy in Chapter 2. For consumers:

$$
\begin{aligned}
& & \max_{y_{st}} \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\theta} - 1}{1-\theta} \\
& c_t &= \left[\sum_{s=1}^{S-1} \zeta_s y_{st}^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \\
s.t. \qquad & \sum_{s=1}^{S-1} q_{st} y_{st} + K_{t+1} &= \sum_{s=1}^{S} \sum_{i \in I_s} r_t K_{it} + \sum_{s=1}^{S} \sum_{i \in I_s} w_t n_{it}
\end{aligned}
$$

Capital and labor market clearing conditions are:

$$
\begin{aligned}
K_t &= \sum_{s=1}^{S} \sum_{i \in I_s} K_{it} \\
1 &= \sum_{s=1}^{S} \sum_{i \in I_s} n_{it}
\end{aligned}
$$

F.O.C w.r.t y_{st} :

$$
\frac{q_{st}}{q_{s't}} = \left(\frac{y_{s't}}{y_{st}} \right)^{\frac{1}{\varepsilon}} \frac{\zeta_s}{\zeta_{s'}} \qquad s, s' = 1, ..., S-1 \tag{3}
$$

or

$$
\frac{y_{st}}{y_{s't}} = \left(\frac{\zeta_s}{\zeta_{s'}} \frac{p_{s't}}{p_{st}} \right)^{\varepsilon} \qquad s, s' = 1, ..., S-1 \tag{4}
$$

Final Goods Sector s maximizes profit:

$$
\begin{aligned}
& \max_{u_{s,i,t}} q_{st} y_{st} - \sum_{i \in I} p_{it} u_{s,i,t} \\
= \; & q_{st} \left[\sum_{i \in I} \xi_{s,i} \times y_{i,t}^{\frac{\varepsilon_s - 1}{\varepsilon_s}} \right]^{\frac{\varepsilon_s}{\varepsilon_s - 1}} - \sum_{i \in I} p_{it} y_{i,t}
\end{aligned}
$$

F.O.C w.r.t $y_{i,t}$:

$$q_{st}\left[\sum_{i\in I}\xi_{s,i}\times y_{i,t}^{\frac{\varepsilon_s-1}{\varepsilon_s}}\right]\xi_{s,i}y_{i,t}^{\frac{-1}{\varepsilon_s}}=p_{it}$$

similarly for $y_{j,t}$:

$$q_{st}\left[\sum_{i\in I}\xi_{s,i}\times y_{i,t}^{\frac{\varepsilon_s-1}{\varepsilon_s}}\right]\xi_{s,j}y_{j,t}^{\frac{-1}{\varepsilon_s}}=p_{jt}$$

So I have:

$$\frac{p_{it}}{p_{jt}}=\left(\frac{y_{j,t}}{y_{i,t}}\right)^{\frac{1}{\varepsilon_s}}\frac{\xi_{s,i}}{\xi_{s,j}} \tag{5}$$

or

$$\frac{y_{i,t}}{y_{j,t}}=\left(\frac{\xi_{s,i}}{\xi_{s,j}}\frac{p_{jt}}{p_{it}}\right)^{\varepsilon_s} \tag{6}$$

For industry i in a given sector:

$$\max p_{it}A_{it}K_{it}^{\alpha}n_{it}^{1-\alpha}-r_tK_{it}-w_tn_{it}$$

F.O.C w.r.t K_{it} :

$$p_{it}\alpha A_{it}K_{it}^{\alpha-1}n_{it}^{1-\alpha}=r_t \tag{7}$$

F.O.C w.r.t n_{it} :

$$p_{it}(1-\alpha)A_{it}K_{it}^{\alpha}n_{it}^{-\alpha}=w_t \tag{8}$$

Dividing one F.O.C. by the other I get that

$$\frac{1-\alpha}{\alpha}\left(\frac{K_{it}}{n_{it}}\right)=\frac{w_t}{r_t}\Rightarrow k_t=\frac{w_t}{r_t}\times\frac{\alpha}{1-\alpha} \tag{9}$$

where the capital labor ratio $k_t\equiv K_{it}/n_{it}$ is a constant across industries. Applying this result to (7) implies that

$$\frac{A_{it}}{A_{jt}}=\frac{p_{jt}}{p_{it}} \tag{10}$$

Using (6), (9) and (10) yields

$$\frac{n_{it}}{n_{jt}} = \left(\frac{\xi_{s,i}}{\xi_{s,j}}\right)^{\varepsilon_s} \left(\frac{A_{it}}{A_{jt}}\right)^{\varepsilon_s - 1} \tag{11}$$

which, rearranging (5), implies that $\frac{n_{it}}{n_{jt}} = \frac{p_{it}y_{it}}{p_{jt}y_{jt}}$. Define the industry i growth factor as :

$$G_{it} = \frac{p_{i,t+1}y_{i,t+1}}{p_{it}y_{it}}$$

and the expression G_{it}/G_{jt} then denotes the growth of industry i relative to industry j

$$\begin{aligned}
\frac{G_{it}}{G_{j,t}} &= \frac{\frac{p_{i,t+1}y_{i,t+1}}{p_{it}y_{it}}}{\frac{p_{j,t+1}y_{j,t+1}}{p_{jt}y_{jt}}} = \frac{\frac{p_{it+1}}{p_{jt+1}}\left(\frac{\xi_{s,i}}{\xi_{s,j}}\frac{p_{jt+1}}{p_{it+1}}\right)^{\varepsilon_s}}{\frac{p_{it}}{p_{jt}}\left(\frac{\xi_{s,i}}{\xi_{s,j}}\frac{p_{jt}}{p_{it}}\right)^{\varepsilon_s}} \\
&= \frac{\left(\frac{p_{it+1}}{p_{jt+1}}\right)^{1-\varepsilon_s}}{\left(\frac{p_{it}}{p_{jt}}\right)^{1-\varepsilon_s}} = \frac{\left(\frac{A_{it+1}}{A_{it}}\right)^{\varepsilon_s - 1}}{\left(\frac{A_{jt+1}}{A_{jt}}\right)^{\varepsilon_s - 1}} \\
&= \left(\frac{g_i}{g_j}\right)^{\varepsilon_s - 1}
\end{aligned}$$

■

Proof of Proposition 1 in Chapter 2. Solving the 2 sector problem and using the equilibrium conditions, I have:

$$A_{S_t} = p_{c_t}A_{c_t} \tag{12}$$

$$\begin{aligned}
r_t &= \frac{\frac{p_{c_t}c_t^{\theta}}{p_{c_{t-1}}c_{t-1}^{\theta}}}{\beta} - 1 + \delta = \frac{\left(\frac{\overline{g}_{A_{St-1}}}{\overline{g}_{A_{ct-1}}}\right)^{1-\theta} g_{c_{t-1}}^{\theta}}{\beta} - 1 + \delta \text{ IF } \beta \neq 0 && (13) \\
\text{where } g_{ct-1} &\equiv \frac{p_t c_t}{p_{t-1}c_{t-1}} \text{ is the growth factor of aggregate consumption} && (14) \\
\overline{g}_{A_{ct-1}} &= \frac{A_{ct}}{A_{ct-1}}, \overline{g}_{A_{St-1}} = \frac{A_{St}}{A_{St-1}} \text{ are known} && (15)
\end{aligned}$$

Let $\phi_t = \alpha^{-1} r_t^{\frac{-\alpha}{1-\alpha}} - \overline{g}_{A_{St}}^{\frac{1}{1-\alpha}} r_{t+1}^{\frac{-1}{1-\alpha}} + (1-\delta)\, r_t^{\frac{-1}{1-\alpha}}$

$$\begin{aligned} k_t &= \frac{K_{S_t}}{n_{S_t}} = \frac{K_{c_t}}{n_{c_t}} = \left(\frac{\alpha A_{S_t}}{r_t}\right)^{\frac{1}{1-\alpha}} \\ K_t &= k_t \end{aligned}$$

The growth factor of capital per capita in each sector is:

$$g_{k_t} = \frac{k_{t+1}}{k_t} = \overline{g}_{A_{St}}^{\frac{1}{1-\alpha}} \left(\frac{r_t}{r_{t+1}}\right)^{\frac{1}{1-\alpha}} \tag{16}$$

Similarly, I get aggregate capital growth factor:

$$g_{K_t} = g_{k_t}$$

Using (12) and (2.25), I derive capital sector output, i.e., investment:

$$\begin{aligned} S_t &= \left(\frac{\alpha A_{S_{t+1}}}{r_{t+1}}\right)^{\frac{1}{1-\alpha}} - (1-\delta)\left(\frac{\alpha A_{S_t}}{r_t}\right)^{\frac{1}{1-\alpha}} \\ &= (\alpha A_{S_t})^{\frac{1}{1-\alpha}} \left[\left(\frac{\overline{g}_{A_{St}}}{r_{t+1}}\right)^{\frac{1}{1-\alpha}} - (1-\delta)\left(\frac{1}{r_t}\right)^{\frac{1}{1-\alpha}}\right] \end{aligned} \tag{17}$$

and the growth factor of investment S_t is:

$$g_{S_t} = \frac{S_{t+1}}{S_t} = \overline{g}_{A_{St}}^{\frac{1}{1-\alpha}} \frac{\left(\frac{\overline{g}_{A_{St+1}}}{r_{t+2}}\right)^{\frac{1}{1-\alpha}} - (1-\delta)\left(\frac{1}{r_{t+1}}\right)^{\frac{1}{1-\alpha}}}{\left(\frac{\overline{g}_{A_{St}}}{r_{t+1}}\right)^{\frac{1}{1-\alpha}} - (1-\delta)\left(\frac{1}{r_t}\right)^{\frac{1}{1-\alpha}}}$$

so that the labor in capital sector is:

$$n_{St} = \alpha \left[\frac{1}{r_t}\left(\frac{\overline{g}_{A_{St}} r_t}{r_{t+1}}\right)^{\frac{1}{1-\alpha}} - \frac{(1-\delta)}{r_t}\right] \tag{18}$$

and the growth factor of n_{St} is:

$$g_{n_{St}} = \frac{n_{St+1}}{n_{St}} = \frac{\frac{1}{r_{t+1}}\left(\frac{\overline{g}_{A_{St+1}} r_{t+1}}{r_{t+2}}\right)^{\frac{1}{1-\alpha}} - \frac{(1-\delta)}{r_{t+1}}}{\frac{1}{r_t}\left(\frac{\overline{g}_{A_{St}} r_t}{r_{t+1}}\right)^{\frac{1}{1-\alpha}} - \frac{(1-\delta)}{r_t}} \tag{19}$$

Notice that n_{St} (and hence $n_{ct} = 1 - n_{St}$) is independent of the level of technology in c and S as long as the interest rate is too. I can get capital in capital sector:

$$K_{S_t} = \alpha \left[\frac{1}{r_t} \left(\frac{\overline{g}_{A_{St}} r_t}{r_{t+1}} \right)^{\frac{1}{1-\alpha}} - \frac{(1-\delta)}{r_{t-1}} \right] \left(\frac{\alpha A_{S_t}}{r_t} \right)^{\frac{1}{1-\alpha}} \tag{20}$$

Define the aggregate output per capita as $y_t = S_t + p_{ct} c_{ct}$. Since $K_{ct} = K_t - K_{St}$ and $n_{ct} = 1 - n_{St}$,

$$\begin{aligned} y_t &= S_t + p_{ct} c_{ct} \\ &= A_{S_t} K_{S_t}^{\alpha} n_{S_t}^{1-\alpha} + p_{c_t} A_{c_t} K_{c_t}^{\alpha} n_{c_t}^{1-\alpha} \\ &= A_{S_t} k_t^{\frac{\alpha}{1-\alpha}} = \left(\frac{\alpha}{r_t} \right)^{\frac{\alpha}{1-\alpha}} A_{S_t}^{\frac{1}{1-\alpha}} \end{aligned} \tag{21}$$

and its growth factor is:

$$g_{yt} = \frac{y_{t+1}}{y_t} = \overline{g}_{A_{St}}^{\frac{1}{1-\alpha}} \left(\frac{r_t}{r_{t+1}} \right)^{\frac{\alpha}{1-\alpha}} \tag{22}$$

Aggregate consumption is:

$$C_t = p_{ct} c_t = y_t - S_t \tag{23}$$

$$\begin{aligned} &= \left(\frac{\alpha}{r_t} \right)^{\frac{\alpha}{1-\alpha}} A_{S_t}^{\frac{1}{1-\alpha}} \\ &\quad - (\alpha A_{S_t})^{\frac{1}{1-\alpha}} \left[\left(\frac{\overline{g}_{A_{St}}}{r_{t+1}} \right)^{\frac{1}{1-\alpha}} - (1-\delta) \left(\frac{1}{r_t} \right)^{\frac{1}{1-\alpha}} \right] \end{aligned} \tag{24}$$

The growth factor of consumption is:

$$g_{ct} = \frac{C_{t+1}}{C_t} = \overline{g}_{A_{St}}^{\frac{1}{1-\alpha}} \frac{\phi_{t+1}}{\phi_t}. \tag{25}$$

Notice that as $t \to \infty$ the expressions for $\overline{g}_{A_{St}}$ and $\overline{g}_{Act}$ converge to constants. ■

Proof of Proposition 2 in Chapter 2. Corollary of the proof of Proposition 1 and (2.16). ■

Proof of Proposition 1 in Chapter 3. : Solve the agents' problem: the FOC wrt k_{12}^s and k_{22}^s yield:

$$-u^{'}(c_1) = \rho E u^{'}(c_2) r_{12}$$

$$-u^{'}(c_1) = \rho E u^{'}(c_2) r_{22}$$

Therefore, in time 2, the interest rate of type 1 and type 2 are the same:

$$r_{12} = r_{22} \tag{26}$$

Solve the producers' problem: at time t, each industry solves the problem of maximizing profit under the borrowing constraint at each t and takes input prices as given.

$$\max \pi_{it} = p_{it} y_{it} - r_{1t} k_{i1t} - r_{2t} k_{i2t}$$

$$s.t. \qquad k_{i1t} + k_{i2t} \leq F(\theta, k_{i1t}, k_{i2t}, z_t)$$

When constraint is not binding, the FOCs w.r.t. $k_{i,1,t}, k_{i,2,t}$ are:

$$\frac{\partial y_{it}}{\partial k_{i1t}} = r_{1t}$$
$$\frac{\partial y_{it}}{\partial k_{i2t}} = r_{2t}$$

then I could get :$k_{i1t} = (\frac{r_{2t}}{r_{1t}} \frac{\alpha_i}{1-\alpha_i}) k_{i2t}$. Since $r_{12} = r_{22}$, then the following holds:

$$k_{i12} = (\frac{\alpha_i}{1-\alpha_i}) k_{i22}, \forall i.$$

When constraint is binding, I substitute k_{i1t}, k_{i2t} into the borrowing constraint:

$$(\frac{r_{2t}}{r_{1t}}\frac{\alpha_i}{1-\alpha_i})k_{i2t} + k_{i2t} = F(\theta, \alpha_i, z_t)k_{i1t}^{\eta_1}k_{i2t}^{\eta_2}$$

Then I obtain k_{i1t}, k_{i2t}:

$$k_{i1t} = (\frac{F(\theta,\alpha_i,z_t)}{\frac{r_{2t}}{r_{1t}}\frac{\alpha_i}{1-\alpha_i}+1})^{\frac{1}{1-\eta_1-\eta_2}}\left(\frac{r_{2t}}{r_{1t}}\frac{\alpha_i}{1-\alpha_i}\right)^{\frac{1-\eta_2}{1-\eta_1-\eta_2}} \tag{27}$$

$$k_{i2t} = \left(\frac{F(\theta,\alpha_i,z_t)\left(\frac{r_{2t}}{r_{1t}}\frac{\alpha_i}{1-\alpha_i}\right)^{\eta_1}}{\frac{r_{2t}}{r_{1t}}\frac{\alpha_i}{1-\alpha_i}+1}\right)^{\frac{1}{1-\eta_1-\eta_2}}$$

When I plug in k_{i1t}, k_{i2t} from (9) into the production function, I obtain the following:

$$y_{it} = z_t k_{i1t}^{\alpha_i}k_{i2t}^{1-\alpha_i} = z_t(\frac{r_{2t}}{r_{1t}}\frac{\alpha_i}{1-\alpha_i})^{\alpha_i}\left(\frac{F(\theta,\alpha_i,z_t)\left(\frac{\alpha_i}{1-\alpha_i}\right)^{\eta_1}(1-\alpha_i)}{r_{2t}}\right)^{\frac{1}{1-\eta_1-\eta_2}} \tag{28}$$

Then substitute equation (28) and (26) for y_{it} into (3.4):

$$\Omega_{ij}(z_t) = \frac{\Psi_i}{\Psi_j} = \left(\frac{F(\alpha_i,z_2)}{F(\alpha_i,z_1)}\frac{F(\alpha_j,z_1)}{F(\alpha_j,z_2)}\right)^{\frac{1}{1-\eta_1-\eta_2}}\overline{r_1}^{\alpha_j-\alpha_i} \tag{29}$$

where $\overline{r_1} = \frac{\overline{r_{21}}}{\overline{r_{11}}}$ is fixed. At time 2, if I get a negative shock $z_2 = z_{low} = 1-\sigma$, the difference in industry growth $\Lambda_{ij}(z_{low})$ is:

$$\Omega_{ij}(z_{low}) = \left(\frac{F(\alpha_i,z_{low})}{F(\alpha_i,z_1)}\frac{F(\alpha_j,z_1)}{F(\alpha_j,z_{low})}\right)^{\frac{1}{1-\eta_1-\eta_2}}\overline{r_1}^{\alpha_j-\alpha_i} \tag{30}$$

Similarly, if I get a positive shock $z_2 = z_{high} = 1+\sigma$, the difference in industry growth $\Omega_{ij}(z_{high})$ is:

$$\Omega_{ij}(z_{high}) = \left(\frac{F(\alpha_i,z_{high})}{F(\alpha_i,z_1)}\frac{F(\alpha_j,z_1)}{F(\alpha_j,z_{high})}\right)^{\frac{1}{1-\eta_1-\eta_2}}\overline{r_1}^{\alpha_j-\alpha_i} \tag{31}$$

Then the difference in growth rate in recession relative to boom is (30) over (31) :

$$\frac{\Omega_{ij}^{recession}}{\Omega_{ij}^{boom}} = \frac{\Omega_{ij}\left(z_{low}\right)}{\Omega_{ij}\left(z_{high}\right)} = \left(\frac{\frac{F(\alpha_i,z_{low})}{F(\alpha_j,z_{low})}}{\frac{F(\alpha_i,z_{high})}{F(\alpha_j,z_{high})}}\right)^{\frac{1}{1-\eta_1-\eta_2}} \tag{32}$$

which is a function of the financing constraint $F(\alpha_i, z)$.Assuming $\alpha_i > \alpha_j$, i.e. industry i's share of intangible assets is higher than industry j, then I can write α_i as $\alpha_i = \alpha_j + \triangle_\alpha$. Similarly since $z_{low} < z_{high}$,I can write z_{high} as $z_{high} = z_{low} + \triangle_z$,where $\triangle_z = 2\sigma$. Then (32) can be rewritten as:

$$\begin{aligned}\frac{\Omega_{ij}^{recession}}{\Omega_{ij}^{boom}} &= \left(\frac{\frac{F(\alpha_j+\triangle_\alpha,z_{low})}{F(\alpha_j,z_{low})}}{\frac{F(\alpha_j+\triangle_\alpha,z_{low}+\triangle_z)}{F(\alpha_j,z_{low}+\triangle_z)}}\right)^{\frac{1}{1-\eta_1-\eta_2}} \\ &= \left(\frac{\frac{F(\alpha_j+\triangle_\alpha,z_{low})\frac{\triangle_\alpha}{\triangle_\alpha}}{F(\alpha_j,z_{low})}}{\frac{F(\alpha_j+\triangle_\alpha,z_{low}+\triangle_z)\frac{\triangle_\alpha\triangle_z}{\triangle_\alpha\triangle_z}}{F(\alpha_j,z_{low}+\triangle_z)\frac{\triangle_z}{\triangle_z}}}\right)^{\frac{1}{1-\eta_1-\eta_2}}\end{aligned} \tag{33}$$

Then take the limit of $\triangle_\alpha$and $\triangle_z$:

$$\lim_{\triangle_\alpha\to 0}\lim_{\triangle_z\to 0}\frac{\Omega_{ij}^{recession}}{\Omega_{ij}^{boom}} = \left(\frac{F_\alpha F_z}{F_{\alpha z}F}\right)^{\frac{1}{1-\eta_1-\eta_2}} \tag{34}$$

where F_x equals the derivative of F with respect to x, F_{xy} the derivative of F with respect to x and y. I also have assumed $1 - \eta_1 - \eta_2 > 0$. The assumptions of the F function are that $\frac{\partial F}{\partial \alpha} < 0$, $\frac{\partial F}{\partial z} > 0$,and $\frac{\partial^2 F}{\partial \alpha \partial z} < 0$,So $\frac{F_\alpha F_z}{F_{\alpha z}F} > 0$. Then $\frac{\Omega_{ij}^{recession}}{\Omega_{ij}^{boom}} \gtrless 1$ depends on $\frac{F_\alpha F_z}{F_{\alpha z}F} \gtrless 1$. ■

Proof of Value Added Growth equation in Chapter 3. I define value added growth rate of industry i as:

$$G_i = \frac{p_{i2}y_{i2}}{p_{i1}y_{i1}}$$

Then the relative value added growth rate of industry i to industry j is:

$$\frac{G_i}{G_j} = \frac{\frac{p_{i2}y_{i2}}{p_{i1}y_{i1}}}{\frac{p_{j2}y_{j2}}{p_{j1}y_{j1}}} \tag{35}$$

Solve the problem of the final good sector: the FOC wrt y_{it} yields:

$$y_t^{\frac{1}{\varepsilon-1}}\phi_i y_{it}^{\frac{1}{\varepsilon-1}} - s_t p_{it} = 0$$

where s_t is total expenditure at time t $s_t = \sum_{i=1}^{I} p_{it}y_{it}$. Similarly for y_{jt} :

$$y_t^{\frac{1}{\varepsilon-1}}\phi_j y_{jt}^{\frac{1}{\varepsilon-1}} - s_t p_{jt} = 0$$

Then I can get the substitution of consumption of good i over good j:

$$\frac{y_{it}}{y_{jt}} = (\frac{p_{jt}}{p_{it}}\frac{\phi_i}{\phi_j})^{\varepsilon} \tag{36}$$

Using (36), I could get:

$$\frac{p_{it}}{p_{jt}} = (\frac{y_{jt}}{y_{it}})^{\frac{1}{\varepsilon}}\frac{\phi_i}{\phi_j} \tag{37}$$

$$s_t = \sum_{j=1}^{I} p_{jt}y_{jt} = p_{it}y_{it}\sum_{j=1}^{I}(\frac{\phi_j}{\phi_i})^{\varepsilon}(\frac{p_{jt}}{p_{it}})^{1-\varepsilon}$$

Then I can write y_{it} as:

$$y_{it} = s_t(\frac{\phi_i}{p_{it}})^{\varepsilon}(\sum_{j=1}^{I} p_{jt}^{1-\varepsilon}\phi_j^{\varepsilon})^{-1}$$

If I plug y_{it} into y_t, the total consumption at time t is:

$$y_t = (\sum_{i=1}^{I}\phi_i y_{it}^{\frac{\epsilon-1}{\epsilon}})^{\frac{\epsilon}{\epsilon-1}} = (\sum_{i=1}^{I}\phi_i[s_t(\frac{\phi_i}{\phi_j})^{\varepsilon}(\sum_{j=1}^{I} p_{jt}^{1-\varepsilon}\phi_j^{\varepsilon})^{-1}]^{\frac{\epsilon-1}{\epsilon}})^{\frac{\epsilon}{\epsilon-1}}$$
$$= s_t(\sum_{j=1}^{I} p_{jt}^{1-\varepsilon}\phi_j^{\varepsilon})^{\frac{1}{\epsilon-1}}$$

Then I substitute equation (37) into (3.4):

$$\frac{G_i}{G_j} = (\frac{y_{i2}/y_{i1}}{y_{j2}/y_{j1}})^{1-\frac{1}{\varepsilon}} \tag{38}$$

Let $\Lambda_{ij}\left(z_t\right) \equiv \frac{G_i}{G_j}$ as the difference in industry value added growth rates at time t. Then substitute equation (28) and (26) for y_{it} into (38):

$$\Lambda_{ij}\left(z_t\right) = \frac{G_i}{G_j} = \left\{ \left(\frac{F(\alpha_i, z_2)}{F(\alpha_i, z_1)} \frac{F(\alpha_j, z_1)}{F(\alpha_j, z_2)} \right)^{\frac{1}{1-\eta_1-\eta_2}} \overline{r_1}^{\alpha_j-\alpha_i} \right\}^{\left(1-\frac{1}{\varepsilon}\right)} \tag{39}$$

So the difference in industry growth rates in recessions relative to in booms is a function of the borrowing constraint $F(\alpha_i, z_t)$ when the constraint is binding:

$$\frac{\Lambda_{ij}^{recession}}{\Lambda_{ij}^{boom}} = \frac{\Lambda_{ij}\left(z_{low}\right)}{\Lambda_{ij}\left(z_{high}\right)} = \left(\frac{\frac{F(\alpha_i, z_{low})}{F(\alpha_j, z_{low})}}{\frac{F(\alpha_i, z_{high})}{F(\alpha_j, z_{high})}} \right)^{\frac{1}{1-\eta_1-\eta_2}\left(1-\frac{1}{\varepsilon}\right)} = \left(\frac{\frac{F(\alpha_j+\triangle_\alpha, z_{low})}{F(\alpha_j, z_{low})}}{\frac{F(\alpha_j+\triangle_\alpha, z_{low}+\triangle_z)}{F(\alpha_j, z_{low}+\triangle_z)}} \right)^{\frac{1}{1-\eta_1-\eta_2}\left(1-\frac{1}{\varepsilon}\right)}$$

$$\lim_{\triangle_\alpha \to 0} \lim_{\triangle_z \to 0} \frac{\Lambda_{ij}^{recession}}{\Lambda_{ij}^{boom}} = \left(\frac{F_\alpha F_z}{F_{\alpha z} F} \right)^{\frac{1}{1-\eta_1-\eta_2}\left(1-\frac{1}{\varepsilon}\right)}$$

where $\alpha_i = \alpha_j + \triangle_\alpha$, $z_{high} = z_{low} + \triangle_z$.According to Ilyina and Samaniego (2011), $\varepsilon > 1$, then $1 - \frac{1}{\varepsilon} > 0$. I also have assumed $1 - \eta_1 - \eta_2 > 0$. The assumptions of the F function are that $\frac{\partial F}{\partial \alpha} < 0$, $\frac{\partial F}{\partial z} > 0$,and $\frac{\partial^2 F}{\partial \alpha \partial z} < 0$,So $\frac{F_\alpha F_z}{F_{\alpha z} F} > 0$. Then $\frac{\Lambda_{ij}^{recession}}{\Lambda_{ij}^{boom}} \gtrless 1$ depends on $\frac{F_\alpha F_z}{F_{\alpha z} F} \gtrless 1$. ■

Taylor Decomposition. I take a second order Taylor approximation of the function $\Omega\left(\alpha_i, z_t\right)$ around some industry at time t with $\alpha_i = \alpha_i^*, z_t = z_t^*$:

$$\begin{aligned} \Omega\left(\alpha_i, z_t\right) &= \Omega\left(\alpha_i^*, z_t^*\right) + \Omega_\alpha\left(\alpha_i^*, z_t^*\right)\left(\alpha_i - \alpha_i^*\right) + \Omega_z\left(\alpha_i^*, z_t^*\right)\left(z_t - z_t^*\right) \\ &+ \frac{1}{2}\Omega_{\alpha\alpha}\left(\alpha_i^*, z_t^*\right)\left(\alpha_i - \alpha_i^*\right)^2 + \frac{1}{2}\Omega_{zz}\left(\alpha_i^*, z_t^*\right)\left(z_t - z_t^*\right)^2 \\ &+ \Omega_{\alpha z}\left(\alpha_i^*, z_t^*\right)\left(\alpha_i - \alpha_i^*\right)\left(z_t - z_t^*\right) \end{aligned}$$

where Ω_x equals the derivative of Ω with respect to x, Ω_{xy} the derivative of Ω with respect to x and y, and Ω_{xyz} the derivative of Ω with respect to x, y and z. This reduces to:

$$\Omega\left(\alpha_i, z_t\right) = B_i + B_z + \beta_{iz}\alpha_i z_t + \epsilon_{it} \tag{40}$$

where coefficients of the interaction terms are their cross-derivatives. All other industry (α_i), country and time (z_t) specific effects are captured in B_i and B_z. Recall that $\ln x \simeq x - 1$. Taking logs of $\Omega = \frac{\Psi_i}{\Psi_j}$ and replacing $\ln \Omega + 1$ with Ω into (40), I have:

$$\begin{aligned} \ln(\Psi_i) &= \beta_i + \beta_z + \beta_{iz}\alpha_i z_t + \epsilon_{it} + \ln(\Psi_j) \qquad (41) \\ &= \widetilde{\beta}_i + \beta_z + \beta_{iz}\alpha_i z_t + \epsilon_{it} \end{aligned}$$

where $\widetilde{\beta}_i = \beta_i + \ln(\Psi_j)$. $\blacksquare$

Measurement of productivity in Manufacturing

I measure productivity using the NBER Manufacturing Productivity Database. The data are more disaggregated that the ISIC3 Classification I need for the UNIDO data, so I aggregate them using Domar weights.

In addition, I use an alternative way of measuring TFP growth rates. Using the UNIDO data set, I compute the TFP growth rates of 28 UNIDO manufacturing industries of the United States using the following equation:

$$\ln(TFP_{it}) = \ln(Y_{it}) - (1-\alpha)\ln(L_{it}) - \alpha \ln\left(K_{it}\right) \tag{42}$$

where Y_{it} is the production index. This requires computing the capital stock at the industry level. The UNIDO data set provides investment data but not capital stock data K_{it}, so I use a perpetual inventory method

$$K_{it+1} = (1-\delta)K_{it} + I_{it}q_{it} \tag{43}$$

to compute growth rate of capital stock, where I_{it} is investment and q_{it} represents investment-specific technical progress[12]. Then the growth rate of K_{it} is the sum of growth rates of I and q. I set $q_{it} = g_{iq}^{t}$, so that growth rates of q_i vary across industries. I use growth factor g_{iq} from Ilyina and Samaniego (2012). (see table 17) Also, $\delta = 0.06$ and $\alpha = 0.3$. These are standard numbers in the literature.[13] Then, if $\Gamma(x)$ is the log growth rate of x over the time period in the data, note that

$$\ln g_i = \Gamma(Y_i) - (1-\alpha)\Gamma(L_i) - \alpha\Gamma(K_i) \tag{44}$$

I obtain $\Gamma(Y_i)$ and $\Gamma(L_i)$ from UNIDO, and set $\Gamma(K_i) = \Gamma(I_i) + \log g_{iq}$, which is the long run relationship in (43).

Simulation procedure

Simulating the model requires overcoming two distinct problems.

The first concerns matching the model with the data. Notice that the model is essentially a 2 sector model where consumption and investment are made by

[12] I need to allow for investment-specific technical progress because the model is one with many industries where productivity growth rates in capital-producing industries may be different from productivity growth elsewhere.

[13] The value of δ is from Greenwood, Hercowitz and Krusell (1997) and is a value typical in models with investment-specific technical change, in other words where $g_q > 1$.

different sectors. As shown in Greenwood, Hercowitz and Krusell (1997), this is the same as a one-sector model with investment specific technical change. In the one-sector growth model, the equilibrium for any initial conditions is a jump to the stable branch of a saddle path that leads to the long run equilibrium (which in this case is the model where the capital sector has converged to contain only one industry). Thus, for general initial conditions K_0, the share of investment will jump after period 1, so that the structure of the manufacturing sector will change abruptly after period zero (and smoothly thereafter).

I handle this problem in two ways. First, I computed everything without worrying about the jump. Second, I calibrated the model so as to focus on an Euler growth path – which are the results reported in the paper (results were very similar either way).

I did not set the initial value of the capital stock K_0 to match the investment share of GDP in each country. The reason was that, in all other periods after $t = 0$, the investment share will follow the Euler equation. It seems arbitrary to assume that in all countries the Euler equation is satisfied in all years except 1963, or whatever happens to be the year for which data are initially available. As a result, I assume that the Euler equation is also satisfied at date zero. I call this an "Euler growth path" or EGP. To do this requires setting the investment share of GDP at a value that is different from that in the data. At the same time, it is critical that I preserve the composition of manufacturing. Hence, I adopted a recursive strategy. I know from the data the composition of investment in year zero. Given an assumption on the investment to GDP ratio, I can preserve the ratio of capital to manufacturing and find a value for the size of manufacturing that preserves its composition.[14] Then I check whether the assumption on the investment to GDP ratio matches an EGP.[15] If not, then I generate another guess based on the predicted EGP value from the last iteration. I find that 3 loops is sufficient for very tight convergence. Then, the sector shares in the rest of the economy are set so as to preserve their relative values. When I regress data on initial manufacturing shares on the model initial manufacturing shares, I find a coefficient of 1.16 (positive and close to one) and an intercept of -0.026 (close to zero), both significant at the 1% level. I take this to imply that, in general, my procedure does not significantly distort the sector structure of the model economy.

The second computational issue I confront is the fact that I am simulating a model economy that does not have a balanced growth path (although it converges to one). Recall that the aggregate behavior of the model is the same as a one-sector model with investment specific technical change. In the one-sector growth model, any approximation to the saddle path will "shadow" it for a period of time, eventually diverging infinitely from it: see Colucci (2001). As a result, I adopt a procedure to provide this "shadowing" without suffering a significant divergence.

[14] Other sectors are resized so that, relative to each other, shares of GDP are preserved.

[15] Recall that computing the equilibrium, including the initial share of investment, requires a series for g_c, which in turn depends on sector productivity growth rates. However, sector productivity growth rates depend on the initial composition and size of the economy. This is why an iterative procedure is necessary to find an EGP.

The procedure is to assume limited computational ability among the agents, a procedure I call "rolling windows of consciousness." Specifically, the structure of the model economy can be computed exactly given the investment share of employment. This can be computed exactly given a series for g_{ct}, which is determined by (25) and the transversality condition. This series eventually converges to $g_{ct} = \overline{g}_{A_{St}}^{\frac{1}{1-\alpha}}$, where $\overline{g}_{A_{St}}$ is known given initial conditions. I assume that an agent at date t acts as though up to some period $t+T$ difference equation (25) characterizes g_{ct}, whereas after $t+T$ the agent believes that $g_{ct} = \overline{g}_{A_{St}}^{\frac{1}{1-\alpha}}$. I tried $T = 50$, 90 and 200. For $T = 90$, the error between the realized value of g_{c1} and the value forecast by the agent in period 0 is about 1% of the actual value (because the series for g_{ct} converges uniformly to its long run value, the forecast errors are the highest in the first period). For $T = 200$ these values are indistinguishable to eight decimal places. At the same time, for all values of T, the Gini nonparametric regressions were indistinguishable regardless of the value of T.

This indicates two results. First, this procedure could yield an arbitrarily accurate approximation to the correct aggregate equilibrium dynamics, given a sufficiently large (but finite) value of T. This is distinct from the shadowing property, which provides arbitrarily precise approximations only for a finite period, after which there is increasing divergence. Second, industry dynamics are robust to using values of T such that aggregate dynamics are computed with some degree of imprecision.

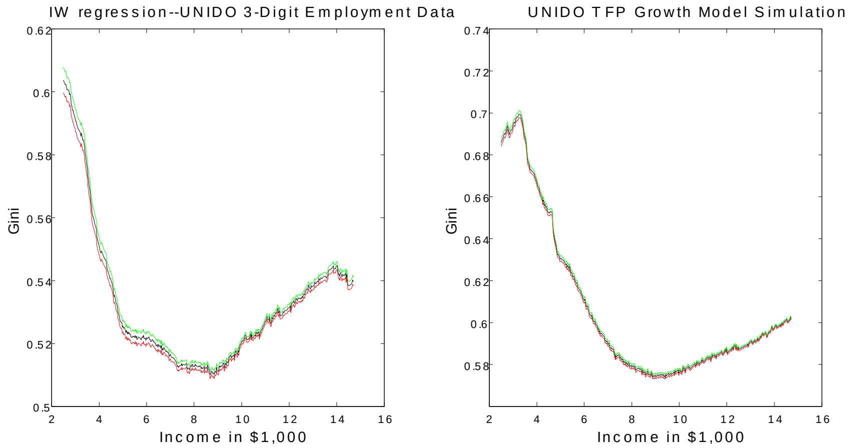

Figure 1: Full model–TFP growth rates from the UNIDO data.

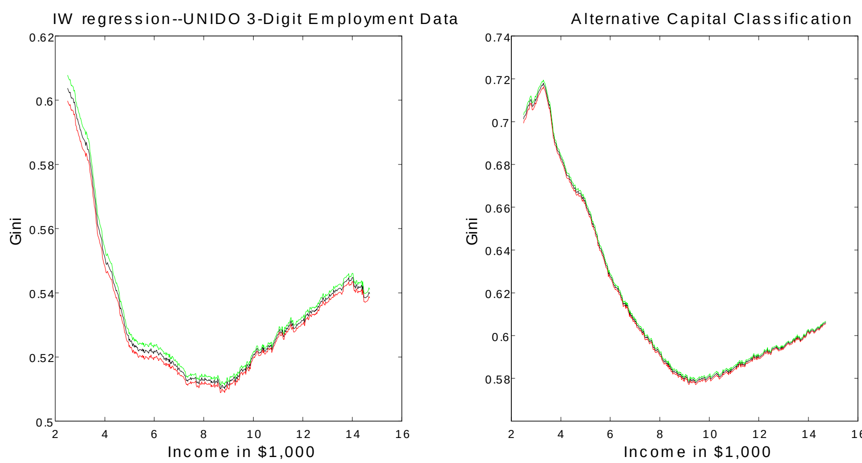

Figure 2: Full model–alternative classification of the capital industry.

Robustness results

Industry TFP growth data

Table 16: NBER TFP Growth Rates for the ISIC revision 2 industry classification.

Industry	ISIC code	NBER TFP Growth Rate
Food products	311	0.0101
Beverages	313	0.0303
Tobacco	314	-0.0345
Textiles	321	0.0269
Apparel	322	0.0121
Leather	323	-0.0034
Footwear	324	-0.0035
Wood products	331	0.0113
Furniture, except metal	332	0.0066
Paper and products	341	0.0088
Printing and publishing	342	-0.0022
Industrial chemicals	351	0.0214
Other chemicals	352	0.0135
Petroleum refineries	353	0.0196
Misc. pet. and coal products	354	0.0223
Rubber products	355	0.0142
Plastic products	356	0.0339
Pottery, china, earthenware	361	0.0078
Glass and products	362	0.0051
Other non-metallic mineral prod.	369	0.0120
Iron and steel	371	0.0047
Non-ferrous metals	372	0.0016
Fabricated metal products	381	0.0029
Machinery, except electrical	382	0.0285
Machinery, electric	383	0.0347
Transport equipment	384	0.0160
Prof. & sci. equip.	385	0.0126
Other manufactured prod.	390	0.0089

Table 17: UNIDO TFP and Price Growth Rate

Industry	ISIC code	UNIDO TFP Growth Rate	UNIDO Price Growth Rate
Food products	311	0.0067	0.0424
Beverages	313	0.0244	0.0295
Tobacco	314	-0.0212	0.0941
Textiles	321	0.0090	0.0328
Apparel	322	0.0060	0.0371
Leather	323	-0.0196	0.0570
Footwear	324	0.0034	0.0438
Wood products	331	-0.0014	0.0464
Furniture, except metal	332	0.0064	0.0352
Paper and products	341	0.0019	0.0410
Printing and publishing	342	-0.0062	0.0499
Industrial chemicals	351	0.0225	0.0201
Other chemicals	352	0.0146	0.0322
Petroleum refineries	353	-0.0089	0.0507
Misc. pet. and coal products	354	-0.0168	0.0552
Rubber products	355	0.0287	0.0172
Plastic products	356	0.0321	0.0132
Pottery, china, earthenware	361	-0.0116	0.0428
Glass and products	362	0.0005	0.0358
Other non-metallic mineral prod.	369	0.0040	0.0375
Iron and steel	371	-0.0006	0.0377
Non-ferrous metals	372	-0.0103	0.0472
Fabricated metal products	381	0.0034	0.0392
Machinery, except electrical	382	0.0330	0.0025
Machinery, electric	383	0.0218	0.0167
Transport equipment	384	-0.0118	0.0488
Prof. & sci. equip.	385	-0.0027	0.0425
Other manufactured prod.	390	0.0170	0.0290

Table 18: Capital Industries

Industry	ISIC code
Wood products	331
Furniture, except metal	332
Rubber products	355
Plastic products	356
Pottery, china, earthenware	361
Glass and products	362
Other non-metallic mineral prod.	369
Iron and steel	371
Non-ferrous metals	372
Fabricated metal products	381
Machinery, except electrical	382
Machinery, electric	383
Transport equipment	384
Prof. & sci. equip.	385
Other manufactured prod.	390