Productivity, Firm Heterogeneity, and Policy Reforms in Latin America

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Chapter 1

Introduction and Thesis Outline

This thesis studies policy reforms and their relation with productivity performance. It argues that heterogeneity at the firm-level is at the core for understanding the relation between policy and productivity. The chapters in this thesis focus on two Latin American countries, namely Brazil and Chile. Latin American countries experienced large swings in government policy during the past decades, therefore providing potentially interesting case studies of the role and impact of firm heterogeneity on the effects of policies on productivity trends.

The main policy reform in Latin America in the past decades was the switch from state-led growth to market-oriented growth. In the aftermath of the 1982 crisis, a market-oriented laissez-faire approach was considered best to achieve macroeconomic stability and accelerate economic growth (Edwards, 1995). Market-oriented reforms did not live up to expectations. Economic growth after the reforms was modest at best and lower than before the crisis. This was partly related to diminished opportunities for catch-up and less vigorous investment in physical and human capital. However, most researchers argue that slow productivity growth is the main culprit behind Latin America's disappointing economic performance after the market-oriented reforms.[1] Low productivity growth is of profound concern to academics and policy makers. As succinctly put by Krugman (1994):

"Productivity isn't everything, but in the long run it is almost everything. A coun-

[1] See for instance Cole et al. (2005); De Gregorio (2006); Inter-American Development Bank (2005); Szirmai (2008).

try's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker. Compared with the problem of slow productivity growth, all our other long-term economic concerns -foreign competition, the industrial base, lagging technology, deteriorating infrastructure, and so on- are minor issues. Or more accurately, they matter only to the extent that they have an impact on our productivity growth." p. 13 and p. 18 in Krugman (1994)

Figure 1.1 presents labor productivity growth rates, defined as growth in output minus growth in employment, for Brazil and Chile. Latin America is added for comparative purposes.[2] During the 60s and 70s, state-led growth in Brazil and Chile was substantial. Labor productivity grew at an annual average of about 3 percent in Brazil and 2 percent in Chile, which implies living standards improved rapidly during this period.[3] However, the 1982 debt crisis, which heralded the lost decade in Latin America, resulted in large capital outflows, macroeconomic instability, and a substantial drop in output per person.

Chile was an early adopter of those policy reforms which the US treasury and the international organizations in Washington considered the best remedies to rise from the sickbed. The proposed market-oriented reforms, summarized as the Washington consensus by Williamson (1990), included privatization, deregulation, macroeconomic adjustments, and the reduction of barriers to trade. Chile was an early reformer. It radically liberalized trade and undertook macroeconomic adjustments. Chile experienced productivity growth after the reforms.

Brazil and most other Latin American countries adopted market-oriented policy reforms much later, mainly during the late 1980s and early 1990s.[4] The reforms, however, failed to result in productivity growth in Brazil and in most other Latin American countries.

Low growth after compliance with the Washington consensus poses a puzzle to researchers and politicians (Rodrik, 2007). The mediocre productivity performance of Brazil and Latin America in general (except for Chile) has led policy makers and international organizations to re-evaluate their policy advice to developing countries (see e.g. World Bank (2005)).

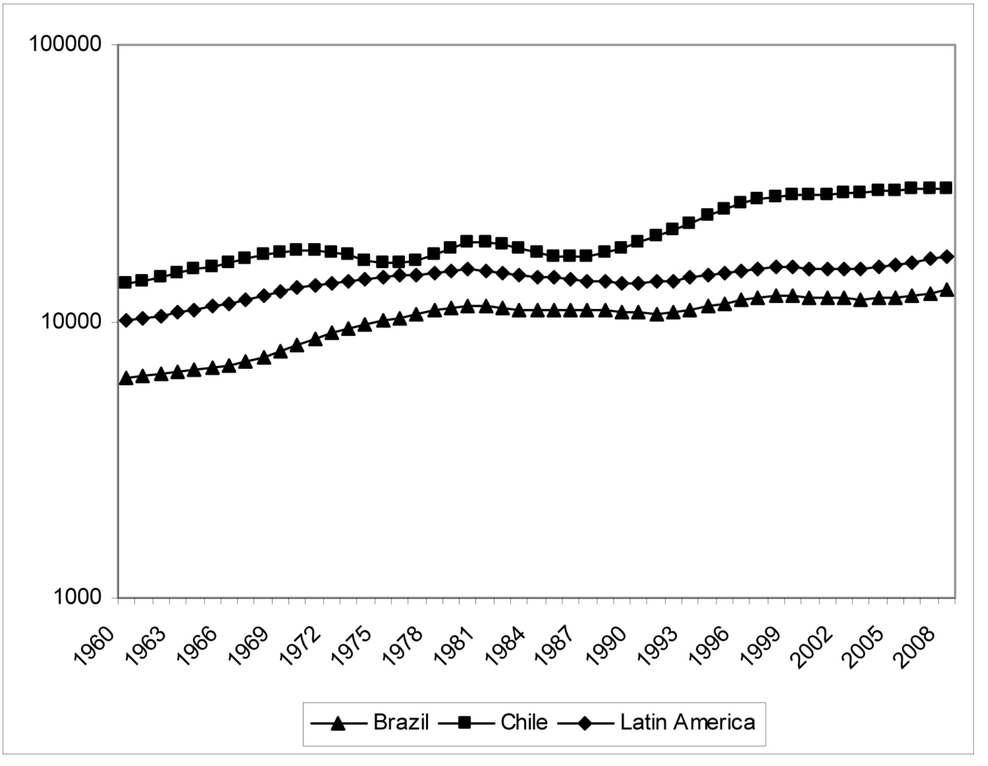
This thesis aims to add various pieces to solving the puzzle why growth in Latin

[2] GDP per person employed in Latin America is an output weighted trend of seventeen Latin American countries, including among others Argentina, Brazil, Chile, and Mexico.

[3] Total factor productivity, defined as growth in output minus share-weighted growth in employment and capital, gives similar results (Hofman, 2000).

[4] Edwards (1995) provides a detailed overview on the timing of reforms in various Latin American countries.

Figure 1.1. Trend growth in GDP per person employed



Data Source: The Conference Board, Total Economy Database, http://www.conference-board.org/economics. Trend is estimated using Hodrick and Prescott (1997) filter on growth in GDP per person employed.

America did not accelerate despite wide-ranging reforms. It explores the relation between policy reforms and productivity performance using firm-level data for a large services sector, namely the retail sector. Latin American growth is becoming increasingly services-led. Currently, over 60 percent of the labor force in Brazil and Chile is employed in the services sector. More people are employed in wholesale and retail services than in manufacturing (Timmer and de Vries, 2009). The traditional thesis of manufacturing as the engine of growth might not be applicable to Brazil and Chile anymore (Szirmai, 2009), which would call for new strategies for accelerating productivity performance. Growth dynamics in the services sector are poorly understood. At the same time, it is subject to a large set of government regulations and policy initiatives such as the opening up to foreign direct investment.

Economic development is a dynamic and complex process. For long it has therefore been argued that a macro approach is too aggregate to take into account the complexity of the growth process (Nelson, 1981). Currently, with the increasing availability of firm-level surveys, the process of productivity growth is studied at the micro-level as well.[5] In addition, new theories loosen up the neo-classical representative firm paradigm and stress the importance of heterogeneity for understanding the relation between policy and productivity growth (Melitz, 2003), which necessitates the use of firm-level data.

Firms differ among others in size, in productivity, in the products they produce or the services they deliver, and in the production process (labor- or capital-intensive technologies) they employ. Many policies, however, are generic. For example, entry barriers and taxes on gross profits are set for all firms, regardless of their heterogeneity. An aggregate analysis using country or industry data collapses firm heterogeneity to a single aggregate and might not capture differential effects of policies due to firm heterogeneity. To understand the heterogeneous effects of policy reforms for productivity performance, this thesis uses micro data for the retail trade sector.

The remainder of this chapter elaborates upon the aims and content of this thesis.

1.1 Trade Liberalization and Productivity

The first aim of this thesis is to explore the relation between liberalization of the retail sector and improvements in productivity. Chile was a pioneer in the liberalization process, opening up industrial and services sectors during the 1970s and 80s. Brazil reformed trade much later. The Brazilian retail sector was opened up only in the World Trade Organization 1995 General Agreement on Trade in Services, and the freeing from restrictions on the participation of foreign capital in retail firms in the Sixth Constitutional Amendment of 1995 (World Bank, 2004). Because firm-level surveys are available at the national statistical institute for Brazil since the mid-1990s, the relation between liberalization and productivity is studied for Brazilian retail firms in this thesis.

Liberalization was expected to result in increased competition, which would induce firms to improve their performance. Indeed, studies of the manufacturing sector found that productivity within firms improved as a result of trade liberalization.[6] In addition, trade reforms aimed to stimulate growth by allowing resources

[5] See for example Bartelsman and Doms (2000); Tybout (2000); Inter-American Development Bank (2005).

[6] E.g. Hay (2001); Muendler (2004); Schor (2004); Pavcnik (2002); Bergoeing et al. (2006).

like capital and labor to move about more freely. If prices signal where inputs should move, profit-maximizing firms reallocate inputs in the direction of their most valued activities. Hence, trade reforms were expected to result in a reallocation of resources toward high marginal-productivity firms.

Various recent theoretical models of growth are consistent with expectations from trade reforms. Vintage capital models (Aghion and Howitt, 1994) and trade models (Melitz, 2003) predict that inputs will reallocate from low-productive to high-productive activities as the economy liberalizes. For example, trade liberalization in Melitz (2003) drives the least-productive domestic firms out of the market, because they are unable to compete with more productive international firms setting up shop there. In contrast, more productive domestic firms are induced to enter the foreign market, thereby increasing profits and expanding production. Hence, the Melitz model predicts that liberalization results in the reallocation of resources toward more productive firms boosting aggregate growth.

Recent studies for the retail sector have shown that productivity growth in OECD countries occurred through a process of creative destruction. That is, growth originated from reallocation dynamics through firm churning (the entry and exit of firms) and resource reallocation to more-productive retail chains. For example, new establishments from retail chains (including, but not only, Wal-Mart) displacing 'mom-and-pop' stores accounted for virtually all growth in the US in the past decades (Foster et al., 2006). Similar findings for the U.K. are presented by Haskel and Sadun (2009) and for Japan by Matsuura and Motohashi (2005).[7]

In chapter 2, similar decomposition methodologies as in these studies are employed to understand the performance of Brazil's retail sector. This chapter examines the question whether resource allocation improved after liberalization of the Brazilian retail sector. It therefore extends the discussion of the productivity gains from liberalization in Latin America to the services sector.

1.2 Regulation and Resource Allocation

The second aim of this thesis is to delve deeper into the relation between regulation and resource allocation by considering how taxes and access to credit affect the allocation of factor inputs across firms.

[7] Although development patterns between the U.K. and the U.S. retail sector are similar, Haskel and Sadun (2009) argue that size restrictions on new establishments from continuing chains are related with the differential productivity performance between the U.K. and the U.S. due to increasing returns to scale for multi-establishment chains.

Recent models of firm productivity follow Banerjee and Duflo (2005) by comparing marginal revenue products with the costs of factor inputs to examine the (mis)use of resources. That is, policies might result in idiosyncratic distortions such that marginal products no longer equal marginal costs at the firm level.

Guner et al. (2008) argue that policy distortions may depend on firm size, which they refer to as *size-dependent policies*. In their model, the key idea is that if a firm wants to expand the use of inputs beyond a given level, it faces a marginal cost of using the inputs that is larger than its price.

Size-dependent policies might be prevalent in developing economies (Gollin, 2006). For example, in Brazil, despite the opening up of the retail sector to foreign firms, labor and product markets are still heavily regulated. Taxes reach over 200 percent of gross profits in Rio de Janeiro (World Bank, 2006). Selective policy implementation and enforcement may create implicit or *de facto* differences in the business environment small and large firms face. For example, governments often find it impractical to collect taxes from small firms. Instead, governments are likely to set higher tax rates and enforce compliance only among larger firms (Tybout, 2000). Likewise, difficulties in access to credit and strict labor market regulations may prevent the growth of successful small retailers and worsen their competitiveness relative to informal retailers. Capital market imperfections might be a bigger constraint for smaller firms that lack collateral.

Chapter 3 also examines the question whether resource allocation improved after liberalization of the Brazilian retail sector. Chapter 2 used average firm productivity to examine the relation between productivity and the opening up of the retail sector. However, this chapter follows Banerjee and Duflo (2005) by comparing marginal revenue products with the costs of factor inputs to examine the (mis)use of resources. Distortions create a wedge between the opportunity cost and marginal revenue product of factor inputs. Implications of these wedges for aggregate productivity are studied. In addition, this chapter relates distortions with taxes and credit.

This chapter argues that difficulty in access to credit creates relatively larger distortions to capital for small firms, because they lack collateral. Similarly, it hypothesizes that taxes on gross profits create relatively larger distortions to output for large firms, because they are easier targets for government authorities (especially if collecting taxes involves fixed costs). Exploiting variation in regulation across the Federal states of Brazil, it examines the relation between regulation and distortions to capital and output in a differences-in-differences approach. This way, regulation is related with changes in allocative efficiency.

1.3 Informality and Productivity

The third aim in this thesis is to relate productivity with regulatory compliance. Firms in developing countries often differ in the degree of compliance with regulations. Those firms that do not register for taxes are commonly defined as informal firms, whereas formal firms are registered for taxes (Fajnzylber et al., 2009).[8] Informal firms account for a large share of output and employment in Latin America. The output share of the informal sector in Brazil is estimated at 40 percent in 1999/2000 (Schneider, 2005).

Programs to simplify and reduce tax burdens for small informal firms have been implemented in recent years in various Latin American countries. The aim of these programs is to lower the costs for informal firms to join the formal sector. For example, Chile simplified income taxes, and Brazil simplified and lowered taxes for small firms in the Brazilian Integrated System for Tax and Social Security Payments for Micro and Small Firms (Sistema Integrado de Pagamento de Impostos e Contribucoes as Microempreses e Empresas de Pequeno Porte, SIMPLES) Program (World Bank, 2007).

The recent literature assumes formal firms are more productive than informal firms and studies the effectiveness of government initiatives in increasing formality.[9] However, studies often do not examine whether the productivity differences between formal and informal firms are robust to controlling for such characteristics as the firm's age and the owner's managerial ability. Controlling for firm and firm-owner characteristics may be unfeasible if only few firms are surveyed or the survey contains little information on firm characteristics. Yet, if these controls are not included, it cannot be ruled out that a positive correlation between formality and productivity is merely spurious. For example, formal firms might be older than informal firms and run by more educated firm owners, explaining their higher productivity performance.

In addition, studies of the relation between formality and productivity usually do not take into account that formality is a choice of the firm. Rauch (1991) presents a model which explains the co-existence of formal and informal firms. The model

[8] Definitions of informality may vary due to differences in the degree of compliance with regulations. For example, a firm might be registered for taxes, but this need not imply that the firm actually fills in the tax forms.

[9] See World Bank (2007) for a survey.

assumes managers differ in ability and informal firms face a limitation on size.[10] Individuals with the lowest managerial ability become workers, and the ones with the highest ability become formal managers. An intermediate group runs informal firms. High-ability managers will naturally run larger firms. As a result they choose to operate in the formal sector, where they do not face a penalty once detected by the government. For an informal firm the costs (e.g. taxes) of joining the formal sector outweigh the benefits (e.g. no size-restrictions). Hence, there may be self-selection into the formal sector by more productive firms who are willing to incur the cost of registering and paying taxes and as a result benefit from access to formal credit, access to public goods, the possibility to advertise, and the ability to increase the customer base by issuing tax receipts.

Chapter 4 examines whether formal firms are more efficient than informal firms. Self-selection and a rich set of firm, industry, and firm-owner characteristics are controlled for when examining differences in productivity between formal and informal firms. Because large retail firms may benefit from economies of scale (Doms et al., 2004), attention is limited to retailers with less than five employees where scale economies are absent or small at best. The study uses stochastic frontier analysis, where self-selection is controlled for by using a proxy for the degree of value-added tax compliance among the firm's suppliers and buyers.

This chapter adds to a nascent literature on the micro-level effects of formality on firms. Fajnzylber et al. (2009) examined the effect of credit, training, paying taxes, and belonging to business associations on the profits of Mexican firms. Using propensity score matching to control for the selection bias, they found a positive effect of formality on profits. McKenzie and Sakho (2009) examined the effect of tax registration on profitability of Bolivian firms. Using distance to the tax office as an instrument in a treatment-effects model, they found that registering for taxes has a positive effect on business profits. These findings suggest that registering for taxes results in profit gains. A related question is whether acquiring a formal status will increase a firm's productivity. It is productivity growth, rather than profit making, which is contributing to a country's welfare.

[10] de Paula and Scheinkman (2007) extent the model with capital, where informal firms face a higher rental cost of capital because they lack collateral.

1.4 ICT adoption and Production Technologies

The final aim of this thesis is to examine the relation between productivity and the adoption of Information and Communication Technologies (ICT). Investments in ICT contribute strongly to economic growth in OECD countries. For the United States, evidence on the growth impact of ICT is paramount, in particular for the growth acceleration after 1995 (Jorgenson et al., 2005). For European countries and Japan, studies also find that ICT investments contribute to growth and productivity (Jorgenson and Motohashi, 2005; van Ark et al., 2008).

At the macro level, de Vries et al. (2010) present series of investment in information and communication technology in Latin American countries, and examine the contribution of ICT to economic growth. During 1990 to 2004, they find that ICT investment levels in Latin America are below those in Europe and the United States except for Chile and Costa Rica who are approaching European levels. ICT investments contribute most to growth in Chile and Costa Rica and least in Argentina. While Latin American countries do not miss out on the ICT revolution, its contribution to growth remains below that in most OECD countries.

At the micro level, it is widely accepted that the adoption of information and communication technology (ICT) influences the organization of firms and their cost structures (Brynjolfsson and Hitt, 2000; Haynes and Thompson, 2000; Bartel et al., 2007). Therefore, a relation is expected between ICT adoption and production processes across firms.

Greene (2005) developed an econometric model to distinguish firms' production technologies in a single estimation procedure. This stochastic frontier panel model, the latent-class stochastic frontier model, allows testing for the existence of multiple production technologies across firms and considering the associated implications for efficiency measures.

Chapter 5 models retail production technologies in a latent class stochastic frontier model, where the firm's probability of technology group membership is determined by ICT use. A unique data set of Chilean retailers is used, including detailed information on ICT capital and ICT use for each firm.

Results from this study help identify those firms for which productivity gains are largest from reducing operational slack, and those firms where gains are largest from adopting ICT. Results from this study therefore have implications for policies that aim at fostering ICT adoption among firms. It may be that economic gains from providing technical assistance to improve the efficiency in using ICT are larger than providing incentives for higher ICT adoption to these firms. Firm-heterogeneity affects the potential of particular policies to improve productivity performance.

1.5 Thesis outline

The remainder of this thesis is organized as follows.

Chapter 2 presents decompositions of productivity growth for a census data set of retail firms in Brazil. Growth is split up into the contribution from within-firm growth, between-firm resource reallocation, and entry- and exit-effects. The observed development pattern differs remarkably for the expansion of multi-establishment retail chains between Brazil and OECD countries.

Chapter 3 also examines the question whether resource allocation improved after liberalization of the Brazilian retail sector. In addition, this chapter relates distortions to output and capital across firms with taxes and credit.

Chapter 4 moves on to study small formal and informal retail firms. This chapter focuses on the question whether formal firms are more productive than informal firms.

Chapter 5 focuses on the importance of technology adoption as a source of productivity growth in Chile. It argues that the production process of retail firms differs with the adoption of information and communication technology (ICT).

Chapter 6 reviews the main research findings and concludes.

Chapter 2

Did Liberalization Start A Retail Revolution In Brazil?*

2.1 Introduction

Brazil's poor growth performance and macroeconomic instability in the 1980s motivated the government to undertake profound structural reforms in the early and mid-1990s (Baer, 2008). The government adopted prudent macroeconomic policies, achieved stabilization after a long period of hyperinflation, and created a more liberal trade and investment climate. The retail sector was opened up in the World Trade Organization 1995 General Agreement on Trade in Services, but also within the MERCOSUL[1], and between the MERCOSUL members and the European Union. In addition, the participation of foreign capital in Brazilian retail firms was freed from restrictions in the Sixth Constitutional Amendment of 1995 (World Bank, 2004).

The reforms created very suitable conditions for investments by foreign chains. As a result, Foreign Direct Investment (FDI) in the retail sector increased rapidly.[2] The FDI stock in the retail sector increased sixfold from 1995 to 2000, and growth was above average FDI growth (Censo de Capitais Estrangeiros). In turn, these

* This chapter is based on the paper 'Did Liberalization Start A Retail Revolution In Brazil?', GGDC research memorandum 105.

[1] Mercado Comum do Sul, the regional trade block consisting of Argentina, Brazil, Paraguay, and Uruguay.

[2] See Santos and Gimenez (1999) and Concha-Amin and Dias de Aguiar (2006) for an overview of foreign retail chains which entered or expanded their market share. Concha-Amin and Dias de Aguiar (2006) concluded that during 1989-2002, 93 percent of all mergers and acquisitions by foreign firms took place after 1997.

investments created the perception that liberalization had started a retail revolution through the expansion of modern retail chains (Reardon and Berdegué, 2002).

The retail sector accounts for a large share of the Brazilian economy, both in terms of GDP and employment. During 1996-2004, the employment and value added share in the total economy was respectively about 11 percent and 5 percent (Timmer and de Vries, 2009). A revolution was considered necessary for the development of a sector long characterized by many small family-run stores operating alongside a few large modern retail chains. In the mid-1990s, various domestic (or partially foreign-owned) chains were active, but the sector mainly consisted of independent retailers, often operating their business in a traditional way at low productivity levels (McKinsey, 1998). The increasing presence of retail chains was expected to spur development by reducing waste (many agricultural products rot before reaching the market), lowering prices for consumers,[3] improving the quality of goods and assurance of its delivery, raising the productivity of supplying industries (Javorcik et al., 2006), and raising the sector's productivity level.[4]

So far, productivity growth of the retail sector has been disappointing under the structural reforms. While productivity growth of the total economy has been disappointing as well (King and Ramlogan, 2008), available evidence suggests that productivity growth of the retail sector was below that of the total economy during the 1990s (de Melo et al., 1998; Mulder, 1999; Timmer and de Vries, 2009). This experience contrasts with OECD countries, where growth of the retail sector was above productivity growth of the total economy during the past decades (Inklaar et al., 2008). Obviously, this raises the question what held back growth of Brazil's retail sector.

Recent studies have shown that productivity growth in the retail sector of OECD countries occurred through a process of creative destruction. That is, growth originated from reallocation dynamics through firm churning (the entry and exit of firms) and resource reallocation to more-productive retail chains. For example, new establishments from retail chains (including, but not only, Wal-Mart) displacing 'mom-and-pop' stores accounted for virtually all growth in the US in the past decades (Foster et al., 2006). Similar findings for the UK are presented by Haskel and Sadun (2009) and for Japan by Matsuura and Motohashi (2005).

We use similar decomposition methodologies as in these studies to understand

[3] Bradford and Gohin (2006) show in a general equilibrium framework that a more efficient wholesale and retail trade produces large welfare gains.

[4] The beneficial effects of foreign retail chains are not undisputed. In particular, concerns about their effects on wages and employment have been raised (Basker, 2007). For example, Durand (2007) argues that FDI in Mexico's retail sector dampened retail wages by introducing higher competitive pressures.

the performance of Brazil's retail sector. While Brazil's retail sector is dynamic, our results suggest that liberalization failed to deliver high growth because a process of creative destruction did not take off. During 1996-2004, we find little evidence for a reallocation of productive inputs and outputs. New establishments from retail chains did not replace low-productive independent stores at a large scale. Instead, large chains acquired other (smaller sized) chains. This contributed to a deepening of the dual structure in which low-productive independent stores continued to co-exist with a declining number of retail chains.

The remainder of this chapter is structured as follows. In the following section we present the data set and discuss the main characteristics of Brazil's retail sector. We describe our productivity decomposition method in section 2.3. Decomposition results are discussed in section 2.4. Conclusions and a discussion why the sector does not show patterns similar to the US are in section 2.5.

2.2 Brazil's Retail Sector

To examine the contribution of reallocation dynamics to growth, we use a census dataset of retail firms. Our principal data source is the annual survey of distributive trade firms (Pesquisa Anual de Comércio, PAC) from 1996 to 2004. Firms registered in the Cadastro Nacional da Pessoa Jurídica from the ministry of Economic Affairs and classified as distributive trade firms in the Cadastro Central de Empresas of the national statistical office are surveyed in PAC. The PAC dataset consists of two groups, namely a group of firms which surpass the threshold and are included by census and another group of firms which are below the threshold and are included by sample. Sampled firms are surveyed for a maximum of three consecutive years and fill in a simplified questionnaire. The empirical analysis focuses on firms included by census only.[5]

Firms in the dataset are linked using their identification numbers from the tax registry. Different national sector definitions are used in PAC over time, which are converted to the International Standard Industry Classification Revision 3.0. After firms are linked, observations of nominal output divided by nominal input that fall into the first and the ninety-ninth percentile of the distribution at the most detailed industry classification are considered outliers and deleted. A detailed discussion of these steps is provided in appendix 2.A.

[5] We discuss implications of excluding firms below the threshold in section 2.4. Registered firms with less than 20 employees are selected by means of a stratified random sampling procedure. The dataset has 12,402 sampled firms in 1996 and 10,596 sampled firms in 2004.

Firms with more than 20 employees or firms with less than 20 employees but with establishments in more than one Federal State are included in PAC by census.[6] For 1996 this amounts to 14,445 firms included by census. In 2004 the number of firms included by census has risen to 17,366. While firms included by census constitute a fairly small share of the total population of retail firms, they represent the major part of the sector in terms of sales (about 60 percent). Furthermore, although our analysis excludes small (often informal) firms, the dataset mainly includes single-establishment stores with low productivity levels. For example, in 2004 about 69 percent of the firms in our dataset are single-establishment firms (see appendix table 2.B.2). Therefore, results are considered representative for the sector.

Output and input variables are available to construct productivity measures. We measure labor productivity (LP) as the volume of sales divided by employment.[7] Because retail firms sell goods to consumers, we used the consumer price index to deflate output. We used the overall consumer price index to deflate output of retail firms. In some cases it was possible to use more detailed price series, for example for firms selling food and drinks.[8]

Figure 2.1 shows pie charts for the employment shares of firms (distinguished by the number of establishments a firm has) in 1996 and 2004 (see appendix tables 2.B.1 and 2.B.2 for further detail). The employment share of single-establishment firms did not decline from 1996 to 2004. In fact, the employment share of independent stores increased from 22 percent to 29 percent in the retail sector. Nevertheless, we find an increasing presence of large-size chains (firms with >100 establishments) at the expense of small and medium-size chains as well. In particular, in food retailing (a sub-industry of the retail sector) the employment share of large-size retail chains increased from 5 percent to 23 percent, reflecting the entry and market expansion of large international retail chains.[9] Thus, we find an increasingly dual market structure.

Table 2.1 shows productivity levels by size class. Clearly, productivity levels rise

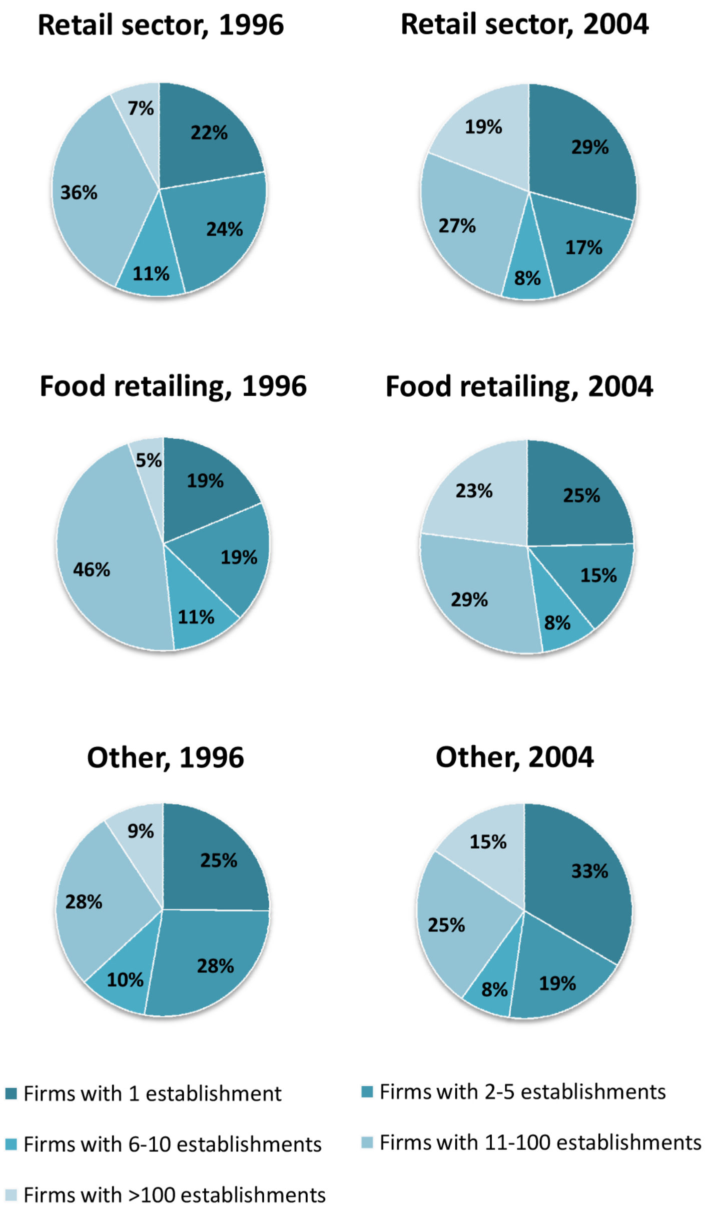
[6] Firms in several northern regions which are located outside the Federal States' capital are not included in the survey because of the high costs involved in collecting information for these firms. These regions are: Rondônia, Acre, Amazonas, Roraima, Pará, Amapá, and Tocantins.

[7] Since some retailers employ part-time workers and family workers, a preferable measure of labor input is hours worked. Data limitations force us to use employment. Productivity is therefore underestimated for retailers who employ relatively more part-time and or family workers.

[8] Further detail is provided in appendix 2.A.

[9] We also computed concentration ratios. For the retail sector, the concentration ratio of the top ten firms by sales is 0.23 in 1996 and increased to 0.27 in 2004. In comparison to OECD countries, concentration ratios are still low (see for instance Boylaud and Nicoletti (2002); Haskel and Sadun (2009)).

Figure 2.1. Firms and employment shares in 1996 and 2004



with size class. Across the retail sector, retail chains tend to be more efficient than single-store retailers because of technology and scale advantages.[10] These differences in productivity levels across size classes indicate the scope of resource reallocation for boosting productivity growth. That is, resource reallocation toward retail chains offers much potential for productivity growth.

Table 2.1. Productivity levels, defined as sales divided by employment, by size class

Number of Employees	Productivity level 1996	Productivity level 2004
20-49	100	100
50-99	104	102
100-249	107	105
250-499	106	106
500+	120	113

Note: Unweighted average productivity by size class. The productivity level for the size class 20-49 is set to 100.

What is puzzling, is the low aggregate productivity growth of the sector despite the combination of a higher productivity level across size classes and an increasing market share of large retail chains. In the remainder of this chapter, we will use the census data set and our productivity decomposition method to understand why productivity growth was not higher. The next section presents the decomposition method, before turning to the results in section 2.4.

2.3 The Productivity Decomposition Method

Starting with the preliminaries of the productivity decomposition, aggregate productivity, LP^A, is the weighted geometric average of firm's productivity:

$$LP_t^A = \prod_i LP_{it}^{\theta_{it}}, \tag{2.1}$$

where subscripts i and t refer to firm and time respectively, θ is a firm-specific share in total employment, LP is labor productivity (sales per worker), and $\prod$ denotes multiplication. If we take the logarithm of productivity, the aggregate productivity level is defined as a weighted arithmetic mean:

$$\ln LP_t^A = \sum_i \theta_{it} \ln LP_{it}. \tag{2.2}$$

[10] See Doms et al. (2004), and Foster et al. (2006) for further detail for the US.

Aggregate productivity growth between two years is the percentage change measured by:

$$\Delta \ln LP^A = \ln LP_t^A - \ln LP_{t-1}^A. \tag{2.3}$$

For the decomposition, consider three types of firms. Continuing firms are denoted by C, entering firms are denoted by E, and exiting firms are denoted by X. Firms in the initial year (t-1) either continue or exit the market. So in year t-1, continuing and exiting firms are active. In the final year (t), only firms that continued or entered the market are present. Hence, in year t, continuing and entering firms are active.

Aggregate productivity growth between two periods can therefore be decomposed into:

$$\begin{aligned} \Delta \ln LP^A &= \ln LP_t^A - \ln LP_{t-1}^A = \Big(\sum_{i\in E}\theta_{it}\ln LP_{it} + \sum_{i\in C}\theta_{it}\ln LP_{it}\Big) \\ &\quad -\Big(\sum_{i\in X}\theta_{i,t-1}\ln LP_{i,t-1} + \sum_{i\in C}\theta_{i,t-1}\ln LP_{i,t-1}\Big). \end{aligned} \tag{2.4}$$

Equation 2.4 is the basic decomposition of productivity growth. It shows that aggregate productivity can be decomposed into the contribution of entering, exiting, and continuing firms. Aggregate productivity growth between two periods is either due to within-firm improvements or reallocation dynamics. So far, however, equation 2.4 does not separate the contribution to growth from continuing firms into within-firm improvements and resource reallocation. Preferably, these contributions from continuing firms are to be separated. Several methods have been developed to distinguish between these two contributions from continuing firms (see Baldwin and Gu (2006) for the derivations). In this chapter we follow the decomposition method developed by Griliches and Regev (1995), hereafter denoted GR:[11]

[11] This method has the advantage that it avoids the mixing of Paasche-type measures with Laspeyres-type measures by using a symmetric decomposition method (Balk, 2001). In addition, by taking period averages, the influence of measurement error becomes smaller. The disadvantage of the GR method is that, because of taking averages, the *within-firm* effect is affected by changes in the market share, and the *between-firm* effect is affected by changes in productivity. In section 2.4 we consider alternative decomposition methods and find that our main conclusions are independent from the particular decomposition method used.

$$
\begin{aligned}
\Delta \ln LP^A = & \sum_{i \in E} \theta_{it} \left(\ln LP_{it} - \overline{LP}^A \right) \quad \text{(entry)} \\
& + \sum_{i \in C} \left(\frac{\theta_{it} + \theta_{i,t-1}}{2} \right) \left(\ln LP_{it} - \ln LP_{i,t-1} \right) \quad \text{(within)} \\
& + \sum_{i \in C} \left(\theta_{it} - \theta_{i,t-1} \right) \left(\frac{\ln LP_{it} + \ln LP_{i,t-1}}{2} - \overline{LP}^A \right) \quad \text{(between)} \\
& - \sum_{i \in X} \theta_{i,t-1} \left(\ln LP_{i,t-1} - \overline{LP}^A \right), \quad \text{(exit)}
\end{aligned}
\tag{2.5}
$$

where $\overline{LP}^A = \frac{\ln LP_t^A + \ln LP_{t-1}^A}{2}$ and the terms on the right-hand side of equation 2.5 are:

- The *entry* effect: the sum of differences between entering firms' productivity and average aggregate productivity, weighted by the firm's market share. This term measures the contribution of entering firms to growth.
- The *within-firm* effect: the sum of productivity change within continuing firms, weighted by the firm's average market share. This term reflects gains from productivity growth within firms.
- The *between-firm* effect: the sum of productivity change due to the expansion or contraction of continuing firms, where the firms' average productivity is measured in deviation from average aggregate productivity. This term captures productivity gains from the expansion of more-productive firms, or the contraction of less-productive firms.
- The *exit* effect: the sum of differences in the productivity of exiting firms and average aggregate productivity, weighted by initial market shares. Exiting firms have a positive effect on aggregate productivity growth if the firms exhibit productivity levels below average productivity.

If liberalization started a retail revolution through the entry and expansions of retail chains, this shows up from the decomposition as large reallocation dynamics (the sum of *entry* effects, *between-firm* market-share changes, and *exit* effects). For OECD countries, these dynamics accounted for most growth. For example, for the US it was found that reallocation dynamics accounted for 83 percent of growth during 1987-1997 (Foster et al., 2002).

Table 2.2 shows descriptive statistics of the census data set we use. Output and input variables are reported by entering, exiting, and continuing firms. Continuing firms are on average the largest firms in terms of sales and employees, and they show the highest productivity (sales per employee) as well. Exiting and entering firms are less productive, with exiting firms marginally more productive than entering firms. Although surprising at first, below average productivity of entering firms is a common finding across countries (Bartelsman et al., 2005). It is generally interpreted as the result of market experimentation in which selection and learning effects eventually sort out the most competitive entrants.[12]

Table 2.2. Descriptive statistics of entering, exiting, and continuing firms

	Continuing firms	Entering firms	Exiting firms
Real Sales	16.05	14.29	14.08
Employment	4.62	3.44	3.18
Labor productivity	10.62	10.26	10.34
Entry rate		0.25	
Exit rate			0.18
Observations	84,101	25,403	18,329

Note: Sales is measured in Brazilian reais. Real sales, employment, and labor productivity are in natural logarithms. The entry (exit) rate is the average annual number of entrants (exiters) divided by the total number of firms. The values are averages for the period 1996 to 2004. Descriptive statistics are for firms included by census in PAC.

Entry and exit rates reveal substantial churning. Table 2.2 reports average annual entry rates of 25 percent and exit rates of 18 percent. In comparison to manufacturing industries in Latin America, there appears more churning in retailing (for instance, Eslava et al. (2006) reports average annual entry rates of 9 percent and exit rates of 10 percent for Colombian manufacturing industries). Firm turnover is higher in the retail sector because it has a much higher share of small businesses, which have a lower probability of survival than large businesses (Foster et al., 2002). Churning in Brazil's retail sector is comparable to that observed in the US retail sector, where Foster et al. (2002) describe the sector as having 'enormous rates of entry and exit' (p. 7) and Jarmin et al. (2004) find that 50 to 60 percent of retailers that exist one year disappear within five years.

2.4 Brazil: No Retail Revolution Here

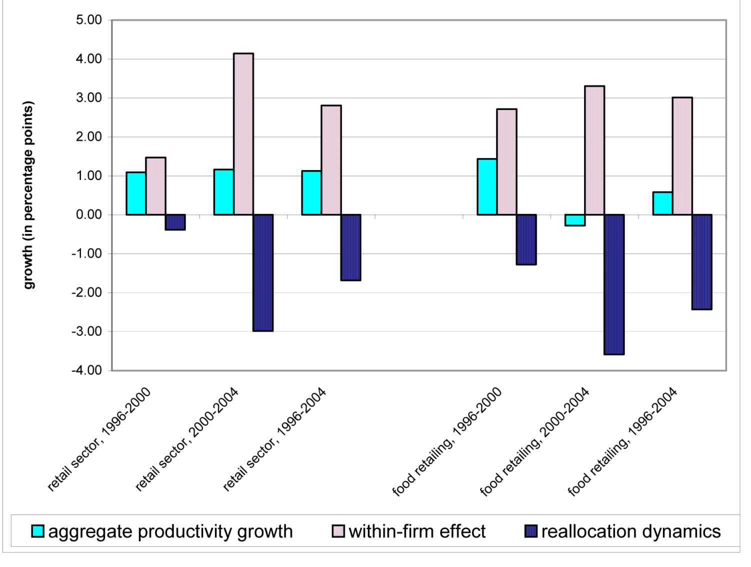
We performed productivity decompositions at detailed industry levels using equation 2.5. However, in this section we report results for the total retail sector (indus-

[12] In our decompositions of productivity growth (see section 2.4) we increased the time horizon to examine the selection and learning effect. We found that increasing the time horizon raises the contribution to growth from entering firms in line with selection and learning effects, but the additional contribution is small.

try 52) and for food retailing (industry 521), because we are mainly interested in the aggregate outcomes. To this end the detailed decomposition results were aggregated.[13] We decomposed growth annually and present period averages of the annual contributions.

Figure 2.2 shows the GR decomposition of labor productivity growth. Aggregate productivity growth averaged 1.1 percent for the retail sector during 1996-204. The within-firm contribution to productivity growth is larger than the contribution from reallocation dynamics in the various periods considered. In fact, the negative value for reallocation dynamics indicates that reallocation often exerts a drag on aggregate productivity growth. For example, the average annual 1.1 percent growth during 1996-2004 is due to a 2.8 percent productivity contribution from within-firm improvements and to a -1.7 contribution from reallocation dynamics.

Figure 2.2. Productivity growth decomposition



Results are similar for food retailing, with the exception of the period 2000-2004. Productivity of food retailers declined during the 2000-2004 period, which might be

[13] The weights which were used to average across the industries are nominal gross output by industry averaged over the first and last year of the period for which the change is measured. These weights were kept constant across the decompositions. Hence, the results are within-industry decompositions and do not reflect changes in the composition of distributive trade industries over time.

due to the expansion in services offered (such as amenities and the breadth of assortment) not accounted for in the output measure we employed (Betancourt and Gautschi, 1993; Ratchford, 2003). However, for both the total retail sector and food retailing, the main finding from the decomposition analysis is that within-firm effects account for most growth. In addition, a comparison of the 1996-2000 period with 2000-2004 shows that despite increasing FDI flows during the period considered (Concha-Amin and Dias de Aguiar, 2006), the contribution of reallocation dynamics did not increase.

Reallocation dynamics consist of between-firm effects and the contributions from firm entry and exit. The contributions of these different components are shown in the last columns of table 2.3. Between-firm effects were positive (with the exception of food retailing during 2000-2004), indicating that more-productive firms expanded their market share at the cost of less-productive firms. The between-effect is modest however, especially in food retailing (we discuss this below). Entry effects are negative reflecting that productivity of entering firms was below average productivity. Finally, the exit effect positively contributed to growth, because the productivity of exiting firms was below average productivity, which is consistent with the idea that competition drives the least competitive firms out of the market.

Table 2.3. Productivity growth decomposition

Industry Period	Average annual growth (in percentage points)	Contribution from: Within-firm effect (1)	Total reallocation effect (2)	Between-firm effect (3)	Entry effect (4)	Exit effect (5)
Retail sector						
1996-2000	1.1	1.5	-0.4	1.5	-4.8	2.9
2000-2004	1.2	4.1	-3.0	1.0	-7.0	3.0
1996-2004	1.1	2.8	-1.7	1.3	-5.9	2.9
of which:						
Food retailing						
1996-2000	*1.4*	*2.7*	*-1.3*	*0.4*	*-2.5*	*0.7*
2000-2004	*-0.3*	*3.3*	*-3.6*	*-0.7*	*-4.3*	*1.5*
1996-2004	*0.6*	*3.0*	*-2.4*	*-0.1*	*-3.4*	*1.1*

Note: Griliches and Regev (1995) decomposition of labor productivity growth. Decompositions are performed annually, average annual percentage points contributions to growth are presented. Total reallocation effect, (2) = (3) + (4) + (5).

We examined the robustness of our results. First, we used alternative decomposition methods proposed by Foster et al. (2006), and Baldwin and Gu (2006). The relative contributions of decomposition components were comparable. Hence, our main conclusions are independent from the particular decomposition method used. Second, since there is a census threshold, entrant firms in our dataset may not be true entrants but simply firms that grow beyond the threshold. We addressed that limitation by artificially raising the threshold and examining changes in the decomposition results. Our findings suggested that raising the threshold leaves the relative contributions of the components unchanged. Similarly, Scarpetta et al. (2002) examined the sensitivity of decomposition results to a threshold for Finnish manufacturing industries. They find that results are insensitive to various artificially set thresholds as well. Third, note that we examine *firm* dynamics using firm-level data. Most studies examined firm dynamics this way (Bartelsman and Doms, 2000; Bartelsman et al., 2005). But some studies examined firm dynamics at the *establishment* level (Foster et al., 2006; Matsuura and Motohashi, 2005). The difference between the two concepts is that firm-level analysis does not distinguish between single-establishment firms and firms with multiple outlets whereas an establishment-level analysis does. Therefore an establishment-level analysis is able to decompose movements in productivity into changes within establishments on the one hand and changes within firms on the other. The unit of analysis should be kept in mind when comparing decomposition results in this chapter with other studies. New establishments from continuing firms are included in *between-firm* effects in our chapter, whereas it is counted as an entering establishment from a continuing firm in Foster et al. (2006). This has no important implications for the interpretation of the results, since both effects are part of the reallocation dynamics. Therefore, our results are robust.

High within-firm effects and modest reallocation dynamics suggest that the reforms did not start a retail revolution through the entry and expansion of foreign and domestic retail chains. Although liberalization in the 1990s did result in the expansion of chains (see section 2.2), our findings question the extent to which retail chains have contributed to aggregate outcomes by entering the market or expanding their market shares. So far, it is more likely that if liberalization did result in productivity gains, they are reflected in within-firm improvements. That is, some firms started to adopt new Information and Communication Technologies (ICT) when the market for ICT goods was liberalized in the 1990s (Baer, 2008), reorganized their business as a result of increased competition, and benefited from cheaper imported goods for resale.[14] These gains, however, are largely temporary. The major gains should originate from a fundamental restructuring of the sector.

Our finding of limited reallocation dynamics correspond with several recent qualitative studies of the retail sector of Brazil (and Latin America in general). For example, Booz-Allen Hamilton (2003) claim that 'Small-scale retailers in Latin American markets have demonstrated remarkable resilience, and previous gains against [large retail chains] are tapering off or even reversing slightly in some cases. In Argentina and Brazil, small-scale retailers have been particularly successful in staving off the large chains' (p. 2-3). They argue that small-scale retailers managed to retain their market share, because they are located close to consumers, offer the product assortment which their customers demand, sell products only at a small price-disadvantage, provide a 'personal touch', and offer special services such as selling on credit.

Further, our results for food retailing confirm concerns raised by Humphrey (2007) that the depth and implications of the food retail transformation in Latin America have been overstated in previous research (for example by Reardon et al. (2003)). In particular, distinguishing the food retailing sector from the total retail sector shows that the between-firm market share changes are low in the former (see table 2.3). This corroborates Farina (2002), who analyzes the supermarket sector in Brazil and shows that the share of food sales by supermarket chains declined from 45.1 percent to 42.8 percent during 1994 to 2000. During this period, the share of independent stores grew from 40 percent to 44 percent (the remaining food sales are by traditional stores). Thus, single-establishment firms were not replaced by retail chains, and our decomposition analysis shows that the observed changes in market shares added little to productivity growth.

2.5 Concluding Remarks

Brazil undertook profound structural reforms during the 1990s. In combination with stabilization after a long period of hyperinflation, this resulted in increasing FDI inflows. In turn, these foreign investments by retail chains were expected to alter the sector which had long been characterized by independent stores operating their businesses in traditional ways with low productivity levels. That is, the opening up of the retail sector was expected to raise productivity growth through the

[14] If price changes of inputs were taken into account, the lower price of purchased goods for resale would not be reflected in the productivity measure. We were unable to take price changes of inputs into account, and it is therefore reflected in productivity growth.

entry and expansion of international retail chains. Thus, the main effects of the reforms were expected to work through reallocation dynamics. However, growth of the sector has been low, averaging about 1.1 percent per annum, raising questions about the effects of the reforms.

This chapter examined the effects of liberalization on productivity growth in Brazil's retail sector. We decomposed growth into the contribution from within-firm improvements and reallocation dynamics during 1996-2004. We found substantial churning, with average annual entry rates of 25 percent and exit rates of 18 percent. However, two findings suggested that reforms did not live up to expectations. First, we found no strong tendency of retail chains displacing independent stores. In fact, the employment share of single-establishment firms increased slightly. Second, the contribution of reallocation dynamics to growth was negative, averaging -1.7 percentage points per year, whereas within-firm improvements contributed 2.8 percentage points per year.

In the US, chains of convenience stores with bargaining power, centrally performed operations, and best-practice operations have been displacing single-shop convenience stores for several decades (Jarmin et al., 2004). For the US, this process explains virtually all growth (Foster et al., 2006) and has transformed the retail sector into a sector which leads the aggregate economy (Inklaar et al., 2008). Clearly, this development process is lagging in Brazil. At least three aspects deserve careful examination in future research to understand why the sector does not show patterns similar to the US.

First, business regulation is slowing down the expansion of retail chains. In particular, regulations concerning zoning and commercial real estate act as barriers to the development of the retail sector. For example, quantitative limits on retail floor space in particular geographical areas (often city centers) are set. This occurs even if national legislation puts little restrictions on floor space, because decisions are often taken at the local level (for instance by city *vereadores*) where choices can be influenced by local pressure groups (e.g. small retailers). In addition, business regulation in other markets such as in transport and logistics limit the expansion of multi-establishment firms. Excessive business regulation distorts the functioning of the Brazilian economy. For example, Brazilians have the saying "to my friends: everything, to my enemies: the law". In fact, according to a World Bank study on doing business across countries, Brazil is one of the most regulated countries in the world (World Bank, 2006). Thus, zoning laws and excessive business regulation in other markets slow down the emergence of chains in Brazil.

Also, the quantity, quality, and orientation of rail and road networks is holding back the emergence of national distribution systems and thereby the expansion of chains. The physical gap in transport networks between Brazil and OECD countries is large (Calderón and Servén, 2004). In addition, only a small part (less than 20 percent) of the road network is paved and the provision of infrastructure did not grow during the past decade as a result of the retrenchment of the public sector in this area (Calderón and Servén, 2004). Furthermore, early investments in railways were meant to integrate Brazil in the international economy (that is, to export primary products) rather than to integrate the regions into a large domestic market (Baer, 2008).

Finally, demand factors influence the expansion of multi-establishment firms. Consumer patterns are culturally determined, and many Brazilians prefer to buy their goods at street markets and local stores instead of at supermarkets from chains with a fixed assortment, because of food preparation habits and the perceived freshness of the produce there (Zinkhan et al., 1999; Humphrey, 2007). Therefore, consumer preferences influence the cohabitation of modern and traditional forms of retailing. In addition, car penetration influences the attractiveness for retail chains to establish large supermarkets outside crowded residential areas. Thus, with lower car penetration, especially in the poorer Northern states, it has been less attractive for chains to invest in large new establishments there. However, other demand factors are slowly favoring modern retail formats, such as the increasing female labor force participation (shifting demand to one-stop shopping), the recent improvements in the income distribution, and the growing middle class. This indicates that once supply constraints are eased, a revolution may be in the making.

2.A Data Appendix

Data Cleaning

IBGE has the policy to encrypt the identification number of firms (CNPJ) before giving researchers access to the data. The method which is used to encrypt identification numbers is equal across years. Therefore, a firm can be traced throughout the sample. We inspected the encrypted firm ID's and deleted firms with duplicate numbers.

We used the following procedure to detect outliers before the productivity decomposition. First, nominal output is divided by nominal input for each firm. Observations of nominal output divided by nominal input that fall into the first and the ninety-ninth percentile of the distribution at the most detailed industry classification (four digits) are identified as outliers. After two periods have been linked, firms with outlying productivity values or missing data in one of the two periods are deleted. Entrant and exiting firms are determined from the remaining data. We also decomposed productivity growth without the outlier procedure. Results from these decompositions are similar.

Price Deflators

Several industry-wide and economy-wide price indices are available for Brazil. Choices, however, are limited. We worked with price indices at fairly aggregated levels. Because retail firms sell goods to consumers, we used the consumer price index to deflate output. Consumer price indices (Índices Nacionais de Preços ao Consumidor - Amplo, INPC-A) are available at IBGE. We use the amplified consumer price index (INPC-A) to deflate output measures, where we use either Brazil's or the Federal states' price index for all goods or one of the following groups of goods: (1) clothing; (2) household equipment; (3) food and beverages. Firms report economic numbers that refer to the calendar year of the survey. Firms whose business year differs from the calendar year are required to adjust their numbers accordingly. Therefore, we used annual (mid-year) price deflators to deflate output.

Conversion of CNAE to ISIC Revision 3.0

Different national sector definitions are used in PAC over time. We used data in PAC from 1996 to 2004. Two national classifications are therefore relevant. First, the CNAE classification (Classificacão Nacional de Atividaded Econômicas), which was adopted in 1995 and used until 2003. Second, from 2003 onwards, the CNAE 1.0 classification.

Our approach has been to first convert CNAE 1.0 in later surveys to CNAE. We followed this approach because only two years with the new classification are available. Next, we converted CNAE to the International Standard Industry Classification Revision 3.0 (ISIC Rev. 3.0). At the one and two digit level, the industry classifications CNAE, CNAE 1.0, and ISIC Rev. 3.0 are identical. Differences between the classifications only occur at the three and four digit level. Usually, more detail is offered in the CNAE/CNAE 1.0 classification and aggregation of CNAE/CNAE 1.0 to groups recomposes ISIC groups. We describe the conversion CNAE x CNAE 1.0 and CNAE x ISIC Rev. 3.0 below.

First, consider the conversion of CNAE 1.0 to CNAE for distributive trade firms. The difference between both classifications is not large. For 68 out of 72 (four digit) industry categories, an exact matching exists. The lack of unique correspondence between both classifications in the remaining 4 categories concerns wholesale of machinery, equipment and supplies and retail trade not in stores. Differences arise, because CNAE 1.0 does not distinguish between the different forms of commercialization. For example, whether sales take place via a store, TV, or Internet, is no longer separated in the new CNAE 1.0. This distinction is made in CNAE (and it is made in ISIC Rev. 3.0). This implies that no strict correspondence between both classifications exists. Firms that belong to CNAE 1.0 industry code 51.64-0 and 51.65-9 all belong to a similar aggregate category in CNAE, namely 51.6 (CNAE). Firms in CNAE 1.0 51.64-0 are all converted to CNAE 51.62-4, and firms in CNAE 1.0 51.65-9 are converted to CNAE 51.63-2. Firms in CNAE 1.0 52.62-0 are converted to CNAE 52.69-8, but some firms in CNAE 52.69-8 are moved to CNAE 1.0 64.12-2. These firms can no longer be traced and artificially disappear from the data set. Firms in CNAE 52.61-2 and some firms in CNAE 52.69-8 are difficult to trace, because CNAE 1.0 does not distinguish between the various forms of commercialization. IBGE (2004b) indicates that in the total population of retailers, only 5 retailers realized 100 percent of their sales via the Internet, 40 via the TV, and 584 via other forms of commercialization. In the total sample, this bias is unlikely to be large. Furthermore, we focus in the productivity decompositions on broader aggregates so to some extent these firms are possibly recomposed in an aggregate.

Second, we converted firms in four-digit CNAE sector classifications to four-digit ISIC Revision 3.0 classifications. In fact, since CNAE is based on ISIC Rev. 3, matching is unique. The only difference between both classifications stems from more detail in the CNAE classification. Hence more detailed categories in CNAE are recomposed in a broader ISIC category.

Firm Dynamics

To estimate the contribution of firm dynamics to growth, it is important to measure 'truly' entering and exiting firms. We use unique firm identification numbers to measure entrants, exiters and continuing firms. But some characteristics of PAC cloud the measurement of true entrants and exiters.

The structure of some firms change during the period analyzed. For example, the structure of some firms change because of mergers, takeovers, and spin-offs. A firm that is taken over, continues operating. But the firm now has a different firm identification number (the same as the firm that has purchased her). Due to the takeover, the previous firm identification number disappears. Without additional information about changes in the structure of firms, we would count a "false" exit. Other studies solved this problem by including information from business registers. We are partly able to solve this problem, because PAC asks firms to report changes in legal and economic status (mudanças na estrutura da empresa). Furthermore, if a change in the legal or economic status of the firm occurs, the firm reports an additional tax number link (PAC provides two firm identification numbers in these cases). Therefore, the additional tax number link changes its meaning depending upon the change in legal or economic status.

Consider the possible changes in the structure of trade firms. First, if no change is reported, the firm can be linked directly. However, note that the industry classification of a firm could change. This happens with a change in its main economic activity. Firms that switched between industry classifications are dropped from the data set. Second, a new firm can emerge from a merger. The merged firm has 2 predecessors. Because we need two additional tax number links (in stead of one) and because the newly emerged firm is often restructured considerably, we consider it a new entrant. Likewise, if a firm emerges from a complete split-up, we considered it a new entrant. The argument for making these choices is that this firm now stands alone and gains experience on its own. Third, consider a partial spin-off. A new firm emerges from a parent firm. We considered it a new firm, again, on the assumption that this new firm stands alone and gains experience on its own. Fourth, if the firm reports that it is acquired by another firm or it has acquired another firm, output and input data are added to the purchasing firm. Fifth, a 'rest' category exists, where firms report other reasons for a change in its tax number link in 'observaçãos.' Here, observations for old and new firm identification numbers were treated as one firm.

2.B Appendix tables

Table 2.B.1. Employment shares by type of firm

Sector	1 All firms	2 Firms with 1 establishment		3 Firms with 2-5 establishments		4 Firms with 6-10 establishments		5 Firms with 11-100 establishments		6 Firms with >100 establishments	
		number	share	number	share	number	share	number	share	number	share
Employment (1996)											
Retail sector	1,043,651	233,446	22%	247,032	24%	111,527	11%	372,837	36%	78,809	8%
Food retailing	*455,799*	*84,627*	*19%*	*83,890*	*18%*	*50,360*	*11%*	*209,395*	*46%*	*24,233*	*5%*
other	*587,852*	*148,819*	*25%*	*163,142*	*28%*	*61,167*	*10%*	*163,441*	*28%*	*54,576*	*9%*
Employment (2004)											
Retail sector	1,344,476	393,834	29%	226,010	17%	107,831	8%	360,578	27%	256,278	19%
Food retailing	*632,153*	*155,476*	*25%*	*91,934*	*15%*	*53,708*	*8%*	*185,563*	*29%*	*145,440*	*23%*
other	*712,323*	*238,358*	*33%*	*134,075*	*19%*	*54,124*	*8%*	*175,015*	*25%*	*110,838*	*16%*

Note: columns 2, 3, 4, 5, and 6 add up to column 1.

Table 2.B.2. Number of firms by type of firm

Sector	1 All firms	2 Firms with 1 establishment		3 Firms with 2-5 establishments		4 Firms with 6-10 establishments		5 Firms with 11-100 establishments		6 Firms with >100 establishments	
		number	share	number	share	number	share	number	share	number	share
Number of firms (1996)											
Retail sector	14,445	7,760	54%	5,314	37%	813	6%	541	4%	17	0%
Food retailing	*3,327*	*2,211*	*66%*	*897*	*27%*	*113*	*3%*	*103*	*3%*	*3*	*0%*
other	*11,118*	*5,549*	*50%*	*4,417*	*40%*	*700*	*6%*	*438*	*4%*	*14*	*0%*
Number of firms (2004)											
Retail sector	17,366	12,066	69%	4,119	24%	644	4%	507	3%	30	0%
Food retailing	*4,684*	*3,760*	*80%*	*716*	*15%*	*110*	*2%*	*88*	*2%*	*10*	*0%*
other	*12,682*	*8,306*	*65%*	*3,403*	*27%*	*534*	*4%*	*419*	*3%*	*20*	*0%*

Note: columns 2, 3, 4, 5, and 6 add up to column 1.

Chapter 3

Productivity in a Distorted Market: The Case of Brazil's Retail Sector*

3.1 Introduction

Latin America's disappointing economic performance after market-oriented reforms in the 1990s is receiving widespread attention. According to a more and more dominant view, slow resource reallocation is the main culprit of low growth in Latin America.[1] In an increasingly competitive market, resources are assumed to flow from low- to high-productive users, improving allocative efficiency. Pages et al. (2009) find that the contribution of resource reallocation to growth was negative in manufacturing industries of Latin America during the period after regulatory reforms. For Brazil's manufacturing sector, Menezes-Filho and Muendler (2007) find labor is flowing away from export industries because their labor productivity increases faster than their production. While output shifts to more productive firms labor is shed, adding to unemployment. Hence, reforms might be related with efficiency gains at the firm level[2], but not at the aggregate when idle resources result.

* This chapter is based on the paper 'Productivity in a Distorted Market: The Case of Brazil's Retail Sector', GGDC research memorandum 112.

[1] See for example Cole et al. (2005); Mukand and Rodrik (2005); Menezes-Filho and Muendler (2007); Pages et al. (2009).

[2] Studies typically find strong firm-level productivity improvements after trade liberalization. For the manufacturing sector in Brazil see: Hay (2001); Cavalcanti Ferreira and Rossi (2003); López-Córdova and Mesquita Moreira (2003); Muendler (2004); Schor (2004).

In contrast to manufacturing, little is know about the role of the services sector in Latin America's economic performance. This is surprising, because the sector accounts for over two-thirds of GDP and employment (Timmer and de Vries, 2009), and insight in the functioning of the services sector is crucial for understanding aggregate economic performance. Evidence suggests that reallocation only marginally contributed to growth in the services sector as well (see Chapter 2). This raises the question, what is preventing the reallocation of resources toward the most efficient firms? This chapter studies allocative efficiency in the retail sector of Brazil, and explores the relation between regulation and resource misallocation building upon the model of Hsieh and Klenow (Hsieh and Klenow (2009), HK hereafter).

Brazil opened up its retail sector in the World Trade Organization's 1995 General Agreement on Trade in Services, but also within MERCOSUL,[3] and between the MERCOSUL members and the European Union. Furthermore, the participation of foreign capital in Brazilian retail firms was freed from restrictions in the Sixth Constitutional Amendment of 1995 (World Bank, 2004). It was expected that these reforms would result in a retail revolution characterized by productive reallocation through the expansion of modern retail chains and the growth of small successful retail businesses (Reardon et al., 2003).

This retail revolution happened in other countries. For example, in the US average annual labor productivity growth of 11 percent in the retail sector during the 1987-1997 period is for 90 percent due to new establishments from retail chains replacing independent mom-and-pop stores (Foster et al., 2006). A similar process, albeit at a lower scale, took place in the UK (Haskel and Sadun, 2009).[4]

The available evidence for Brazil's retail sector suggests a different development pattern. In Brazil, retail chains did not replace mom-and-pop stores during the period following reforms (see Chapter 2). Instead, large chains both domestic and foreign typically acquired other existing (smaller-sized) chains. The share of small low-productive firms remained stable or even increased. The limited role of reallocation in Brazil's retail sector may explain its low labor productivity growth, averaging only 1 percent annually during 1996-2004 (Chapter 2). Limited reallocation of resources in Brazil's retail sector contradicts expectations from pro-competitive reforms.

[3] Mercado Comum do Sul, the regional trade block consisting of Argentina, Brazil, Paraguay, and Uruguay.

[4] Haskel and Sadun (2009) argue that lower growth in the UK retail sector relative to the US is due to retail chains opening up smaller new establishments because of size restrictions. In other words, growth in UK's retail sector originates from resource reallocation, but occurs at a slower pace because scale economies cannot be fully exploited by retail chains.

Various policies and institutions contribute to resource misallocation. Despite the reforms, regulation in labor and product markets may have prohibited the start of a retail revolution in Brazil. For example, taxes are high and reach over 200 percent of gross profits in Rio de Janeiro (World Bank, 2006), reducing incentives for retail firms in other states to enter the market in Rio de Janeiro. Also, difficulties in access to credit and strict labor market regulations may prevent the growth of successful small retailers and worsen their competitiveness relative to informal retailers. Consistent with the idea that regulation in labor and product markets may forestall growth in Brazil's retail sector, Restuccia (2008) calibrated the implications of taxes and entry costs for the misallocation of resources in Latin American countries. He found that taxes and entry costs can easily generate large misallocation of resources and hence explain a lower aggregate total factor productivity level in Latin America as compared to the US. Stringent regulations may prevent allocative efficiency improvements in Brazil's retail sector, and thereby impede growth.

This chapter measures distortions in the retail sector by comparing marginal revenue products with the costs of factor inputs, following the tradition of models from Banerjee and Duflo (2005). We apply the Hsieh-Klenow (Hsieh and Klenow (2009) model to study changes in resource allocation in Brazil's retail sector during the period from 1996 to 2006. Distortions to output and capital are inferred from residuals in first-order conditions in a model of monopolistic competition with heterogeneous firms. Wedges are measured if there is a difference between the cost and the marginal revenue product of factor inputs. In turn, these wedges are used to derive implications for aggregate productivity.

We apply the HK model to a dataset of retail firms in Brazil. The principal data source is the annual census of retail firms from 1996 to 2006. This dataset offers detailed information on output, inputs, and location of retail firms (and their establishments). The findings suggest there are large potential output gains from the reallocation of resources to the most efficient retailers. More importantly, the potential aggregate productivity gains from resource reallocation have gone largely unexploited during the post-liberalization period. We find no allocative efficiency improvements for the total retail sector and for most Federal states of Brazil separately. These results are consistent with the view that allocative efficiency is the main culprit of low productivity growth in Latin America.

The implications of distortions for aggregate productivity are examined, and distortions to output and capital are related to regional variation in regulation using a differences-in-differences approach. Selective policy implementation and enforcement may create implicit or *de facto* differences in the business environment faced by small and large firms. For example, governments often find it impractical to collect taxes from small firms. Instead, governments are likely to set higher tax rates and enforce compliance only among larger firms (Tybout, 2000). In contrast, capital market imperfections might be a bigger constraint for smaller firms that lack sufficient collateral. Therefore, we allow the coefficients in our econometric model to vary by firm size. A novel aspect of the empirical approach is that we examine distortions to output and capital separately. HK examined the combination of distortions to output and capital. We show that separating both types of distortions is important due to opposing effects of regulation across size class and type of distortion.

We find that difficulty in access to credit results in distortions to capital for small and medium firms, but not for large firms. In contrast, taxes on gross profits create distortions to output for large firms, but do not significantly affect the output of small and medium firms. Hence, the results suggest that regulation results in distortions to output and capital, but the effects differ by firm size.

The remainder of this chapter is organized as follows. Section 3.2 sketches the HK model and derives measures and implications of distortions for aggregate productivity. Section 3.3 describes the dataset. Potential gains and changes over time from productive resource reallocation are estimated in section 3.4. Thereafter, section 3.5 examines the relation between regulation and distortions to output and capital. Finally, section 3.6 provides concluding remarks.

3.2 Theoretical framework

This section illustrates the relation between aggregate productivity and the allocation of resources. Implications of the misuse of resources for aggregate productivity can be studied in a model of monopolistic competition with heterogeneous firms.[5] We follow the model introduced by HK. Based on the canonical model of Melitz (2003), HK introduced distortions to output and capital.[6] Here, we only discuss the core elements and present the competitive equilibrium of the model in a format which suits our empirical analysis.

[5] Firms are heterogeneous with respect to marginal costs.

[6] Various authors focused on specific mechanisms that could result in resource misallocation. For example, Lagos (2006) studied the impact of labor market regulation on allocative efficiency; Buera and Shin (2008) examined implications of financial frictions, and Guner et al. (2008) developed a model to examine resource misallocation as a result of size restrictions.

Two firm-specific distortions are considered. First, a capital distortion τ_{Ksi}, which changes the marginal revenue product of capital relative to the marginal revenue product of labor. Second, an output distortion τ_{Ysi}, which distorts the marginal revenue product of capital and labor in equal proportions. The former leads firms to substitute labor for capital, while the latter results in a suboptimal size of the firm.

Following HK, assume aggregate output Y is the combination of goods Y_s in s retail industries under perfect competition in both the output and input market:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s}. \tag{3.1}$$

where the sum of industry shares $\sum_{s=1}^{S} \theta_s = 1$.[7] Output Y_s in industry s, is the combination of N_s differentiated products sold by all firms $(i = 1, ..., N_s)$, which face a constant elasticity of substitution σ:[8]

$$Y_s = \left(\sum_{i=1}^{N_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{3.2}$$

The Cobb-Douglas production function of each retailer selling a differentiated good in industry s is given by:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}, \tag{3.3}$$

where Y_{si} denotes the retailer's value added, A_{si} productivity, K capital, and L labor. The capital share α_s and labor share $(1 - \alpha_s)$ are only allowed to vary across industries. Costs C_{si} for a retailer are given by:

$$C_{si} = wL_{si} + (1 + \tau_{Ksi}) r K_{si}, \tag{3.4}$$

[7] Under cost minimization $p_s Y_s = \theta_s p Y$, where p_s is the price of sales Y_s in industry s and $p \equiv \prod_{s=1}^{S} (\frac{p_s}{\theta_s})^{\theta_s}$ is the price of the final good sold (which is set the numéraire, so $p = 1$). Throughout, quantities will be denoted by capital letters, and prices by lower-case letters.

[8] Firms sell a single type of good or variety. These varieties are symmetrically differentiated, with a common elasticity of substitution σ between any two variables. In addition, we assume the elasticity of substitution is time-invariant and does not differ across goods. We discuss the restrictiveness and examine the sensitivity of the results to these assumptions in section 3.4.

where w is the wage rate, r is the rental cost of capital, and the capital distortion τ_{Ksi} raises the cost of capital relative to that of labor. Cost minimization results in the optimal capital-labor ratio:

$$\frac{K_{si}}{L_{si}} = \left(\frac{\alpha_s}{1-\alpha_s}\right)\left(\frac{w}{r}\right)\left(\frac{1}{1+\tau_{Ksi}}\right). \tag{3.5}$$

Retailer's profits are given by:

$$\Pi_{si} = (1-\tau_{Ysi})p_{si}Y_{si} - wL_{si} - (1+\tau_{Ksi})rK_{si}, \tag{3.6}$$

where p_{si} is the price of the good sold by firm i in industry s, and τ_{Ysi} is the output distortion which affects the marginal products of capital and labor in equal proportions. Profit maximization results in the mark-up price over marginal cost, which is fixed because we assumed constant returns to scale in production, and is given by:

$$p_{si} = \left(\frac{\sigma}{\sigma-1}\right)\left(\frac{w}{1-\alpha_s}\right)^{1-\alpha_s}\left(\frac{r}{\alpha_s}\right)^{\alpha_s}\left(\frac{(1+\tau_{Ksi})^{\alpha_s}}{A_{si}(1-\tau_{Ysi})}\right). \tag{3.7}$$

If retail industry output Y_s is maximized, we obtain the allocation of capital, labor, and firm output across firms. The allocation of labor is (see HK for details):[9]

$$L_{si} = c_1 \cdot \frac{(1-\tau_{Ysi})^{\sigma} A_{si}^{\sigma-1}}{(1+\tau_{Ksi})^{\alpha_s(\sigma-1)}}. \tag{3.8}$$

The allocation of capital is:

$$K_{si} = c_2 \cdot \frac{(1-\tau_{Ysi})^{\sigma} A_{si}^{\sigma-1}}{(1+\tau_{Ksi})^{\alpha_s(\sigma-1+\frac{1}{\alpha_s})}}. \tag{3.9}$$

[9] The parameter c_1, c_2, and c_3 are constant within industries and given by:
$c_1 = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(\frac{(1-\alpha_s)}{w}\right)^{\sigma(1-\alpha_s+\frac{\alpha_s}{\sigma})}\left(\frac{\alpha_s}{r}\right)^{\alpha_s(\sigma-1)} I^{\sigma-1}\theta_s Y;$
$c_2 = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(\frac{(1-\alpha_s)}{w}\right)^{\sigma(1-\alpha_s+\frac{\alpha_s}{\sigma}-\frac{1}{\sigma})}\left(\frac{\alpha_s}{r}\right)^{\alpha_s(\sigma-1+\frac{1}{\alpha_s})} I^{\sigma-1}\theta_s Y;$
$c_3 = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(\frac{(1-\alpha_s)}{w}\right)^{\sigma(1-\alpha_s)}\left(\frac{\alpha_s}{r}\right)^{\alpha_s\sigma} I^{\sigma-1}\theta_s Y;$
where $I = \left(\sum_{i=1}^{N} p_{si}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$.

And retailer's output is:

$$Y_{si} = c_3 \cdot \frac{(1-\tau_{Ysi})^{\sigma} A_{si}^{\sigma}}{(1+\tau_{Ksi})^{\alpha_s \sigma}}. \tag{3.10}$$

In equation 3.10, output across firms within industries may differ because of heterogeneity in productivity A_{si} (as in Melitz (2003)), and because of firm-specific output and capital distortions. Absent distortions, relative to other firms in the industry a more productive firm will be larger. If a firm faces higher tax (enforcement) on profits, its size will be smaller than in the absence of distortions. This might be particularly binding for large firms, since collecting taxes may involve fixed costs inducing authorities to enforce taxes on larger firms for which the effort has a positive payoff.

To the extent resource allocation in an industry is driven by distortions alongside firm productivity, this will result in differences in the marginal revenue products of capital and labor across firms. The marginal revenue product of labor is:

$$MRPL_{si} = \frac{p_{si} Y_{si}}{L_{si}} = \frac{w}{(1-\tau_{Ysi})} \left(\frac{\sigma}{\sigma-1}\right) \left(\frac{1}{1-\alpha_s}\right). \tag{3.11}$$

The marginal revenue product of capital is:

$$MRPK_{si} = \frac{p_{si} Y_{si}}{K_{si}} = \frac{r(1+\tau_{Ksi})}{(1-\tau_{Ysi})} \left(\frac{\sigma}{\sigma-1}\right) \left(\frac{1}{\alpha_s}\right). \tag{3.12}$$

The after-tax marginal revenue products of capital and labor are equalized across firms within industries because only distortions to output and capital are firm-specific. But before-tax marginal revenue products may differ depending on the distortions the firm faces. This has important implications for the firm's revenue productivity, which is an input share-weighted combination of the marginal product of capital and labor.

Solving for the equilibrium allocation of resources across industries, aggregate output can be expressed as (see HK for details):

$$Y = \prod_{s=1}^{S} \left(TFP_s K_s^{\alpha_s} L_s^{1-\alpha_s}\right)^{\theta_s}. \tag{3.13}$$

Next, to determine industry productivity TFP_s, it is useful to distinguish between the firm's revenue productivity, $TFPR_{si}$, and the firm's physical productivity, $TFPQ_{si}$. The use of a firm-specific deflator yields a 'pure' measure of productivity, termed physical productivity $TFPQ_{si}$. In contrast, if an industry deflator is used, firm-specific differences in prices are not taken into account. Using an industry deflator gives a 'contaminated' measure of productivity, which is termed revenue productivity $TFPR_{si}$. Both firm productivity measures ($TFPR_{si}$ and $TFPQ_{si}$) are relative to the industry average. Following Foster et al. (2008), physical and revenue productivity are defined as:[10]

$$\begin{aligned} TFPR_{si} \quad &\equiv \quad p_{si}A_{si} \equiv \frac{(p_{si}Y_{si}/\overline{p_sY_s})}{(rK_{si}/\overline{rK_s})^{\alpha_s}(wL_{si}/\overline{wL_s})^{1-\alpha_s}} \\ &= c_5 \cdot \frac{(1+\tau_{Ksi})^{\alpha_s}}{(1-\tau_{Ysi})}. \end{aligned} \tag{3.14}$$

$$\begin{aligned} TFPQ_{si} \quad &\equiv \quad A_{si} \equiv \frac{(Y_{si}/\overline{Y_s})}{(rK_{si}/\overline{rK_s})^{\alpha_s}(wL_{si}/\overline{wL_s})^{1-\alpha_s}} \\ &= c_4 \cdot \frac{(p_{si}Y_{si}/\overline{p_sY_s})}{(rK_{si}/\overline{rK_s})^{\alpha_s}(wL_{si}/\overline{wL_s})^{1-\alpha_s}}. \end{aligned} \tag{3.15}$$

In comparison to HK, we improve the productivity estimates for $TFPR_{si}$ and $TFPQ_{si}$ by making them unit invariant (that is, dividing output and inputs by the industry averages for output and inputs). From equation 3.14, it follows that revenue productivity $TFPR_{si}$ only varies across firms within industries if firms face output and capital distortions. Firms with higher physical productivity $TFPQ_{si}$ demand more capital and labor up to the point where the higher output results in a lower price and thus the same $TFPR_{si}$ as the other firms.

Industry TFP_s can be shown to be:

$$TFP_s = \left(\sum_{i=1}^{N_s} \left\{ A_{si} \cdot \frac{\overline{TFPR_s}}{TFPR_{si}} \right\}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}. \tag{3.16}$$

An important aspect of the expression for industry productivity is that if all

[10] The parameters $c_4 = \frac{w^{1-\alpha_s}(p_sY_s)^{-\frac{1}{\sigma-1}}}{p_s}$ and $c_5 = \left(\frac{\sigma}{\sigma-1}\right)\left(\frac{1-\alpha_s}{1}\right)^{\alpha_s-1}\left(\frac{r}{\alpha_s}\right)^{\alpha_s}$ are constant within industries.

firms face the same distortions, industry TFP_s will be unaffected. That is, if $\tau_{Ysi} = \tau_{Ys}$ and $\tau_{Ksi} = \tau_{Ks}$ for all i, the distortions disappear from the expressions for equilibrium industry TFP_s, and TFP_s is given by $\overline{A_s} = \left(\sum_{i=1}^{N_s} A_{si}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$. This property of the model allows us to isolate the effects of policies on TFP through resource misallocation. The property is due to inelastic factor demand with respect to the distortions. A change in average taxes only changes factor prices, such that the first-order conditions of all firms are satisfied with the same allocations.

Firm-level distortions cannot be observed from the empirical data and must be identified. Distortions to output and capital are estimated from:

$$(1-\tau_{Ysi}) = \frac{\sigma}{\sigma-1}\frac{(wL_{si}/\overline{wL_s})}{(1-\alpha_s)(p_{si}Y_{si}/\overline{p_sY_s})}. \tag{3.17}$$

$$(1+\tau_{Ksi}) = \frac{\alpha_s}{1-\alpha_s}\frac{(wL_{si}/\overline{wL_s})}{(rK_{si}/\overline{rK_s})}. \tag{3.18}$$

Firm-specific output distortions are inferred from equation 3.17 (itself derived from equation 3.11), when the firm's labor share is low compared to the industry elasticity of output with respect to labor. Capital distortions are inferred from equation 3.18 when the firm's ratio of labor compensation to capital services is high relative to what one expects from the output elasticities of capital and labor of the industry.

An important parameter in inferring distortions to output and their implications for aggregate productivity is the elasticity of substitution σ between firm value added. Aggregate productivity gains from the removal of distortions are increasing in σ. HK assume a common σ across goods equal to $\sigma = 3$. Initially, we use $\sigma = 3$ as well, but the sensitivity of the results to the choice of σ will be considered.

To estimate the firm's productivity and its distortions to capital and output, a choice has to be made on the benchmark capital share α_s. Because the average capital distortion and the capital production elasticity in each industry cannot be separately identified, we use the industry shares for the Federal district Brasilia as the benchmark. HK use industry shares for the United States as the benchmark. We do not use the US as the undistorted benchmark, because US industry characteristics might not match those in the states of Brazil. That is, differences in institutions, market structure, and geography may induce input shares to differ across countries.

Instead, we assume Brasilia is comparatively undistorted. Our benchmark choice is motivated by the observations that GDP per capita is highest, overall business regulation is least restrictive (see next section), and state-specific estimates of the substitution elasticity σ (explained in the sensitivity analysis in section 3.4) suggests competition is strongest in Brasilia. Deviations of the firm's input cost shares from the median shares in that particular industry for Brasilia will show up as a distortion to output and/or capital for the firm.

3.3 Data

To derive measures of productivity and distortions, we use the annual census of retailers for the period from 1996-2006. The measures of distortions will be used to examine implications for aggregate productivity in section 3.4. In addition, the measures of distortions are related with indicators of regulation to examine whether taxes and difficulty in access to credit result in distortions to output and capital in section 3.5. This section describes the regulatory indicators and retail census data.

3.3.1 Regulation: Taxes and Access to Credit

Information on regulation is provided by the World Bank's Doing Business for Federal states in 2006 (World Bank, 2006). The indicators we use are paying taxes and getting credit. Taxes are considered, because the complex and burdensome tax system potentially distorts output. Getting credit is considered, because it is identified as one of the most important constraints on growth in Brazil (Rodrik, 2007). In particular, small firms are constrained (World Bank, 2006), which may result in relatively larger distortions to capital for these firms.[11]

The indicator of paying taxes records all taxes paid by a medium-sized firm, which is dedicated to general commercial activities and services within the second year of operation. Taxes are measured at all levels of government, resulting in more than 25 different public, state, and municipal taxes. These taxes include among others corporate income taxes, turnover taxes, and value-added taxes. Importantly, labor taxes (such as payroll taxes and social security contributions) are not inclu-

[11] Another candidate would be labor market distortions. See Lagos (2006); Almeida and Carneiro (2007); and Petrin and Levinsohn (2008) for firm-level analysis of the effects of labor regulation in Latin America.

ded. Hence, the indicator of paying taxes can be used to examine distortions to output as they are expected to proportionally affect the marginal revenue product of labor and capital.

The indicator on getting credit measures the time and cost to create and register collateral. The collateral agreement must be registered with the Registry of Deeds and Documents in the city of the debtor. These registries are not linked across regions, and often not digitalized. The cost to register a security includes official duties and notary fees.

Information on taxes and access to credit is provided in table 3.1. The cost of registering collateral (as a percent of loan value) ranges from 0.2 in Rio de Janeiro to 3.8 in Ceará. In comparison, the cost of registering collateral is 0.01 percent of loans in Canada and the United Kingdom. Taxes range from 89 percent of gross profits in the Amazone to 208 percent in Rio de Janeiro. Taxes in the United States are 45 percent of gross profits. Hence, although taxes and collateral registration procedures are essential for an economy to function, both appear burdensome in Brazil.

Table 3.1. Business regulations across the Federal states of Brazil, 2006

Federal state		Federal district	Amazonas	Minas Gerais	Rondônia	Maranhão	Rio Grande do Sul	Mato Grosso do Sul
Final Rank		1	2	3	4	5	6	7
Getting credit	Time to create collateral	45	6	2	30	4	25	30
	Cost to create collateral	0	2	1	2	1	1	1
Paying taxes	Total tax payable	149	89	150	146	147	153	146
	Number of payments	12	23	23	12	12	12	12
Federal state		Rio de Janeiro	Santa Catarina	Bahia	São Paulo	Mato Grosso	Ceará	
Final Rank		8	9	10	11	12	13	
Getting credit	Time to create collateral	27	25	26	na	23	40	
	Cost to create collateral	0	3	2	na	3	4	
Paying taxes	Total tax payable	208	144	144	148	146	137	
	Number of payments	12	23	12	23	23	23	

Notes: Time to create collateral in days, cost to create collateral in percentage of loan value, total tax payable as percentage of gross profits. Number of payments per year. Source: Doing Business in Brazil (World Bank, 2006).

The first row of table 3.1 shows the final ranking of states in terms of business regulation (1 for the least regulated state, 13 for the most regulated state). This final ranking is a simple average of the ranking of a state on each indicator made by the World Bank.[12] The ranking suggests business regulation is least restrictive in Brasilia, while most restrictive in Ceará.

3.3.2 Retail-firm data

The principal data source of retail trade firms is the annual survey of distribution (Pesquisa Anual de Comercio, PAC) from 1996 to 2006. Firms registered in the Cadastro Nacional da Pessoa Jurídica (CNPJ) from the ministry of Economic Affairs and classified as wholesale and retail trade firms in the Cadastro Central de Empresas (CEMPRE) of the national statistical office (IBGE) are surveyed in PAC. The PAC dataset consists of two groups, namely a group of firms which surpass the threshold and are included by census, and another group of firms below the threshold included by sample only. The empirical analysis focuses on firms included by census, because we do not have appropriate weights to assure the sample reflects the population.

Firms with more than 20 employees or firms with less than 20 employees but with establishments in more than one Federal State are included in PAC by census.[13] For 1996 this amounts to 14,445 firms included by census. In 2006, the number of firms included by census has risen to 19,346. While firms included by census constitute a fairly small share of the total population of retail firms, they represent the major part of the sector in terms of sales (about 60 percent). Firms are linked across years using their identification numbers from the tax registry.

The census includes detailed information on output and inputs. Gross value added is obtained by subtracting purchases of goods sold and the costs of intermediate inputs from sales. Value added consists of compensation for labor and capital inputs. Labor input is measured by the firm's wage bill, which crudely controls for differences in human capital and hours worked (Hsieh and Klenow, 2009). Consistent with the flow measures of output and labor input, we measure capital services instead of capital stocks.[14]

[12] A wider set of indicators is considered for the final ranking, also including starting a business, registering property, and enforcing contracts.

[13] Firms in several northern states located outside the Federal States' capital are not included in the survey because of the high costs involved in collecting information for these firms. These states are: Rondônia, Acre, Amazonas, Roraima, Pará, Amapá, and Tocantins.

[14] Renting and leasing expenditures are excluded from costs of intermediate inputs and included in capital services.

Table 3.2 shows descriptive statistics for selected states and all states combined. Estimates of TFPR and TFPQ using equations 3.14 and 3.15 are close to one, because output and inputs are measured relative to the industry's average. Distortions to output are estimated from equation 3.17. Output distortions are negative on average, thus labor's share is high compared to what one would expect from the industry elasticity of output with respect to labor. The positive values for distortions to capital (estimated using equation 3.18) indicate that the ratio of labor compensation to the capital stock is high relative to what one would expect from the output elasticities with respect to capital and labor. Hence, both distortions suggest a relatively intensive use of labor compared to the benchmark. Distortions to capital are high in Ceará, where access to credit is also most restrictive (see table 3.1), suggesting a positive relation between the two. Output and input data suggest that firm size in Rio de Janeiro is below average, which might be related with above average taxes distorting output more in this state than in others. We will formally examine the relation between regulation and distortions to output and capital in section 3.5.

Table 3.2. Descriptive statistics for retail firms, 2006

Variable	All states	Ceará (UF=23)	Rio de Janeiro (UF=33)	Brasilia (UF=53)
Sales	14.44	14.70	13.91	14.75
	1.55	*1.63*	*1.38*	*1.60*
Value added	12.96	12.95	12.75	13.28
	1.25	*1.47*	*1.15*	*1.38*
Remuneration	12.67	12.49	12.47	12.85
	1.11	*1.29*	*1.05*	*1.19*
Capital services	11.24	11.25	11.23	11.69
	1.36	*1.60*	*1.29*	*1.49*
TFPR	1.16	1.22	1.11	1.23
	0.81	*1.11*	*0.59*	*1.10*
TFPQ	1.04	1.08	0.98	1.14
	1.00	*1.37*	*0.75*	*1.15*
τ_{Ysi}	-1.71	-2.29	-1.32	-1.65
	2.61	*3.57*	*1.63*	*2.56*
τ_{Ksi}	0.15	0.15	-0.09	0.11
	1.70	*1.40*	*1.08*	*1.58*
Observations	19346	396	2607	413

Notes: The mean values (in natural logarithmic form) for Sales, Value added, Remuneration, and Capital services are in current Reais. The standard deviation is below in italics. TFPR is estimated using equation 3.14, TFPQ is estimated using equation 3.15, output distortions are estimated from equation 3.17, and capital distortions are estimated from equation 3.18. Source: Pesquisa Anual de Comercio (IBGE, 2006b).

3.4 Allocative efficiency in Brazil's retail sector

We consider the productivity distribution and the gains in aggregate productivity if distortions were to disappear. If there were no distortions (or all distortions were the same across firms within industries), the TFPR distribution would be equal to one, and there would be no potential gains in productivity from resource reallocation. Hence, the variance of the TFPR distribution reflects firm-specific distortions across states. One can estimate potential aggregate productivity gains by hypothetically removing these idiosyncratic distortions.

3.4.1 The revenue productivity distribution

Table 3.3 shows statistics for the revenue productivity distribution. We estimated the distribution of TFPR for each Federal state separately and for all states combined. Output and factor inputs are relative to the industry mean, so the mean and median of the TFPR distribution approximate one. The dispersion of TFPR varies considerably across states. The variance ranges from 0.22 in Rondônia to 1.35 in Espíritu Santo. If we correlate the variance in TFPR with the ranking of states on the strictness of business regulation we find a positive but insignificant relation, which suggests a weak positive relation between regulation and dispersion in marginal revenue products across firms within states. Obviously, these results are indicative at best and will be further explored in the next section.[15]

3.4.2 Potential gains from resource reallocation

Potential gains in aggregate productivity across states are estimated by hypothetically removing distortions. If marginal products are equal across firms, industry TFP is $\overline{A_s} = \left(\sum_{i=1}^{N_s} A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$. Potential gains are estimated from:

$$\frac{Y}{Y_{efficient}} = \prod_{s=1}^{S} \left[\sum_{i=1}^{N_s} \left\{ \frac{A_{si}}{\overline{A_s}} \cdot \frac{\overline{TFPR_s}}{TFPR_{si}} \right\}^{\sigma-1} \right]^{\frac{\theta_s}{(\sigma-1)}} . \tag{3.19}$$

For each industry, we calculate the ratio of actual TFP_s (equation 3.16) to the efficient level of TFP_s, and then aggregate this ratio across industries using the

[15] The number of firms differs considerably across states (see table 3.3). The limited number of observations for several states may result in incorrectly measured TFPR distributions. In section 3.5 we consider the sensitivity of the relation between regulation and distortions to dropping states one at a time.

Table 3.3. TFPR distribution, 2006

Federal state	n	mean	median	variance
Rondônia	69	1.06	1.02	0.22
Acre	51	1.06	0.97	0.29
Amazonas	198	1.04	0.72	1.03
Roraima	31	1.00	0.88	0.26
Pará	182	1.08	0.90	0.56
Amapá	45	1.04	0.91	0.50
Tocantins	37	1.28	1.00	1.11
Maranhão	193	1.11	0.90	1.02
Piauí	163	1.10	0.87	0.77
Ceará	396	1.22	0.94	1.22
Rio Grande do Norte	265	1.18	1.04	0.55
Paraíba	185	1.22	0.97	0.83
Pernambuco	573	1.20	0.96	1.11
Alagoas	165	1.07	0.75	1.21
Sergipe	157	1.12	1.00	0.47
Bahia	917	1.17	0.91	1.04
Minas Gerais	2148	1.16	0.99	0.53
Espírito Santo	499	1.20	0.96	1.35
Rio de Janeiro	2607	1.11	0.99	0.35
São Paulo	5451	1.24	1.10	0.53
Paraná	1432	0.98	0.91	0.29
Santa Catarina	821	1.25	1.01	0.94
Rio Grande do Sul	1104	1.11	0.97	0.61
Mato Grosso do Sul	299	1.04	0.90	0.66
Mato Grosso	394	1.23	1.01	0.80
Goiás	551	1.15	0.93	1.06
Distrito Federal	413	1.23	0.94	1.21
Total economy	19346	1.16	1.00	0.65

Notes: TFPR is estimated using equation 3.14, TFPQ is estimated using equation 3.15, output distortions are estimated from equation 3.17, and capital distortions are estimated from equation 3.18.

Cobb-Douglas aggregator (equation 3.1). Table 3.5 provides percentage TFP gains by state from fully equalizing TFPR across firms in each industry for the years 1996, 2001, and 2006. The potential gains are large. For example, for 1996 potential TFP gains are 217 percent in Brasilia (Distrito Federal), 239 percent in Rio de Janeiro, and 244 percent in São Paulo.

Estimates of potential gains in retailing are higher than estimated productivity gains from equalizing TFP within manufacturing industries. For China and India, gains in manufacturing range from 86 to 128 percent (Hsieh and Klenow, 2009). Estimates for the manufacturing sector in Latin America are not yet available, but preliminary evidence for Bolivian manufacturing suggests that it is roughly in the same ballpark as Chinese and Indian manufacturing (Machicado and Birbuet, 2008).

The approach to estimate potential gains is not without limitations, because 'non-neoclassical' features such as markups, adjustment costs, returns to scale, and fixed costs are also reflected in the gaps. The margin of error in estimated gains, which is further examined below, preclude us from stating that distortions are larger in São Paulo as compared to Rio de Janeiro, because potential gains are smaller in the latter (see table 3.5).

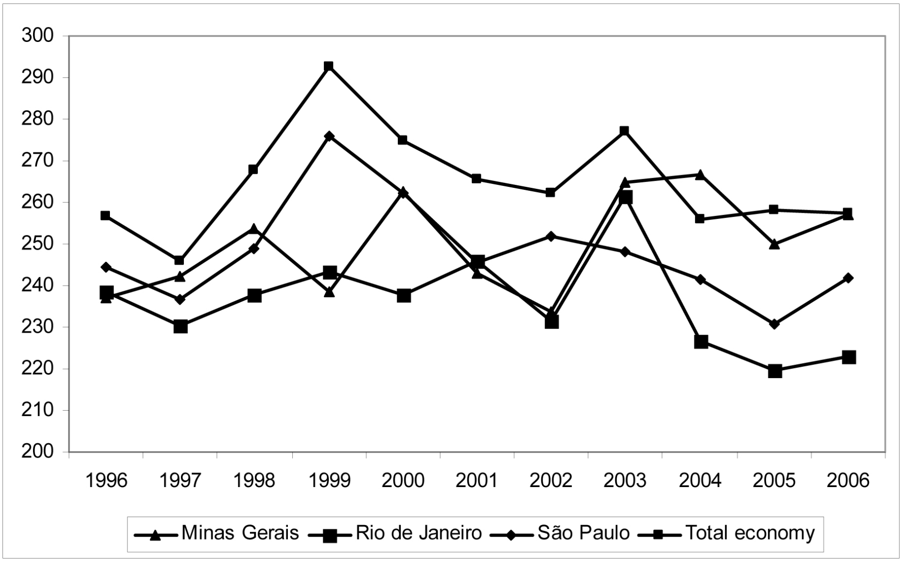
However, large potential gains are not out of line with estimates of TFP gaps in retail between the US and Brazil. Estimates indicate that productivity levels in Brazilian retailing are between 14 and 28 percent of the US productivity level (McKinsey (1998) Mulder (1999); Lagakos (2009)). Mulder (1999) finds that the relative productivity level dropped from 28 to 14 percent during the period from 1975-1995. This finding is consistent with the 14 percent level for food retailing in 1995 obtained by McKinsey (1998). Also, preliminary evidence based on differences in the size composition between the US and Brazil, suggests that resource allocation improvements may account for half of this retail TFP gap (Lagakos, 2009). Assuming larger firms have higher productivity levels, our estimates of the large potential TFP gains from resource reallocation are in line with these findings. That is, improvements in resource reallocation may improve TFP levels by a factor of two, which would bring productivity levels in Brazil's retail sector between 28 and 56 percent of the US productivity level.

More important is whether potential TFP gains from resource reallocation have been realized during the period following services liberalization. Changes in the opportunity for increasing aggregate productivity by removing distortions are examined by comparing the potential gains between 1996 and 2006. Figure 3.1 presents results for the total economy and three large Federal states (Rio de Janeiro, São Paulo, and Minas Gerais). The figure suggests potential gains from resource reallocation have gone largely unexploited despite liberalization of the retail sector since the 1990s.

In table 3.4, the last column shows the β-coefficient from an OLS regression where % TFP gains are regressed against time. A significant negative value indicates improvements in allocative efficiency. In most states, the coefficient is positive and insignificant. For some states we find a significant positive coefficient, but the change over time is small. This finding suggests slow resource reallocation following pro-competitive reforms as well.

Our finding of limited resource reallocation is consistent with earlier research

Figure 3.1. Potential aggregate productivity gains from resource reallocation



attributing Latin America's disappointing performance after market-oriented reforms in the 1990s to the slow reallocation of inputs toward more efficient firms.[16] In particular, in chapter 2 we find limited evidence of improvements in allocative efficiency after reforms in the retail sector of Brazil.[17]

3.4.3 Sensitivity analysis of the potential TFP gains

We examined the sensitivity of estimated potential aggregate TFP gains in various ways. The sensitivity analysis suggests that various adjustments affect the magnitude of potential TFP gains. However, changes over time in the opportunity for increasing aggregate productivity by removing distortions are hardly affected.

First, potential gains are increasing in σ, and HK argue that the 'estimated gains

[16] See for example Cole et al. (2005); Mukand and Rodrik (2005); Menezes-Filho and Muendler (2007); Pages et al. (2009); Chapter 2.

[17] An alternative for considering the efficient allocation of resources is by focusing on the productivity distribution using the Olley and Pakes (OP) (Olley and Pakes, 1996) method. This method does not weight input movements using differences in the gaps between marginal revenue products and input prices, but measures whether resources are allocated efficiently in the cross section of firms by looking at the differences between weighted and unweighted productivity at a given moment in time. If distortions are present, the difference between unweighted productivity and cross-sectional efficiency is smaller. Applying this method to the retail sector in Brazil, we find the difference between weighted and unweighted log(TFPR) is 0.26 log points in 1996. This implies that aggregate productivity would be around 26 percent lower if resources were allocated randomly. We do not find an improvement in the OP cross term over time. Hence, the OP method suggests allocative efficiency did not improve, which is consistent with the findings using the HK model.

Table 3.4. TFP Gains from equalizing TFPR within industries

Federal state	1996	2001	2006	β
Rondônia	190	196	204	-1.52
Acre	231	187	214	1.91
Amazonas	188	216	235	2.93**
Roraima	212	236	229	0.72
Pará	204	212	218	1.19
Amapá	226	216	217	1.73
Tocantins	239	262	238	-0.48
Maranhão	179	196	238	2.83
Piauí	204	220	230	1.57*
Ceará	218	226	244	1.97*
Rio Grande do Norte	211	221	227	3.15**
Paraíba	224	227	237	1.56
Pernambuco	233	262	235	1.07
Alagoas	197	228	250	4.13***
Sergipe	203	223	206	0.57
Bahia	245	255	264	1.89
Minas Gerais	237	243	257	1.75
Espírito Santo	242	239	274	2.33*
Rio de Janeiro	239	246	223	-1.13
São Paulo	244	246	242	-1.12
Paraná	243	231	235	-1.40
Santa Catarina	235	247	254	1.84
Rio Grande do Sul	237	250	274	2.93
Mato Grosso do Sul	232	251	260	2.52
Mato Grosso	241	248	267	2.65*
Goiás	229	243	269	3.81***
Distrito Federal	217	239	250	4.45***
Total economy	257	266	257	-0.26

Notes: TFP Gains from equalizing TFPR within industries, elasticity of substitution is 3. The last column shows the β-coefficient from an OLS regression where % TFP gains are regressed against time. A significant negative value indicates improvements in allocative efficiency. * significant at 10%; ** significant at 5%; *** significant at 1%.

are highly sensitive to this elasticity' (p. 1425).[18] Therefore, we examined the sensitivity of TFP gains to the elasticity of substitution. Hopenhayn and Neumeyer (2008) show $\sigma = 3$ is a low value relative to what has been used in the literature.[19] The parameter ν ($\nu = 1/(\sigma - 1)$) is usually calibrated taking a value $\nu = 0.15 - 0.2$,

[18] We considered other common elasticities of substitution (e.g. 5 and 7) as well. In general, gains increase in σ.

[19] In the absence of firm-specific distortions, there is an equivalence between aggregate productivity in the decreasing returns perfect competition economy (Restuccia and Rogerson, 2008) and the constant returns monopolistic competition economy (the HK model). Without distortions (or equal distortions across firms), TFP is:

$TFP_s^{RR} = \left(\sum_{i=1}^{N_s} A^{\frac{1}{\nu}}\right)^{\nu}$

which implies $\sigma = 6 - 7\frac{2}{3}$ (e.g. Atkeson and Kehoe (2005); Buera and Shin (2008); Guner et al. (2008)). In addition to the assumption of a low elasticity of substitution in HK ($\sigma = 3$ implies $\nu = 0.5$), the assumption of a common elasticity may not reflect differences in market circumstances.

More in line with calibration analysis of models with decreasing returns to scale and perfect competition (e.g. Restuccia and Rogerson (2008)), we let the elasticity of substitution vary between 3 and 7. Further, we relax the assumption of a common elasticity of substitution by allowing it to vary across states in Brazil. Substantial differences in market characteristics across the states of Brazil motivate this approach. The elasticity of substitution by state is estimated using indicators that capture the degree of substitutability between firm's value added in each state. Population and retail-firm density, in combination with demand factors are likely to increase competition. The variables considered are: population per km^2, number of retail firms per 1000 inhabitants, GDP per capita, female labor force participation (a higher participation rate shifts preferences toward one-stop shopping), and the share of households with a car. An unweighted average for the normalized values of these indicators determines the elasticity of substitution. Appendix table 3.A.1 shows the indicators and the resulting σ. The elasticity of substitution between the output of firms is highest for Brasilia, and lowest for Pará.

The potential gains using state-specific σ's are shown in figure 3.2. The gains for the total economy are larger as compared to the benchmark estimates, which is mainly due to the higher estimates for São Paulo. This suggests that potential TFP gains from resource reallocation are sensitive to the choice of σ. However, if we use state-specific σ's there is no apparent improvement in allocative efficiency over time as well.

Second, we examined the influence of the tails of the TFPR distribution, because measurement error could influence the potential gains. We trimmed the 2.5 percent tails of TFPQ and the output and capital distortions.[20] We allow the elasticity of substitution to vary across states. Figure 3.2 shows these results as well. Hypothetical TFP gains fall, from 257 to 248 percent for all states combined. Hence, measurement error in the remaining 2 percent tails could matter, but if so it only partially accounts for the big gains from removing distortions. Changes in allocative efficiency are similar, and again suggest a limited role of resource reallocation

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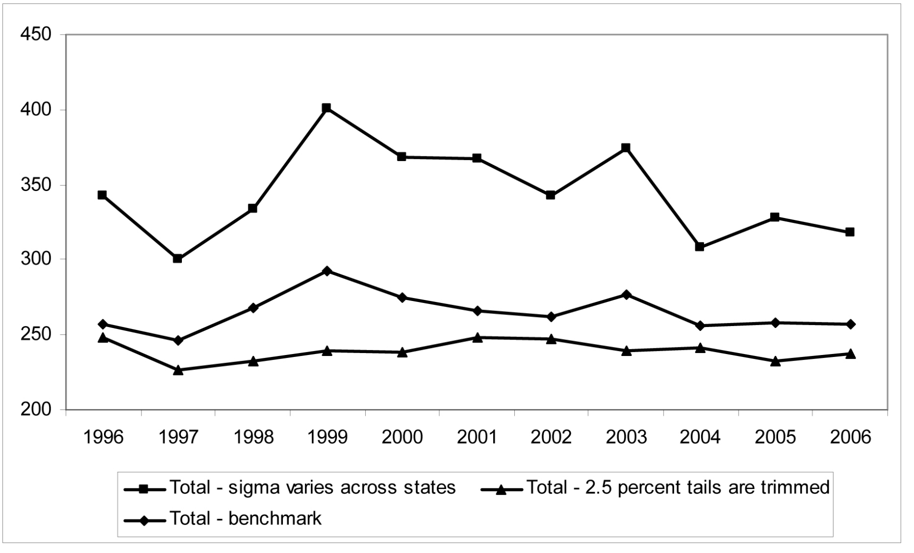
$TFP_s^{HK} = \left(\sum_{i=1}^{N_s} A_{si}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$

Hence, for the parameter $\nu = 1/(\sigma - 1)$, aggregate productivity is similar in both models.

[20] In the benchmark estimations of TFP gains, we trimmed the 0.5 percent tails of TFPQ and the output and capital distortions.

Figure 3.2. Potential aggregate productivity gains from resource reallocation



to productivity growth.

3.5 Regulation and distortions to output and capital

In an exploratory data analysis, we correlated the variables used in this chapter. Correlations are shown in table 3.5. The relation between value added and productivity is positive suggesting larger firms are more productive, which is consistent with core models of the size-productivity distribution of firms (Melitz, 2003). The correlation between employment and distortions to output is positive. This may reflect larger firms facing larger distortions to output. In contrast, the relation between employment and distortions to capital is negative suggesting that smaller firms face larger distortions to capital, although the relation is not significant. Hence, distortions may differ with firm-size.

Table 3.5. Correlation between variables, 2006

	Value added	Employment	Capital services	TFPR	TFPQ	τ_{Ysi}	τ_{Ksi}
Value added	1						
Employment	0.94	1					
Capital services	0.84	0.82	1				
TFPR	0.02	-0.01^c	-0.01^b	1			
TFPQ	0.13	0.09	0.05	0.89	1		
τ_{Ysi}	0.04	0.02^a	0.02^b	0.42	0.37	1	
τ_{Ksi}	-0.02	-0.01^c	-0.03	0.25	0.14	-0.22	1

Note: Pearson correlation coefficients. All pairwise correlations are significant except for [a] Significant at 5 percent level, [b] Significant at 10 percent level, and [c] not significant.

In this section we relate regulation to distortions using a particular form of a differences-in-differences (DD) approach, popularized by Rajan and Zingales (1998).[21] The advantage of this approach is that we are able to examine a causal relation between regulation and distortions as compared to a simple correlation between both.

The substantial variation in regulation across states (see table 3.1) allows us to examine the effects of regulations in a differences-in-differences approach. We examine how taxes and access to credit impact on distortions to output and capital. For taxes, we examine whether retail industries with higher commercialization margins will be more affected by higher sales taxes.[22] For example, commercialization margins in the retail sale of household appliances, articles and equipment (CNAE 1.0 industry 5233) are higher than in specialized bakery and dairy stores (CNAE 1.0 industry 5221) (IBGE, 2006b).[23] Therefore, retailers selling household appliances will be more affected by taxes as compared to retailers selling food, beverages, and tobacco. In turn, this will translate into higher distortions for high-margin firms in states with high taxes relative to low-margin firms in the same state.

For access to credit, we examine whether retail industries that depend more on external financing are more affected by difficulty in access to credit (Rajan and Zingales, 1998). Our measure for external financial dependence is expenditures related to outstanding debt (e.g. interest payments on loans). This measure should reflect the amount of desired investment that cannot be financed through internal cash flows generated by the same firm. Using this proxy suggests that the relative dependence on external finance is higher in more capital-intensive retail industries. For example, dependence on external finance is highest in hypermarkets (CNAE 1.0 industry 5211) and lowest in stores selling candy and chocolates (CNAE 1.0 industry 5222).

The differences-in-differences approach requires a relatively frictionless market. We use the Federal State Brasilia as the comparatively undistorted benchmark. Obviously, distortions are present in Brasilia as well, as suggested by the potential gains from resource reallocation we found in section 3.4. However, what matters is that the relative industry ordering of commercialization margins and external financial dependence in Brasilia corresponds to the ordering of natural commercialization margins and natural external financial dependence across industries, and that these orderings carry over to other states in Brazil (Klapper et al., 2006).

[21] For recent applications, see Aghion et al. (2007), and Bruno et al. (2008).

[22] Commercialization margins, gross profits, are defined as resale revenues minus the cost of goods sold, remuneration, and intermediate expenditures, over sales.

[23] CNAE is Classificação Nacional de Atividades Econômicas, the national industry classification, which closely maps the International Standard Industrial Classification 3.1.

3.5.1 Model specification

For 2006, we regress distortions to output and capital on regulation interacted with an industry-specific indicator. Initially, we do not allow effects to vary by firm size (z), and therefore exploit three dimensions: (i) firm; (s) industry; and (r) region. If we label the regulatory variable (taxes or access to credit) as 'policy' and the related industry-specific factor as 'industry factor', the estimated specification is as follows:

$$\begin{aligned} \gamma_{i,s,r} &= \delta(policy_r \cdot industryfactor_s) + \sum_{r=1}^{R} \beta_r D_r \\ &\quad + \sum_{s=1}^{S} \beta_s D_s + \epsilon_{i,s,r}. \end{aligned} \tag{3.20}$$

The dependent variable, $\gamma_{i,s,r}$, is either a measure of the distortion to output (τ_{Ysi}) or capital (τ_{Ksi}), or a combination of both ($TFPR_{si}$). Region dummies, D_r, and industry dummies, D_s, are included to control for other market, technological, or regulatory factors not included in the regressions. This specification allows us to relate regulation with idiosyncratic distortions. Since the specification controls for region- and industry-specific effects, the only effects that are identified are those relative to the interaction term (the regulatory variable and the industry-specific factor) that varies both cross regions and cross industries. For example, for taxes we may examine whether differences in distortions to output between firms in industries with high or low commercialization margins are smaller in regions with lower taxes.

In the introduction, it is argued that the effects of taxes and difficulty in access to credit are likely to vary by firm size. The exploratory data analysis in this section suggested that distortions may vary with firm size as a result of regulation. Furthermore, Bartelsman et al. (2008) use the World Bank Investment Climate Surveys to examine the differential impact of policy factors on performance and growth prospects of firms of different size in Latin America. They present descriptive evidence that medium-size and, especially, large firms are more affected by high taxes and cumbersome tax administration than small firms. Medium and large businesses tend to be relatively less affected by lack of access to, and the cost of, financing. To allow for differential effects of policies, in a second specification we allow the effect to vary by firm size z:

$$\begin{aligned}\gamma_{i,s,r,z} &= \sum_{z=1}^{Z} \delta_z(policy_r \cdot industryfactor_s) + \sum_{r=1}^{R}\sum_{z=1}^{Z} \beta_{r,z} D_{r,z} \\ &+ \sum_{s=1}^{S}\sum_{z=1}^{Z} \beta_{s,z} D_{s,z} + \epsilon_{i,s,r,z}.\end{aligned} \tag{3.21}$$

The employment-size categories distinguished are firms with z1 (< 50 employees), z2 (51-100 employees), z3 (101-249 employees), and z4 (250 employees).[24]

A clear advantage of the DD approach compared to standard cross-state/cross-industry studies is that it allows to control for state and industry effects, thereby reducing problems with model misspecification and omitted variable bias. However, recent research has highlighted some disadvantages of the DD approach as well. Bertrand et al. (2004) argue that standard errors are biased due to autocorrelation if a long time series is considered. In our model set up, a single cross-section is considered, which is not susceptible to serial correlation problems. Donald and Lang (2007) show potential problems with grouped error terms, because the dependent variable differs across individuals while the policies being studied are constant among all members of a group. Failure to account for the presence of common group errors can generate biased standard errors as well. Therefore, we correct the standard errors using a robust covariance estimator, where state-industries are clustered. The large number of groups (13 states $\times$ 20 industries) is expected to result in an asymptotically normally distributed t-statistic.

3.5.2 Results

Table 3.6 shows results from estimating equation 3.20. Results show the average impact of regulation without differentiating by size. In the uneven columns, regional taxes on gross profits are interacted with the industry's commercialization margin. For the even columns, difficulty in access to credit is interacted with the industry's financial dependence. In columns (1)-(4), we consider the effects on revenue ($TFPR_{si}$) and physical ($TFPQ_{si}$) productivity. Recall that revenue productivity is a composite measure reflecting also distortions to output and capital, whereas physical productivity measures 'true' productivity of the firm only (see equations 3.14 and 3.15). Therefore, regulations are expected to be related with revenue productivity, and not with physical productivity.

[24] Aghion et al. (2007), and Bruno et al. (2008) distinguish similar employment-size categories.

Table 3.6. Regulation and distortions to output and capital, no allowance for size effects of regulation

Variable	TFPR (1)	TFPR (2)	TFPQ (3)	TFPQ (4)	τ_{Ysi} (5)	τ_{Ysi} (6)	τ_{Ksi} (7)	τ_{Ksi} (8)
Taxes $\times$ Commercialization margins	0.094		0.037		-0.007		0.667	
	(1.09)		(0.60)		(0.05)		(2.74)***	
Credit $\times$ Financial dependence		0.144		0.180		0.126		0.131
		(1.98)**		(2.57)**		(1.14)		(1.29)
Observations	15010	9559	15010	9559	15010	9559	15010	9559
R^2	0.05	0.04	0.08	0.08	0.06	0.07	0.16	0.11

Notes: OLS regressions, robust standard errors in brackets, region and industry dummies are included (not shown), clusters by region-industry. Number of observations for regressions where access to credit is interacted with financial dependence is smaller because no information on access to credit is available for São Paulo. * significant at 10%, ** significant at 5%, *** significant at 1%.

Results in column (1)-(4) suggest that taxes and access to credit are positively related with distortions (higher revenue productivity) in industries with higher commercialization margins and dependence on external finance, although the relation is significant for access to credit only. However, a similar relation is observed between regulation and physical productivity (columns 3 and 4). This creates doubts on the accurateness of distinguishing TFPR and TFPQ, because distortions should solely be reflected in revenue productivity. Both productivity measures are highly correlated and therefore TFPR may reflect distortions to output and capital as well as true productivity to some extent. Furthermore, revenue productivity is a composite measure of distortions, which may obscure channels by which regulation affects resource misallocation. Therefore, examining distortions to output and capital separately appears more appropriate.

Regressions for distortions to output and capital are shown in columns (5)-(8). Results suggest taxes are negatively related with distortions to output and positively related with distortions to capital. The opposing effects may explain why taxes are not significantly related with revenue productivity. Access to credit is positively related with both distortions to output and capital, which may explain why is it significantly related with revenue productivity.

A single coefficient for all firms may hide opposing affects across firm size. For example, distorting effects of difficulty in access to credit may be particular severe for small firms lacking sufficient collateral. Therefore, we allow the impact of regulation to vary by firm size. Results from estimating equation 3.21 are shown in table 3.7. Our interest centers on the relation between regulation and distortions to output and capital separately.

Results in table 3.7 suggest different patterns across firm size. In relative terms, taxes on gross profits act as an output subsidy for small firms $z1$ (because of the negative coefficient), have ambiguous effects for medium firms ($z2$ and $z3$), and distort output of large firms $z4$ (because of the positive coefficient, see column 1). Output distortions for large firms are higher in regions with higher taxes and in industries with higher commercialization margins. This finding is consistent with earlier literature (e.g. Gollin (2006); Guner et al. (2008)) and recent findings from interviews with CEO's of retail chains in Argentina (Sánchez and Butler, 2008). It may be due to higher enforcement for large firms if tax collection involves fixed costs, or a combination of both.

Table 3.7. Regulation and distortions to output and capital, allowance for size effects of regulation

Variable	τ_{Ysi} (1)	τ_{Ysi} (2)	τ_{Ksi} (3)	τ_{Ksi} (4)
Taxes × Commercialization margins × z1	-0.041		0.606	
	(0.30)		(2.51)**	
Taxes × Commercialization margins × z2	0.147		1.019	
	(0.69)		(3.36)***	
Taxes × Commercialization margins × z3	-0.175		0.748	
	(0.87)		(2.89)***	
Taxes × Commercialization margins × z4	0.350		0.484	
	(2.29)**		(2.04)**	
Credit × Financial dependence × z1		0.368		0.304
		(1.54)		(1.37)
Credit × Financial dependence × z2		0.153		0.546
		(0.56)		(1.77)*
Credit × Financial dependence × z3		-0.161		0.077
		(0.95)		(0.49)
Credit × Financial dependence × z4		0.016		-0.068
		(0.42)		(1.99)**
Observations	15010	9559	15010	9559
R^2	0.06	0.07	0.16	0.11

Notes: OLS regressions, robust standard errors in brackets, size-specific region and industry dummies are included (not shown), clusters by region-industry. The employment-size categories distinguished are firms with z1 (< 50 employees), z2 (51-100 employees), z3 (101-249 employees), and z4 (250 employees). Number of observations for regressions where access to credit is interacted with financial dependence is smaller because no information on access to credit is available for São Paulo. * significant at 10%, ** significant at 5%, *** significant at 1%.

To explore the estimated impact of taxes on distortions to output we follow the approach outlined in Aghion et al. (2007). We estimate the difference in distortions to output between firms in industries with high commercialization margins (90^{th} percentile of distribution in Brasilia) and firms in industries with low commercialization margins (10^{th} percentile of the same distribution) in the region with the highest taxes compared to the region with the lowest taxes:

$$\delta_z[(Margin_{90th} - Margin_{10th})(Taxes_{max} - Taxes_{min})]. \tag{3.22}$$

Using the coefficients in column (1), the impact of taxes on distortions to output is -0.02 for small firms and 0.19 for large firms. The differential impact is 0.21, which is about 12 percent of the sample mean distortion to output, suggesting that taxes have a modest but non-negligible impact on output distortions.

Difficulty in access to credit results in distortions to capital for small and medium firms, but not for large firms (column 4). In other words, difficulties in access to credit induce small and medium firms to substitute labor for capital. Smaller firms are more likely to face borrowing constraints because of limited liability and imperfections in the enforcement of debt repayment (Albuquerque and Hopenhayn, 2004). Therefore, small firms in industries that depend relatively more on external finance are more likely to employ labor instead of capital. In a similar fashion as for the effect of taxes, we examine the estimated impact of access to credit on distortions to capital. The differential impact between small and large firms is 0.57, suggesting that difficulty in access to credit has a substantial impact on distortions to capital at the sample mean.

3.5.3 Sensitivity of the results

The sensitivity of the main result, namely that the effects of regulations differ by firm size and type of distortion, are examined along different dimensions. Overall, the results are robust, but the sensitivity analysis uncovers several other interesting findings. First, regressions might be affected by the hierarchical setup of the model specification. That is, distortions measured at the firm-level are related with region-industry indicators. Although region-industry clusters were used to adjust the standard errors, an alternative approach might be to include firm-specific variables as explanatory variables (also using clustered standard errors). In columns (1) and (2) of table 3.8, regressions are shown where the firm's employment is included. Employment was considered, because it proxies for firm size. Therefore, we examine whether the results are driven by differences in profit margins and dependence on external finance between industries across size classes and not by independent size effects. Including a firm-specific variable does not change the distortionary effects of taxes and access to credit across firm size.

Table 3.8. Regulation and distortions to output and capital, sensitivity analysis

Variable	τ_{Ysi} (1)	τ_{Ksi} (2)	τ_{Ysi} (3)	τ_{Ksi} (4)
Taxes × Commercialization margins × z1	-0.041		-0.067	
	(0.30)		(0.51)	
Taxes × Commercialization margins × z2	0.147		0.099	
	(0.69)		(0.49)	
Taxes × Commercialization margins × z3	-0.175		-0.305	
	(0.87)		(1.44)	
Taxes × Commercialization margins × z4	0.350		0.090	
	(2.29)**		(0.51)	
Credit × Financial dependence × z1		0.301		0.353
		(1.36)		(1.51)
Credit × Financial dependence × z2		0.545		0.590
		(1.77)*		(1.84)*
Credit × Financial dependence × z3		0.078		0.113
		(0.49)		(0.70)
Credit × Financial dependence × z4		-0.070		-0.060
		(2.52)**		(1.70)*
Observations	15010	9559	15041	9581
R^2	0.06	0.11	0.04	0.11

Notes: OLS regressions, robust standard errors in brackets, size-specific region and industry dummies are included (not shown), clusters by region-industry. The employment-size categories distinguished are firms with z1 (< 50 employees), z2 (51-100 employees), z3 (101-249 employees), and z4 (250 employees). Number of observations for regressions where access to credit is interacted with financial dependence is smaller because no information on access to credit is available for São Paulo. * significant at 10%, ** significant at 5%, *** significant at 1%. Columns (1) and (2) include firm's employment; columns (3) and (4) show results when the elasticity of substitution is allowed to vary across size groups.

Second, we considered the sensitivity of the results to the elasticity of substitution varying by firm size. It may be argued that the elasticity of substitution is higher for small firms, perhaps because of customer-binding marketing strategies and the broader assortment of large firms, and less fixed costs in small firms. As a crude proxy, we allow the elasticity to vary between 7 and 3 for the different size groups instead of letting it vary between states. Results from regressing the different measures of distortions to output and capital are shown in columns (3) and (4). For difficulties in access to credit, the relation with distortions to capital is similar. However, for taxes we no longer find a significant distortionary influence on output for large firms. This suggests competition reduces the effect of tax policies on distortions.

Finally, we examined the sensitivity of the results to changes in the sample. We re-estimated the main regression of interest (columns (5) and (8) in table 3.6) removing one region at a time from the sample. This approach is motivated by substantial differences in the number of observations between states. Appendix figure 3.A.1 and 3.A.2 present the estimated coefficients differentiated by size classes. The first set of results (figure 3.A.1) suggests the amplitude of the coefficient for taxes interacted with commercialization margins is insensitive to the regions included in the sample. In particular, the distorting effect of taxes for large firms is stable across the different regressions, although the effect is at the 5 percent border of significance if Rio Grande do Sul (UF 43) is excluded from the sample. The second set of results (figure 3.A.2) indicates that the results for difficulty in access to credit interacted with financial dependence are affected by the exclusion of certain regions. In particular, excluding Minas Gerais, the state where access to credit is least difficult, affects the coefficient for large firms. Nevertheless, the sensitivity analysis still indicates substantial different effects across size classes irrespective of the exclusion of regions one at a time.

3.6 Concluding remarks

An increasingly dominant view holds the limited role of allocative efficiency as the main culprit of low growth following reforms in Latin America since the 1990s. So far, this view has been largely based on evidence from the manufacturing sector. In this chapter, we extended the analysis by examining allocative efficiency in the retail sector of Brazil. A novel methodological approach, following Banerjee and Duflo (2005), which uses the gaps between marginal revenue products and input prices to measure resource allocation, was followed.

We applied the HK model to a detailed census dataset of retail firms. Wedges between the opportunity cost and marginal product of factor inputs were measured and implications for aggregate productivity were imputed. The results indicate large potential productivity gains from the reallocation of resources toward the most efficient retailers. The potential TFP gains appear larger for the retail sector found in this study than that of the manufacturing sector found by others, but comparative evidence for the manufacturing sector in Brazil and the retail sector of other countries is still missing.

Importantly, we find no evidence for improvements in allocative efficiency. Potential output gains from resource reallocation have not been realized during the 1996 to 2006 period as the gap remained more or less constant. This finding is in line with the view that the absence of productive reallocation is underlying low growth in Latin America following reforms.

After obtaining measures of distortions at the firm level and examining its implications for aggregate productivity, we related these distortions with regional variation in regulation using a differences-in-differences approach. Selective policy implementation and enforcement may create implicit or *de facto* differences in the business environment faced by small and large firms. Therefore, we allowed the coefficients in our econometric model to vary by firm size. We find that difficulty in access to credit results in distortions to capital input for small and medium firms, but not for large firms. In contrast, taxes on gross profits create distortions to output for large firms, but do not significantly affect the output of small and medium firms. Hence, the results suggest that regulation results in distortions to output and capital, but the effects differ by firm size.

The approach in this chapter to measure distortions and their implications for aggregate productivity is theoretically a preferable measure of aggregate productivity with firm-level data (Petrin and Levinsohn, 2008). However, the approach is not without limitations, because 'non-neoclassical' features such as markups, adjustment costs, returns to scale, and fixed costs are also reflected in the gaps. Results in this chapter therefore await further comparisons to potential TFP gains in the services sector of other developed and developing countries. In addition, future research may address what specific distortions generate greater dispersion in marginal products.

Despite liberalization of the services sector in the 1990s, allocative efficiency in Brazilian retailing did not improve. Our results suggest that regulations are positively related to distortions in output and input choice, and may have prevented improvements in allocative efficiency. In particular, our results call for a closer examination of the differential impact of various regulations on firms of different sizes (see also Syverson (2010)).

3.A Appendix tables and figures

Table 3.A.1. Elasticities of substitution by Federal state

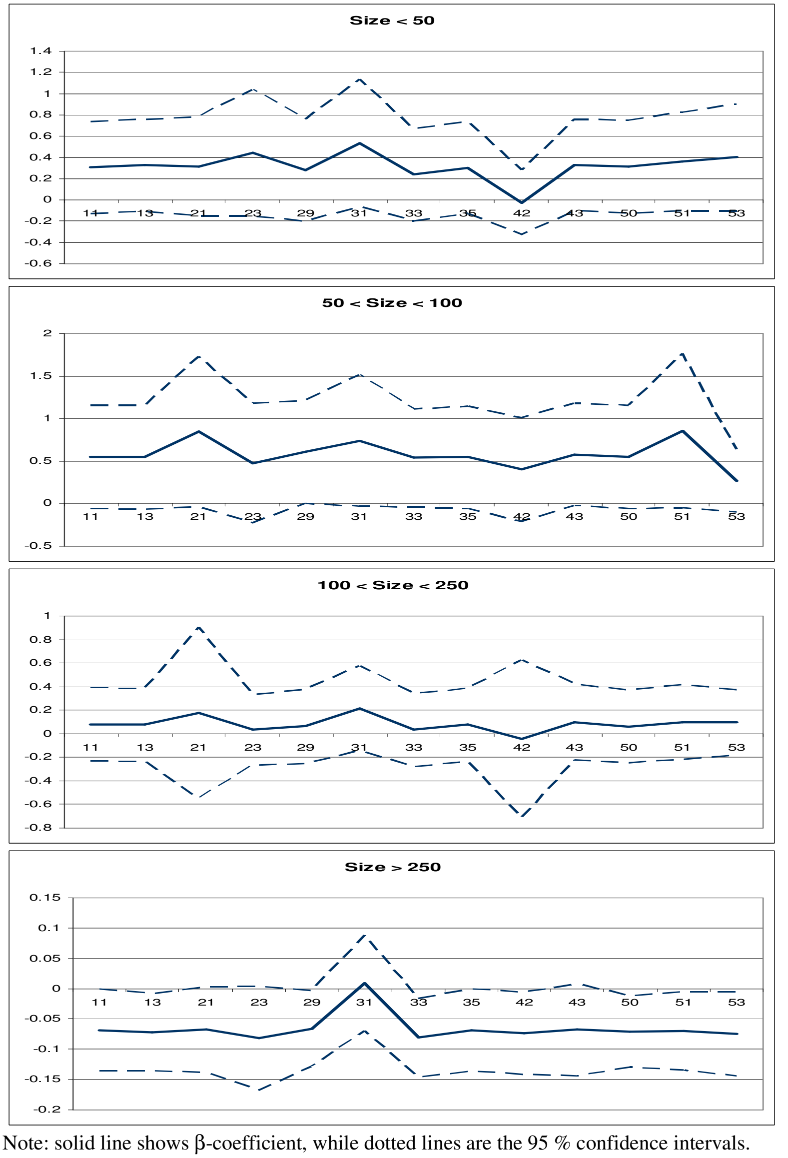
Federal State	UF	Pop.	Firm dens.	GDP pc	Fem. part.	Car	σ
Acre	12	3.66	1.86	3.91	0.40	14.13	3.37
Alagoas	27	101.46	3.22	2.80	0.39	13.51	3.64
Amazonas	13	1.79	1.38	6.02	0.42	12.40	3.50
Amapá	16	3.34	2.77	5.15	0.42	15.66	3.62
Bahia	29	23.16	3.64	3.76	0.44	15.37	3.82
Ceará	23	51.00	4.99	3.10	0.39	15.56	3.75
Distrito Federal	53	353.53	6.45	21.37	0.54	52.05	7.00
Espírito Santo	32	67.26	5.25	6.86	0.48	31.22	4.78
Goiás	52	14.71	5.60	5.88	0.46	34.37	4.58
Maranhão	21	17.03	2.69	2.19	0.38	7.79	3.16
Minas Gerais	31	30.50	7.13	5.73	0.45	32.98	4.71
Mato Gr. do Sul	50	5.82	5.15	5.81	0.46	33.13	4.46
Mato Grosso	51	2.77	4.84	6.58	0.43	28.24	4.24
Pará	15	4.96	0.49	3.25	0.38	9.93	3.00
Paraíba	25	61.12	3.94	2.94	0.39	17.62	3.66
Pernambuco	26	80.37	3.44	3.59	0.41	18.37	3.81
Piauí	22	11.31	4.01	2.11	0.39	13.74	3.43
Paraná	41	47.99	6.92	7.43	0.48	43.35	5.14
Rio de Janeiro	33	328.59	4.97	9.58	0.45	33.79	5.42
Rio Gr. do Norte	24	52.32	4.06	3.52	0.38	20.33	3.71
Rondônia	11	5.81	0.99	4.45	0.42	19.72	3.51
Roraima	14	1.45	4.32	5.41	0.49	24.90	4.36
Rio Gr. do Sul	43	37.90	9.38	8.35	0.51	45.72	5.65
Santa Catarina	42	56.21	7.22	8.28	0.51	51.73	5.55
Sergipe	28	81.25	3.11	4.20	0.42	17.53	3.86
São Paulo	35	149.22	7.09	11.01	0.48	49.61	5.73
Tocantins	17	4.17	0.66	3.80	0.43	17.25	3.47

Notes: Pop: population per km^2 in 2000, Firm dens: retail firms per 1000 inhabitants, GDP pc: GDP per capita in 1000 reais in 2006, Fem. part: female labor force participation in 2000, and Car: the share of households with a car in 2000 from IPEA (www.ipeadata.gov.br). Number of retail firms per 1000 inhabitants from Pesquisa de Comercio (IBGE, 2006b). The elasticity of substitution σ is obtained as the unweighted average of the normalized values from these variables and allowed to range between 3 and 7.

Figure 3.A.1. Taxes and distortions to output, excluding one state at a time

Note: solid line shows β-coefficient, while dotted lines are the 95 % confidence intervals.

Figure 3.A.2. Difficulty in access to credit and distortions to capital, excluding one state at a time



Note: solid line shows β-coefficient, while dotted lines are the 95 % confidence intervals.

Chapter 4

Small Retailers in Brazil: Are Formal Firms Really More Productive?*

4.1 Introduction

The informal (or unregistered) sector accounts for a large share of output and employment in developing countries (Schneider and Enste, 2000). For Brazil, the share of the informal sector in total output is estimated at 40 percent in 1999/2000 (Schneider, 2005). Typically, studies find that informal firms are less productive than formal firms.[1] As a result, a large share of the informal sector in the total economy is viewed as having a negative effect on aggregate productivity, and government initiatives therefore aim to increase formality. However, these studies usually compare mean productivities, without adding controls. This chapter aims to contribute to the literature, by controlling for self-selection and a rich set of firm, industry, and owner characteristics when examining differences in productivity between formal and informal firms.

The recent literature takes the difference in productivity between formal and informal firms for granted and studies the effectiveness of government initiatives in increasing formality. For example, the introduction of the SIMPLES program in Brazil in 1996 lowered taxes and reduced procedures for becoming formal. Mon-

* This chapter is based on the paper 'Small Retailers in Brazil: Are Formal Firms Really More Productive?' The paper is forthcoming in the Journal of Development Studies.

[1] See for example McKinsey (1998); Sleuwagen and Goedhuys (2003); and Chapelle and Plane (2005).

teiro and Assunção (2007) and Fajnzylber et al. (2007) find a significant increase in formal licensing after the introduction of this program. Another government initiative to increase formality was the opening up of the retail sector in the World Trade Organization 1995 General Agreement on Trade in Services, but also within MERCOSUL,[2] and between the MERCOSUL members and the European Union. Furthermore, the participation of foreign capital in Brazilian retail firms was freed from restrictions in the Sixth Constitutional Amendment of 1995 (World Bank, 2004). The liberalization of the retail sector aimed at the expansion of modern retail chains through foreign direct investment, which would drive the independent small retailers, which are often informal, out of the market (Reardon and Berdegué, 2002).

However, studies often do not examine whether the productivity differences between formal and informal firms are robust to controlling for such characteristics as the firm's age and the owner's managerial ability. Controlling for firm and firm owner characteristics may be unfeasible if only few firms are surveyed or the survey contains little information on firm characteristics. Yet, if these controls are not included, it cannot be ruled out that a positive correlation between formality and productivity is merely spurious. For example, formal firms might be older than informal firms and run by more educated firm owners, explaining their higher productivity performance.

In addition, so far studies of the relation between formality and productivity do not take into account that formality is a choice of the firm. That is, there may be self-selection into the formal sector by more productive firms who are willing to incur the cost of registering and paying taxes and as a result benefit from access to formal credit, access to public goods, the possibility to advertise, and the ability to increase the customer base by issuing tax receipts (Rauch (1991); Loayza (1996); McKenzie and Sakho (2009)). This issue of self-selection has its parallel in recent studies of the relation between exporting and productivity (e.g. van Biesebroeck (2005); Wagner (2007)). Here, the traditional view is that exporters acquire knowledge of new production methods, inputs, and product designs from their international contacts. This learning leads to higher productivity for exporters relative to their more insulated domestic counterparts. The alternative view is that the higher productivity of exporters may simply reflect the self-selection of more efficient producers into a highly competitive export market. Similarly, if firms self-select into the formal sector, business registration reforms may result in a higher number of formal firms but not necessarily in improvements in productivity. Thus, it is important to examine

[2] Mercado Comum do Sul, the regional trade block consisting of Argentina, Brazil, Paraguay, and Uruguay.

whether the relation between formality and productivity is positive and significant after controlling for self-selection.

In this chapter, we study whether formal firms are more efficient than informal firms. We aim to control for self-selection and a rich set of firm, industry, and firm-owner characteristics when examining differences in productivity between formal and informal firms. Because large retail firms may benefit from economies of scale (Doms et al., 2004), we limit attention to retailers with less than five employees where scale economies are absent or small at best. For the year 2003, we use a large and representative data set of 11,000+ small Brazilian retailers, consisting of small full-service stores (e.g. treillers, which serve pavement traffic and biroscas, which are retail businesses within someone's home), small self-service stores (convenience stores), and business at traditional markets (feira livres). Our working definition of formality is tax registration, which is the most common indicator of formality in the literature (Fajnzylber et al., 2009), but we are able to explore alternative definitions as well.[3] For this data set, we simultaneously estimate a stochastic production frontier and an efficiency model as in Battese and Coelli (1995).

Our research adds to a nascent literature on the micro-level effects of formality on firms. Fajnzylber et al. (2009) examined the effect of credit, training, paying taxes, and belonging to business associations on the profits of Mexican firms. Using propensity score matching to control for the selection bias, they found a positive effect of formality on profits. McKenzie and Sakho (2009) examined the effect of tax registration on profitability of Bolivian firms. Using distance to the tax office as an instrument in a treatment-effects model, they found that registering for taxes has a positive effect on business profits. These findings suggest that registering for taxes results in profit gains. A related question is whether acquiring a formal status will increase a firm's productivity. It is productivity growth, rather than profit making, which is of interest to policymakers.

This chapter finds that formal firms are indeed more productive. When we do not control for self-selection and firm characteristics, we find large differences in productivity between formal and informal retailers, consistent with previous studies (e.g. Chapelle and Plane (2005)). Following de Paula and Scheinkman (2007), we control for self-selection by using a proxy for the degree of value-added tax compliance among the firm's suppliers and buyers. Value-added taxes transmit formality, because purchases from informal firms are ineligible for tax credits. Thus, value added taxes create an incentive for propagation of formality upstream or downs-

[3] Typically, the formality of a firm is a matter of degree. We take this into account in our empirical analysis by exploring the productivity gains for different definitions (degrees) of formality.

tream in the production chain. After controlling for self-selection and a large set of firm, location, and firm-owner characteristics, we find that the relation between formality and productivity is still positive and significant.

The remainder of the chapter is structured as follows. In section 4.2, we document the poor productivity performance of the retail sector in Brazil and discuss the potential role of the informal sector. Next, section 4.3 presents the data set. Stochastic frontier analysis, which is used to examine differences in productivity between formal and informal retailers, is described in section 4.4. Results are discussed in section 4.5. Finally, conclusions are presented in section 4.6.

4.2 The Productivity Performance of the Retail Sector in Brazil

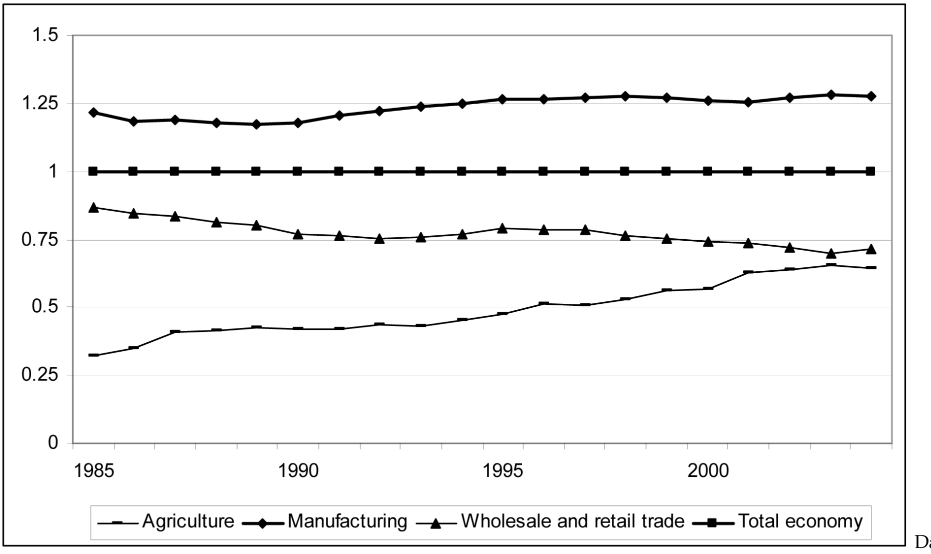
The Pesquisa Anual de Comércio (PAC), the annual survey of wholesale and retail trade firms, estimates that approximately 1.1 million retail trade firms are active in Brazil in 2003 (IBGE, 2003). For that year, the employment and value added share of retailing in the total economy was respectively about 11 percent and 5 percent (IBGE, 2004a). Therefore, the retail sector accounts for a large share of the Brazilian economy.

Figure 4.1 shows labor productivity (value added/employment) of the agricultural, manufacturing, and the wholesale and retail trade sector relative to the average productivity of the Brazilian economy during the 1985-2004 period.[4] The relative levels confirm the general pattern that on average the agricultural sector is least productive, the manufacturing sector most productive, and services are somewhere in between. Disturbing, however, is the trend in the wholesale and retail trade sector. During 1985-2004, the relative productivity level is falling, which implies that productivity growth in this sector is below productivity growth of the total economy. The productivity performance of the retail sector in Brazil differs from that in OECD countries during the past decades. For a similar period, Inklaar et al. (2008) show that productivity growth in the retail sector of OECD countries was above total economy productivity growth. At least three (interrelated) reasons might underlie the poor productivity performance of the retail sector.

First is the limited role of reallocation dynamics relative to within-firm productivity growth in Brazil's retail sector. During the period 1996-2004, Chapter 2

[4] The sectoral dataset presented in Timmer and de Vries (2009) does not allow us to separate wholesale trade from retail trade.

Figure 4.1. Sectoral productivity relative to the total economy



Data Source: Timmer and de Vries (2009).

found little evidence for a reallocation of productive inputs and outputs. Typically, new establishments from retail chains did not replace low-productive independent stores. Instead, large chains acquired other (smaller sized) chains. This contributed to a deepening of the dual structure in which low-productive independent stores continued to coexist with a declining number of retail chains.

A second reason is that retailers have been slow to adopt Information and Communication Technologies (ICT) (McKinsey, 1998). The potential to improve business performance by investing in ICT was initially largely foregone, because Brazil was closed to foreign hardware and software until 1992 (Luzio and Greenstein, 1995). Also, hyperinflation during the mid 1980s until 1994 distorted relative factor prices. ICT investment prices were high relative to labor costs, inducing retailers to hire extra workers instead of automating processes. Furthermore, the benefits of ICT adoption (and hence the ICT investments undertaken) are higher for large firms, such as retail chains (Doms et al., 2004). Thus, the large share of small firms in the total number of firms (IBGE, 2004a) may result in low ICT adoption.

Finally, a third reason may be the large presence of informal firms. If informal firms are less productive than formal firms, the large share of the informal sector in the retail sector has a negative effect on aggregate productivity. In addition, because informal firms do not expand their business in order to remain undetected by the government, the relatively large presence of informal firms in the retail sector is related with lower growth (McKinsey, 2004).[5]

In the remainder of this chapter we examine productivity differences between formal and informal retailers. Our findings shed light on the implications of informal firms for the aggregate productivity level and growth rate of the retail sector. Before turning to the empirical analysis, we first describe the data and method.

4.3 Small Formal and Informal Retailers in Brazil: The Data

The data set we use is the 2003 survey of small urban firms (Pesquisa de Economia Informal Urbana, ECINF), collected by the Statistical Office of Brazil (IBGE) in October 2003. The survey, which is the result of interviews by trained interviewers, is representative of the urban own-account workers and firms with at most five workers. Large retail firms may benefit from economies of scale (Doms et al., 2004), in particular with respect to the costs involved in setting up distribution centers and using ICT to keep track of inventories. Therefore, we focus on retail firms with less than five workers (and with firm owners at least 15 years old) where scale economies are absent or small at best. The dataset includes detailed individual information on the firm owner, the employees, and the (possible) family members working in the firm. In this chapter we follow the set up of the survey and define the total number of workers in the firm as the sum of employees and family members.

The survey is set up as follows. In preliminary interviews before the survey, households are screened for the presence of one or more entrepreneurs with a business employing five or less people based on the 2000 demographic census. Households without such entrepreneurs are excluded from the sample frame of the survey. The sampling is designed in two stages. First, in each Federal state, urban sectors are stratified geographically in three strata (capital, other urban sectors in the capital metropolitan area, and remaining urban sectors). Second, the urban sectors are stratified according to income levels within the geographical stratum. Urban sectors are randomly selected, with the probability proportional to the number of households in the urban sectors. From each selected urban sector a total of 16 households are randomly selected for interviews.[6] In total, the survey includes

[5] In our representative data set of small firms in Brazil, most informal firms are in the retail sector (about 25 percent). See also (McKinsey, 1998).

[6] See IBGE (2006a) for more information on the sampling strategy.

11,158 retailers.

The data set allows us to examine the degree of formality in various ways. The information provided by the surveyed firms is confidential and only utilized for statistical purposes, so we may assume that individuals truthfully report about licenses and tax compliance.[7] In order to formalize, a firm has to undertake several steps (see appendix table 4.A.1), and many firms do not complete all steps. Therefore, 27 percent of the firms in our sample have a municipal license, 19 percent are registered for taxes, 18 percent are registered as a micro-enterprise, and 15 percent actually fill in tax declarations.[8]

The variables employed in this chapter are described in appendix 4.A with summary statistics in table 4.1 distinguishing between formal and informal firms. A non-parametric Wilcoxon rank-sum test is used to examine whether the distributions of the variables significantly differ between formal and informal firms.[9] All distributions differ significantly at the 5 percent level.

On average, formal firms are larger. For example the average number of workers per firm (including the firm owner) is 2.65 for formal retailers and 1.28 for informal retailers. Formal firms are older (8.88 years versus 6.63 for informal firms), although the average age for both types is relatively high. The high average age shows the ability of most retailers to survive, often by means of locating close to consumers, offering the product assortment that their customers demand, providing a 'personal touch', and offering special services such as selling on credit (Booz-Allen Hamilton, 2003).

Both age and (labor) productivity are significantly higher for formal firms. This observation is consistent with models of firm dynamics (e.g. Jovanovic (1982)), where (more) efficient firms grow and survive over time, while inefficient firms stagnate and fail. However, it remains to be seen whether formal firms are more productive if we control for a set of characteristics. For example, table 4.1 shows

[7] On the questionnaire, a disclaimer states the information is confidential and protected by law.

[8] Registering for taxes is step 4, whereas obtaining a municipal license is step 6. Therefore, it is surprising that the share of firms with a municipal license is larger than that for tax registration. This might be the result of greater interaction with municipal officials or stronger enforcement at the municipal level (McKenzie and Sakho, 2009). Alternatively, except for municipal licensing, the answers on licenses and tax compliance depend upon the answer to an ambiguous question on the legal constitution. In appendix 4.B we show that formality positively affects productivity across the different definitions. We prefer to focus on tax registration in the main text, because it is one of the first steps towards formalizing a business. Firms that report they have a municipal license but are not registered for taxes are excluded. The main results are similar if these firms are not excluded.

[9] In the Wilcoxon rank-sum test, the values of the variables for formal and informal firms are pooled and jointly ranked. The test-statistic is the sum of the ranks for the formal retailers. Wilcoxon (1945) shows that the sum of the ranks is normally distributed, and gives formulas for the mean and variance of the sum of the ranks under the null hypothesis that the two samples are drawn from identical distributions.

Table 4.1. Descriptive statistics

	Informal firms (without tax registration)	Formal firms (with tax registration)
Production variables		
Sales	1502.51	9356.32
Value added	360.21	1877.01
Capital	2407.61	27016.41
Hours worked	267.99	660.67
Total employment (including owner)	1.28	2.65
Labor productivity		
Value added/Hours worked	3.33	3.83
Owner characteristics		
Education owner	3.88	5.22**
Owner has second job	0.11	0.09
Motivation to start a business	0.4	0.14
Firm characteristics		
ICT	0.03	0.31
Age firm	6.63	8.88
Credit granted in the last three months	0.08	0.17
Credit granted was a bank loan	0.04	0.13
Participation in a guild	0.03	0.27
Technical assistance provided by others	0.01	0.1
Technical assistance provided by the government	0.01	0.02
Observations	9011	2147

Notes: Mean values are shown. Sales, value added, and capital are in current prices in Reais. Tax registry is the Cadastro Nacional de Pessoas Jurídicas in the 2003 survey. Education is a categorical value: 1=no education; 2=reads and writes; 3=some primary education; 4=graduated primary school; 5=some secondary education; 6=graduated secondary school; 7=some college education; 8=graduated college. See appendix 4.A for a description of the variables. A Wilcoxon rank-sum test is used to examine whether differences between formal and informal firms are significant. All variables significantly differ at the 1 percent level, except for ** at the 5 percent level. Source: Economia Informal Urbana 2003.

that formal firm owners are higher educated and make more intensive use of ICT and credit, which might explain their higher productivity. In the next sections we therefore outline an econometric approach and test whether formal firms are more productive once we control for self-selection, and firm, industry, and firm owner characteristics.

The reason for starting a business differs markedly across formal and informal retailers. Table 4.2 shows that individuals who started a business to escape from unemployment more frequently own informal (40 percent) than formal firms (14 percent). In addition, a larger share of informal (24 percent) than formal firm owners (12 percent) report they started a business to complement their family's income. In contrast, it is more common that formal firm owners started their business to be independent (26 percent for formal firms versus 15 percent for informal firms) or that they saw it as a profitable business opportunity (5.3 percent for formal firms versus 0.5 percent for informal firms). Not being able to find a job provides, besides the educational level, an additional signal of the managerial ability of the firm owner, which we will exploit in our efficiency analysis.

On the location of the business, table 4.2 shows important differences between formal and informal firms as well. Although the share of firms that have their business at home (biroscas) does not differ much, the share of formal firms with a store is much larger (73 percent for formal firms versus 15 percent for informal firms). Indeed, many informal firms do not have a fixed location. For example, about 27 percent of the informal retailers in our sample report that their business takes place along the road or in a public area (treillers). Not having a fixed location may affect the reported capital stock and therefore the production function estimates. We address this issue in detail in appendix 4.B, and find that the productivity differences between formal and informal firms are robust to adjustments for the inaccurate reporting of capital.

4.4 Stochastic Frontier Analysis

In frontier analysis, a production frontier for formal and informal retailers is defined as the maximum possible output given a certain combination of inputs. Efficiency is measured as the distance to the frontier. In this study we will use frontier analysis to compare the efficiency levels of formal and informal firms.

The production frontier can be obtained deterministically using data envelopment analysis (DEA), which usually neglects possible measurement error. Alternatively, the frontier can be estimated using stochastic frontier analysis (SFA), which allows for measurement error (Coelli et al., 2005).[10] Given that our sample of small retailers in a developing country is sensitive to measurement error, SFA is the preferable approach. Another advantage is that SFA allows estimating the stochastic frontier and the efficiency model simultaneously.[11] Consider the stochastic frontier

[10] Stochastic frontier analysis has been applied frequently in efficiency analysis of the manufacturing sector. See, for example, Lundvall and Battese (2000) for Kenyan manufacturing firms, Hossain and Karunaratne (2004) for manufacturing industries in Bangladesh, Oczkowski and Sharma (2005) for Nepalese manufacturing firms, and Chapelle and Plane (2005) for the manufacturing sector in Côte d'Ivoire.

[11] A two-stage approach assumes that efficiency effects are identically distributed in the first stage. However, in the second stage a model is specified for predicted efficiency effects, which contradicts the assumption of identically distributed efficiency effects in the first stage. Therefore, estimating the frontier and efficiency model simultaneously is preferred.

Table 4.2. Characteristics of formal and informal retailers

	Percentage of informal firms (without tax registration)	Percentage of formal firms (with tax registration)
Main reason to start a firm		
Did not find a job	39.9	14.4
Profitable business	0.5	5.3
Flexible hours	2	0.8
Be independent	15.2	26.2
Family tradition	5.2	14.3
To help family income	24.2	11.6
Accumulated experience	2.8	9.9
Make a good deal	6.6	12.1
As a secondary job	1	2.1
Other	2.5	3.4
The business takes place		
At home	27.8	21.7
Store or office	15.2	73.2
At home of client(s) or place decided upon by him	24.8	2.4
From a vehicle	1.9	0.7
Along the road or in a public area	26.9	1.2
Other	3.5	0.8

Source: Economia Informal Urbana 2003.

production function (Battese and Coelli, 1995):

$$Y_i = exp\left(\beta' X_i + v_i - u_i\right), \tag{4.1}$$

where Y is the output of firm i, X is a (k*1) vector of inputs, and β is a (k*1) vector of unknown parameters to be estimated. Random error v_i is assumed independent and identically distributed, with $v_i \sim N(0, \sigma_v^2)$, and u_i is a non-negative random variable, which is assumed to be independently distributed.

The term u_i is an estimate of the technical efficiency of a firm.[12] It is measured as the ratio of the observed output to the corresponding potential output as given

[12] The economic efficiency (productivity) of a firm consists of technical and allocative efficiency. The latter reflects the ability of a firm to use inputs in optimal proportions given their prices and the production technology. Price information is unavailable, so allocative efficiency cannot be estimated. Following standard practice, we drop allocative efficiency from the analysis by assuming that the ratios of the elasticities of inputs to the total elasticity are equal to the expenditure shares of the inputs (Kumbhakar and Lovell, 2000).

by the frontier. Therefore, efficiency ranges from 0 (fully inefficient) to 1 (fully efficient). Technical efficiency, u_i, in equation 4.1 is specified as:

$$u_i = \delta' z_i + w_i. \tag{4.2}$$

The random variable w_i is defined by the truncation of the normal distribution with zero mean and variance σ^2, such that the point of truncation is $-\delta z_i$, that is $w_i \geq -\delta z_i$. Hence, u_i is obtained by truncation at zero of the normal distribution, with mean δz_i and variance σ^2. The (m*1) vector z_i includes firm-specific variables, and δ is a (m*1) vector of unknown coefficients of the firm-specific inefficiency variables. The prediction of technical efficiency (TE) in production for firm i is based on its conditional expectation given the assumptions of the model, and defined as:

$$TE_i = exp(-u_i) = exp(-\delta z_i - w_i). \tag{4.3}$$

We estimate the parameters of the stochastic frontier and the efficiency model simultaneously using the method of maximum likelihood. The likelihood function and the partial derivatives with respect to the model parameters are described in Battese and Coelli (1993). To estimate the production frontier, we specify a translog functional form:[13]

$$\begin{aligned} \ln Y_i \quad = \quad & \beta_0 + \beta_1 \ln K_i + \frac{1}{2}\beta_2 \ln K_i^2 + \beta_3 \ln H_i \\ & + \frac{1}{2}\beta_4 \ln H_i^2 + \beta_5 \ln K_i . \ln H_i \\ & + industrydummies + v_i - u_i. \end{aligned} \tag{4.4}$$

Y, K, and H denote value added, capital, and hours worked respectively. Since technology and market conditions may vary over retail industries, we include industry dummy variables (which act as intercept dummies) in the production func-

[13] We specify a translog functional form because it is more flexible than a Cobb Douglas form and therefore allows for scale effects. A Cobb Douglas form is first-order flexible (that is, it has enough parameters to provide a first-order differential approximation), whereas a translog form is second-order flexible. Increased flexibility requires more parameters to estimate, which may give rise to multicollinearity. We examine the robustness of our results to the choice of the functional form in appendix 4.B.

tion in order to control for it.[14]

Technical efficiency, u_i, in equation 4.4 is estimated simultaneously, and related to formality, where we control for firm and firm-owner characteristics:

$$\begin{aligned} u_i &= \delta_0 + \delta_1 x_{1i} + \delta_2 x_{2i} + \delta_3 x_{3i} + \delta_4 x_{4i} \\ &+\delta_5 x_{5i} + \delta_6 x_{6i} + \delta_7 x_{7i} + \delta_8 x_{8i} \\ &+\delta_9 x_{9i} + \delta_{10} x_{10i} + \delta_{11} x_{11i} + \delta_{12} x_{12i} + w_i. \end{aligned} \tag{4.5}$$

Where:[15]

- x1: represents one of the four indicators of formality;
- x2: represents a dummy indicating whether the firm uses credit;
- x3: represents a dummy indicating whether the credit was obtained through a bank loan;
- x4: represents a dummy indicating whether the firm participates in a guild;
- x5: represents a dummy indicating whether the firm uses ICT;
- x6: represents the age of the firm in years;
- x7: represents the age of the firm squared;
- x8: represents a dummy indicating whether the firm receives technical assistance;
- x9: represents a dummy indicating whether the technical assistance is provided by the government;
- x10: represents a categorical value for the education of the owner;
- x11: represents a dummy indicating whether the firm owner started his business because he/she could not find a job;
- x12: represents a dummy indicating whether the firm owner has a second job;

[14] See appendix 4.A for the industries distinguished, and appendix 4.B for estimations of the model for various sub-industries.
[15] See appendix 4.A for a detailed description of the variables.

In the setup of our model, the results from the variables included in equation 4.5 reflect correlations with efficiency. Since formality may be the choice of a firm, we instrument formality to examine the effect of formality on efficiency. As instrument we consider the degree of tax compliance across Federal states. Our instrument is motivated by the suggestion that value added taxes transmit formality (de Paula and Scheinkman, 2007). That is, the formality of a firm appears to be positively correlated with the formality of firms from which it buys and sells. Ideally we use firm-specific information on the formality of the firm's supply chain. However, information on the formality of suppliers and customers is only available at a higher level. Therefore, we expect the average degree of tax compliance in a state to be positively related with the choice of being formal for individual retailers.[16] The probit model we estimate is:

$$x_{1is} = \gamma_1 taxcompliance_s + \epsilon_{is}, \tag{4.6}$$

The construction of the variable tax compliance is described in Appendix 4.A. Subscript s refers to the Federal state. Predicted values of formality from equation 4.6 are used in equation 4.5 to examine the effect of formality on efficiency, which may control for the selection bias.[17]

4.5 Determinants of Efficiency

Results from estimating equation 4.6 are presented in Table 4.3. The degree of tax compliance is positively related with the indicators of formality. However, the strength of the relationship varies across the indicators.[18] The relation is strongest for firms that actually fill in tax forms (column 4). This is consistent with the idea that tax compliance is a more binding constraint, and therefore a better instrument, for firms that actually pay taxes. We substitute the predicted values for each indicator of formality in equation 4.5. Since four indicators for the degree of formalization are considered, there are four different model specifications.

[16] Results are similar if we include firm controls in equation 4.6.

[17] In appendix 4.B we consider the average educational level as an alternative instrument. The average educational level might be considered a proxy for the degree of formality in the firm's supply chains, because higher human capital firm owners are more likely to own a formal firm (see table 4.1). We find similar results if the average educational level in a state is used to instrument formality.

[18] The number of correct predictions from the probit model varies from 73 percent for municipal license to 85 percent for filled in tax forms.

Table 4.3. Probit estimates

Variable	Tax registration (1)	Municipal license (2)	Micro-firm registration (3)	Filled in tax forms (4)
Constant	-1.382	-1.148	-1.398	-1.702
	(5.82)***	(5.73)***	(5.88)***	(8.07)***
Tax compliance	5.509	5.738	5.109	7.163
	(2.01)**	(2.48)**	(1.86)*	(2.98)***
Observations	11158	11158	11158	11158
Pseudo-R^2	0.004	0.005	0.004	0.008
χ^2	4.06**	6.13**	3.46*	8.91***
Correct predications (percentage share)	80.76	73.06	82.18	84.88

Notes: β-coefficients are shown, and below the absolute value of z-statistics in parentheses. * significant at 10 percent level of significance, ** significant at 5 percent level, *** significant at 1 percent level. Robust standard errors are clustered by Federal state.

Estimation results from simultaneously estimating equation 4.4 and equation 4.5 are shown in Table 4.4.[19] The upper part displays the parameters from the production frontier, whereas the lower part shows the effects of formality and other variables on efficiency. The majority of the production frontier parameter estimates are significant at the 1 percent level of significance. The statistical insignificance of some coefficients is typical of translog functions were high multicollinearity is common among the inputs (e.g. Lundvall and Battese (2000); Oczkowski and Sharma (2005)). The elasticities of capital and hours worked are obtained by taking the first-order derivative of the translog functional form (see equation 4.4) with respect to capital and labor. The sum of the elasticity of capital (0.238) and hours worked (0.258) indicates decreasing returns to scale (0.496). The β-estimates in the other models are similar, indicating decreasing returns to scale as well. Thus, our findings suggest that small retailers are unlikely to benefit from economies of scale.

[19] In the model specification in column (2) of table 4.4, we were forced to exclude the age of the firm and whether the owner has a second job before the model converged. We performed various tests for the parameters of the frontier and efficiency models. First, we tested whether the additional parameters of the translog functional form are significantly different from zero. The test indicates that a translog specification fits the data better than a Cobb-Douglas at the 1 percent significance level. Second, we tested whether the inefficiency effects are not a function of the explanatory variables in equation 4.5. The joint effect of the explanatory variables is significant at the 1 percent level. Thus, it appears that a stochastic frontier model with inefficiency effects is the appropriate choice. However, $\gamma \equiv \sigma_u^2/\sigma^2$ is low, which suggests that much of the variation in the composite error term is due to the random error component. In appendix 4.B we study the heterogeneity of the sample in more detail. Estimating the model using sales instead of value added, and for sub-industries separately, increases the variance in the error term due to the inefficiency component. The findings across the different models, however, are similar.

From the model specification in column 1 of table 4.4 we predict technical efficiency for each retailer.[20] The mean efficiency is 0.28, which is low and implies that firms can achieve substantially higher productivity levels if they use production factors more efficiently. However, formal retailers (0.38) are more efficient than informal retailers (0.23), and a Wilcoxon rank-sum test shows that the distributions are significantly different at the 1 percent level.

[20] Efficiency results for the other models are similar.

Table 4.4. Stochastic frontier and efficiency model

Variable	β	SE	β	SE
	(1)		(2)	
Production frontier				
ln Capital	0.240	(19.76)***	0.253	(21.13)***
ln Capital^2	0.000	(0.07)	0.002	(0.72)
ln Hours worked	0.287	(4.60)***	0.303	(5.03)***
ln Hours worked^2	0.064	(7.28)***	0.066	(7.67)***
ln Capital $\times$ ln Hours worked	0.013	(1.68)*	0.012	(1.62)
Sector dummies	Yes		Yes	
Efficiency model				
Tax registration (CNPJ)[a]	-3.852	(7.11)***	-	-
Municipal license[a]	-	-	-3.346	(7.19)***
Microfirm registration[a]	-	-	-	-
Filled tax form[a]	-	-	-	-
Credit	-0.109	(1.47)	-0.126	(1.46)
Credit was bank loan	-0.116	(1.27)	-0.144	(1.33)
Participation in guild	-0.269	(5.26)***	-0.391	(4.68)***
ICT	-0.370	(6.97)***	-0.562	(2.59)***
Age of the firm	-0.016	(4.44)***	-	-
Age of the firm^2	0.000	(2.59)***	-	-
Technical assistance elsewhere	-0.233	(3.00)***	-0.260	(2.38)**
Technical assistance gov.	-0.086	(0.47)	-0.288	(1.07)
Education owner	-0.104	(11.53)***	-0.099	(9.78)***
Motivation	0.129	(4.15)***	0.117	(3.46)***
Owner has second job	0.160	(3.27)***	-	-
σ^2	0.882		0.892	
γ	0.029		0.029	
Observations	4740		4826	

Variable	β	SE	β	SE
	(3)		(4)	
Production frontier				
ln Capital	0.240	(19.76)***	0.240	(19.77)***
ln Capital^2	0.000	(0.07)	0.000	(0.08)
ln Hours worked	0.287	(4.60)***	0.287	(4.60)***
ln Hours worked^2	0.064	(7.28)***	0.064	(7.27)***
ln Capital $\times$ ln Hours worked	0.013	(1.68)*	0.013	(1.68)*
Sector dummies	Yes		Yes	
Efficiency model				
Tax registration (CNPJ)[a]	-	-	-	-
Municipal license[a]	-	-	-	-
Microfirm registration[a]	-4.355	(7.10)***	-	-
Filled tax form[a]	-	-	-3.411	(7.04)***
Credit	-0.109	(1.47)	-0.109	(1.47)
Credit was bank loan	-0.116	(1.27)	-0.117	(1.27)
Participation in guild	-0.269	(5.26)***	-0.269	(5.27)***
ICT	-0.370	(6.97)***	-0.370	(6.96)***
Age of the firm	-0.016	(4.44)***	-0.016	(4.44)***
Age of the firm^2	0.000	(2.59)***	0.000	(2.59)***
Technical assistance elsewhere	-0.233	(3.00)***	-0.233	(3.00)***
Technical assistance gov.	-0.087	(0.47)	-0.085	(0.47)
Education owner	-0.104	(11.53)***	-0.104	(11.53)***
Motivation	0.129	(4.15)***	0.129	(4.16)***
Owner has second job	0.160	(3.27)***	0.160	(3.28)***
σ^2	0.882		0.882	
γ	0.029		0.030	
Observations	4740		4740	

Constants not shown. The output and input variables in the production frontier are rescaled to have unit means. Absolute value of z-statistics in parentheses. * significant at 10 percent level of significance, ** significant at 5 percent level, *** significant at 1 percent level. $\sigma^2 \equiv \sigma_u^2 + \sigma_v^2$ and $\gamma \equiv \sigma_u^2/\sigma^2$.
[a] Predicted values from equation 4.6 are used for tax registration, municipal license, micro-firm registration, and filled in tax form.

For comparison, we estimated the frontier and efficiency model without controls as well. For this 'naive' specification, we find a larger difference in efficiency levels between formal and informal retailers. The difference in mean efficiency is 0.24 in the model without controls, which compares favorably with the difference of 0.15

in the model with controls. Therefore, formal firms are more productive, although the difference is smaller if such factors as selection bias and the educational level of the firm owner are taken into account.

The coefficients of the explanatory variables in the inefficiency model (equation 4.5) are of interest as well. In this model, a negative coefficient indicates that a higher value of the explanatory variable is associated with more efficiency (or less inefficiency). Below, we examine the sign and significance of the explanatory variables.

Formality, which is instrumented, is significant and has a positive effect on efficiency. This result is robust to controlling for some of the benefits of formality (such as obtaining bank loans), and by controlling for other firm and owner characteristics. Efficiency gains from registering may arise because of access to public goods (such as the judicial system), and the ability to increase the customer base by advertising and issuing tax receipts (Rauch (1991); Loayza (1996); McKenzie and Sakho (2009)).

The coefficient for education indicates a positive correlation between managerial ability and efficiency. The negative relation between efficiency and firm owners who could not find a job and therefore started the business indicates an additional channel of managerial ability. Firms for which the owner has a second job are less efficient. This result may arise, because owners who operate a business as an additional source of income have fewer incentives to operate their business as efficiently as those for which the business is their primary source of income. ICT is positively related with efficiency, which is consistent with studies of the relationship between ICT and productivity for the retail sector in developed countries (e.g. Broersma et al. (2003); Doms et al. (2004)).

The age of a firm is significantly related with higher efficiency, and we find support of diminishing returns to learning by doing. Previous studies show mixed results on the age-efficiency nexus. Lundvall and Battese (2000) review the literature and show that findings on the age-efficiency relationship are negative, positive, or non-existent across studies. The results in this chapter suggest a positive age-efficiency relationship for small retailers. Credit granted over the last three months is correlated with higher efficiency, but the relation is not significant. Whether credit is obtained from a bank does not have an additional positive effect on efficiency. Informal firms can obtain credit via various channels, for instance from friends, relatives, or from other firms. Apparently, the channel for obtaining credit does not matter much for efficiency. However, the interest rate may vary across the different credit channels, thereby affecting profits, which we are unable to examine further in this chapter. Participation in a trade association is associated with higher efficiency, perhaps because of the exchange of information on successful business practice.

Finally, although only a limited number of firms in our sample received technical assistance (about 4 percent), we find a significant positive relation between technical assistance and technical efficiency. However, whether the government provides technical assistance does not appear to exert an additional influence on efficiency. Hence, the channel for providing technical assistance does not appear to matter for technical efficiency.

We examined the robustness of our results (see appendix 4.B for details). The productivity difference between formal and informal firms appears robust to different specifications and adjustments for the inaccurate reporting of capital. However, the significance of several inefficiency effects varies across the models specified in the robustness analysis. In particular, credit is positively related with efficiency in regressions where we adjust for the inaccurate reporting of capital by firm owners. Also, in some specifications we find limited evidence for learning by doing with diminishing returns. Thus, results related to credit and the age of firms in the efficiency model appear not robust which may be due to the limited use of credit by small retailers and the high average age.

4.6 Concluding Remarks

This chapter examined whether small formal retailers are more productive than their informal counterparts. We simultaneously estimated a stochastic production frontier and an efficiency model. We find that the efficiency of firms is positively related with ICT adoption, managerial ability, technical assistance, and participation in a guild. Efficiency is negatively related with firm owners having a second job. The difference in efficiency levels between formal and informal retailers is large in a ’naive’ specification without controls for selection bias and our set of characteristics. However, if we control for selection bias and firm, industry, and firm-owner characteristics, our findings still indicate that formal retailers are more efficient, although the difference is smaller. Hence, our results suggest that business registration reforms, which positively affect the decision of firms to formalize (e.g. the SIMPLES program in Brazil, see Monteiro and Assunção (2007); Fajnzylber et al. (2007)), will increase productivity growth.

In the literature, it is suggested that productivity gains after registration may arise from access to public goods, the ability to advertise, and the ability to issue tax receipts. Public goods provision includes protection for formal firms by the police and judicial courts. For example, contracts related to formal activities can be enforced through the judicial system, which increases their value and usefulness. The ability to sign contracts enforceable through the courts creates certainty and reduces the transaction and monitoring costs in business dealings conducted by formal firms. In turn, this increases investment that may come both from internal sources (retained earnings) and from capital markets (Loayza, 1996). Also, formal firms do not face obstacles in using public services such as social welfare, skill-training programs, and government-sponsored credit facilities. Furthermore, the ability to advertise and issue tax receipts by formal firms may increase the customer base by raising awareness of the business, and permitting clients to use the tax receipts for claims or tax refunds (McKenzie and Sakho, 2009).

The analysis in this chapter indicates that formal retailers are more productive, even after controlling for self-selection. Hence, the findings support the view that registration results in productivity gains. However, the instrument we use to control for selection bias has its limitations. As instrument we used the average degree of tax compliance across Federal states, motivated by the suggestion that value added taxes transmit formality (de Paula and Scheinkman, 2007). Ideally, firm-specific information on the formality of the firm's supply chain should be used, and other instruments may be considered as well in future research. For example, following McKenzie and Sakho (2009) it may be argued that distance from the tax office affects the information a firm has about registration, but does not independently affect productivity. Therefore, if available, a GPS-measured distance of a firm from the tax office can be considered as an instrument for whether or not a firm is registered for taxes. Extending the set of firm characteristics in this direction seems to be a promising avenue for future research into the differences in productivity between formal and informal firms.

4.A Description of the Variables in the Dataset

Variables

Production variables:

- *Sales*: total nominal revenues (in Reais) in October 2003.
- *Value added*: nominal revenues minus cost of goods sold and intermediate inputs (in Reais) in October 2003.
- *Capital*: the nominal value of fixed assets (building(s), installations, equipment, vehicles et cetera, in Reais).
- *Employment*: total number of workers, including the owner, employees, and (possible) family workers.
- *Hours worked*: total number of hours worked in October 2003, including hours worked by the owner, employees, and (possible) family workers.

Efficiency variables (+ (-) indicates whether the expected relation with efficiency is positive (negative)):

- *Formality*: tax registration, which is the fourth step towards formalization (see appendix table 4.A.1). Other indicators of (the degree of) formality include a municipal license, micro-firm registration, and filled in tax forms. + Because of access to public goods, and the possibility to increase the customer base by means of advertising and issuing tax receipts.
- *Education*: educational level of the owner, which is a categorical value ranging from no education (education = 1) to graduated from college (education = 8). + A proxy of managerial ability.
- *Motivation to start a business*: dummy which equals one if the owner states that he/she started the business because he/she could not find a job. - Reflecting necessity and not managerial ability.
- *Owner has a second job*: dummy for owners with a second job. - Business might be treated as a secondary source of income.
- *ICT*: dummy which equals one if at least one computer is used by the firm. + ICT enables the owner to improve its business performance.

- *Age firm*: age of the firm in years. *Age* $firm^2$: square of *Age firm*. + , - The efficiency is positively related with the age of the firm due to a process of learning by doing, but with diminishing returns.
- *Credit*: dummy variable, indicating whether the firm used credit in the last three months. + Lenders select credit worthy borrowers, and borrowers improve business performance in order to be able to repay the debt.
- *Bank loan*: indicates whether the bank provided the credit (as opposed to friends, relatives, or other firms). + A benefit of being formal.
- *Guild*: dummy for firms affiliated to a guild. + A benefit of being formal.

Instruments for formality:

- *Tax Compliance*: Volume of revenues by state from SMEs that paid federal taxes in 2003 under the simplified tax system, normalized by the total number of SMEs in each state (Masci et al., 2007).
- *Educational level*: Average number of years of education for those above 25 years old by state (IBGE, available at www.ibge.gov.br).

Industry dummy variables (sectors of activity):

- SEC1: Retailing of agricultural products.
- SEC2: Retailing of food, beverages and tobacco.
- SEC3: Retailing of textile materials.
- SEC4: Retailing of clothing, footwear and complementary goods.
- SEC5: Retailing of wood, construction material, hardware and tools.
- SEC6: Retailing of electronic household articles, furniture, and other household articles.
- SEC7: Retailing of books, newspapers, and magazines.
- SEC8: Retailing of pharmaceutical and medical goods, cosmetic and toilet articles.
- SEC9: Retailing of (non-electronic) machinery, equipment, and supplies.
- SEC10: Retailing of automotive fuel, excluding tank stations.

- SEC11: Retailing of waste.
- SEC12: Retailing of raw materials (minerals).
- SEC13: Retailing of non-specialized goods, including second-hand goods.
- SEC14: Supermarkets and hypermarkets.
- SEC15: Non-specialized retail stores, without predominance in food products.
- SEC16: Retail trade via catalogues, television, Internet, or other forms of communication.
- SEC17: Retail trade outside a fixed locale, but located along public roads or at markets.

Outlier correction

We corrected for outliers. First, we deleted observations on value added, hours worked, and capital that fell into the 1st or 99th percentile of the distribution. Second, we examined the various combinations of variables (for example, total employment and total hours worked) and dropped unreliable observations.

Output measurement

To measure retail output, several concepts can be used. In this chapter, we use value added. Sales are the number of goods sold multiplied by their respective price. This is the broadest output concept, and both the product mix and the quantity of goods sold affect output. If the cost of goods sold is subtracted from sales, the resulting output concept is gross margin, which is preferably extended by the provision of distribution services (Betancourt and Gautschi, 1993). Thus, higher gross margins generally reflect higher value-added services. The gross margin output concept has several inherent difficulties. First, subtracting cost of goods sold from sales suggests that the costs of goods are separable from other costs the firm faces. Second, gross margins can be affected by volume discounts. Firms with market power might negotiate lower prices, thereby increasing their gross margin. Third, volume measures of gross margin are difficult to measure since price data on cost of goods sold is needed. A third output concept is obtained by subtracting intermediate inputs from gross margin, resulting in value added. Only labor and capital costs are included in the value added output concept. Although the value added output concept is usually regarded as the preferable output measure (McGuckin et al., 2005), it is vulnerable to measurement error. Value added is exposed to measurement error, because the value added to sales ratio is typically small for a retailer. Hence, measurement error in intermediate inputs will exacerbate errors in the output variable. This partly explains the small efficiency to white noise ratio (the γ's reported in table 4.4). In appendix table 4.B.1 (column 7), we estimate the model using sales as a measure of output. Results for the production frontier and the efficiency model are similar, but a larger share of the variation in the composite error term is due to the inefficiency component. Hence, value added is more sensitive to measurement error, but the results are not affected.

Although the various definitions of output differ in reliability, all measures are imperfect. Many small retailers do not keep financial records, making data collection generally reliant on recall. However, recall error, for example, over four months compared to one month is 10 to 15 percent larger (de Mel et al., 2009). Therefore, information for a single month in our dataset might be of higher quality as compared to information over larger periods.

Correlations

Appendix table 4.A.2 shows the correlation between the main variables in our analysis. All of the bivariate correlations between value added and the variables included in the model are statistically significant at the 1 percent level. In addition, we find a strong and significant correlation between the different indicators of formality. However, the correlation is not equal to one, indicating that many firms only partially comply with regulations.

Table 4.A.1. Steps needed to register a business

Step 1. Consult whether the business is welcome
Consult at the secretariat of federal revenues (DRF), the administration of state revenues (SEMFAZ), through the CPF of the bearer or partner, and SEMSUR for approval of the commercial location of the firm.
Step 2. Consult the name of the firm at the Trade Board
Consult whether there already exists a registered firm with the same or a similar name as the name that was chosen for the firm.
Step 3. Register at the Trade Board
A business with a social objective whose activity is related to industry, commerce and/or services has to be registered at the Trade Board.
Step 4. Register at the secretariat of federal revenues
Register for taxes. A firm obtains an identification number: Cadastro Nacional da Pessoa Jurídica (CNPJ).
Step 5. State registration
Register at the state's police department (Delegacia da Receita Estadual) in case the activity of the business is: in commerce, in interstate industry or transport services, a restaurant, a snack bar, a nightclub, in communication services, a bar, or in the construction business.
Step 6. Business license
Obtain a municipal license
Step 7. Sanitary certificate
Allow the center for the surveillance of sanitary conditions to examine whether the conditions of the activities related to food, health services, products, and the environment are sufficient.
Step 8. Register for social security (INSSS)
The bearer or partner of the firm (commerce, industry or services), in accordance with the social welfare expenditure plan, is required to register and monthly collect contributions for social security.
Step 9. Business entity registry
A business whose activity necessitates a professional business entity registry is required to undertake the corresponding registration.
Step 10. Request for the emission of the fiscal documents
Step 11. Register employees
A firm with employees, irrespective whether they are family workers, is required to register them.

Source: SEBRAE (www.sebrae.com.br).

Table 4.A.2. Correlation matrix

	ln Value added	ln Capital	ln Hours worked	Tax registration (CNPJ)	License to operate	Micro-firm registration	Filled in tax forms	Educ. owner	Other job
ln Value added	1.00								
ln Capital	0.64	1.00							
ln Hours worked	0.46	0.46	1.00						
Tax registration (CNPJ)	0.51	0.53	0.38	1.00					
License to operate	0.41	0.39	0.32	0.50	1.00				
Micro-firm registration	0.48	0.50	0.37	0.95	0.47	1.00			
Filled in tax forms	0.46	0.47	0.34	0.86	0.63	0.81	1.00		
Education owner	0.33	0.34	0.06	0.30	0.16	0.27	0.26	1.00	
Owner has second job	-0.07	0.01[c]	-0.14	-0.02[a]	-0.05	−0.02[a]	−0.02[a]	0.11	1.00
ICT	0.36	0.33	0.18	0.39	0.24	0.36	0.36	0.33	0.01[c]
Age firm	0.13	0.12	0.09	0.12	0.17	0.11	0.12	-0.14	-0.06
Credit granted in last three months	0.15	0.14	0.10	0.13	0.10	0.12	0.12	0.07	0.03
Credit granted was bank loan	0.16	0.14	0.11	0.15	0.11	0.14	0.15	0.09	0.03[a]
Participation in guild	0.28	0.25	0.19	0.35	0.29	0.33	0.32	0.17	0.00[c]
Technical assistance by others	0.15	0.15	0.09	0.21	0.12	0.20	0.19	0.13	0.01[c]
Technical assistance by government	0.05	0.04	0.03	0.06	0.05	0.05	0.05	0.03	0.01[c]
Motivation to start a business	-0.18	-0.23	-0.05	-0.21	-0.15	-0.19	-0.18	-0.12	-0.10

	ICT	Age firm	Credit	Bank loan loan	Guild	Technical assistance by others	Technical assistance by gov.	Mot. to start a bus.
ln Value added								
ln Capital								
ln Hours worked								
Tax registration (CNPJ)								
License to operate								
Micro-firm registration								
Filled tax forms								
Education owner								
Owner has second job								
ICT	1.00							
Age firm	0.00[c]	1.00						
Credit granted in the last three months	0.09	0.01[c]	1.00					
Credit granted was bank loan	0.12	0.01[c]	0.75	1.00				
Participation in guild	0.26	0.09	0.07	0.08	1.00			
Technical assistance by others	0.17	0.02[b]	0.10	0.10	0.15	1.00		
Technical assistance by government	0.03	0.01[c]	0.11	0.15	0.05	-0.02[b]	1.00	
Motivation to start a business	-0.15	-0.08	-0.04	-0.05	-0.10	-0.07	-0.02[b]	1.00

Note: All pairwise correlations are significant at the 1 percent level, except for: [a] significant at 5 percent level, [b] significant at 10 percent level, [c] not significant.

4.B Robustness Checks

In this appendix we present results from robustness tests for the productivity difference between formal and informal retailers. First, we examined issues related to the measurement of capital. Second, several other specifications were explored. In the model specifications estimated in this section, (instrumented) tax registration is used as the indicator of formalization. We find that the positive relation between formality and productivity is robust to different specifications and adjustments for inaccurate reporting of capital.

The measurement of capital

Our estimate of capital is subject to measurement error and missing observations. For example, a firm may not break down multifunctional equipment in case the firm does not have a location exclusively designated to business. Also, approximately 40 percent of the firms in our sample do not report capital. This may either imply that the firm incorrectly reports it has no capital, that the firm does not make use of capital, or a combination of both. Furthermore, firms that do not report capital may share certain characteristics, raising doubts about sample selection. We examined whether the productivity difference between formal and informal firms is robust to different specifications taking some of the limitations of capital measurement into account.

First, we estimated the model using firms that had a location exclusively designated to business.[21] Estimating the model for these firms alleviates concerns that firms that do not separate home from business report capital inaccurately. Column 1 in appendix table 4.B.1 shows that the productivity difference and the elasticity of output with respect to capital are robust to examining firms with a designated business location only.

Second, we considered the possibility that some retailers might not use capital at all, in which case the estimated output elasticity with respect to capital is biased (Battese, 1997). If some retailers do not use capital, this may affect the stochastic efficiency component as well. Zero values for firms not using capital can be addressed for Cobb-Douglas production functions by replacing equation 4.4 with the

[21] Owners are asked whether they have a location exclusively designated to business (yes/no).

following equation:

$$lnY_i = \beta_0 + \beta_1 D + \beta_2 lnK_i + \beta_3 lnH_i + v_i - u_i, \quad (4.B.1)$$

where $D_i = 1$ if $lnK_i = 0$, $D_i = 0$ if $lnK_i > 0$, and $lnK_i^* = Max(lnK_i, D_i)$. We estimated equation 4.B.1 and equation 4.5 simultaneously (after instrumenting tax registration). The results are shown in column 2 of appendix table 4.B.1. Accounting for zero values for firms not using capital does not change the results. The sign and significance of the coefficients in the efficiency model are similar to the base model, except for the effect of credit and bank loan, which are now significantly related with efficiency. This suggests that measurement error in the reporting of capital does not affect the productivity difference, but it does affect the relation between the firm's use of external finance and productivity.

Third, we used regression mean imputation and substituted the predicted mean for missing values of capital. First, we regressed capital on value added and hours worked (it does not matter which of the variables is the 'response' in the model of interest). Next, coefficients of this regression were used to estimate the expected value of the capital stock for firms not reporting capital. Regression based imputation can generate unbiased estimates of means, but the variability of the imputations might be too small. Hence, the estimated precision of regression coefficients may be incorrect and should therefore be treated with care. Column 3 of appendix table 4.B.1 shows that results are similar to the base model.[22]

Other robustness checks

In this subsection we consider other robustness checks. First, we estimated a Cobb Douglas production function. Column 4 in appendix table 4.B.1 shows that the sign and significance of the coefficients are similar if a Cobb Douglas functional form is chosen.

Second, the odds of survival may differ across formal and informal retailers, raising concerns about a sample selection problem. We examined the sensitivity of our results to differences in survival probability between formal and informal retailers, by excluding firms more than 3 years old (column 5). The results indicate

[22] Mean imputation gives similar results. Also regression mean imputation for formal and informal retailers separately gives similar results.

that productivity differences between formal and informal retailers are significant for these groups as well.

Third, we estimated the model where we included an interaction between the various factor inputs and tax registration (column 6). This model allows us to examine whether formal and informal firms share a common technology. The result suggest that the elasticity of capital may be different for informal firms, as reflected in the significant coefficient for squared capital interacted with tax registration.[23] However, results from the efficiency model are not affected if we allow production technologies to vary across formal and informal retailers.

Fourth, we estimated the model using sales instead of value added (column 7). Results are similar, but the efficiency to white noise ratio is higher compared to the base model. Hence, measuring output by value added is more sensitive to measurement error, but the results are not affected.

Fifth, we estimated the model for different sub-industries. Columns 8-9 show the results for industry 2 (Commerce of food, beverages, and tobacco), and industry 13 (Commerce of non-specialized goods, including second-hand goods).[24] We used hours worked as the single input variable in these specifications. The output elasticity of labor is similar for the sub-industries, and formal retailers are significantly more productive than their informal counterparts. The efficiency to white noise ratio is higher compared to the base model, suggesting that some of the heterogeneity in the sample may be captured by estimating the model for sub-industries.

Finally, we used the average educational level for each state as an instrument for tax registration. Higher ability firm owners are more likely to be formal in order to benefit from access to public goods and the ability to increase the customer base by advertising and issuing tax receipts. Formality transmits itself along the production chain as a result of value added taxes. We used the probit model outlined in equation 4.6, where we replaced tax compliance with the average educational level for each state (results not shown). The average educational level positively predicts formality (tax registration) at the 1 percent significance level. Column 10 shows the result from estimating equation 4.4 and equation 4.5 simultaneously, where formality is instrumented using the average educational level. The findings suggest that formal firms are more productive after controlling for the selection bias and firm, industry, and firm-owner characteristics.

[23] Also, a Wald test of the joint significance of the coefficients suggests differences in technology between formal and informal retailers.

[24] We present results for these sub-industries, because they are relatively large.

Table 4.B.1. Alternative stochastic frontier and efficiency models

Variable	β	SE	β	SE
	(1)		(2)	
Production frontier				
ln Capital	0.237	(21.39)***	-	-
ln Capital^2	0.005	(2.01)**	-	-
D	-	-	1.017	(30.97)***
ln Capital $\times$ D	-	-	0.210	(31.22)***
ln Hours worked	0.389	(6.39)***	0.276	(27.01)***
ln Hours worked^2	0.075	(8.84)***	-	-
ln Capital $\times$ ln Hours worked	-0.001	(0.07)	-	-
Sector dummies	Yes		Yes	
Efficiency model				
Tax registration (CNPJ)[a]	-3.883	(7.90)***	-4.482	(11.26)***
Credit	-0.063	(1.00)	-0.108	(2.03)**
Credit was bank loan	-0.115	(1.46)	-0.187	(2.72)***
Participation in guild	-0.262	(6.13)***	-0.303	(7.46)***
ICT	-0.355	(7.34)***	-0.511	(11.98)***
Age of the firm	-0.015	(4.54)***	-0.028	(9.80)***
Age of the firm^2	0.000	(2.41)**	0.000	(5.88)***
Technical assistance elsewhere	-0.213	(3.00)***	-0.212	(3.32)***
Technical assistance gov.	-0.091	(0.73)	-0.005	(0.05)
Education owner	-0.102	(12.42)***	-0.136	(21.01)***
Motivation	0.162	(5.76)***	0.163	(7.44)***
Owner has second job	0.165	(3.66)***	0.196	(5.73)***
σ^2	0.844		0.980	
γ	0.037		0.162	
Observations	5429		9641	

Variable	β	SE	β	SE
	(3)		(4)	
Production frontier				
ln Capital	0.335	(34.88)***	0.243	(34.48)***
ln Capital^2	-0.006	(2.79)***	-	-
ln Hours worked	0.199	(11.66)***	0.232	(16.46)***
ln Hours worked^2	0.081	(13.73)***	-	-
ln Capital $\times$ ln Hours worked	-0.033	(5.63)***	-	-
Sector dummies	Yes		Yes	
Efficiency model				
Tax registration (CNPJ)^a	-3.021	(8.60)***	-3.624	(7.43)***
Credit	-0.065	(1.38)	-0.088	(1.38)
Credit was bank loan	-0.140	(2.31)**	-0.107	(1.35)
Participation in guild	-0.250	(6.96)***	-0.297	(6.88)***
ICT	-0.377	(9.98)***	-0.415	(8.62)***
Age of the firm	-0.018	(7.29)***	-0.017	(5.28)***
Age of the firm^2	0.000	(4.62)***	0.000	(2.87)***
Technical assistance elsewhere	-0.190	(3.39)***	-0.245	(3.46)***
Technical assistance gov.	-0.026	(0.25)	-0.102	(0.81)
Education owner	-0.085	(14.87)***	-0.101	(12.47)***
Motivation	0.112	(5.77)***	0.153	(5.51)***
Owner has second job	0.149	(4.96)***	0.162	(3.64)***
σ^2	0.756		0.878	
γ	0.051		0.073	
Observations	9641		5746	

Variable	β	SE	β	SE
	(5)		(6)	
Production frontier				
ln Capital	0.283	(12.35)***	0.270	(17.80)***
ln Capital^2	0.006	(1.34)	0.006	(1.98)**
ln Hours worked	0.283	(2.77)***	0.226	(3.70)***
ln Hours worked^2	0.065	(4.63)***	0.038	(4.42)***
ln Capital × ln Hours worked	0.018	(1.37)	0.006	(0.76)
ln Capital × Tax registration	-	-	-0.103	(4.25)***
ln Capital^2 × Tax registration	-	-	-0.000	(0.06)
ln Hours worked × Tax registration	-	-	0.268	(1.13)
ln Hours worked^2 × Tax registration	-	-	0.153	(5.92)***
(ln Capital × ln Hours worked) ×				
Tax registration	-	-	-0.011	(0.41)
Sector dummies	Yes		Yes	
Efficiency model				
Tax registration (CNPJ)[a]	-6.134	(5.50)***	-3.852	(8.01)***
Credit	-0.060	(0.45)	-0.077	(1.23)
Credit was bank loan	-0.218	(1.27)	-0.094	(1.21)
Participation in guild	-0.230	(1.44)	-0.228	(5.32)***
ICT	-0.668	(2.55)**	-0.343	(7.15)***
Age of the firm	-0.168	(2.19)**	-0.016	(4.89)***
Age of the firm^2	0.034	(1.36)	0.000	(2.67)***
Technical assistance elsewhere	-0.097	(0.53)	-0.195	(2.78)***
Technical assistance gov.	-0.564	(1.32)	-0.086	(0.68)
Education owner	-0.142	(8.51)***	-0.095	(11.92)***
Motivation	0.083	(1.57)	0.127	(4.64)***
Owner has second job	0.175	(2.13)**	0.148	(3.37)***
σ^2	0.903		0.847	
γ	0.070		0.038	
Observations	1808		5746	

Variable	β	SE	β	SE
	(7)		(8)	
Production frontier				
ln Capital	0.236	(20.49)***	-	-
ln Capital^2	-0.005	(1.84)*	-	-
ln Hours worked	0.238	(3.81)***	0.538	(19.83)***
ln Hours worked^2	0.068	(7.79)***	0.105	(10.73)***
ln Capital $\times$ ln Hours worked	0.022	(2.95)***	-	-
Sector dummies	Yes		Yes	
Efficiency model				
Tax registration (CNPJ)[a]	-0.721	(11.66)***	-7.197	(8.18)***
Credit	-0.307	(3.40)***	-0.320	(2.74)***
Credit was bank loan	-0.037	(0.32)	-0.093	(0.62)
Participation in guild	-0.221	(2.72)***	-0.531	(4.84)***
ICT	-0.779	(4.72)***	-1.014	(3.34)***
Age of the firm	-0.021	(5.26)***	-0.056	(8.94)***
Age of the firm^2	0.000	(3.87)***	0.001	(5.57)***
Technical assistance elsewhere	-0.122	(0.94)	-0.885	(3.41)***
Technical assistance gov.	-0.231	(1.04)	-0.732	(2.61)***
Education owner	-0.112	(10.38)***	-0.197	(14.14)***
Motivation	0.086	(2.57)**	0.192	(4.44)***
Owner has second job	0.076	(1.39)	0.262	(3.62)***
σ^2	0.946		1.222	
γ	0.195		0.118	
Observations	5365		3183	

Variable	β	SE	β	SE
	(9)		(10)	
Production frontier				
ln Capital	-	-	-	-
ln Capital^2	-	-	-	-
ln Hours worked	0.676	(10.67)***	0.602	(39.71)***
ln Hours worked^2	0.078	(4.02)***	0.076	(15.63)***
ln Capital $\times$ ln Hours worked	-	-	-	-
Sector dummies	Yes		Yes	
Efficiency model				
Tax registration (CNPJ)^a	-5.340	(3.04)***	-4.237	(16.45)***
Credit	0.459	(1.51)	-0.219	(3.72)***
Credit was bank loan	-0.943	(2.44)**	-0.245	(3.12)***
Participation in guild	-0.525	(2.95)***	-0.447	(8.77)***
ICT	-0.695	(3.41)***	-0.901	(11.29)***
Age of the firm	-0.038	(2.98)***	-0.038	(12.56)***
Age of the firm^2	0.000	(1.50)	0.001	(6.66)***
Technical assistance elsewhere	-0.119	(0.34)	-0.274	(3.39)***
Technical assistance gov.	-0.263	(0.43)	-0.148	(1.07)
Education owner	-0.157	(5.56)***	-0.178	(25.90)***
Motivation	0.262	(2.68)***	0.234	(10.07)***
Owner has second job	0.063	(0.37)	0.205	(5.53)***
σ^2	1.109		1.103	
γ	0.562		0.198	
Observations	622		9641	

Constants not shown. The output and input variables in the production frontier are rescaled to have unit means. Absolute value of z-statistics in parentheses. * significant at 10 percent level of significance, ** significant at 5 percent level, *** significant at 1 percent level. $\sigma^2 \equiv \sigma_u^2 + \sigma_v^2$ and $\gamma \equiv \sigma_u^2/\sigma^2$. ^{a} Predicted values from equation 4.6 are used for tax registration, except for column (10), where the average educational level across states is used as an instrument for formalization.

Chapter 5

ICT Adoption and Heterogeneity in Production Technologies: Evidence for Chilean Retailers*

5.1 Introduction

It is widely accepted that the adoption of information and communication technology (ICT) influences the organization of firms and their cost structures (Brynjolfsson and Hitt, 2000; Haynes and Thompson, 2000; Bartel et al., 2007). The potential of ICT to reshape the retail industry was already acknowledged by Achabal and McIntyre (1987). According to McKinsey (2001), more intensive ICT use should improve retail productivity in two ways. Direct benefits from ICT are due to, for example, bar codes and scanners which reduce checkout time and eliminate the need to manually price tag products thereby reducing labor costs. Most studies on the relation between ICT and retail firm productivity therefore specify ICT capital as an additional production factor (OECD, 2003; Broersma et al., 2003; Doms et al., 2004).

But the indirect gains from a more intensive use of ICT for administration, in-

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ventory control, storage optimization, and pricing and promotion of products may be economically more important and should also influence the retailer's productivity (McKinsey, 2001; McGuckin et al., 2005).[1] In contrast to direct effects from acquiring additional ICT hardware, these indirect ICT effects may require substantial organizational changes (Bertschek and Kaiser, 2004). In fact, the implications of ICT adoption for company organization and cost structures may be so pervasive that it makes sense to generalize the production technology by allowing separate technology regimes, rather than treat ICT capital as just an additional factor input, which would be the more orthodox approach. To our knowledge, this indirect relation between ICT use and the production technology of retailers has received little attention.[2]

In this chapter, we use a unique sample from the Chilean population of retailers and consider, in line with previous studies, *ICT capital* as a component of fixed capital in the production process. In addition, we allow firms to operate different production technologies. Instead of assuming certain group compositions a priori, we specify observed indicators of *ICT use* as determinants of a firm's probability to belong to different technology regimes. Hence, we impose substantially less structure on retail technologies than a more conventional analysis based on a single regime.

This chapter addresses two limitations in previous studies, which examine the relation between ICT and retail productivity by estimating production functions (OECD, 2003; Broersma et al., 2003; Doms et al., 2004). The first concerns the common, yet strong assumption that firms share a single production technology. But incomplete ICT diffusion in developing countries (World Bank, 2008) may indicate different production technologies across firms. And even for firms in developed countries, the assumption of a single production technology is unlikely to hold since both inter-firm and intra-firm ICT diffusion are incomplete in these countries as well.[3] Therefore, we hypothesize that firms have different production techno-

[1] Detailed examples include an improved matching of inventory to customer demand, more responsive price changes, more efficient use of shelf space, reduced inventory and fewer out-of-stock situations, the potential to evaluate and optimize advertising campaigns, and more efficient use of trucking and shipping.

[2] A notable exception is Bertschek and Kaiser (2004) who estimate an endogenous switching regression model to allow different factor elasticities across two groups as a result of ICT-related workplace reorganization. The method adopted in this chapter is different in several respects. For example, we allow inefficiency in the firm's use of resources, and (potentially) a larger number of different production technologies as a result of differences in ICT use across firms.

[3] We do not aim to explain why ICT diffusion differs. Stoneman (2002) discusses exogenous and endogenous reasons for heterogeneous ICT diffusion across and within firms. For example, investments such as cable networks, other infrastructure, or internet connections are necessary to eliminate exogenous constraints on ICT adoption. Endogenous constraints related to ICT adoption include firm-level

logies because of differences in ICT use. A second, equally strong assumption in much of the existing literature is that all firms operate fully efficiently.[4] We hypothesize that in developing countries some retailing firms make suboptimal use of production factors. Some evidence for this hypothesis is available in related literature. For example, for semi-formal financial intermediaries (Popular Savings and Credit Institutions) in Mexico, Paxton (2007) finds much dispersion in efficiency. But also firms and industries in developed countries show inefficiency in the production process (Kneller and Stevens, 2006). Both the existence of different production technologies and the presence of inefficiency need to be accounted for when estimating production functions. We seek to address both issues by modelling retail production technologies in a latent class stochastic frontier model (LCSF model), where the firm's probability of technology group membership is determined by ICT use. In the LCSF model, multiple group-specific production parameters, group-membership probabilities and firm-specific inefficiencies are estimated in a single stage.

An alternative (two-stage) approach to account for cross-firm differences in production technology is to cluster firms, for example based on indicators of ICT adoption.[5] But clustering has several shortcomings. First, any a priori selection criteria is ultimately arbitrary. The common approach is to divide firms in a developing country by employment size (Tybout, 2000). However, some small firms use advanced technologies and should be compared with larger firms doing so as well, rather than with other small firms that use traditional technologies.[6] Second, the number of groups is unknown ex ante. Ideally the number of clusters should follow endogenously from the data as a reflection of production technology heterogeneity. In contrast to cluster analysis, the LCSF model allows us to remain agnostic as to the number and composition of production technology regimes. Finally, cluster

differences of technological literacy and skills to install and maintain ICT systems. This chapter starts from the observation that ICT adoption differs across firms and examines if differences in ICT use are related to different production technologies.

[4] Note that industrial organization (IO) methods of production function estimation allow for firm-level differences in TFP, which may imply efficiency differences to play a role, too. But these approaches focus on addressing simultaneity problems when input variables are correlated with the unobserved productivity term and do not model inefficiency explicitly (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2005). A shortcoming of stochastic frontier models is that they (so far) do not address this endogeneity problem. But in contrast to IO methods, they allow to disentangle the contribution of efficiency from other components to TFP levels and changes by making explicit distributional assumptions regarding the error term. Combining both approaches is clearly a preferred solution, which we consider, however, out of the scope of the present chapter.

[5] Related approaches include regression tree analysis and threshold estimation, as in Durlauf and Johnson (1995) and Hansen (2000).

[6] In our data set of Chilean retailers, ICT adoption is not confined to larger firms.

analysis splits a sample using the *value* of the separating variables, whereas the LCSF model splits a sample according to the *effects* of the separating variables on the dependent variable (Corral and Álvarez, 2004).

We use a unique data set of approximately 1,100 Chilean retailers surveyed by the National Statistical Office of Chile in its Encuesta Anual de Comercio for 2003 and 2004. The data include detailed information on ICT capital and ICT use for each firm, and balance sheet and supplementary economic information such as the number and types of employees. Our main result is the identification of three production technologies across Chilean retailers, which differ in terms of productivity, efficiency, and production factor elasticities.

We find that ICT use is a significant determinant of a firm's group membership probability. The probability of membership in a high-productivity regime is positively related to ICT use. Most firms are allocated to a technology regime which exhibits an intermediate level of productivity. On average, firms within this group operate close to their regime-specific production frontier, that is they incur very little operational slack. A second (relatively small) group of high-intensive ICT users is significantly more productive. Retailers in this group, however, exhibit inefficiency on the order of 12 percent on average. Potentially, the use of more productive and innovative technologies requires adjustments and implies initially some operational slack. Finally, a third group of retailers lag behind in ICT use and also have the least productive production technology. Retailers in this group incur the largest operational slack and forego on average more than half of their output due to suboptimal use of resources. Hence, a considerable number of firms face substantial room for performance improvement within their technology regime without having to further intensify the use of ICT.

The remainder of this chapter is structured as follows. In Section 5.2 we present a baseline frontier model and the latent class stochastic frontier model. Chilean retail data and model specification are described in Section 5.3. Results are discussed in Section 5.4, and we conclude in Section 5.5.

5.2 Method

We first introduce a baseline frontier model that accounts for inefficiency and helps to highlight the limitations of assuming a single production technology. Next, we present the latent class stochastic frontier (LCSF) model to account for the relation between ICT use and heterogeneous production technologies.

5.2.1 Fixed Effects Stochastic Frontier Model

Retailers use production factors to sell goods and deliver services. Output-oriented frontier analysis estimates the maximum possible output given a certain combination of inputs.[7] Deviations from optimal output measure technical inefficiency due to the suboptimal use of input factors. A stochastic fixed-effects panel production frontier is written in logs as (Greene, 2005):

$$y_{it} = \alpha_i + \beta' x_{it} + v_{it} - u_{it}, \tag{5.1}$$

where y is the log output of firm i at time t, and the matrix x_{it} includes the log of (ICT and non-ICT) capital (K), high-skilled labor (HSL), and low-skilled labor (LSL). To partially account for heterogeneity in production technologies across firms, we specify firm-specific fixed effects α_i. Contrary to previous retail productivity studies (OECD, 2003; Broersma et al., 2003; Doms et al., 2004), we specify a composed error term accounting for both measurement error v and technical inefficiency u.[8] Technical efficiency is measured as the ratio of observed output to the estimated stochastic frontier output (including the measurement error). The (exponent) value of technical efficiency ranges from 0 (fully inefficient) to 1 (fully efficient). For example, a firm exhibiting 20% inefficiency produced only 80% of its potential output had it employed its inputs efficiently. To estimate Equation (5.1) with the method of maximum likelihood, we follow the convention in the stochastic frontier literature and assume that the measurement error term v_{it} is *iid* with $v_{it} \sim N(0, \sigma_v^2)$ and independent of the explanatory variables (Kumbhakar and Lovell, 2000). The inefficiency term is assumed to be *iid* with $u_{it} \sim N|(0, \sigma_u^2)|$ and independent of v_{it}.

Two issues deserve consideration. First, neglecting cross-firm heterogeneity may confound heterogeneity with inefficiency. Firm-specific effects α_i aim to capture heterogeneity. But in a disparate sample, fixed effects will capture much cross-firm heterogeneity as well as any inefficiency in the production process (Greene, 2005). Second, a fixed effects production frontier model is still inflexible since factor elasticities are assumed to be constant across potentially different firms. We include ICT capital as a production factor in Equation (5.1). In addition, we hypothesize that factor elasticities differ across firms because of ICT use. Heterogeneity in production technology, however, is hard to define in terms of ICT use a priori.

[7] The production frontier can be obtained deterministically (using Data Envelopment Analysis, DEA) or stochastically (using Stochastic Frontier Analysis, SFA). We use stochastic frontier analysis (SFA) to estimate the frontier, because this approach has been extended to a latent class structure.

[8] Most studies using frontier analysis find that at least some firms operate inefficiently. See Alvarez and Crespi (2003) for an efficiency analysis of Chilean manufacturing firms.

Therefore, we turn next to a latent class stochastic frontier model to separate inefficiency and heterogeneity.

5.2.2 Latent Class Stochastic Frontier Model

To model inefficiency and heterogeneity separately, we use a latent class stochastic frontier (LCSF) model proposed by Greene (2005). While latent class models are frequently used in mixture analysis (McLachlan and Peel, 2000), the adaptation to frontier analysis is fairly recent.[9] In this chapter, we examine whether retailers can be grouped based on ICT use. Following Greene (2005), we write the latent class stochastic frontier model as:

$$y_{it} = \alpha_j + \beta_j' x_{it} + v_{it|j} - u_{it|j}. \tag{5.2}$$

In contrast to the fixed effects stochastic frontier in Equation (5.1), parameters differ across the latent classes $j = 1, ..., J$ and firm-specific effects α_i are replaced by class-specific constants. We thus assume a sorting of retailers into J latent production technologies. Equation (5.2) is estimated using the method of maximum likelihood. Maintaining the standard frontier assumption of a half normal distribution of the inefficiency term, the likelihood function is:

$$LF(i,t|j) = f(y_{it}|x_{it}, \alpha_j, \beta_j, \sigma_j, \lambda_j) = \frac{\phi(\lambda_j \epsilon_{it|j}/\sigma_j)}{\phi(0)} \frac{1}{\sigma_j} \phi\left(\frac{\epsilon_{it|j}}{\sigma_j}\right), \tag{5.3}$$

where $\epsilon_{it|j} = y_{it} - \alpha_j - x_{it}'\beta_j$, $\lambda_j = \sigma_{uj}/\sigma_{vj}$, $\sigma_j = \sqrt{(\sigma_{uj}^2 + \sigma_{vj}^2)}$ and ϕ is the standard normal density. Conditional on the firm being in class j, the contribution of each firm to the likelihood function is:

$$LF(i|j) = \prod_{t=1}^{T} LF(i,t|j). \tag{5.4}$$

[9] Mixture analysis estimates a "finite mixture" distribution. In a frontier setting, Greene (2004) segments different health care systems based on their orientation, for example, towards AIDS in developing African countries and cancer in developed OECD countries. Orea and Kumbhakar (2004) use an LCSF model to study Spanish bank efficiency and find that banks can be grouped according to business scope and size.

The unconditional likelihood for each firm is averaged over the latent classes using the prior probability as weights to membership in group j:

$$LF(i) = \sum_{j=1}^{J} P(i,j) LF(i|j) = \sum_{j=1}^{J} P(i,j) \prod_{t=1}^{T} LF(i,t|j). \tag{5.5}$$

In Equation (5.5), the term $P(i,j)$ is the prior probability, which is attached to membership of firm i in class j. Firms reside in a class permanently.[10] This prior probability therefore reflects the state of nature. The probability is specified for each firm if there are characteristics, z_i, that sharpen the prior. Group membership probabilities are estimated using a multinomial logit:

$$P(i,j) = \frac{\exp(z_i' \pi_j)}{\sum_{j=1}^{J} \exp(z_i' \pi_j)}, \pi_J = 0, \tag{5.6}$$

where, $j = J$ is the last group serving as the reference group and z_i are firm-specific characteristics, ICT use in our study, which co-determine firm-specific group membership probabilities. If no firm characteristics are specified in z_i, latent classes would still exist. But they would depend solely on production factors in the kernel and $P(i,j)$ would be a group-specific constant $P(j)$. Hence both firm-specific ICT use and the overall fit of the stochastic frontiers are used during the maximum likelihood procedure.

A caveat of the LCSF model pointed out by Greene (2005) is the necessity to specify the number of groups J prior to estimation. In principle the number of groups is only bounded by the number of cross-sectional units N. But the appropriate number of groups is likely much smaller and already for a number of groups J substantially lower than N, the exceedingly large number of parameters in practice leads to over-fitting problems. Therefore, we follow below Greene (2005) and use a 'top-down' approach to select the preferred model based on both statistical tests and maximization diagnostics (see also Orea and Kumbhakar (2004)).

In sum, we estimate class-specific production factor coefficients β_j and relate firm-specific group membership probabilities in different latent technology regimes to ICT use in a multinomial logit model.[11] The relative ability of each firm to convert production factors into output given its technology, i.e. the efficiency of

[10] This assumption might be reasonable for a 2 year panel data set.

[11] Group membership and hence efficiency estimates are based on the posterior probability. An alternative to calculate efficiency is to sum all posterior probabilities multiplied by the efficiency in using the technology of class j (Orea and Kumbhakar, 2004). The difference between both efficiency estimates is higher when the highest posterior probability is lower.

a firm, is estimated relative to the frontier of its class. Hence, productivity and efficiency should be carefully distinguished. The average productivity of retailers in the different classes can be directly compared and straightforwardly interpreted. However, efficiency of retailers is measured by the firm's position relative to its appropriate technology frontier, reflected in $u_{it|j}$.

5.3 Data And Model Specification

We first describe our dataset of Chilean retailers and specify the model next.

5.3.1 Chilean Retail Firms

We use a short and largely balanced panel data set of registered, mainly single-establishment Chilean retailers from the commercial survey (Encuesta Anual de Comercio, EAC) for 2003 and 2004. Retailers are linked using their firm-identification numbers. The commercial survey is conducted annually by the statistical office of Chile and covers a sample of approximately 1,100 retail firms from the total population of retail firms in Chile.[12] Firms report in EAC: (a) balance sheet and income statement information, such as cost, revenue, and profit information; (b) economic information beyond the balance sheet and income statement information, such as investment flows and the number of employees; (c) ICT information. We use detailed data on internet use to proxy for ICT use. We create a discrete variable labelled ICT use, which ranges from 0 to 7 based on the dummies for internet connection, e-mail address, website, intranet, extranet, purchases and/or sales via the internet.[13]

To measure retail output, several concepts can be used. In this chapter, we use value added. The broadest output concept for distributive trade firms is sales. Sales

[12] The commercial survey concerns firms registered at Servicio de Impuestos Internos (Declaración Anual de Impuestos a la Renta, formulario 22 y Declaración Mensual del IVA, formulario 29). The final set of firms from which the sample is drawn comprises firms with accumulated sales of 95 percent for the sector. This cut off at 95 percent is due to a large number of extremely small firms that are difficult to monitor and display large instability over time. Some firms that would significantly affect the precision of the aggregate variables are included (Inclusión Forzosa (IF) or forced inclusion). Other firms are sampled from the remaining population of firms.

[13] The pairwise correlation between the ICT use variables ranges from 0.10 to 0.87. The highest correlation is between having an internet connection and having an e-mail address. It might be inappropriate to give each variable the same weight. To address this, we took the first principal component of the seven dummies. All variables load positively on the first factor, and the proportion of variation accounted for by the first principal component is 49 percent. The first eigenvalue is 3.06, the second eigenvalue is 1.21. The first principal component is highly correlated (0.995) with the simple average of the dummy variables. This suggests they convey similar information.

are the number of goods sold multiplied by their respective price.[14] This output concept implies that both the product mix and the quantity of goods sold affect output. If the cost of goods sold is subtracted from sales, the resulting output concept is gross margin.[15] Thus, higher gross margins generally reflect higher value-added services. The gross margin output concept has several inherent difficulties. First, subtracting cost of goods sold from sales suggests that the costs of goods are separable from other costs the firm faces. Second, gross margins can be affected by volume discounts. Firms with market power might negotiate lower prices, increasing their gross margin. Third, volume measures of gross margin are difficult to measure since price data on cost of goods sold is needed. A third output concept is obtained by subtracting intermediate inputs from gross margin. This results in value added. Only labour and capital costs are included in the value added output concept. We use value added because it is common practice in national accounts. In addition, by using a value added output concept we are able to distinguish whether a retailer increased its value added output either by selling more or by reducing the costs of intermediate inputs.[16]

Firms report depreciation of capital assets and investment. Firms do not report gross fixed capital assets. We approximate the non-ICT capital stock as follows. First, the initial capital stock is estimated from $D_{i,l,t} = \delta_l K_{i,l,t-1}$. The value of depreciation D by capital type l is given and we use depreciation rates, δ, for the different capital types by US retailers from the Bureau of Economic Analysis to estimate $K_{i,l,t-1}$ (Fraumeni, 1997).[17] Several caveats apply. Firms report accounting depreciation and not economic depreciation. Hence the capital stock is likely overestimated in our approach. Also, we assume that capital depreciation rates for US retailers are similar for Chilean retailers. However, differences in competition and the functioning of financial markets might drive a wedge between capital depreciation rates in developed and developing countries. If depreciation rates are lower in developing countries, we underestimate the capital stock of Chilean retailers using depreciation rates for US assets. Second, we estimate the capital stock using the perpetual inventory method $K_{i,t} = \sum_{l=1}^{L} K_{i,l,t} = \sum_{l=1}^{L} \left((1-\delta_l) K_{i,l,t-1} + I_{i,l,t} \right)$, where I is investment. We proxy the ICT capital stock by multiplying the number of com-

[14] Sales include net inventory adjustment. Sales, wages, the cost of goods sold, and intermediate inputs for 2004 are deflated using the consumer price index.

[15] Preferably the gross margin output concept is extended by the provision of distribution services (Betancourt and Gautschi, 1993).

[16] For further discussion of the appropriate output concept for retailers, see O'Mahony et al. (1998) and McGuckin et al. (2005).

[17] The capital assets distinguished are: buildings, constructions, and installations, transport equipment, machinery, equipment, and tools, office equipment, and leasing equipment.

puters, laptops, and servers per firm by their respective price. These prices are obtained from the statistical office of Chile.[18]

Firms report the number of employees quarterly. We use the average annual employment as a measure of labor input.[19] EAC distinguishes between various types of labor. We group these types into high-skilled labor (owners, executives, and managers), and low-skilled labor (family without fixed income, normal workers, temporary workers, and subcontracted workers).[20] The sample includes 926 retailers in 2003 and 972 in 2004. The data set is smaller than the original sample of approximately 1,100 firms from the EAC due to missing information for some variables and the exclusion of outliers.[21]

Chilean retailers differ considerably in their activities. EAC reports the two main activities of the firm, and the four main products it sells. Based on this information, we classify retailers into three-digit ISIC revision 3 categories and create four according indicator variables, $Sector_m$. $Sector_1$ comprises non-specialized retail trade in stores, $Sector_2$ comprises retail sale of food, beverages and tobacco in specialized stores, $Sector_3$ comprises other retail trade of new goods in specialized stores, and $Sector_4$ comprises other retail services.

Table 5.1 reports average sales, cost of goods sold, value added, and the production factors capital, high-skilled labor, and low-skilled labor as well (in natural logarithms). Comparing indicators of ICT adoption by Chilean retailers with those for developed OECD countries (OECD, 2003) shows that ICT diffusion is lower in Chile. For example, around 80 percent of businesses in Japan, Australia, New Zealand, and Nordic countries use the internet while the Chilean average is 51 percent. Likewise, the share of businesses using the internet for purchases and sales ranges between 10 and 20 percent in these developed countries while only 3-4 percent of Chilean firms score on this account. The data for Chilean retailers suggest that ICT diffusion is incomplete. Next, we test if the incomplete diffusion of ICT use observed among Chilean retailers is a determinant of firms' group membership

[18] We are aware of the limitations regarding our approach and therefore experimented with several alternatives. For example, we used depreciation rates as proxies for the firms' capital stock. Alternatively, we estimated the initial capital stock using the expression for steady-state capital implied by the Solow growth model. These alternative approaches did not affect the main results.

[19] Seasonal and part-time employment affect the precision of our employment estimate.

[20] Ideally we use an employment classification based on actual skills rather than on occupations. However, information on education and experience by persons engaged is not available in the survey. We assume occupations reflect skills.

[21] We trim the 2.5 percent tails of the labor productivity distribution (VA/L) and the capital productivity distribution (VA/K), respectively. This is somewhat higher than the common trimming of 1 percent tails since measurement error for a sample of services firms in a developing country is likely to be higher. The main results remain intact if we trim the 1 percent tails, but there are differences at more detailed levels.

probability.[22]

Table 5.1. Descriptive statistics

Production factors	**Mean**	**SD**
ln Sales	13.02	1.96
ln Cost of goods sold	12.61	2.15
ln Value added	10.92	1.91
ln K	9.78	3.48
ln HSL	0.42	0.73
ln LSL	2.44	1.77
ICT use frequency distribution	**n**	**Share**
Internet connection	968	51%
E-mail address	878	46%
Website	335	18%
Intranet	299	16%
Extranet	111	6%
Purchases via internet	71	4%
Sales via internet	62	3%
Subsector frequency distribution	**n**	**Share**
$Sector_1$:	560	29%
$Sector_2$:	420	22%
$Sector_3$:	732	39%
$Sector_4$:	187	10%
Observations	1898	

Note: Observations for 2003 and 2004 are combined. Values are in thousands of Chilean pesos. Other retail services include: retail sale of second-hand goods in stores, retail trade not in stores, and repair of personal and household goods. The values of sales, cost of goods sold, value added, and capital for 2004 are deflated. K is the capital stock, HSL is high-skilled employment, LSL is low-skilled employment. $Sector_1$: Non-specialized retail trade in stores; $Sector_2$: Retail sale of food, beverages and tobacco in specialized stores; $Sector_3$: Other retail trade of new goods in specialized stores; $Sector_4$: Other retail services.

5.3.2 Model Specification

We specify a LCSF model for retailers using the translog functional form:

$$\begin{aligned}
\ln Y_{it|j} \quad = \quad & \alpha_j + \beta_{1j} \ln K_{it} + \beta_{2j} \ln HSL_{it} + \beta_{3j} \ln LSL_{it} + \frac{1}{2}\beta_{4j} \ln K_{it}^2 \\
& + \frac{1}{2}\beta_{5j} \ln HSL_{it}^2 + \frac{1}{2}\beta_{6j} \ln LSL_{it}^2 + \beta_{7j} \ln K_{it} \ln HSL_{it} \\
& + \beta_{8j} \ln K_{it} \ln LSL_{it} + \beta_{9j} \ln HSL_{it} \ln LSL_{it} + \beta_{1nj} Sector_n + v_{it|j} - u_{it|j},
\end{aligned} \tag{5.7}$$

[22] Unregistered firms are not sampled by the EAC. Since unregistered firms are less-intensive ICT users, our data set overestimates ICT adoption by Chilean retailers. In addition, if more intensive ICT use is related to higher productivity it also increases survival probabilities. Therefore, the dataset might suffer from selection bias. If selection bias is present, this problem is small given the short sample period of two years.

where subscripts i, t, j, and n refer to firm, time, class, and $m-1$ sector indicators, respectively. Y, K, HSL, and LSL denote output, capital, high-skilled labor, and low-skilled labor, respectively. Note that our measure of physical capital K also contains the value of ICT assets, for example the value of desktop computers. Ideally, we would like to specify different types of capital separately. But since both proxies for K are fairly noisy and due to maximization problems associated with more elaborate specifications, we opted for a joint measure of capital. As separating variables in the identification of latent classes we use our proxy for ICT use. Latent class probabilities are written as:

$$P(i,j) = \frac{exp(\pi_{0j} + \pi_{1j}\ ICTuse_i + \pi_{nj}\ Sector_n)}{\sum_{j=1}^{J} exp(\pi_{0j} + \pi_{1j}\ ICTuse_i + \pi_{nj}\ Sector_n)}, \pi_J = 0. \tag{5.8}$$

In Equation (5.8), the last class serves as the reference group. To account for heterogeneity in the retail sector, we include sector dummies both in the translog function form in Equation (5.7) and as separating variables in the latent class specification. Given the short period of two years, no time element is included in Equation (5.8) and firms remain in a technology regime conditional on ICT characteristics in 2003.[23]

5.4 Results

In this Section, we first present estimates from a fixed effect stochastic frontier model. Next, we examine the results when estimating a latent class stochastic frontier model.[24] Finally, we examine the robustness of our results.

5.4.1 Specification

We first estimate a standard fixed effects stochastic frontier panel model (FESF) as in Equation (5.1) to test if efficiency prevails. Results are shown in the first column of table 5.2. First-order coefficients of capital, and high- and low-skilled labor are significant at the 1 percent level. Individual parameter estimates of λ and σ show that inefficiency prevails. Wald tests confirm that both inefficiency terms are individually and jointly significant. Hence, a stochastic frontier specification which

[23] Since our data set covers two years only, we do not extend the method to allow transitions between technology regimes.

[24] We estimate the fixed effect stochastic frontier model and the latent class stochastic frontier model using LIMDEP version 9.0.

allows inefficiency in the production process is the appropriate choice. In addition, a Wald test of the additional input coefficients from the translog functional form supports the specification of the translog as opposed to the Cobb Douglas functional form.[25]

Next, we estimate a latent class stochastic frontier model to test if different technology regimes prevail. Firm heterogeneity is then generated by a discrete distribution. To specify the appropriate number of groups, we follow Greene (2005) and use a 'top-down' approach to select the preferred model. We tried to specify up to $J = 9$ groups and compared the model to a nested specification with $J - 1$ groups. The model with the highest likelihood ratio, the lowest Bayesian criterion, and the lowest Akaike information criterion is preferred (see Greene (2005), and Orea and Kumbhakar (2004)). In addition, we consult maximization diagnostics and prefer a model with three latent classes, $j = 3$.[26] Wald tests of the significance of differences between group-specific production parameters confirm that factor elasticities are significantly different across groups.

5.4.2 ICT Adoption and Heterogeneity in Production Technologies

Results from estimating the LCSF model with three classes are shown in table 5.2. Parameter estimates used to calculate output elasticities with respect to capital, high- and low-skilled labor are shown for each class. Note that the regime-specific vectors of production technology parameters are estimated simultaneously. Scale economies at the firm level equal the sum of these partial derivatives per input with respect to output. For each technology regime of retailers these are larger than unity, which indicates (on average) the presence of increasing returns to scale at the firm level (see table 5.3 and the discussion of scale economies in retailing below). Parameter estimates for λ ($\lambda_j = \sigma_{uj}/\sigma_{vj}$, where σ_{uj} is the standard error of the inefficiency term and σ_{vj} the standard error of the measurement error term) are significantly different from zero, which implies the presence of inefficiency. In the bottom row, the share of firms shows the allocation of the mass of the discrete distribution to the latent classes. Approximately 16 percent of the retailers in our

[25] The P-value for the Wald test of no inefficiency is 0.00, and the P-value for the additional input coefficients from the translog functional form is 0.00 as well.

[26] All models with more than three pre-specified classes failed to converge. These maximization problems mirror those in other studies (e.g. Orea and Kumbhakar (2004) fail to achieve convergence for a model with five classes). By adjusting convergence criteria, we obtained class-specific production frontier parameter estimates for a model with four classes. However, the fourth class was small (less than one percent). More importantly, the first-order derivatives did not approximate zero.

sample belong to the first class. This compares with 25 percent in the second class, and 59 percent in the third class.

Of particular interest are the ICT coefficients in the latent class probability functions (the bottom part of table 5.2). For all classes ICT coefficients are statistically significant at the 1 percent level. Therefore, retailers do not share a common technology and ICT use significantly determines the firm-specific group membership probability. For the first class, we find a significant positive sign for ICT use. This implies that higher ICT use is related to a higher probability for a retailer of belonging to the first technology regime relative to belonging to the reference group (group three in our case). For the second class, the negative sign for ICT use indicates that lower ICT use is related to a higher probability of belonging to the second class (again relative to the reference group).

Before investigating the characteristics of the different regimes in more detail, note that the parameter estimates of the fixed effects frontier in general lie within the range of parameters from the latent classes (see table 5.2). Wald tests indicated already that parameters of the latent classes are significantly different. The results indicate systematic differences in production technologies, to the extent that assuming a single technological regime may be a poor approximation.

Descriptive statistics of the latent classes are presented in table 5.3. Three main differences across Chilean retailers emerge from the distinction of technology regimes by the LCSF model. First, firms in the first class are largest on average. These firms have the highest number of unskilled employees, which are probably hired to stock shelves and check out customers. These firms make relatively more use of the "advanced" ICT options, such as realizing sales and purchases via the internet. Second, firms in the second class are smallest on average. Firms in the second class show substantial variation in efficiency, and make less use of ICT. Third, most firms are in the third class. Firms in this class operate their production technology most efficiently. And ICT adoption is somewhat higher than for firms in the second class, although it is below the first class on all indicators of ICT use. We label the first group of Chilean retailers as high-intensive ICT users, the second group as low-intensive ICT users, and the third group as medium-intensive ICT users. The positive correlation between ICT use and firm size will be discussed in Section 5.4.3.

The output elasticities of the production factors are obtained by taking the derivative of Equation (5.7) with respect to the inputs. Some direct and interacted parameter estimates are negative, but the average output elasticities of the produc-

Table 5.2. Production frontier parameter estimates FESF and LCSF models

Model	FESF	LCSF		
Class		**1**	**2**	**3**
Production frontier				
Intercept		11.04***	8.31***	9.01***
$\ln K$	-0.10***	-0.21***	-0.13**	-0.09***
$\ln HSL$	0.70***	0.27**	-0.39	0.69***
$\ln LSL$	0.73***	0.57***	1.56***	0.67***
$\frac{1}{2}\ln K^2$	0.03***	0.03***	0.05***	0.03***
$\frac{1}{2}\ln HSL^2$	0.04	-0.01	0.46	0.10*
$\frac{1}{2}\ln LSL^2$	0.03***	0.002	0.11*	0.05***
$\ln K \times \ln HSL$	-0.02***	0.002	0.12**	-0.04***
$\ln K \times \ln LSL$	-0.01***	0.01***	-0.10***	-0.01***
$\ln HSL \times \ln LSL$	-0.05***	-0.04*	-0.31***	-0.03
$Sector_1$		-0.18	0.02	-0.05
$Sector_2$		-0.28**	-0.04	-0.03
$Sector_3$		0.004	0.13	0.14***
σ	1.17***	0.40***	1.68***	0.40***
λ	2.38***	1.47***	5.18***	0.97*
Probabilities				
Intercept		-3.47***	-0.58*	ref. gr.
ICT use		0.43***	-0.26***	ref. gr.
$Sector_1$		1.65***	0.17	ref. gr.
$Sector_2$		2.06***	0.03	ref. gr.
$Sector_3$		1.84***	0.05	ref. gr.
Share of firms		0.16	0.25	0.59

Notes: FESF is fixed effects stochastic frontier. LCSF is latent class stochastic frontier. The number of observations is 1,898. Log-likelihood ratio fixed effects stochastic frontier is -1428.16. Log-likelihood ratio latent class stochastic frontier is -1652.35, AIC is 1.56, BIC is 1.71. *** indicates significance at 1 percent level, ** at 5 percent level, and * at 10 percent level. K is the capital stock, HSL is high-skilled employment, LSL is low-skilled employment, ICT use is a discrete variable which ranges from 0 to 7 from the dummies of internet connection, e-mail address, website, intranet, extranet, purchases and sales via the internet. $Sector_1$: Non-specialized retail trade in stores; $Sector_2$: Retail sale of food, beverages and tobacco in specialized stores; $Sector_3$: Other retail trade of new goods in specialized stores; $Sector_4$: Other retail services, serving as reference group. $\lambda_j = \sigma_{uj}/\sigma_{vj}$, and $\sigma_j = \sqrt{(\sigma_{uj}^2 + \sigma_{vj}^2)}$, where σ_{uj} is the standard error of the inefficiency term and σ_{vj} the standard error of the measurement error term.

tion factors are positive. For each class, we find evidence of (on average) increasing returns to scale. Economies of scale in retailing are a common finding in the literature (see e.g. Ofer (1973); Ingene (1984); Broersma et al. (2003)). Betancourt (2004) discusses three broad sources of economies of scale in retailing: those that are due to some element of fixed cost, those that are due to demand uncertainty, and those that are due to the association between average transaction size and store size. For high-intensive ICT users we find that the relative elasticity of output with respect to capital is higher, whereas for low-intensive ICT users, the relative elasticity of out-

Table 5.3. Descriptive statistics per latent class

Class	**1**		**2**		**3**	
Intensity of ICT use	*High*		*Low*		*Medium*	
	Mean	SD	Mean	SD	Mean	SD
Frontier variables						
ln K	11.00	3.26	8.61	3.49	9.74	3.41
ln HSL	0.67	0.93	0.24	0.48	0.39	0.71
ln LSL	3.12	1.99	1.72	1.60	2.44	1.65
ICT use	2.34	1.76	0.90	1.37	1.29	1.54
Ancillary parameters						
Log of labor productivity	9.06	0.41	7.27	1.03	8.32	0.39
Technical efficiency	0.88	0.05	0.43	0.22	0.90	0.04
Output elasticity K	0.40	0.19	0.56	0.28	0.36	0.15
Output elasticity HSL	0.15	0.09	0.32	0.53	0.28	0.17
Output elasticity LSL	0.68	0.04	1.04	0.31	0.82	0.14
Returns to scale	1.23	0.16	1.92	0.48	1.46	0.17
	Share		Share		Share	
Share of firms with						
Internet connection	74%		36%		48%	
E-mail adress	70%		31%		43%	
Website	35%		8%		15%	
Intranet	29%		9%		13%	
Extranet	14%		2%		4%	
Purchases via internet	6%		2%		3%	
Sales via internet	6%		2%		3%	
Share of firms in						
$Sector_1$:	29%		31%		29%	
$Sector_2$:	19%		25%		22%	
$Sector_3$:	49%		33%		37%	
$Sector_4$:	3%		11%		12%	
Observations	394		366		1138	

Note: Observations for 2003 and 2004 are combined. Labor productivity is value added divided by the sum of high- and low-skilled labor. The values (in thousands of Chilean pesos) of value added, and capital are deflated. Other retail services include: retail sale of second-hand goods in stores, retail trade not in stores, and repair of personal and household goods. K is the capital stock, HSL is high-skilled employment, LSL is low-skilled employment, ICT use is a discrete variable which ranges from 0 to 7 from the dummies of internet connection, e-mail address, website, intranet, extranet, purchases and sales via the internet. Standard deviations are in italics. $Sector_1$: Non-specialized retail trade in stores; $Sector_2$: Retail sale of food, beverages and tobacco in specialized stores; $Sector_3$: Other retail trade of new goods in specialized stores; $Sector_4$: Other retail services.

put with respect to low-skilled labor (LSL) is higher. This suggests differences in output enhancing strategies across the different production technologies. It should be noted, however, that the standard deviations for several scale elasticities (in particular HSL) across firms within the three classes are fairly large.

Labor productivity is highest in the first class. Productivity and efficiency in table 5.3 should be carefully distinguished. The average productivity of retailers in the different classes can be directly compared and straightforwardly interpreted.

However, the efficiency of retailers is measured by each firm's position relative to its group-specific technology frontier, reflected in $u_{it|j}$. For example, most retailers in the third class are close to their technology frontier. Many retailers in the second class are far from their frontier. So ample scope exists in the second class to increase productivity by reducing inefficiency and thereby moving closer to their appropriate technology frontier. Labor productivity is lowest in the second class. Thus, productivity is higher in classes with more intensive ICT use. In particular, the first class uses ICT most intensively and is also the most productive regime. Indicators of internet use confirm the differences. For example, the share of retailers in the first class with an internet connection is 74 percent. This compares with 36 percent in the second class. While 35 percent of retailers in the first class had a website, this is only 8 percent in the second class. Labor productivity in the first class is 1.7 log points higher than in the second class.

Finally, subsectors appear reasonably distributed across classes. For example, the share of firms within a class from non-specialized retail trade in stores is approximately equal. Nevertheless, we cannot rule out that some of the uncovered heterogeneity may be partly associated with variation across subsectors of the retail sector. For example, retail of second-hand goods is mainly grouped into the low- and medium intensive ICT using class.[27]

5.4.3 Robustness Analysis

Based on the estimation of a LCSF model with three classes, we find that Chilean retailers do not share a common production technology and ICT use has a significant influence on the probability of more productive production technology regime membership. Here, we examine the robustness of these results.

First, ICT use is positively related to firm size. That is, some potential indirect benefits from ICT use (such as intranet) are not used by smaller retailers, and larger retailers have higher investments in ICT (see also Doms et al. (2004)).[28] While higher ICT investments by larger retailers are already accounted for in the production frontier, we are able to further examine the effects of ICT use in the probability model. To examine this issue, we divide our measure of ICT use in two parts. The

[27] Estimating the model without retailers of second-hand goods gives similar results.

[28] To examine the relation between the size distribution and ICT use, we grouped retailers according to firm size. We find that 68 percent of small firms (less than 20 employees) make no use of internet connection, e-mail address, and a website. 92 percent of small firms do not use an intranet, extranet, or make purchases and or sales via the internet. This compares to 12 percent and 39 percent respectively for large firms (more than 100 employees).

first part, labelled $ICTuse_{low}$, incorporates the dummies on internet connection, e-mail address, and a website. These proxies for ICT use are not necessarily related to firm size. The second part, labelled $ICTuse_{high}$, incorporates the dummies on intranet, extranet, and purchases and sales via internet. Results are shown in table 5.4. Coefficients of the production frontier are similar in this model specification compared with the results reported in table 5.2. Coefficients in the probability model for $ICTuse_{low}$ and $ICTuse_{high}$ are consistent with the previous results as well. In addition, these results suggest that heterogeneity in production technologies is related to the use of relatively "simple" technologies, which are not necessarily related to firm size.

Second, ICT use in the probability model might be endogenously related to inputs in the production frontier. In particular, the use of ICT might be related to skilled employment (Brynjolfsson and Hitt, 2000). Interestingly, the correlation between ICT use and high-skilled employment is 0.43, whereas the correlation between ICT use and low-skilled employment is 0.54. This suggests that ICT skill complementarities are not obvious in our sample of Chilean retailers. Instead, more intensive ICT use in the retail industry might suggest a substitution effect of relatively well-skilled staff and ICT. For example, some tasks of local branch managers such as identification of candidate products for sales activities may be automated by ICT.

Ideally, we would combine the approach suggested in Olley and Pakes (1996) and Levinsohn and Petrin (2003) to address further simultaneity problems when factor inputs are correlated with productivity with the flexibility of the LCSF model suggested here. Unfortunately, stochastic frontier models do not explicitly allow controlling for this endogeneity concern. This might result in biased parameter estimates in the production function, although there is no reason to expect that biases in the parameters will move in opposite directions across the latent classes. In a partial attempt to control for endogeneity, we specified the (one year) lag in ICT use. This effectively halved our sample and based on likelihood ratios, Akaike and Bayesian information criteria we chose a model with three classes. While this specification corroborates the result of a significant relation between ICT and heterogeneity of production technologies, we caution that a generally higher sensitivity of the model towards maximization choices limits the scope to draw firm inference.[29] Future research towards more explicit methodological advances to control for endogenous factor choice in stochastic frontier analysis is warranted.

[29] Results are available from the authors upon request.

Table 5.4. Distinction between size-related and size-unrelated ICT measures

Model	LCSF		
Class	**1**	**2**	**3**
Production frontier			
Intercept	11.02***	8.47***	9.01***
$\ln K$	-0.21***	-0.11**	-0.09***
$\ln HSL$	0.25	-0.61	0.62***
$\ln LSL$	0.57***	1.43***	0.65***
$\frac{1}{2}\ln K^2$	0.03***	0.04***	0.03***
$\frac{1}{2}\ln HSL^2$	-0.02	0.85	0.09*
$\frac{1}{2}\ln LSL^2$	0.005	0.08	0.05***
$\ln K \times \ln HSL$	0.003	0.12*	-0.04***
$\ln K \times \ln LSL$	0.01	-0.08***	-0.01***
$\ln HSL \times \ln LSL$	-0.04	-0.32***	-0.03*
$Sector_1$	-0.19*	-0.05	-0.06
$Sector_2$	-0.28***	-0.05	-0.03
$Sector_3$	0.02	0.10	0.15***
σ	0.42***	1.56***	0.37***
λ	1.53***	4.99***	0.85*
Probabilities			
Intercept	-3.37***	-0.25	ref. gr.
$ICTuse_{low}$	0.50***	-0.31***	ref. gr.
$ICTuse_{high}$	0.27*	-0.22	ref. gr.
$Sector_1$	1.72***	-0.03	ref. gr.
$Sector_2$	2.12***	-0.04	ref. gr.
$Sector_3$	1.78***	0.02	ref. gr.
Share of firms	0.17	0.29	0.54

Notes: the number of observations is 1,898. Log-likelihood ratio latent class stochastic frontier is -1662.77, AIC is 1.57, BIC is 1.73. *** indicates significance at 1 percent level, ** at 5 percent level, and * at 10 percent level. K is the capital stock, HSL is high-skilled employment, LSL is low-skilled employment, $ICTuse_{low}$, incorporates the dummies on internet connection, e-mail address, and a website, $ICTuse_{high}$, incorporates the dummies on intranet, extranet, and purchases and sales via internet. $Sector_1$: Non-specialized retail trade in stores; $Sector_2$: Retail sale of food, beverages and tobacco in specialized stores; $Sector_3$: Other retail trade of new goods in specialized stores; $Sector_4$: Other retail services, serving as reference group. $\lambda_j = \sigma_{uj}/\sigma_{vj}$, and $\sigma_j = \sqrt{(\sigma_{uj}^2 + \sigma_{vj}^2)}$, where σ_{uj} is the standard error of the inefficiency term and σ_{vj} the standard error of the measurement error term.

5.5 Conclusion

This chapter examines the relation between ICT use and heterogeneity in production technologies for retailers in a developing country, namely Chile. We argue that the implications of ICT adoption for company organization and cost structures may be so pervasive that it makes sense to generalize the translog by allowing separate regimes, rather than treat ICT capital as just an additional factor input, which would be the more orthodox approach. Methodologically, we aim to advance by estimating in a single stage a latent class stochastic frontier model in order to obtain class-specific production frontier parameters, firm-specific inefficiency, and the probability that a firm belongs to a latent technology regime related to ICT use. We use a unique data set provided by the Chilean statistical office which includes detailed firm-level data on ICT, financial accounts, and further economic information for 2003 and 2004.

We identify three significantly different production technologies across Chilean retailers. In addition, ICT use is a significant determinant of firm-specific technology regime membership probabilities. Firms in the first group, comprising around 20 percent of all retailers, incur some inefficiency but also exhibit the highest productivity in our sample. The (relatively large) firms in this group are the most intensive ICT users as well. The inefficiencies that firms in this group incur are moderate and might be attributable to operational slack associated with learning effects in using new technologies. The second group comprises around 25 percent of all Chilean retailers. Firms in this group are smaller, have the lowest labor productivity, and are inefficient. Firms in this technology class have ample scope to improve their performance by optimizing the use of their production technology. Their inefficiency implies that policies to foster ICT adoption among these firms is not the only and perhaps not even the best way to enhance performance. Perhaps economic gains from providing technical assistance are larger than providing incentives for ICT adoption to these firms.

Overall, the significant relation between ICT use and group membership identification remains intact across a range of different ICT and capital proxies. The significance of this relation is also robust to an alternative lag structure, which we specify to address endogeneity concerns regarding ICT use and production factors. Other simultaneity problems when factor inputs are correlated with productivity have been addressed by industrial organization methods of production function estimation, such as Olley and Pakes (1996), Levinsohn and Petrin (2003), or Ackerberg et al. (2005). Stochastic frontier models do not allow controlling for these endogeneity concerns, and future research to combine their rigorous endogeneity treatment with the adjustment for multiple technologies and inefficiency in this chapter would certainly be fruitful. A related literature explores why firms differ in terms of ICT adoption (see Stoneman (2002) for an overview). Uncertainty related to the payoffs from new technologies and differential rates of returns from ICT adoption across firms are potential underlying reasons for the incomplete diffusion of ICT.

Given the paucity of research on inter-firm and intra-firm ICT diffusion in developing countries, this is a second important area for future research. Finally, although our analysis concerns ICT adoption among retailers, the approach may be extended to other industries and technologies that have far-reaching effects on the nature of production technologies. For example, the adoption of genomic technologies by pharmaceutical companies is incomplete and may result in different production technologies for these firms.

Chapter 6

Conclusions

This thesis studied the relation between policy reforms and productivity performance. Latin America offers a fertile ground to study this relation because of large swings in government policy. The chapters in this thesis used retail firm-level data for two Latin American countries, namely Brazil and Chile. The results showed that heterogeneity at the firm-level is at the core for understanding the relation between policy and productivity. This thesis addressed the following research questions:

- Did the opening up of the retail sector improve firm-productivity dynamics?
- Do taxes and access to credit affect the allocation of factor inputs across firms?
- Are formal firms more productive than informal firms?
- Is ICT related with heterogeneity in production processes across firms?

In this chapter, we present an overview of the results reported in the thesis.

Chapter 2 examined the effects of liberalization on productivity growth in Brazil's retail sector. The opening up of the retail sector was expected to raise productivity growth through the entry and expansion of high-productivity national and international retail chains. Thus, the main effects of the reforms were expected to work through reallocation dynamics.

We decomposed growth into the contribution from within-firm improvements and reallocation dynamics during 1996-2004. We found substantial churning, with average annual entry rates of 25 percent and exit rates of 18 percent. However, two findings suggested that reforms did not live up to expectations. First, we found no strong tendency of retail chains displacing independent stores. In fact, the employment share of single-establishment firms increased slightly in the period following the reforms. Second, the contribution of reallocation dynamics to growth was negative, averaging -1.7 percentage points per year, whereas within-firm improvements contributed 2.8 percentage points per year.

In the US, chains of convenience stores with bargaining power, centrally performed operations, and best-practice operations have been displacing single-shop convenience stores for several decades. Three aspects were considered that might explain why the Brazilian retail sector does not show patterns similar to the US. First, business regulation is slowing down the expansion of retail chains. Second, the quantity, quality, and orientation of rail and road networks is holding back the emergence of national distribution systems and thereby the expansion of chains. Furthermore, early investments in railways were meant to integrate Brazil in the international economy (that is, to export primary products) rather than to integrate the regions into a large domestic market. Third, demand factors, such as ingrained preferences for shopping on markets, influence the expansion of multi-establishment firms. However, other demand factors are slowly favoring modern retail formats, such as the increasing female labor force participation (shifting demand to one-stop shopping), the recent improvements in the income distribution, and the growing middle class. The analysis in chapter 2 indicated that distinguishing firms by size is important to understand the relation between the opening up and the productivity performance of the retail sector.

In **chapter 3** we examined the role of allocative efficiency in explaining low growth following the reforms. In this chapter, we followed a novel methodological approach which uses the gaps between marginal revenue products and input prices to measure resource allocation. We applied the model to the detailed census dataset of Brazilian retail firms that was used in chapter 2 as well. Wedges between the opportunity cost and marginal product of factor inputs were measured and implications for aggregate productivity were imputed. The results indicate large potential productivity gains from the reallocation of resources toward the most efficient retailers. Importantly, we find limited evidence for improvements in allocative efficiency. Potential output gains from resource reallocation have not been realized during the 1996 to 2006 period. This finding is consistent with chapter 2 and supports the view that the absence of productive reallocation is underlying low growth in Latin America following reforms.

After obtaining measures of distortions and examining its implications for aggregate productivity, we related these distortions with regional variation in regulation using a differences-in-differences approach. Selective policy implementation and enforcement may create implicit or *de facto* differences in the business environment small and large firms face. Therefore, we allowed the coefficients in our econometric model to vary by firm size. We find that difficulty in access to credit results in distortions to capital for small and medium firms, but not for large firms. In contrast, taxes on gross profits create distortions to output for large firms, but do not significantly affect the output of small and medium firms. Hence, the results suggest that regulation results in distortions to output and capital, but the effects differ by firm size. Separating output and capital distortions is important to relate regulation with productivity distortions due to opposing effects of regulation across size class and type of distortion.

Chapter 4 focused on heterogeneity in regulatory compliance. While the census dataset used in chapter 2 and chapter 3 only considered firms registered at the tax authority, this chapter used a survey of about 11,000 small Brazilian retail firms with detailed information on regulatory compliance. This chapter examined whether small formal retailers are more productive than their informal counterparts. We simultaneously estimated a stochastic production frontier and an efficiency model.

We find that the difference in efficiency levels between formal and informal retailers is large in a 'naive' specification without controls for selection bias and a set of firm, industry, and firm-owner characteristics. However, if we control for selection bias and the set of characteristics, our findings still indicate that formal retailers are more efficient, although the difference is smaller. Hence, our results suggest that business registration reforms, which positively affect the decision of firms to formalize (e.g. the SIMPLES program in Brazil), will increase productivity growth.

Chapter 5 examined the relation between ICT use and heterogeneity in production technologies for retailers in Chile. We argued that the implications of ICT adoption for company organization and cost structures may be so pervasive that it makes sense to generalize the production function by allowing separate technology regimes, rather than treat ICT capital as just an additional factor input, which would be the more orthodox approach. We used a unique data set provided by the Chilean statistical office which includes detailed firm-level data on ICT, financial accounts, and further economic information for 2003 and 2004.

We identified three significantly different production technologies across Chilean retailers. In addition, ICT use is significantly related with differences in production processes across firms. We find important differences across the groups.

One group consists of firms that are intensive ICT users. The inefficiencies that firms in this group incur are moderate and might be attributable to operational slack associated with learning effects in using new technologies. Another group comprises firms with high inefficiency. Firms in this technology class have ample scope to improve their performance by optimizing the use of their production technology. Their inefficiency implies that policies to foster ICT adoption among these firms is not the only and perhaps not even the best way to enhance performance. Perhaps economic gains from providing technical assistance to improve the efficiency in using ICT are larger than providing incentives for ICT adoption to these firms. Hence, firm-heterogeneity affects the potential of policies to improve productivity performance.

In a nutshell, the studies in this thesis have shown that firm-heterogeneity affects the potential of particular policies to improve productivity performance.

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Samenvatting

Dit proefschrift bestudeert de relatie tussen beleidshervormingen en productiviteitsgroei. Het beargumenteert dat het onderkennen van de diversiteit van bedrijven aan de basis ligt voor het begrijpen van de relatie tussen beleid en productiviteit. De verschillende hoofdstukken in dit proefschrift richten zich op twee Latijns Amerikaanse landen, namelijk Brazilië en Chili. Latijns Amerika heeft een grote verandering in overheidsbeleid ondergaan. Deze radicale beleidsverandering biedt mogelijkheden om het effect van beleid op productiviteit te bestuderen.

De beleidsverandering was de verschuiving van een door de staat geleide economie naar een door de markt geleide economie. Na de schuldencrisis van 1982 werd de invloed van de overheid drastisch gereduceerd en vervangen door marktwerking. Helaas voldeden de hervormingen niet aan de verwachtingen. De groei na de hervormingen was matig en zelfs lager dan voor de crisis. De lage productiviteitsgroei in Latijns Amerika is een bron van zorg voor beleidsmakers, omdat het de welvaart van een land bepaalt.

Dit proefschrift probeert een bijdrage te leveren aan het oplossen van de puzzel van een lage groei in Latijns Amerika ondanks hervormingen. Aan de hand van bedrijfsdata voor de detailhandelssector wordt dieper op deze puzzel ingegaan. Specifiek komen de volgende onderzoeksvragen aan bod:

- Zorgt het openstellen van de detailhandelssector voor buitenlandse concurrentie in een verbetering van de productiviteit?

- Beïnvloeden belastingen en toegang tot krediet de plaatsing van werknemers en kapitaal over bedrijven?

- Zijn geregistreerde bedrijven productiever dan bedrijven die de regelgeving en wetten ontduiken?

- Is het gebruik van Informatie en Communicatietechnologie (ICT) een onderscheidend karakteristiek van het productieproces van een bedrijf?

Hoofdstuk 2 bestudeert het effect van buitenlandse concurrentie op productiviteit in de Braziliaanse detailhandelssector. Brazilië stelde de detailhandelssector open voor buitenlandse bedrijven in 1995. Academici en politici verwachtten dat de toetreding en uitbreiding van nationale en internationale detailhandelsketens, als gevolg van de liberalisatie, zou leiden tot een groei in productiviteit.

In dit hoofdstuk wordt een uitgebreide database van detailhandels gebruikt om te bestuderen wat er gebeurde met productiviteit na de liberalisatie. Twee met elkaar samenhangende resultaten verklaren waarom de beleidshervormingen niet tot een groei in productiviteit hebben geleid. Ten eerste is er geen noemenswaardige tendens te bespeuren dat detailhandelsketens de minder productieve zelfstandige ondernemingen uit de markt concurreren. Ten tweede vindt er geen verschuiving van werknemers en investeringen naar meer productieve ondernemingen plaats na de hervormingen.

In de V.S. is al langere tijd een tendens gaande dat kleine 'mom-and-pop stores' plaatsmaken voor detailhandelsketens. Dit leidt in de V.S. tot een substantiële groei in productiviteit. Waarom vindt er niet iets soortgelijks plaats in Brazilië? Ten eerste verhindert zeer strikte regelgeving de uitbreiding van detailhandelsketens. Ten tweede weerhoudt de kwantiteit, kwaliteit en oriëntatie van spoor- en wegennetwerken de opkomst van nationale distributiesystemen voor detailhandels. Investeringen in het verleden in spoorwegen hadden bijvoorbeeld tot doel om Brazilië te integreren in de wereldeconomie (dat is, primaire goederen te exporteren), in plaats van het creëren van een grote binnenlandse markt. Ten derde beïnvloeden vraagfactoren, zoals de voorkeur voor het winkelen op de markt, de uitbreiding van detailhandelsketens. Echter, andere vraagfactoren, zoals de toenemende participatie van vrouwen in de arbeidsmarkt en de recente verbeteringen in de inkomensdistributie, zorgen voor een verschuiving in het voordeel van ketens. Dit suggereert dat wanneer regulering versoepelt en de infrastructuur verbetert, een detailhandelsrevolutie mogelijk is.

In hoofdstuk 3 wordt dieper ingegaan op de vraag waarom er geen verschuiving van werknemers en investeringen naar meer productieve ondernemingen plaats vindt na de hervormingen. Opnieuw wordt de census van detailhandels gebruikt, net als in hoofdstuk 2. De toepassing van een nieuwe methodologie - die verschillen tussen de marginale opbrengsten en de marginale kosten van kapitaal en arbeid meet - zorgt voor een frisse blik op de vraag waarom productieve bedrijven niet groter worden na de hervormingen. Ook hier suggereren de resultaten dat er geen herverdeling van kapitaal en arbeid plaats vindt. Dit is consistent met de bevindingen in hoofdstuk 2 en onderbouwt de visie die stelt dat het ontbreken van herplaatsing van werknemers en investeringen naar productieve ondernemingen verantwoordelijk is voor de lage groei in Latijns Amerika na de hervormingen.

De nieuwe methodologie die wordt toegepast in dit hoofdstuk biedt ook de mogelijkheid om te bestuderen of de verkeerde plaatsing van arbeid en investeringen over bedrijven gerelateerd is aan regulering. Ondanks de liberalisatie zijn de arbeids- en de productmarkt van Brazilië nog sterk gereguleerd. Belastingen bedragen bijvoorbeeld 200 procent van de bruto winsten in Rio de Janeiro. De selectieve wetshandhaving kan impliciet of de facto zorgen voor verschillen in de marktomstandigheden voor kleine en grote bedrijven. Vaak vinden overheden in Latijns Amerika het onpraktisch om belasting te heffen op kleine bedrijven. Overheden vinden het makkelijker om hogere belastingvoeten te handhaven en die te heffen op grote bedrijven. Maar de toegang tot krediet en strikte arbeidsregulering zijn mogelijk grotere obstakels voor de groei van kleine bedrijven. Imperfecties in de kapitaalmarkt kunnen bijvoorbeeld een groter probleem zijn voor kleine bedrijven ten opzichte van grote ondernemingen, omdat ze niet over voldoende onderpand beschikken.

Door middel van econometrische methoden vinden we dat het moeilijk verkrijgen van krediet de investeringsbeslissingen van kleine- en middelgrote bedrijven beïnvloedt, maar niet die van grote bedrijven. In tegenstelling, belastingen op bruto winsten beïnvloeden de productie van grote bedrijven, maar niet die van kleine- en middelgrote bedrijven. De resultaten suggereren dus dat de effecten van regulering afhangen van de grootte van het bedrijf. Beleidsmakers moeten daarom rekening houden met de diversiteit van bedrijven wanneer regulering wordt herzien.

Hoofdstuk 4 richt zich op verschillen in de naleving van wetten en regels door bedrijven. In dit hoofdstuk wordt gebruik gemaakt van een zeer gedetailleerde vragenlijst die is afgenomen onder meer dan 11000 kleine Braziliaanse detailhandels, met uitgebreide informatie over de naleving van wet- en regelgeving. De enquêteurs bezochten huishoudens en verzekerden eventueel aanwezige eigenaren van de detailhandels dat alle informatie die ze verstrekten niet tegen hen kon worden gebruikt in de rechtszaal. Hierdoor biedt deze enquête een unieke mogelijkheid om ondernemers te bestuderen die zich normaal verborgen houden voor de staat.

Specifiek bestudeert dit hoofdstuk of bedrijven die de wet- en regelgeving naleven (geregistreerde bedrijven) productiever zijn dan bedrijven die dat niet doen (niet-geregistreerde bedrijven). De econometrische aanpak controleert onder meer voor bedrijfs-, industrie- en ondernemerskarakteristieken, om er zeker van te zijn dat verschillen in productiviteit tussen bedrijven zich daadwerkelijk voordoen, en niet komt doordat bijvoorbeeld een bedrijf wordt geleid door een betere manager. De resultaten suggereren dat verschillen in productiviteit tussen geregistreerde bedrijven en niet-geregistreerde bedrijven groot zijn als er niet wordt gecontroleerd voor zelfselectie en de bedrijf-, industrie- en ondernemerskarakteristieken. Echter, als we controleren voor zelfselectie en de serie karakteristieken, dan suggereren de resultaten nog steeds dat geregistreerde bedrijven productiever zijn, hoewel de verschillen kleiner worden.

De implicaties van deze bevindingen zijn belangrijk voor het overheidsbeleid. Veel overheden in Latijns Amerika hebben namelijk hervormingen in de bedrijfsregistratie doorgevoerd om bedrijven ertoe te bewegen de wetten en regels na te leven. De resultaten in dit hoofdstuk suggereren dat wanneer meer bedrijven zich registreren, de productiviteit zal toenemen. Dit is mogelijk, omdat geregistreerde bedrijven vrijuit kunnen adverteren en technische assistentie krijgen van de overheid. Echter, alleen bedrijven verleiden om zich te registreren is niet genoeg. Zoals beargumenteerd in hoofdstuk 3, is het verbeteren van de toegang tot krediet en hervormingen van de arbeidsmarkt noodzakelijk voor het verbeteren van de groeivooruitzichten van kleine productieve bedrijven.

Het laatste doel van dit proefschrift is het bestuderen van de relatie tussen productiviteit en informatie en communicatie technologie. Hoofdstuk 5 beargumenteert dat de adoptie van ICT zulke verstrekkende gevolgen heeft voor de organisatie en de kostenstructuur van bedrijven, dat de adoptie van ICT het volledige productieproces beïnvloedt. In dit hoofdstuk wordt gebruik gemaakt van een unieke dataset, verstrekt door het statistisch bureau van Chili, met gedetailleerde informatie over de investeringen en het gebruik van ICT door Chileense detailhandels.

De toepassing van een nieuwe econometrische techniek, een 'latent class stochastic frontier model', biedt de mogelijkheid om te bestuderen of ICT een latente factor is die het productieproces van een bedrijf verandert. We vinden dat het productieproces van detailhandels inderdaad van elkaar onderscheiden kan worden naar gelang de intensiteit waarmee gebruik wordt gemaakt van ICT. De resultaten suggereren dat ICT niet de enige en mogelijk ook niet de beste manier is om de efficiëntie van detailhandels in Latijns Amerika te verbeteren. De economische voordelen van het geven van assistentie in het verbeteren van management en organisatieprocessen zijn mogelijk groter dan het verstrekken van economische prikkels voor de adoptie van ICT. Dit verschilt echter tussen bedrijven naar gelang het gebruik van ICT.

Kort samengevat, de diversiteit van bedrijven is een cruciale factor die meegenomen moet worden in het analyseren en verklaren van het effect van beleid op productiviteit.