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Essays on Technology, Productivity and Misallocation

Tanida Arayavechkit

University of Pennsylvania, tanidayui@gmail.com

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Essays on Technology, Productivity and Misallocation

Abstract
There is a growing consensus that aggregate productivity is the most important factor in determining income per capita and living standards. The deep causes of productivity are technology and resource misallocation, which are the outcomes of firms' decision making. Thus, a solid understanding of a firm-level mechanism is central to economic development. This dissertation consists of three chapters, each of which studies firms' decision making under different economic environments.

Chapter 1 studies firms' technology and production choices in the context of information frictions and financial frictions. Empirical evidence suggests a positive role of financial development in firms' technology adoption and the speed of technology diffusion. The chapter examines the role of information acquisition and financial development in explaining how technology differences may arise and persist during the technology adoption process. This, in turn, affects a country's total factor productivity (TFP) level and the speed of TFP convergence. The quantitative study is applied to the Chilean manufacturing sector during the period of 1986-2007.

Chapter 2 studies firms' technology and production choices in the context of trade liberalization. Empirical evidence shows that, in a low-income country, trade liberalization triggers within-industry changes in firms' skill intensity and productivity, as well as between-industry labor reallocation. The chapter examines the role of comparative advantage and trade cost reduction in determining aggregate productivity and the demand for skills through firm-level adjustment. The quantitative study is applied to the impact of Indonesia's trade reform in 1995 on the Indonesian manufacturing sector.

Chapter 3 studies firms' rent-seeking behavior and production choices when tax benefits are tied to capital holding. Evidence shows that the dominant issue of corporate lobbying in the U.S. is taxation. Firms that lobby are granted tax benefits and enjoy systematically lower effective tax rates than non politically active firms. Thus, corporate lobbying distorts the allocation of capital in the economy. The chapter explores the macroeconomic effects of capital-based tax benefits and their interaction with endogenous corporate lobbying behavior. The quantitative study is applied to the U.S. firm-level data during the period of 1998-2011.

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First Advisor
Jeremy Greenwood

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ESSAYS ON TECHNOLOGY, PRODUCTIVITY AND MISALLOCATION

Tanida Arayavechkit

A DISSERTATION

in

Economics

Presented to the Faculties of the University of Pennsylvania

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Supervisor of Dissertation

Jeremy Greenwood, Professor of Economics

Graduate Group Chairperson

George J. Mailath, Professor of Economics,
Walter H. Annenberg Professor in the Social Sciences

Dissertation Committee

Ana Cecilia Fieler, Assistant Professor of Economics
Guillermo Ordonez, Assistant Professor of Economics
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ABSTRACT

ESSAYS ON TECHNOLOGY, PRODUCTIVITY AND MISALLOCATION

Tanida Arayavechkit

Jeremy Greenwood

There is a growing consensus that aggregate productivity is the most important factor in determining income per capita and living standards. The deep causes of productivity are technology and resource misallocation, which are the outcomes of firms’ decision making. Thus, a solid understanding of a firm-level mechanism is central to economic development. This dissertation consists of three chapters, each of which studies firms’ decision making under different economic environments.

Chapter 1 studies firms’ technology and production choices in the context of information frictions and financial frictions. Empirical evidence suggests a positive role of financial development in firms’ technology adoption and the speed of technology diffusion. The chapter examines the role of information acquisition and financial development in explaining how technology differences may arise and persist during the technology adoption process. This, in turn, affects a country’s total factor productivity (TFP) level and the speed of TFP convergence. The quantitative study is applied to the Chilean manufacturing sector during the period of 1986-2007.

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Chapter 1

Technology Choice, Learning Dynamics and Financial Development

Abstract

Why are firms in some countries slower to adopt new technology than firms in other countries? Why do firms in different countries eventually end up with different levels of technology? This chapter studies the role of information acquisition and financial development in explaining how technology differences may arise and persist during the technology adoption process. This, in turn, affects a country’s total factor productivity (TFP) level and the speed of TFP convergence. Empirical evidence suggests a positive role of financial development in firms’ technology adoption and the speed of technology diffusion. A general equilibrium dynamic model is developed to study this relationship. In the model, the process of technology adoption involves learning and financing a higher-level technology project. Financial development affects the cost of information acquisition, which either delays the learning process or causes it to cease prematurely. Firms then operate with sub-optimal levels of technology and production. As a result, poor financial development can cause persistent TFP differences between two countries even if both have the same talent and have access to the same technology ladder. Applying the model to Chilean manufacturing firms, the quantitative analysis shows that an improvement in financial development to a fully efficient level not only increases a country’s TFP by 25% but also doubles the speed of TFP convergence.
1.1 Introduction

Why are firms in some countries slower to adopt new technology than firms in other countries? Why do firms in different countries eventually end up with different levels of technology? Technology, defined broadly as production techniques and knowledge relevant to production, is an important determinant of cross-country variation in total factor productivity (TFP). For a developing country, technology adoption presents an opportunity to close the TFP gaps between it and more advanced economies. Understanding why there are significant differences in technology adoption across countries is thus essential for explaining this observed variation in TFP. The process of technology adoption is known to involve both learning about a new technology and financing its adoption. This paper studies the role of information acquisition and financial development, both theoretically and quantitatively, in explaining how technology differences may arise and persist during the technology adoption process. This, in turn, affects a country’s TFP level and the speed of convergence to a more advanced level of development.

Cross-country data suggest that it is TFP rather than capital accumulation that determines the income per capita differences across countries. [Klenow and Rodriguez-Clare (1997); Prescott (1998); Blundell et al. (1999)]. Two sources of variation in TFP are emphasized in the literature. Parente and Prescott (1994) argue that differences in TFP across firms and countries can generally be explained by barriers to the usage intensity of technologies that embody a higher level of productivity than do older technologies. Hsieh and Klenow (2009), later on, propose that greater misallocation of resources across firms can have important negative effects on aggregate TFP. Following strong evidence supporting the role of financial development in economic development, documented by King and Levine (1993), there is an extensive literature proposing the framework to study the link between TFP and a country’s level of financial development. However, this literature focuses on the impact of financial development through the resource misallocation and capital accumula-
tion channel [Amarel and Quintin (2010); Buera et al. (2011); Greenwood et al. (2010, 2013)]. This paper, by looking at another channel, hypothesizes that variation in TFP is driven by differences in technology adoption, which, in turn, are affected by different levels of financial development. The hypothesis is supported by empirical evidence documented in this paper.

Technology adoption presents an opportunity for developing countries below the technological frontier to close the income gap. Keller (2004) finds that foreign sources of technology account for over 90% of TFP growth for most developing countries. There are two potential factors that determine the technology adoption process: the unknown nature of new technology and the economic environment. Uncertainty is caused by the firm’s lack of prior production history and relevant data about production in a local context. This idea is emphasized by the role of learning in the technology adoption process in the work of Parente (1994) and Jovanovic and Nyarko (1996). The economic environment includes human capital, financial development, and business environment, which determine the ability to absorb and adapt international knowledge and technology. In this paper, evidence is found to support the positive role of financial development in firms’ technology adoption and the speed of technology diffusion. Three data sets are used. First, data in the World Bank Enterprise Surveys is employed to show that firms are less likely to adopt foreign technology if the individual cost of financing is high, or if they operate in a country with poor financial development. Second, the speed of the technology adoption process is studied using the Historical Cross-Country Technological Adoption data set. This provides a long historical time series of technology-use intensity. Technology diffusion is faster in countries with better financial development. Last, panel data from Chilean manufacturing industries is used to keep track of firms’ technology adoption over time. Firms tend to continue using foreign technology if their productivity increased in the previous year. One can think of this as part of a learning and experimenting process using new technology.

To address the impact that financial development has on TFP through the technology
adoption channel, a dynamic model of firm technology adoption and competitive financial intermediaries is developed. Heterogeneous firms climb up a technology ladder to catch up with the world technological frontier. They decide whether to move to a higher technology level and how much to invest in capital. Funding is obtained from financial intermediaries. Without long-term experience with higher-level technology, how talented a firm is at using the technology is initially unknown. Financial intermediaries produce information. They evaluate firms and offer a firm-specific debt contract. There are two methods of loan evaluations. An \textit{ex ante} evaluation is performed using the available loan evaluation technology before an intermediary lends out for the first time. After each production period, an \textit{ex post} evaluation is performed. An intermediary re-evaluates a firm based on its performance and adjusts the debt contract accordingly. In the event of default after each production, financial intermediaries can recover a fraction of output.

Based on these ingredients, both firms and financial intermediaries are Bayesian learners in the context of an information problem. They have some beliefs about how talented the firm is in using higher-level technology. Firms learn and update their beliefs about their talent type by observing their success with a higher-level technology. Therefore, firms make technology adoption decisions by considering both operating profits and learning benefits. Financial intermediaries observe the outcomes of previous loans and update their beliefs given the information available about individual firms and the market as a whole. Financial development is characterized by two indicators: the quality of pre-lending evaluation and the recovery rate on defaulted loans.

The framework provides a link between financial development and firms’ technology adoption. Learning and information accumulation provide a way to overcome the information problem arising in the technology adoption process. Analytical results show that financial development can either impede or facilitate learning through two channels. First, firm-specific borrowing costs and credit access are tied to loan recovery rates. A low recovery rate not only limits adopting firms to starting with a small production size, but also prevents
firms that believe they are low in talent from experimenting with new technology, as these credit constraints increase the information gathering costs. Second, inaccurate pre-lending evaluation precludes potential firms that either receive a bad evaluation or experience a sequence of bad outcomes from adopting higher-level technology. Furthermore, if firms’ capabilities in using higher-level technology are positively correlated with their abilities to use their current technology, firms will need time to accumulate information about their current technology before moving forward, thus delaying the choice of higher-level technology. Because poor financial development either delays the learning process or causes it to cease prematurely, firms operate with sub-optimal levels of technology production. Therefore, even if two countries have the same talent and have access to the same technology ladder, poor financial development can cause TFP differences to arise and persist.

In order to quantify the effect of financial development on a country’s TFP level and speed of convergence, the model is calibrated to the Chilean Annual Manufacturing Survey. The model posits a steady state, in which 50% of potential firms operate at a sub-optimal technology level and cannot move up the technology ladder. The results show that an improvement in financial development to a fully efficient level increases a country’s TFP by 25%. Some transitional dynamics are then undertaken to explore the dynamics of Chilean manufacturing TFP in response to access to the world technology frontier. The resulting path for TFP matches the Chilean TFP index time series relatively well. The path shows a gradual increase in the manufacturing TFP before it levels off. Finally, the speed of TFP convergence is doubled when there is efficient finance.

The paper is organized as follows. Section 1.2 presents empirical findings on technology adoption and financial development to support the hypothesis that variation in TFP is driven by differences in technology adoption, which in turn are affected by different levels of financial development. Then, Section 1.3 gives an overview of the model. Section 1.4 sets up the analytical model with two technology choices and provides analytical results. Section 1.5 proposes the full model where firms have to move up the technology ladder in
order to get closer to the world technological frontier. The quantitative analysis, including the stationary equilibrium and transition dynamics, is performed in Section 1.6. Concluding remarks are then offered in Section 1.7. Appendix A.1 provides details about the data sets used in this paper. Appendix A.2 provides the proofs for all lemmas and propositions from Section 1.4.

1.2 Empirical Evidence

This section documents a positive impact of financial development on technology adoption. First, cross-country firm-level data show a positive relationship between financial development and firms’ decisions on foreign technology adoption. In particular, firms in countries with high levels of financial development, and facing a low cost of financing, tend to adopt foreign technology. Second, cross-country aggregate-level data suggest that financial development and the speed of technology adoption are positively correlated. A country with better financial development experiences a faster rate of technology diffusion and a higher level of TFP.

1.2.1 Firms’ Technology Adoption Decisions and Financial Development

The *World Bank Enterprise Surveys*\(^2\), a firm-level data set collected by the World Bank, is employed to study the relationship between firms’ technology adoption decisions and financial development. In the survey, firms report whether they use foreign technology. This will be used as a proxy for the firm’s technology adoption decision. To get an idea of how this decision is related to the level of financial development, Figure (2) plots a fraction of firms reporting that they employ foreign technology in their production process with two measures of financial development: domestic credit to the private sector and the interest-rate spread. Both measures are taken from the *World Development Indicators*, averaged

\(^2\)See Appendix A.1 for all data definitions.
over the years 2002-2005. Domestic credit to the private sector as a share of GDP reflects how easily a firm has access to credit. With common usage in the literature on finance and growth, the higher ratio of private credit to GDP indicates a higher level of financial development. The interest rate spread is the difference between the interest rate charged by banks on loans to private sector customers and the interest rate paid by banks for demand, time, or saving deposits. It reflects the cost of intermediation. A narrow interest rate spread, therefore, implies a higher level of financial development. Figure (1) shows that the higher the level of financial development, the higher the fraction of firms adopting advanced foreign technology. In other words, firms in a country with a lower cost of financing and better access to finance are more likely to adopt advanced technology.

![Figure 1: Technology Adoption: Firm-Level Data](image)

To formalize the above results, the following logit model is estimated by pooling all firms in the selected sample together:

$$ Adopt_{jkc} = \beta_0 + \beta_{fin} \times FD_{jc} + \beta_j \times Firm_j + \beta_k \times Industry_k + \beta_c \times Country_c + \epsilon_{jkc} $$

where $j$ indexes firms, $k$ indexes industries and $c$ indexes countries. $Adopt_{jkc}$ is a dummy variable that takes value 1 if the firm employs foreign technology in its production process.
and 0 otherwise. \( F_{D_{jc}} \) corresponds to a measure of financial development which will be measured using four indicators: (1) loan recovery rate, (2) interest rate spread, (3) credit depth information index, and (4) firm-specific interest rate.\(^3\) The first three indicators are a country’s level of financial development, while the last indicator is a firm-specific financing barrier. \( Firm_j \) is a matrix of firm characteristics including size, human capital, foreign ownership and foreign activity. \( Industry_k \) are industry dummies. \( Country_c \) is a matrix including GDP per capita, regulation environment, and country dummies.\(^4\)

The estimated coefficients reported in Table (1) confirm that financial development plays an important role in determining the firm’s adoption choice. Higher loan recovery rates reflect a lower expected cost imposed on creditors when insolvency might occur. The positive coefficient on this term indicates that firms in the country with higher recovery rates are more likely to adopt foreign technology. Similarly, the negative coefficient on interest rate spreads indicates that firms in the country with lower spreads tend to adopt foreign technology. Spreads, which reflect a combination of credit risk exposure and costs of intermediation, are the relative cost of financing a project. A credit depth information index, which is a proxy for the quality of loan evaluation, has a positive coefficient. Countries with high quality and accessible credit information usually have higher firm adoption rates. These countries also have high TFP and a low percentage of non-performing loans to gross loans.

At the firm level, self-reported financing obstacles and high interest rates impede firms from adopting foreign technology. In addition, the likelihood of adopting foreign technology is positively related to size, human capital, foreign activity and foreign ownership.

1.2.2 Technology Usage Lags, TFP and Financial Development

The role of financial development is related not only to the technology adoption decision, but also to the speed of technology adoption. This role is suggested by the Historical Cross-...
Table 1: Determinants of Advanced Technology Adoption

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<td>Recovery rate</td>
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<td></td>
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<td>-</td>
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<td>Credit depth of</td>
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<td>0.120**</td>
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<td>information index</td>
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<td>-</td>
<td>-0.086**</td>
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<td>rate</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Workers</td>
<td>0.640***</td>
<td>0.640***</td>
<td>0.640***</td>
<td>0.558***</td>
</tr>
<tr>
<td></td>
<td>(0.089)</td>
<td>(0.089)</td>
<td>(0.089)</td>
<td>(0.112)</td>
</tr>
<tr>
<td>Skilled</td>
<td>0.252**</td>
<td>0.253**</td>
<td>0.252**</td>
<td>0.443***</td>
</tr>
<tr>
<td></td>
<td>(0.114)</td>
<td>(0.114)</td>
<td>(0.114)</td>
<td>(0.162)</td>
</tr>
<tr>
<td>Foreign owned</td>
<td>1.545***</td>
<td>1.544***</td>
<td>1.544***</td>
<td>1.128***</td>
</tr>
<tr>
<td></td>
<td>(0.128)</td>
<td>(0.128)</td>
<td>(0.128)</td>
<td>(0.198)</td>
</tr>
<tr>
<td>Importer</td>
<td>0.697***</td>
<td>0.697***</td>
<td>0.697***</td>
<td>0.454***</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.091)</td>
<td>(0.091)</td>
<td>(0.128)</td>
</tr>
</tbody>
</table>

Industry dummies: Yes, Yes, Yes, Yes
Country controls: Yes, Yes, Yes, Yes
Pseudo $R^2$: 0.13, 0.13, 0.13, 0.10
Number of observations: 6,333, 6,333, 6,333, 2,633

1 *significant at 10%, **significant at 5%, ***significant at 1%
2 †Country controls include GDP per capita, regulation environment, and country dummies.

Country Technological Adoption data set (HCCTA) which provides historical time series of technology usage across countries. Following Comin et al. (2008), the focus is on cross-country technology usage lags: how many years ago the technologies were used in the U.S. with the same intensity as they are used in the countries in the samples. The examples here consider two technologies used in an agricultural sector and a manufacturing sector: fertilizer usage and electric arc furnace steel production technology. Table (2) summarizes technologies, sets of years and sample sizes for this analysis.

Consider the scatterplots presented for a sample of countries in Figure (2). The left panel of each subfigure displays how higher levels of productivity are connected with shorter technology usage lags. Productivity of the agricultural sector and the manufacturing sector
Table 2: Summary of the Date for Technology Usage Lags

<table>
<thead>
<tr>
<th>Technology</th>
<th>Year</th>
<th>Invention year</th>
<th>#Obs</th>
<th>Period of average TFP year</th>
<th>TFP year</th>
</tr>
</thead>
</table>

are proxied by the country’s TFP and the value added in the agricultural sector, respectively. On the left panel in Figure (2), observe that higher levels of financial development are also linked with shorter technology usage lags. Financial development is measured by private credit to GDP ratios. Based on data availability, the measure of financial development is the average private credit to GDP ratios from 1970 to the selected year. This link happens when better financial development implies better access to credit.

(a) Agricultural Technology, Correlation=-0.57  
(b) Manufacturing Technology, Correlation=-0.55

Figure 2: Technology Usage Lags of Two Technolgies

Countries with better financial development exhibit higher speeds of technology diffusion. This result holds even if GDP and per-capita income are controlled for. In particular,
for fertilizer usages:

\[ Lags_{fertilizer} = 56.48 - 0.08 \text{DomCredit} - 0.63 \ln(GDP) - 0.0003 \text{PerCapita}, \quad R^2 = 0.50 \]

and for Electric arc furnaces technology in steel production:

\[ Lags_{Steel} = 203.79 - 0.21 \text{DomCredit} - 5.27 \ln(GDP) - 0.001 \text{PerCapita}, \quad R^2 = 0.61. \]

In sum, a country with a less developed financial system has a smaller fraction of firms adopting foreign technology and a slower technology adoption rate. This country, at the aggregate level, has lower TFP and is slower to catch up with the world technology frontier. The next section proposes a mechanism though which financial development plays a role in a firm’s technology adoption process.

### 1.3 Model

A dynamic model with heterogeneous firms facing technology adoption choices is proposed. Time is discrete and indexed by \( t = 1, 2, 3, \ldots \). The analysis focuses on two types of agents: firms and financial intermediaries. Firms produce output in the economy. They face technology adoption choices in their production process. Productivity of new technology is unknown and risky. Firms might not be talented enough in adopting and adapting new technology to a local context. Without long-term experience with new technology, a firm’s talent is unknown. Production requires working capital, which is funded by financial intermediaries. Financial intermediaries evaluate firms and offer a firm-specific debt contract. There are two types of loan evaluations. An \textit{ex ante} evaluation is performed using the available loan evaluation technology before an intermediary lends out for the first time. After each production, an \textit{ex post} evaluation is performed. An intermediary re-evaluates a firm based on its performance and adjusts the debt contract accordingly. In the event of default after each production, financial intermediaries can recover a fraction of output.
The structure of a debt contract will depend on the estimated default probability and the recovery rate.

Because information about a firm’s talent is unknown, agents in the economy hold some beliefs. A firm and a financial intermediary accumulate information to update their beliefs in a Bayesian fashion. In particular, new information is acquired when a firm decides to operate with new technology. A firm uses the realized profit to update its belief about its talent. An intermediary uses the realized profit to re-evaluate a firm and update its belief on a firm’s default probability. The technology adoption process is then characterized by the processes of learning-by-doing and learning-by-lending.

Next, the analytical model with two technology choices will be set up. A firm’s technology adoption decision is whether or not to adopt a high-level technology. This helps explain the key mechanism and derive the analytical results. After that, the full model, where a technology adoption decision lies along the technology ladder, is presented. A firm’s technology adoption decision is whether to adopt a higher-level technology and move up the technology ladder.

1.4 Analytical Model: Two Technology Choices

For analytical purposes, this section proposes a dynamic model with heterogeneous firms facing only two choices of technology in their production process. In each period, firms choose to operate using either new technology or old technology.

1.4.1 Firms and Technology

There exists a continuum of heterogeneous risk-neutral firms of measure 1 indexed by \( j \in [0, 1] \). The discount factor for firms is denoted by \( \beta \). Given a productivity \( z \), a firm
produces output, $o$, with the following production function.

$$o = zk^\alpha, \ 0 < \alpha < 1.$$  \hspace{1cm} (1.1)

Note that there are diminishing returns to scale in production. A firm finances its input using working capital, $k$, provided by the financial intermediary.

The productivity $z \in \{z^o, z^n\}$, depending on the technology that a firm chooses. There are two kinds of production technology available for each firm: old technology and new technology. In each period, firms choose to operate using either new technology or old technology. Productivity of both technologies is firm-specific. Old technology is an existing technology, with which firms have been operating for a certain period of time. They then have complete knowledge about their productivity, implying the productivity is deterministic. Each firm $j$ possesses the productivity of old technology $z^o$, which is drawn from the distribution $\Phi(z^o)$ on the support $[z^o, \pi^o]$. Assume that every agent in the economy possesses information about existing technology, either from experience or from historical data which are publicly available.

Firms that operate using new technology can either be a high talent type $h$ or a low type $l$. This captures how talented firms are in adopting new technology. Specifically, there is a setup period denoted by $t = 0$ that nature assigns each firm $j$ of the type $\tau^j \in \{h, l\}$, which is unobservable. In this analytical section, assume fraction $\mu$ of firms are high-type firms. This is, however, the common knowledge of every agent. In addition, firms are subject to idiosyncratic risks. For high-type firms, the productivity of new technology $z^n$ is drawn from the distribution $\Psi^h(z^n)$. For low-type firms, it is drawn from the distribution $\Psi^l(z^n)$. Both distributions are defined on the same support $[z^n, \pi^n]$. High-type firms are, on average, more productive, implying $\mathbb{E}_{\Psi^h}(z^n) \geq \mathbb{E}_{\Psi^l}(z^n)$. Lastly, assume that investing in new technology requires the minimum investment size $\varphi$.\(^6\)

\(^6\)Technology adoption usually requires an initial fixed cost. This will prevent firms from investing even a very small amount in new technology to acquire information.
Although information about firm types is incomplete, firms have a prior belief about their type. At the beginning of each period $t$, the firm has a belief that it is of type $h$ with probability $\lambda_f^t$. After each period of production, the firm acquires new information only if it chooses to operate with new technology. The firm observes its realized productivity $z^n$ and updates its belief using Bayes’ rule. In this setting, firms hold heterogeneous beliefs but learn and act in isolation.

1.4.2 Financial Intermediaries and Loan Evaluation

Financial intermediaries are risk neutral and operate in a competitive market. They can borrow in the international credit market at some fixed rate $r$. An intermediary evaluates a firm’s default probability and makes one-period loans to a firm. For regulatory reasons, assume a financial intermediary can only hold debt claims. In the event of default after each production, financial intermediaries can recover a $\xi$ fraction of output. As mentioned before, there are two methods of loan evaluations: an \textit{ex ante} and an \textit{ex post} evaluation. The level of financial development is manifest in the recovery rate and the accuracy of an \textit{ex ante} loan evaluation.

Suppose the firm $j$ borrows to operate a risky project using new technology. There is a probability that it will be insolvent and default. A debt contract specifies loan size, $k$, and the interest rate $i$, which reflect the firm’s default probability. The estimated default probability varies across types. Because the firm’s type is unknown, the structure of a debt contract offered to the firm will depend on the intermediary’s belief about the firm’s type. Denote $\lambda_b^t$ the belief of an intermediary that the firm is of type $h$ at the beginning of each period $t$. If the firm with productivity $z^o$ borrows to finance an old technology project and a new technology project, the sets of debt contracts offered by an intermediary will be denoted by $D^o(z^o, \lambda_b^t)$ and $D^n(z^o, \lambda_b^t)$, respectively.

Consider the pre-lending period $t = 0$. Let $\rho^j$ be common knowledge in the economy.
that firm \( j \) is a high type. With the assumptions that fraction \( \mu \) of firms are type \( h \) and that all firms are equally likely to be type \( h \), \( \rho^j = \mu \) for all \( j \). When firm \( j \) starts borrowing from an intermediary, without any loan evaluation, the most accurate belief that the intermediary can hold about firm \( j \) being a high type is merely the probability \( \rho^j \). However, the intermediary evaluates the firm \textit{ex ante} before lending out for the first time. An initial belief of the intermediary that the firm is of type \( h \), \( \lambda_0^{b,j} \), is set using the available loan evaluation technology. This technology can refer to a default probability model based on firms’ characteristics or financial statistics. To be consistent with the Bayesian feature of the model, the evaluation technology is represented by the intermediary getting the signal about the firm’s type. Specifically, the signal \( \upsilon^j \) is drawn once firm \( j \) starts borrowing from a financial intermediary, where \( \upsilon^j \) can be either \( h \) or \( l \). Conditional on the true type of the firm, the signal is drawn from the distribution

\[
\upsilon^j | \tau^j \begin{cases} 
= \tau^j \text{ with probability } \theta \\
\neq \tau^j \text{ with probability } 1 - \theta
\end{cases}
\]  

where \( \theta \in [0.5, 1] \). The quality of loan evaluation is determined by the parameter \( \theta \), which measures the accuracy of the signal. At one end, the signal is uninformative when \( \theta = 0.5 \). At the other end, the signal perfectly reveals the firm’s type when \( \theta = 1 \). After receiving the signal, the financial intermediary forms an initial belief using Bayes’ rule:

\[
\lambda_{0}^{b,j} (\rho^j, \upsilon^j = h) = \frac{\theta \rho^j}{\theta \rho^j + (1 - \theta)(1 - \rho^j)} \\
\lambda_{0}^{b,j} (\rho^j, \upsilon^j = l) = \frac{(1 - \theta) \rho^j}{(1 - \theta) \rho^j + \theta(1 - \rho^j)}.
\]  

The updating rule shows that an initial belief depends on the quality of the evaluation.

---

\(^7\)As in most developing countries, financial intermediaries play a crucial role in evaluating potential borrowers. The assumption that financial intermediaries perform the evaluation task is valid for several reasons. First, financial intermediaries can use the available loan evaluation technology at a lower cost. In other words, they can be more efficient in evaluating firms than other agents, such as firms, consulting firms or accounting firms. This is a result of specialization and economies of scale. Second, debt contracts offered by an intermediary are usually based on an intermediary’s own evaluation. Firms are less credible when claiming that their project will be successful.
technology $\theta^i$, the signal $v$ and the uninformative prior $\rho^j$. For simplicity of the analysis, assume that the initial belief of firm $j$ is adjusted to that of the intermediary.\footnote{Even though the firm has its own belief, the results from the analysis still hold as long as the intermediary offers debt contracts based on its own evaluation.}

For period $t \geq 1$, if the firm has operated its business using new technology, the intermediary observes the productivity realizations of $z^n$ after production. It then evaluates \textit{ex post} to revise its belief about the firm’s type by Bayesian updating. This posterior belief is used to re-estimate the firm’s default probability, which then determines the interest rate offered to that particular firm in the future. Lastly, assume that there are publicly available historical data and perfect information sharing among financial intermediaries, so every agent shares a common belief.\footnote{An alternative assumption is that the firm signed a contract, so it engages in a long-term lending relationship with the intermediary.}

### 1.4.3 Firms’ Production Choices

A firm starts period $t$ with old technology productivity $z^o$ and belief $\lambda_t$ that it is a highly productive firm in operating new technology. After deciding on the technology choice, the firm chooses how much to invest. This is a static maximization problem. For simplicity, the subscript $t$ will be omitted.

Let $D^o(z^o, \lambda)$ and $D^n(z^o, \lambda)$ be the sets of possible debt contracts offered by an intermediary if the firm borrows to finance an old technology project and a new technology project, respectively. The firm will default on its debts if the production is so unprofitable that a firm is not able to pay back the loan. The problem is trivial if the firm chooses old technology, as $z_o$ is known at the time of borrowing. Denote $\pi^o(z^o, k, i) = \max\{z^o k^o - (1 + i)k, 0\}$. Given $D^o(z^o, \lambda)$, the firm maximization problem is

\[
\max_{(k, i) \in D^o(z^o, \lambda)} \pi^o(z^o, k, i) \tag{1.5}
\]
If the firm chooses to operate using risky new technology, it will choose a debt contract to maximize the expected profit. Let \( \pi^n(z^n, k, i) = \max\{z^n k^\alpha - (1 + i)k, 0\} \) be the firm’s profit after the productivity \( z^n \) is realized. With probability \( \lambda \), \( z^n \) is drawn from the distribution \( \Psi^h(z^n) \) and with probability \( 1 - \lambda \), \( z^n \) is drawn from the distribution \( \Psi^l(z^n) \).

Given \( \mathcal{D}^n(z^o, \lambda) \), the firm maximization problem is

\[
\max_{(k, i) \in \mathcal{D}^n(z^o, \lambda), k \geq \phi} \left\{ \lambda \int \pi^n(z^n, k, i) d\Psi^h(z^n) + (1 - \lambda) \int \pi^n(z^n, k, i) d\Psi^l(z^n) \right\}
\]

1.4.4 Debt Contracts

Firms which operate using old technology never default in this model. As productivity is predetermined when the firm makes the production decision, it is suboptimal for firms to choose \( b \) such that they make negative profit. Thus, the set of debt contracts for these firms is trivial:

\[
\mathcal{D}^o(z^o, \lambda) = \{(k, i) : k \in \mathbb{R}_{++} \text{ and } i = r\}. \tag{1.7}
\]

Firms which operate using new technology, on the contrary, may not be able to repay the loan if the realization of \( z^n \) is low. Given loan size \( k \) and the interest rate \( i \), denote \( z^{n*}(k, i) = \frac{(1+i)k}{k^\alpha} \), which is a default threshold. This is a cutoff value of \( z^n \) that firms will default if \( z^n \leq z^{n*}(k, i) \). For the firm that is believed to be a high type with probability \( \lambda \), the estimated default probability \( p(k, i, \lambda) \) is given by

\[
p(k, i, \lambda) = \lambda \Psi^h(z^{n*}(k, i)) + (1 - \lambda) \Psi^l(z^{n*}(k, i)). \tag{1.8}
\]

As the market for financial intermediaries is competitive, financial intermediaries take the interest rate \( i \) as given. Suppose the firm is believed to be a high type with probability \( \lambda \) and wants to borrow \( k \). Taking \( i \) as given, the financial intermediary’s profit from a debt
contract is
\[
\tilde{\pi}(k;\lambda,i) = [1 - p(k,i,\lambda)](1 + r)k + p(k,i,\lambda)\xi \mathbb{E}[z^n k^\alpha | z^n < z^n^* (k,i)] - k(1 + r) \tag{1.9}
\]

where \(p(k,i,\lambda)\) is an estimated default probability from equation (1.8) and \(\xi\) is a fraction of output that an intermediary can recover from an insolvent firm. Financial intermediaries will participate in selling only those contracts that make non-negative profits in expectation. The competitive market assumption implies that a financial intermediary breaks even in expected value with every debt contract:
\[
\tilde{\pi}(k;\lambda,i) = 0. \tag{1.10}
\]

For a firm that is believed with probability \(\lambda\) to be a high type, a set of debt contracts that allows a financial intermediary to break even in expected value can be characterized by
\[
\mathcal{D}^n(z^\alpha,\lambda) = \left\{(k,i) \bigg| 1 + r = (1 + i) \left(1 - \Psi^h \left(\frac{(1+i)k}{k^\alpha}\right)\right) + \xi^i k^{\alpha - 1} \int_0^{(1+i)k/k^\alpha} z^n d\Psi^\lambda(z^n)\right\} \tag{1.11}
\]

where \(\Psi^h\) represents the distribution \(\lambda \Psi^h(\cdot) + (1 - \lambda) \Psi^l(\cdot)\). For the rest of this paper, \(\psi^h\) will be the associated density function \(\lambda \psi^h(\cdot) + (1 - \lambda) \psi^l(\cdot)\). A financial intermediary equalizes the cost and the expected revenue of each debt contract. The interest rate offered is determined by a firm’s default risk and loan recovery rate. Particularly, a loan risk premium is high if a firm is likely to default and a financial intermediary expects to recover a small fraction of defaulted loans.

**Assumption 1.** The distribution \(\Psi\) is such that \(\Psi^h(\cdot)\) and \(\Psi^l(\cdot)\) satisfy the monotone likelihood ratio property (MLRP), which implies that \(\Psi^h(\cdot)\) first order stochastically dominates \(\Psi^l(\cdot)\) on the support \([z^n, \infty]\).

Assumption 1 states that, ceteris paribus, high-type firms always have lower a probability of default.\(^{11}\) From (1.11), the structure of debt contracts is determined by both

\(^{11}\)This MLRP is a sufficient condition for monotonicity results. In some cases, only the first order stochastic
the firm-specific default probability and the country-specific recovery rate. The former is directly determined by the belief $\lambda$. The interest rate can then be expressed as a function $i = I(k, \lambda)$. Proposition 1 characterizes debt contracts in terms of an interest rate schedule and loan availability in equilibrium.

**Proposition 1** (Debt Contracts).

(i) (Interest rate schedule) The equilibrium interest rate $i$ is increasing in the size of the loan $k$ and decreasing in the recovery rate $\xi$, given the belief $\lambda$.

(ii) (Interest rate schedule) The equilibrium interest rate $i$ is decreasing in the belief $\lambda$ and the recovery rate $\xi$, given the size of the loan $k$.

(iii) (Loan availability) Given the belief $\lambda$, there exists a maximum loan size $\bar{k}(\lambda)$ such that, for all $k > \bar{k}(\lambda)$, there does not exist an interest rate $i$ such that the financial intermediary’s break-even condition is satisfied. The maximum loan size $\bar{k}(\lambda)$ is increasing in the belief $\lambda$ and the recovery rate $\xi$.

*Proof.* See Appendix A.2.1.

For a particular firm, the firm is more likely to default if it borrows a larger amount of loan. Thus, the larger the loan size the firm wants to borrow, the higher the interest rate that the firm will be charged. Now, compare two different firms. If $\lambda^i > \lambda^j$, the estimated default probability of a $\lambda^i$-type firm will be lower than that of a $\lambda^j$-type firm. As a result, $D^n(z^o, \lambda^i)$ offers the same set of $k \in \mathbb{R}_{++}$ at a lower interest rate compared to $D^n(z^o, \lambda^j)$. If it is the case that an intermediary charges an infinite interest rate to a $\lambda$-type firm that wants to borrow $k$, this will be interpreted as the intermediary not issuing any debt contract with loan size $k$ to that firm. In other words, the firm has no credit access. Proposition 1 also implies that, if a loan of size $k$ is not approved for the $\lambda^i$-type firm, it will not be dominance property is necessary to obtain the monotonicity results.
offered to the \( \lambda^i \)-type firm either. In this sense, the set of contracts \( D^n(z^o, \lambda^j) \) is said to be weakly dominated by the set of contracts \( D^n(z^o, \lambda^i) \).

Turn now to the recovery rate \( \xi \). With higher recovery rates, financial intermediaries can recoup a larger fraction of a loan through reorganization, liquidation or debt enforcement proceedings in the event of insolvency. This implies a lower expected cost of debt contracts and, hence, a lower interest rate that intermediaries charge to firms. The impact of \( \xi \) varies across \( \lambda \) and default probabilities. That is, low recovery rates tend to have a larger impact on firms with low \( \lambda \) and high default probability. Proposition 1, therefore, gives an idea of how an inaccurate evaluation and a low recovery rate can create a sub-optimal technology level as well as resource misallocation. This is because some high-type firms may face high financing costs and some high-type firms may not even have credit access.

### 1.4.5 Firms’ Technology Adoption

A firm starts period \( t \) with old technology productivity \( z^o \) and belief \( \lambda_t \) that it is a highly productive firm in operating new technology. The firm then makes a choice of technology. The optimal technology choice not only includes a flow profit component, but also an experimentation component reflecting the value of acquiring new information. This is then a dynamic decision problem. If the firm decides to use old technology, it faces a static maximization problem of choosing the production level, as shown in (1.5). The firm then receives a deterministic return but adds no new information to its information set. If the firm decides to use new technology, it faces a static maximization problem of choosing the production level, as shown in (1.6). After \( z^n \) is realized, the firm has an option to default. The realized return is a noisy signal of the firm’s type. The posterior belief is obtained using Bayes’ rule. This reflects how the firm learns about its actual type over time.

The problem is a Belief Markov Decision Process. Bayesian updating rules suggest that a belief about firm type depends on a previous belief, a firm’s technology choice, and a
realization of $z^n$. Therefore, the firm’s technology choice problem can be written recursively with belief $\lambda$ as a state variable:

$$V(z^o, \lambda) = \max_{e \in \{0, 1\}} (1 - e)W^o(z^o, \lambda) + eW^n(z^o, \lambda)$$  \hspace{1cm} (1.12)

where the options are two types of technology:

$$W^o(z^o, \lambda) = \max_{(k, i) \in D^o(z^o, \lambda)} \pi^o(z^o, k, i) + \beta V(z^o, \lambda)$$ \hspace{1cm} (1.13)

$$W^n(z^o, \lambda) = \max_{(k, i) \in D^n(z^o, \lambda), k \geq \phi} \int \pi^n(z^n, k, i) + \beta V(z^o, \Lambda(\lambda, 1, z^n))d\Psi^\lambda(z^n)$$ \hspace{1cm} (1.14)

subject to the following belief updating function

$$\lambda' = \Lambda(\lambda, e, z^n) = \begin{cases} \frac{\lambda \psi^h(z^n)}{\lambda \psi^h(z^n) + (1 - \lambda) \psi^l(z^n)}, & \text{if } e = 1, \\ \lambda, & \text{if } e = 0. \end{cases}$$ \hspace{1cm} (1.15)

Given the belief updating rule (1.15), the resulting optimal recursive policy functions are two production choice policy functions: $K^n(z^o, \lambda)$, $K^o(z^o, \lambda)$, and a technology choice policy function: $E(z^o, \lambda)$. For simplicity of notation, denote the maximized flow profit of (1.13) and (1.14) as $\pi^o^*(z^o, \lambda)$ and $\pi^n^*(z^o, \lambda)$, respectively.

**Lemma 1** (Profit Functions and Value Functions).

(i) $\pi^o^*(z^o, \lambda)$ and $\pi^n^*(z^o, \lambda)$ are bounded and nondecreasing in $\lambda$.

(ii) There exists a unique solution to the Bellman equation (1.12).

(iii) $V(z^o, \lambda)$ is nondecreasing in $\lambda$.

(iv) Supposing $\pi^n^*(z^o, \lambda)$ is convex in $\lambda$, then $V(z^o, \lambda)$ is convex in $\lambda$.

**Proof.** See Appendix A.2.2. \hfill \Box
Flow profits from using old technology do not depend on beliefs. When using new technology, firms with a good prospect of being high type enjoy higher expected profits and can experiment at a lower cost. The weak monotonicity is obtained for profit functions and preserved in the value functions. This will be crucial for deriving the threshold rule of technology adoption. The assumption that the new technology profit function is convex in beliefs is a natural property for information measures. The expected profit is relatively high for firms whose belief is close to 1 compared to firms whose belief is uninformative. As in a standard Bayesian learning model, the convexity is preserved in the value functions.

**Proposition 2** (Technology Adoption).

(i) There exists a cutoff $\lambda(z^o)$ such that all firms with beliefs $\lambda > \lambda(z^o)$ and productivity $z^o$ choose to adopt new technology.

(ii) The cutoff $\lambda(z^o)$ is increasing in $z^o$.

*Proof.* See Appendix A.2.2. □

A firm decides to experiment on new technology as long as its belief is greater than the cutoff level. The firm expects a higher profit from new technology. Moreover, it can experiment at a lower cost because debt contracts are more favorable with larger loan amounts at lower interest rates. Because a deterministic profit from old technology is the opportunity cost of experimenting with new technology, the cutoff also depends on productivity $z^o$. Firms are less likely to use new technology if the profit from using old technology is already high. Nevertheless, in this dynamic problem, firms make a technology choice based on two values: the value from flow profit and the value from information acquisition. Thus, it may appear that some firms are willing to receive lower flow profit to experiment with new technology and acquire new information. In fact, if acquiring new information is highly valuable, the only reason that firms refrain from experimenting with new technology is the high cost of using new technology, determined by the structure of
1.4.6 The Impact of Financial Development

How does a country’s level of financial development affect technology adoption by firms? As mentioned before, the level of financial development in this setting is proxied by two indicators: the recovery rate $\xi$ and the accuracy of loan evaluation $\theta$. Proposition 2 suggests that the level of financial development can affect technology adoption through two main channels. First, it affects the equilibrium cutoff level. Second, by fixing the cutoff, the level of financial development determines how likely it is that beliefs will fall below this threshold. Consider the set of firms, $I$, defined by

$$I = \{ (\lambda, z^o) \mid \lambda < \lambda(z^o) \}$$  \hspace{1cm} (1.16)

Firms which lie in this inactive set will stop experimenting with new technology and operate using old technology. Suppose that firms are distributed over beliefs and productivity in accordance with the distribution function $\Gamma(z^o, \lambda)$. Then the measure of firms in an inactive set $I$ is

$$\gamma^o = \int_{z^o}^{\lambda(z^o)} d\Gamma(z^o, \lambda)$$  \hspace{1cm} (1.17)

**Proposition 3 (Inactive Set).** The cutoff $\lambda(z^o)$ is decreasing in the recovery rate $\xi$. For any distribution of firm’s belief and productivity $(\lambda, z^o)$, a measure of firms in an inactive set $I$ is decreasing in $\xi$.

**Proof.** See Appendix A.2.3. \qed

Apply Proposition 3 to an initial joint distribution of $(\lambda_0, z^o)$. There will be more firms that start experimenting with new technology if an intermediary can recover a larger fraction of output in the event of default. This gives firms more chances to learn their true type. In
other words, a low recovery rate leads to higher financing costs and less credit access. As a result, many firms are precluded from acquiring new information. A low recovery rate not only limits adopting firms to starting with a small production size, but also prevents firms that believe they are low in talent from experimenting with new technology, because these credit constraints increase the information gathering costs.

We turn now to how the level of financial development affects the final technology decision. The analysis is extended to consider the limiting distribution of \((\lambda, z^o)\). Note that this limiting distribution is an invariant distribution of beliefs. It is, however, possible that the economy achieves an invariant distribution of technology choices even though the distribution of beliefs is still evolving over time. In the limit, all firms stop experimenting and choose the more productive technology given their information sets.

**Lemma 2** (Martingale Properties).

(i) Unconditional on the true types, \(\{\lambda_t\}_{t=1}^{\infty}\) is a martingale.

(ii) For any given policy functions \(K^o(z^o, \lambda), K^n(z^o, \lambda)\) and \(E(z^o, \lambda)\), \(\{\lambda_t\}_{t=1}^{\infty}\) form a bounded non-negative supermartingale if the true type is \(l\) and a bounded non-negative submartingale if the true type is \(h\).

**Proof.** See Appendix A.2.4.

Because the result of belief convergence holds for every firm, this holds for the economy, given an initial belief distribution of \((z^o, \lambda_0)\) and sequences of \(z^n\) realization \([\{z^n_t\}_{t=1}^{\infty}(j)]_{j \in [0,1]}\). Theoretically, the economy weakly converges to the equilibrium with invariant distribution of \((z^o, \lambda)\) where \(\lambda\) represents the beliefs of the absorbing states, \(\lambda = 1\) or \(\lambda < \Lambda(z^o)\).

\(^{12}\)The measure of sequences \([z^n_t]_{t=1}^{\infty}\) which lead to \(\lambda \to 1\) is, however, zero. As a result, the belief converges almost surely to \(\lambda \leq \Lambda(z^o)\) and no firm adopts new technology. This problem is solved once the full model with exogenous exit is introduced. With exogenous exit, the stationary distribution consists of firms operating with new technology.
Proposition 4 (Sorting). For almost all sequences of $z^n$ realization $\{z^n\}_{t=1}^{\infty}$ for each firm $j$,

(i) (All low type firms are weeded out) If the true type is $\ell$, firm $j$’s belief converges almost surely as $t \to \infty$ to $\lambda \leq \Lambda(z^o)$.

(ii) (Not all high-type firms rise to the top.) If the true type is $h$, firm $j$’s belief converges almost surely as $t \to \infty$ to the absorbing states, $\lambda = 1$ or $\lambda \leq \Lambda(z^o)$.

Proof. See Appendix A.2.4.

The problem will not be interesting if the technology features are such that all firms should adopt new technology or no firm should adopt new technology. Therefore, the interesting case is the intermediate case where it is optimal for some high-type firms to adopt new technology. These firms will be referred to as potential firms. Proposition 4 implies that the optimal adoption rules do not almost surely reveal the truth. Apparently, all low-type firms, whose optimal policy is to operate using old technology, will finally fall into the inactive set even though their beliefs do not converge to zero. However, not all potential firms will end up using new technology. This is either due to an inaccurate initial prior or a sequence of bad shocks. If the initial prior is highly inaccurate, such that potential firms cannot even start experimenting with new technology, they end up operating with sub-optimal technology. Even though the offered set of debt contracts allows potential firms to go through the learning process, the sequence of bad shocks, together with the inaccurate initial prior, can drive the belief below the cutoff. This causes the firms to stop experimenting and to choose not to adopt new technology.

The fraction of potential firms experimenting and eventually adopting new technology is then directly linked to the accuracy of ex ante loan evaluation $\theta$ and the recovery rate $\xi$. Clearly, $\xi$ determines the equilibrium cutoff level, while $\theta$ determines the accuracy of initial beliefs and how likely it is that beliefs will fall below the cutoff level. Therefore,
given the same fraction of high-type firms in the economy, the lack of development in the financial sector would result in more high-type firms falling in an inactive region. From this point, TFP differences can arise and persist even if two economies have the same talent and have access to the same technology. The low level of financial development hinders and prematurely halts the learning process, resulting in firms operating with a sub-optimal technology level and a sub-optimal production level.

1.5 Full Model: Technology Ladder and Technological Frontier

During the early and medium stages of economic development, catching up to the world technological frontier is the main channel that developing countries can gain in terms of productivity and growth. The adoption of existing technologies seems to be a viable channel compared to the riskier and costlier innovation channel. In this section, a model of choosing between two technologies is incorporated in an environment where firms have to move up the technology ladder in order to get closer to the world technological frontier. With the technology ladder setting, the effect of financial development on both the timing of adoption and the final technology choice can be explored. Moreover, this effect will be amplified. If a firm is precluded from adopting a low-level technology, it is precluded from all higher-level technology. The delay in adopting a low-level technology will also delay the adoption of all higher-level technology.

1.5.1 Environment

The technology ladder is indexed by step $s = 0, 1, 2, ..., S$. Step $s = 0$ refers to old technology, implying that old technology is $S$ steps behind the technological frontier. For step $s \geq 1$, firms can either be high type, $h$, or low type, $l$, at each step. At step $s$, the productivity of high-type firms is drawn from the distribution $\Psi^h_s(z^n)$, while the productivity
of low-type firms is drawn from the distribution $\Psi_l(z^n)$. Both distributions are defined on the same support $[z^n, z^n]$. Assume that high-type firms are, on average, more productive $E_{\Psi_h}(z^n) \geq E_{\Psi_l}(z^n)$. Average productivity of high-type firms is increasing when firms move up the technology ladder, $E_{\Psi_h}(z^n) \geq E_{\Psi_h-1}(z^n) \geq E_{\Psi_1}(z^n)$.

Time is discrete and indexed by $t = 1, 2, 3, \ldots$. Each period, new firms enter at step $s = 0$. A new firm possesses old technology productivity $z^o$, which is drawn from the distribution $\Phi(z^o)$ on the support $[z^o, z^o]$. Nature also assigns the firm’s type at each step $\tau^s_j \in \{h, l\}$ for $s = 1, \ldots, S$. This is unobservable. The firm can move up the ladder one step at a time. After each production, it exits the economy with probability $\delta$. Once deciding to step down, the firm has to operate using old technology from that period onward until it exogenously exits. Denote this as $s = 0$.

Suppose a firm enters a period $t$ at some step $s$ on the technology ladder from the previous period. The firm has a belief $\lambda_s$ that it is high type in its skill at using step-$s$ technology. The firm chooses the technology level and decides how much to invest. It has three technology options. First, it can return to old technology and operate using this technology forever until it exogenously exits. In this case, the firm can borrow from a set of debt contracts $D^o(z^o)$. Second, the firm can continue using the current technology. If the firm decides to do so, it can borrow from an intermediary who will offer a set of debt contracts $D^n_s(z^o, \lambda_s)$. After the productivity $z^n$ is realized, the ex post evaluation is performed. If the firm survives, it enters the next period with the same step $s$ and the updated belief $\lambda'_s$. The last option is to move up to the next step $s + 1$. Because the firm has never before operated at this technology step, there will be an initial belief that the firm is of type $h$, with probability $\lambda_{0,s+1}$. The firm can then borrow from an intermediary who will offer a set of debt contracts $D^n_s(z^o, \lambda_{0,s+1})$. As in the analytical model, this is obtained by the ex ante evaluation. Figure (3) illustrates how firms climb up the technology ladder.

For generality, let the average probability that firms are type $h$ at step $s + 1$ vary across
firms, denoted by $\rho^j_{s+1}$.\textsuperscript{13} This is a common knowledge. After receiving the pre-lending signal, a financial intermediary forms an initial belief using Bayes’ rule:

$$\lambda^j_{0,s+1}(\rho^j_{s+1}, v^j_{s+1} = h) = \frac{\theta \rho^j_{s+1}}{\theta \rho^j_{s+1} + (1 - \theta)(1 - \rho^j_{s+1})}$$ \hspace{1cm} (1.18)

$$\lambda^j_{0,s+1}(\rho^j_{s+1}, v^j_{s+1} = l) = \frac{(1 - \theta) \rho^j_{s+1}}{(1 - \theta) \rho^j_{s+1} + \theta(1 - \rho^j_{s+1})}$$ \hspace{1cm} (1.19)

These two equations are analogous to equations (1.18) and (1.19) from the analytical model.

### 1.5.2 Decision Problems

As in the analytical model, financial intermediaries operate in a competitive market and offer a set of debt contracts such that they break even in expected value with every

\textsuperscript{13}Firms’ capabilities in using higher-level technology might be positively correlated with their abilities to use the current technology. That is, firms are more likely to be type $h$ at $s + 1$ if they are type $h$ at $s$. In the quantitative analysis, this will be designated.
contract. Given a set of debt contracts $D_o(z^o)$ and $D_n(z^o, \lambda_s)$, the firm’s profit maximization problem is analogous to (1.5) and (1.6). Denote $\pi_o^*(z^o, \lambda)$ the maximized flow profit from old technology and $E\pi_n^*(z^o, \lambda)$ the maximized flow profit from step-$s$ technology.

We turn now to the technology choice problem. This dynamic problem can be written in a recursive form as in the analytical model. If the firm enters a period with $s = 0$, it has no option but to use old technology. The value function depends only on old technology productivity:

$$V_0(z^o) = \frac{\pi_o^*(z^o)}{1 - (1 - \delta)\beta}. \quad (1.20)$$

Next, for all steps $1 \leq s \leq S - 1$, the value function can be expressed as a function of state variables, including old technology productivity $z^o$, a technology step $s$, a belief $\lambda_s$, and a pre-lending signal $v_{s+1}$. The firm can switch back to old technology, continue with its current technology, or move up to higher-level technology. The firm maximizes the expected present value of discounted profit with discount factor $\beta$. The technology choice problem can be expressed as

$$V(z^o, s, \lambda_s, v_{s+1}) = \max \{ V_0(z^o), W_c(z^o, s, \lambda_s, v_{s+1}), W_u(z^o, s + 1, \lambda_s, v_{s+1}) \} \quad (1.21)$$

where

$$W_c(z^o, s, \lambda_s, v_{s+1}) = E\pi_n^*(z^o, \lambda) + (1 - \delta)\beta \int V(z^o, s, \Lambda(\lambda_s, 1, z^n), v_{s+1})d\Psi_s(z^n) \quad (1.22)$$

$$W_u(z^o, s+1, \lambda_s, v_{s+1}) = \begin{cases} E\pi_n^*(z^o, \lambda_0, s+1, v_{s+1}) + (1 - \delta)\beta \int E[v(V(z^o, s + 1, \Lambda(\lambda_0, s+1, 1, z^n), v_{s+2}))]d\Psi_s(z^n) & \\ (1 - \delta)\beta \int E[v(V(z^o, s + 1, \Lambda(\lambda_0, s+1, 1, z^n), v_{s+2}))]d\Psi_s(z^n) \end{cases} \quad (1.23)$$

and the belief updating function

$$\Lambda_s(\lambda, 1, z^n) = \frac{\lambda \psi_s^h(z^n)}{\lambda \psi_s^h(z^n) + (1 - \lambda)\psi_s^d(z^n)}; \quad s = 1, \ldots, S. \quad (1.24)$$

If the firm decides to switch back to old technology, it will stay with old technology.
forever until it exogenously exits. If it chooses to continue, its profit will be stochastic and the continuation value will depend on the updated evaluation after the productivity $z^n$ is realized. If the firm chooses to experiment with higher-level technology, an intermediary will perform the pre-lending evaluation. An initial belief determines the structure of debt contracts. The profit is stochastic depending on the firm’s type at step $s+1$. The continuation value depends on the updated evaluation after the productivity $z^n$ is realized, as well on as a pre-lending signal for step $s+2$.

Lastly, if the firm enters a period with $s = S$, it has no option to move up. The firm can either continue with its frontier technology or switch back to old technology. The value of the firm is given by

$$V_S(z^o, \lambda_S) = \max \left\{ V_0(z^o), \mathbb{E}_{\pi_S^*(z^o, \lambda_S)} + (1 - \delta)\beta \int V_S(z^o, \Lambda_S(\lambda_S, 1, z^n))d\Psi^S_S(z^n) \right\}$$

(1.25)

where the belief updating function is (1.24).

### 1.5.3 Stationary Equilibrium

In the technology ladder setting, the goal is to understand how the level of financial development affects the distribution of firms along the ladder. A definition for a stationary equilibrium is introduced below. This will prove useful in comparing the manufacturing TFP across countries in the quantitative analysis.

**Definition 1.** Given the exogenous risk-free rate $r$, a stationary equilibrium consists of technology choice and production policy functions; value functions of firms; a belief updating function; debt contracts offered by financial intermediaries; and probability measure $\Gamma_0(z^o)$, $\Gamma_{0< S < S}(z^o, \lambda, v; \tau_S)$ and $\Gamma_S(\lambda, z^o; \tau_S)$ such that

1. The interest rate schedule is determined in competitive fashion, reflecting the firm’s default probability.
2. Technology choice and production policy functions are optimal decision rules for the firms’ decision problems.

3. The belief updating function satisfies Bayes’ rule.

4. Probability measures \( \Gamma_0, \Gamma_{s\leq S} \) and \( \Gamma_S \) are stationary. They evolve according to the equilibrium mapping given the firm’s technology choice policy functions and the belief updating functions.

1.6 Quantitative Analysis

This section evaluates quantitatively how the level of financial development shapes the patterns and the timing of firms’ technology adoption as well as firms’ production decisions. This, in turn, determines the country’s level and speed of TFP convergence. To simulate the model, values must be assigned to its parameters. This will be done by calibrating the technology ladder model presented in Section 1.5 to match the stylized facts from the Chilean Annual Manufacturing Survey (ENIA).\(^{14}\) Two analyses are performed. First, the stationary equilibrium analysis explores a stationary distribution of firms along the ladder. The level of TFP in Chile, relative to that in the U.S., is computed to quantify the effect of financial development on the TFP gap. Second, the transitional dynamics analysis is performed to see the impact of financial development on the speed of TFP convergence in Chile.

Although the main reason that the model is matched to Chilean data is the availability of technology adoption data, Chile, as one of the successful fast-growing developing countries, can be an interesting case study. Crespi (2006) addresses several features of the Chilean economy that make the study of long-run trends of growth more compelling. One is that the micro-economic regime has remained the same for the last 25 years, resulting in a context of stability in the incentive system.

\(^{14}\)See Appendix A.1.
1.6.1 Dynamics of Technology Adoption: Evidence on Learning

Before proceeding to the quantitative analysis, the presence of foreign technology adoption dynamics is explored. Using *Chilean Annual Manufacturing Survey (ENIA)* data over the period 1995-2007, expenditures on licenses and foreign technical assistance of each firm are tracked over time. Figure (4) shows that there is a coincidence between a firm’s productivity and how much it has spent on foreign technology in the past three years.

![Figure 4: ln(TFP) of Increased Spending and Decreased Spending Firms](image)

Firms that spent some amount of money on foreign technical assistance and licensing are categorized into two types: *increased spending* and *decreased spending*. *Increased spending* is a firm which has increased its foreign technology spending in the past three years. *Decreased spending* is a firm which has decreased its foreign technology spending in the past three years. The ln(TFP) of *increased spending* firms is, on average, higher than that of *decreased spending* firms. The difference in mean log TFP between these two groups is statistically different from zero at the 1% significance level. The result is robust to the analysis with two sub-samples: a high-technology industry and a low-technology industry.\(^\text{15}\) The conjecture is that *increased spending* firms behave like the high-type firms in the model, while *decreased*——

\(^{15}\)Industry types are classified by ISIC REV.2 where the high-technology industry includes ISIC: 35, 38. All other industries are categorized into the low-technology industry.
spending firms behave like low-type firms.

Table 3: Dynamics of Technology Adoption

<table>
<thead>
<tr>
<th>Dependent Variable (1{FTA_t &gt; 0})</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFP_{t-1}</td>
<td>0.074</td>
<td>0.073***</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.015)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TFP_{t-1} \times 1{FTA_{t-1} &gt; 0}</td>
<td>0.173***</td>
<td>0.301***</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔTFP_{t-1}</td>
<td>-</td>
<td>-</td>
<td>0.042</td>
<td>0.031</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.054)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>ΔTFP_{t-1} \times 1{FTA_{t-1} &gt; 0}</td>
<td>-</td>
<td>-</td>
<td>0.155**</td>
<td>0.104**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.091)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>Firm-level controls</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Year dummies</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Logit, FE</th>
<th>Probit, RE</th>
<th>Logit, FE</th>
<th>Probit, RE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>9,493</td>
<td>53,214</td>
<td>7,314</td>
<td>43,035</td>
</tr>
</tbody>
</table>

1 "significant at 10%, ** significant at 5%, *** significant at 1%
2 FE: Fixed effects model, RE: Random effects model

The spending on foreign technical assistance and licensing has the advantage of having a panel structure that can be used to control for unobserved firm and industry characteristics. Therefore, a binary panel regression is performed to see whether a firm’s decision to continue using foreign technology depends on its successful experience with the technology. The dependent variable is a binary measure of foreign technology adoption, taking value 1 if the spending on foreign technical assistance and licensing is positive. The focus is on an interaction between productivity (or changes in productivity) and foreign technology adoption in the previous period. High productivity, or an increase in productivity, are interpreted as successful experiences when firms adopt foreign technology. Year dummies and firm-level characteristics are included as controls; these include the number of workers, capital per worker, skill intensity and foreign ownership. Estimation results are reported in Table (3) where panel (1) and (3) report the fixed-effect logit model and panel (2) and (4) report the random-effect probit model. The positive coefficient on the interaction terms suggests that, if firms spend money on foreign technology and their productivity turns out to be high, firms are more likely to continue spending money on foreign technology.
Because the results are also robust to changes in productivity, firms tend to continue with foreign technology if their productivity has improved. Evidence shows that firms tend to change their foreign technology decisions after observing the productivity gain from using the technology. One can think of this as part of a learning and experimenting process with foreign technology.

1.6.2 Fitting the Model to Chilean Data

Both stationary equilibrium and transitional dynamics analyses will use a common set of parameter values, which are calibrated in this section. Values are assigned to the model’s parameters so that the stationary equilibrium is matched with the Chilean economy in 2007. The length of a period is one year. Some standard parameters are assigned the conventional values. The real interest rate $r$ is 3%, to match the Chilean real interest rate in 2007. The discount factor is set so that $\beta = 0.98$, implying around this 3% return. The decreasing returns to scale parameter is set to 0.85 as in Cole et al. (2012). The exogenous exit rate $\delta$ is the average yearly exit rate in the Chilean manufacturing sector, which is 9%, taken from Fernandes and Paunov (2012). The minimum working capital for operating new technology, $\varphi$, is set such that the ratio of the minimum input to the maximum input of firms adopting new technology is 0.003, as observed in the Chilean data.

The next step is to parameterize the technology ladder. The logarithm of old technology productivity is assumed to be a truncated and discretized version of a normal distribution with mean $\mu_o$ and variance $\sigma^2_o$. The logarithm of new technology productivity $z^n$ is a truncated normal distribution with mean $\mu_s$ if a firm is high type at step $s$ and variance $\sigma^2_n$. If a firm is low type, productivity has the same variance with mean $\mu_l$.

Note that the log-normal distribution of $z^n$ with $\mu_s > \mu_l$ only satisfies the first order stochastic dominance property but not the MLRP. However, $\int V_t(z^n, \Lambda(\lambda, 1, z^n))d\Phi(z^n)$ can be rewritten as $\int V_t(z^n, \Lambda(\lambda, 1, \varepsilon))d\Phi(\varepsilon)$, where $\Lambda(\lambda, 1, \varepsilon) = \left[1 + \frac{1}{\lambda} \exp \left\{ -\frac{1}{2} \left( \frac{\Delta \mu_s}{\sigma_n} + \frac{\Delta \mu_l + 2\varepsilon}{\sigma_n} \right) \right\} \right]^{-1}$. $\Phi$ is the cumulative standard normal distribution and $\Delta \mu_s = \mu_s - \mu_l$. It can easily be shown that $U_t(\Lambda(\lambda, 1, z^n))$ is increasing in $\lambda$ and the proof of monotonicity can then follow.
as in Cole et al. (2012) by

\[ \mu_s = \ln(\tilde{\mu}_0 + \tilde{\mu}_1 s + \tilde{\mu}_2 s^2 + \tilde{\mu}_3 s^3) \quad \text{for } s = 0, 1, \ldots, 5. \]

The underlying type on each step of the technology ladder \( \tau^j_s \in \{l, h\} \) is chosen to allow firm types to be correlated across steps. In particular, firms are more likely to be type \( h \) at step \( s + 1 \) if they are type \( h \) at step \( s \). This is a very plausible assumption. Firms which are talented at using technology are more likely than untalented firms to be talented at using a higher-level technology. Let \( \rho_s \) be the probability that the firm is type \( h \) at step \( s \).

Assume that \( \Pr(\tau_1 = h \mid z^o) = \rho_1(z^o) = \kappa_0 \Phi(\ln z^o - \mu_0/\sigma_o), \) so that \( \rho_1(z^o) \) is increasing in \( z^o \).

\( \Pr(\tau_{s+1} = h \mid \tau_s = h) = \kappa_s > 0 \) and \( \Pr(\tau_{s+1} = h \mid \tau_s = l) = 0, \) implying \( \rho_{s+1}(\lambda_s) = \kappa_s \lambda_s. \)

Recall that \( \rho_s \) is common knowledge in the economy. An initial belief at each step \( \lambda_{0,s+1} \) is set using \textit{ex ante} evaluation technology introduced in (1.18) and (1.19). The parameter \( \kappa_s \) governing the conditional probability of being type \( h \) follows

\[ \kappa_s = \left[1 + (\tilde{\kappa}_0 + \tilde{\kappa}_1 s + \tilde{\kappa}_2 s^2 + \tilde{\kappa}_3 s^3)^2\right]^{-1} \quad \text{for } s = 0, 1, \ldots, 4. \]

Lastly, the parameters governing the country’s level of financial development are the accuracy of pre-lending evaluation \( \theta \) and the loan recovery rate \( \xi. \)

### Table 4: Parameter Values

<table>
<thead>
<tr>
<th>Value</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Predetermined Parameters</strong></td>
<td></td>
</tr>
<tr>
<td>( \alpha )</td>
<td>0.85</td>
<td>Return to Scale Cole et al. (2012)</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.98</td>
<td>Discount factor 3% return</td>
</tr>
<tr>
<td>( \delta )</td>
<td>0.09</td>
<td>Exit rate Fernandes and Paunov (2012)</td>
</tr>
<tr>
<td>( r )</td>
<td>0.03</td>
<td>Real Interest Rate Real interest rate 2007</td>
</tr>
<tr>
<td></td>
<td><strong>Calibrated Parameters</strong></td>
<td></td>
</tr>
<tr>
<td>( \mu_l )</td>
<td>-0.29</td>
<td>Low type productivity</td>
</tr>
<tr>
<td>( \sigma_{z^n} )</td>
<td>0.89</td>
<td>New technology productivity std</td>
</tr>
<tr>
<td>( \sigma_{z^o} )</td>
<td>0.33</td>
<td>Old technology productivity std</td>
</tr>
<tr>
<td>( \theta )</td>
<td>0.55</td>
<td>Accuracy of pre-lending evaluation</td>
</tr>
<tr>
<td>( \xi )</td>
<td>0.21</td>
<td>Loan recovery rate</td>
</tr>
<tr>
<td>( \tilde{\mu}_0, \tilde{\mu}_1, \tilde{\mu}_2, \tilde{\mu}_3 )</td>
<td>(3.25, 2.8, 0.003, -0.04)</td>
<td>Technology ladder parameters</td>
</tr>
<tr>
<td>( \tilde{\kappa}_0, \tilde{\kappa}_1, \tilde{\kappa}_2, \tilde{\kappa}_3 )</td>
<td>(0.3, 1.02, -0.34, 0.028)</td>
<td>High-type probability parameters</td>
</tr>
</tbody>
</table>
Table 5: Targeted Moments

<table>
<thead>
<tr>
<th>Targeted moments</th>
<th>Data (2007)</th>
<th>Model (stationary distribution)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of ...each sales 50th, 75th, 90th percentile:</td>
<td>(0.10, 0.33, 0.62)</td>
<td>(0.07, 0.33, 0.63)</td>
</tr>
<tr>
<td>New technology</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Share of ...each sales 50th, 75th, 90th percentile:</td>
<td>(0.05, 0.16, 0.40)</td>
<td>(0.04, 0.16, 0.41)</td>
</tr>
<tr>
<td>Old technology</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ratio of mean sales</td>
<td>0.30</td>
<td>0.29</td>
</tr>
<tr>
<td>Ratio of mean input</td>
<td>0.29</td>
<td>0.31</td>
</tr>
<tr>
<td>Default rate (Ratio of firms with negative profit)</td>
<td>0.15</td>
<td>0.13</td>
</tr>
<tr>
<td>Recovery rate as a fraction of loans</td>
<td>0.20</td>
<td>0.20</td>
</tr>
<tr>
<td>Cumulative distribution of sales by age (5, 9, 13 years)</td>
<td>(0.19, 0.36, 0.49)</td>
<td>(0.16, 0.35, 0.49)</td>
</tr>
</tbody>
</table>

The parameters \{\bar{\mu}_0, \bar{\mu}_1, \bar{\mu}_2, \bar{\kappa}_0, \bar{\kappa}_1, \bar{\kappa}_2, \bar{\kappa}_3, \mu_L, \sigma_z^n, \sigma_z^o, \theta, \xi\} are calibrated to match the following target moments: (i) the share of sales at the 50th, 75th, and 90th percentile for firms using new technology; (ii) the share of sales at the 50th, 75th, and 90th percentile for firms using old technology; (iii) the default rate; (iv) the ratio of mean sales of non-adopting firms to mean sales of adopting firms; (v) the ratio of mean input of non-adopting firms to mean input of adopting firms; (vi) the Chilean recovery rate as a fraction of loans; and (vii) the cumulative distribution of sales by age – 5, 9 and 13 years. Table (4) reports the parameter values and Table (5) reports the target moments. The technology ladder is the heart of the analysis.

Figure (5) then illustrates the calibrated features of the technology ladder. The left panel shows that the mean productivity of high-type firms increases when firms move up the ladder. The middle panel displays the conditional probability \(\rho_1(z^o)\) as an increasing function of \(z^o\). The probability of becoming high type at step \(s + 1\) conditional on being high type at step \(s\) is illustrated in the right panel.

1.6.3 Stationary Equilibrium Analysis

The stationary equilibrium analysis is done by simulating an economy consisting of 50,000 firms with entry and exit until the distribution becomes stationary. The stationary distribution of firms along the ladder suggests how the lack of development in the financial
sector precludes firms from reaching their optimal technology levels. This can be seen from Figure (6), which plots the distribution of firms along the ladder steps for the benchmark case along with the full-information case. The benchmark distribution on the left panel is obtained when all parameters are assigned the calibration values. The right panel displays the distribution when the type of each firm in the economy is common knowledge. This is analogous to setting $\theta = 1$.

Recall that the potential firm refers to the firm that would adopt higher-level technology if it knew its true type, given the same debt schedule that it currently faces. Compared to the full-information distribution, all potential firms at step 5 are precluded from adopting their optimal technology level in the benchmark case. Most firms are precluded from adopting low-level technology, especially at step 1 technology, bringing the chance to adopt any higher-level technologies to zero. As can be seen, as firms move up the technology ladder, the effect of financial development becomes more severe. Observe that 50% of potential firms end up with sub-optimal technology levels. In that setting, information friction is
the main obstacle to technology adoption. A low level of financial development results in only 50% of potential firms accumulating enough information and eventually choosing an optimal technology level. Table (6) shows that the model does a good job of matching the technology adoption decisions of Chilean manufacturing firms.

Table 6: Technology Adoption in the Stationary Equilibrium

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of firms adopting foreign technology</td>
<td>22.1</td>
<td>22.8</td>
</tr>
</tbody>
</table>

We move on now to the TFP gap analysis to see how financial development can explain the TFP gap between the U.S. and Chile. The TFP here is defined as an aggregate manufacturing TFP, given by $\ln(O) - \alpha \ln(K)$. Both countries face the same technology ladder toward the technological frontier but have different levels of financial development and talent. Therefore, all productivity parameter values are based solely on the previous calibration, while the values of $\{\bar{\kappa}_0, \bar{\kappa}_1, \bar{\kappa}_2, \bar{\kappa}_3, \theta, \xi\}$ are reassigned for the U.S. economy. The pre-lending evaluation technology in the U.S. is assumed to be efficient. That is, $\theta^{US} = 1$. The rest are reassigned values so that the model yields the U.S. loan recovery rate and
Table 7: TFP Gap and Financial Development

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Relative TFP</th>
<th>%Δ TFP</th>
<th>% TFP Gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>i. Benchmark</td>
<td>ξθκs</td>
<td>0.59</td>
<td>-</td>
</tr>
<tr>
<td>ii. Recovery rate</td>
<td>ξθκs</td>
<td>0.62</td>
<td>5.5</td>
</tr>
<tr>
<td>iii. Evaluation</td>
<td>ξθκs</td>
<td>0.71</td>
<td>21.5</td>
</tr>
<tr>
<td>iv. Fully efficient</td>
<td>ξθκs</td>
<td>0.73</td>
<td>25.1</td>
</tr>
<tr>
<td>v. Talent</td>
<td>ξθκs</td>
<td>0.96</td>
<td>64.5</td>
</tr>
</tbody>
</table>

Chile’s TFP relative to the U.S. as observed in the data. In particular, the U.S. recovery rate as a fraction of loans is 0.7 reported by the World Bank’s Doing Business Report. The Chile’s TFP relative to the U.S. is 0.59, reported by the UNIDO World Productivity Database. This yields ξUS = 0.91 and κUSs = 2κs.17

How important is efficiency in the financial sector for explaining the TFP gap between the U.S. and Chile? Table (7) shows the composition effect of financial development and talent. Given the talent of the Chilean economy, if the country could adopt U.S. financial practices, it would be able to close 34% of its TFP gap. However, simply by improving its talent to the U.S. level, Chile could close as much as 90.2% of its TFP gap. In other words, adoption of U.S. financial practice raises the relative TFP by 0.14 or 21.5% if the economy has talent κs, but increases the relative TFP by only 0.04 or 4.1% if the economy has talent κUSs. This implies that an improvement in financial development has larger benefits for countries with talent shortfalls. This is because the information problem is more severe in these countries. The result is consistent with the fact that financial development plays a larger role in explaining the TFP gap of less developed countries.

1.6.4 Transitional Dynamics Analysis

In this section, the speed of technology adoption and the speed of TFP convergence will be explored. The period studied is from 1986 to 2007. In 1986, the economy was in the state

17The values of κUSs are reassigned to be a multiplier of the benchmark case.
where only old technology was available. The Chilean economy started to have access to the technology ladder toward the world technological frontier in 1987. This is because, in 1987, Chilean manufacturing imports from high-income countries started to grow exponentially. Although the main reason import data are used as a proxy for foreign technology adoption is that the series are long enough to determine the transition period, the data on imports of machinery and equipment are also widely used in the literature as a proxy for foreign technology adoption [Caselli and Coleman II (2001); and Caselli and Wilson (2002)]. This is supported by the evidence that import activities are important channels for the transfer of technology [Almeida and Margarida Fernandes (2008)].

To simulate the transitional dynamics in response to the access to the technology ladder in 1987, two exogenous processes of real risk-free rates talents are given. These are treated as the expected processes. The fraction of new talented firms entering the economy is likely to increase over time when human capital and skills have been improving. This change is captured by changes in the parameters governing the conditional probability of being high type, $\kappa_{s,t}$, over time. Let $\kappa_{s,t} = x_t \kappa_s$, where $\kappa_s$ represents the benchmark parameter values calibrated to match the data in 2007. $x_t$ is then obtained from the human capital index at time $t$ relative to 2007. Figure (7) shows the process of risk-free rates on the left panel and an increase in the fraction of new talented firms entering the economy over the period 1986-2007. After simulating an economy consisting of 50,000 firms with entry and exit over the period of study, the time series of aggregate manufacturing TFP is obtained. To compare our model’s results with the actual data, Figure (8) presents the transitional dynamics of the model’s aggregate manufacturing TFP along with Chile’s aggregate TFP from Fuentes et al. (2007). Both are expressed as a TFP index, with the TFP of 1986 normalized to 100. The model does a very good job of matching the time path of the Chilean aggregate TFP, which exhibits a gradual increase in TFP once the economy has access to the world technological frontier.  

\[ ^{18} \text{In this transitional dynamics analysis, the distribution of firms in 2007 is not necessarily a stationary distribution.} \]
There are two underlying mechanisms driving this gradual change in the TFP when
development is lacking in the financial sector. First, firms need some time to accumulate
information in order to overcome financing problems. Because firm types are positively
correlated across steps, potential firms have to accumulate information until they get a
good pre-lending evaluation for investing in higher-level technology. This might delay the
speed of moving up the ladder, as well as the speed of choosing the optimal production
level. The time path, therefore, reflects higher-level technology adoption and more efficient
resource allocation over time when firm types are more accurately identified through the
process of learning and experimenting. Second, the economy waits until the information
problem becomes less severe. The fraction of new talented firms entering the economy
increases over time, so, from the intermediary’s point of view, firms on average become
more talented. Firms born in the latter periods then face fewer financing obstacles. Over
time, there will be more talented firms which face fewer obstacles to adopting higher-level
technology. This results in a gradual increase in the aggregate manufacturing TFP.

The impact of financial development on the TFP gap has already been shown. Now, it
is interesting to see how an improvement in financial development affects the level and speed
of TFP convergence. Figure (9) illustrates the transitional dynamics of TFP for different levels of financial development. The solid line is the benchmark case with the recovery rate and the accuracy of pre-lending evaluation calibrated for Chile’s economy. Better financial development leads to productivity improvement by stimulating technological progress through technology adoption and by increasing the efficiency of resource allocation. On the one hand, higher recovery rates, either from reducing liquidation process costs or from regulatory reforms, result in a lower cost of information accumulation. An increase in the loan recovery rate from 21% to 91% improves the TFP level by approximately 5% as more firms are allowed to learn their true types. However, the speed of convergence is actually quite slow. Firms still need some time to accumulate information. On the other hand, a more accurate pre-lending evaluation reduces the need for information accumulation and enables high-type firms to move up the technology ladder at a faster pace. Compared to the benchmark case, when the country adopts the U.S. financial practice, the TFP not only converges to a level which is approximately 30% higher, but the speed of convergence is
Figure 9: Transitional Dynamics and Financial Development

also doubled.

1.7 Conclusion

Why are firms in some countries slower to adopt new technology than firms in other countries? Why do firms in different countries eventually end up with different levels of technology? Empirical evidence in this paper suggests that, as financial development improves, more firms adopt new technology and the technology diffusion process is faster. The role of financial development in explaining differences in technology adoption and TFP is then explored here. To do so, a dynamic model of firm technology adoption and competitive financial intermediaries is developed. Without long-term experience with higher-level technology, how talented a firm is at using the technology is initially unknown. Learning and information accumulation provide a way to overcome this information problem in the technology adoption process. How severely financial intermediaries impede information
accumulation depends on the level of financial development.

Analytical results show that firms value the information from technology experimentation. They are willing to receive lower flow profits in exchange for the opportunity to acquire new information. The lack of development in the financial sector, however, precludes potential firms from accumulating information and adopting higher-level technology. A low recovery rate raises firm-specific borrowing costs and limits credit access. This not only discourages technology experiments by firms that have low beliefs about their ability to use new technology, but also limits adopting firms to small loans and low production at the beginning of technology adoption. Inaccurate pre-lending evaluation also precludes potential firms, which either receive a bad evaluation or experience a sequence of bad luck, from adopting higher-level technology. In the technology ladder setting, when firms’ capabilities to use higher-level technology are positively correlated with their abilities to use their current technology, poor financial development delays the choice of higher-level technology. This is because firms need time to accumulate information about their current technology before moving forward.

Consider two countries which have the same talent and have access to the same technology ladder. The country with a lower level of financial development will have the learning process delayed or prematurely ended. As a result, firms are slower to adopt higher-level technology and more firms end up operating with a sub-optimal technology level and a sub-optimal production level. This is then followed by a slower speed of TFP convergence toward a lower level of TFP.

The result is confirmed and quantified by the quantitative analysis. The model is calibrated to the Chilean Annual Manufacturing Survey. In a steady state, 50% of potential firms operate at a sub-optimal technology level and cannot move up the technology ladder. An improvement in financial development to a fully efficient level increases a country’s TFP by 25%. The results also show that a marginal return to an improvement in financial development is larger for a country with talent shortfalls. Some transitional dynamics are
then undertaken to explore the dynamics of Chilean manufacturing TFP in response to access to the world technology frontier. The model generates a gradual increase in the manufacturing TFP before it levels off. The resulting path for TFP matches the Chilean TFP index time series relatively well. Finally, the speed of TFP convergence is doubled when there is efficient finance.
Chapter 2

Technology, Skills and Productivity: A Perspective of Comparative Advantage and Heterogeneous Firms

Abstract

Trade liberalization triggers changes in productivity and the demand for skills, at both firm and aggregate levels. A unified model of international trade with multiple sectors, heterogeneous firms, and endogenous technology choices is developed to study this impact in developing countries. Advanced technologies improve productivity but they are skill biased. Productivity gains from adopting advanced technology are greater in skill-intensive industries. Analytical results show that, within industry, more firms adopt advanced technology and become more skill intensive, but, between industries, labor is reallocated toward comparative advantage industries. These two effects work in opposite directions in determining aggregate productivity and the demand for skills, resulting in an ambiguous effect of trade liberalization. The model is parameterized using Indonesian manufacturing data before trade reform. The counterfactual reform matches the data qualitatively well. In Indonesia, the skill premium falls, implying a decrease in the aggregate demand for skills. An increase in industrial productivity is large enough such that aggregate productivity increases, although slightly dampened due to between-sector reallocation.
2.1 Introduction

Trade plays a crucial role in the development process of most developing countries. Trade liberalization triggers changes in productivity and the demand for skills, at both firm and aggregate levels. Previous studies on developing economies have explored this effect through three main channels: between-industry reallocation, within-industry reallocation and technology upgrading. Most literature, however, focuses on middle-income countries, such as Brazil and Columbia, to which the standard Heckscher-Ohlin theory does not directly apply. The literature then studies the within-industry reallocation and technology decision channels in the context of a standard one-sector heterogeneous firm model. The model ignores various effects, when both comparative advantage and firm-level decisions are present, when in fact the comparative advantage effect is not negligible in low-income countries, in which skilled labor is relatively scarce. Unlike middle-income countries, low-income countries experience a large labor reallocation across sectors and a fall in the skill premium following trade liberalization. To account for this, a unified model of international trade with multiple sectors, heterogeneous firms, and endogenous technology choices is developed. The model provides a rich setting for explaining how productivity and skill intensity of firms in different industries respond to trade liberalization. This, in turn, provides some implications for the effect of trade liberalization on changes in aggregate productivity and the aggregate demand for skilled labor.

Empirical evidence shows a large labor reallocation across sectors following trade liberalization in low-income countries. This pattern, however, is not the case in middle-income countries. Figure (10) shows the measure of cross-sector labor shifts around each country’s trade liberalization period, normalized and averaged across all countries in each group. This measure is the average value of changes in sector shares of manufacturing employment proposed by Wacziarg and Wallack (2004). The average change in a sector’s share of employment over two years increases around the trade liberalization period in the group of

1See Romalis (2004) for evidence on comparative advantage.
Using the standard one-sector heterogeneous firm model, thus, ignores the role played by comparative advantage, which can be large in low-income countries. Because firm response to trade liberalization is different across industries depending on comparative advantage and the nature of technology, the goal of this paper is to provide a unified framework which captures both technology and inter-industry reallocation channels.\footnote{Trade liberalization periods of each country are taken from Wacziarg and Welch (2008). Low-income countries refer to lower-middle-income countries, as categorized by the World Bank, including Morocco, Bolivia, Ghana, Sri Lanka, Philippines, Indonesia, and Guatemala. Middle-income countries refer to upper-middle-income countries, as categorized by the World Bank, including Argentina, Brazil, Bulgaria, Columbia, Ecuador, Romania, Peru, and Turkey. This pattern is robust to the average change in sector shares over 3, 4, and 5 years. See Appendix B.1 for details and evidence from middle-income countries and other time intervals.} To allow for such interaction, endogenous technology choices are introduced in a general equilibrium model of comparative advantage with heterogeneous firms from Bernard et al. (2007b). The framework considers a world of two countries, two factors, and two industries. Each industry consists of a continuum of firms, each producing a differentiated variety within their industry, subject to both fixed and marginal costs. Factors of production are defined as skilled...
and unskilled labor, and the two industries vary in the relative skill intensity. The supply of skilled labor varies across countries, leading to comparative advantage trade. Heterogeneous firms endogenously choose their technology level. Advanced technology improves productivity, but it is skill-biased, and it is more biased in a skill-intensive sector.\(^4\)

The model provides a rich setting for obtaining analytical results, not only for explaining how productivity and skill intensity of firms in different industries change following trade liberalization, but also for analyzing the implications for aggregate productivity and the aggregate demand for skilled labor. In a low-income country, a reduction in trade costs, on the one hand, affects domestic and export revenues leading to (i) labor reallocation toward comparative advantage industries, i.e., low-tech industries; (ii) technology upgrading among exporters, especially in comparative advantage industries; and (iii) more intensive firm selection into the market, especially in comparative advantage industries. On the other hand, changes in the skill premium, caused by a reduction in trade costs, have an ambiguous effect on technology upgrading and firm selection. If comparative advantage plays a significant role, more exporters upgrade their technology and become more skill intensive. The aggregate demand for skills and aggregate productivity are determined by within-industry transformation and between-industry reallocation. While the former raises the demand for skills, the latter decreases it. Although within-industry transformation improves productivity in both types of industries through firm selection and technology upgrading, it is possible that its positive effect on aggregate productivity is dampened by between-industry reallocation. This is the case if low-tech industries have a lower productivity gain from technology upgrading. When comparative advantage reallocates resources toward low-tech industries, which on average have lower productivity, it creates a negative effect on aggregate productivity.\(^5\)

\(^4\)For skill-biased technical change, see e.g., Bernard et al. (2007a) for evidence for the US, Verhoogen (2008) for Mexico, Alcala and Hernandez (2010) for Spain, Molina and Muendler (2013) for Brazil, and Bustos (2011) for Argentina. For sector bias of skill-biased technical change, see e.g., Kahn and Lim (1997) for evidence for the US, Haskel and Slaughter (2002) for OECD countries, and Esposito and Stehrer (2009) for Poland and Hungary.

\(^5\)This is the usual composition effect when two industries are different in terms of average productivity gain.
All analytical results hold for the case of a small open economy. To obtain the extended results, the quantitative analysis is applied to Indonesia’s trade reform in 1995 during the WTO wave. The goal is to explain a transformation in the Indonesian manufacturing sector and quantify the impact of the trade reform on aggregate productivity and the aggregate demand for skills. Indonesia is a lower-income economy, which has undergone comprehensive trade liberalization in the last four decades. The response of Indonesian manufacturing firms to trade reform and changing skill supply also shows different patterns across industries, according to the degree of specialization and the nature of technology. The model is parameterized to Indonesian manufacturing firms in 1990. A counterfactual reform is compared to a post-reform period in 1998. The results match the data qualitatively well. The skill premium falls. The exporter skill-intensity premium, which measures the extent to which exporters are more skill intensive than non-exporters, increases in a low-tech industry and decreases in a high-tech industry. The exporter productivity premium, measured by log value added per worker, increases in a low-tech industry and decreases in a high-tech industry. These changes suggest that a comparative advantage effect plays a significant role in a very skill-scarce country like Indonesia. Although not directly observed in the data, the counterfactual reform predicts that industrial productivity increases in both industries but that labor is also reallocated toward a low-tech industry, which on average has a lower productivity gain. In Indonesia, an increase in industrial productivity is large enough such that aggregate productivity increases, although slightly dampened due to compositional change.

The paper makes two main contributions. First, the framework extends previous work on comparative advantage and heterogeneous firms [e.g., Bernard et al. (2007b); Bernard et al. (2003); Burstein and Vogel (2012)], and heterogeneous firms and technology upgrading [e.g., Atkeson and Burstein (2010); Bustos (2011)]. The framework simultaneously explains how the productivity and skill intensity of firms in different industries respond to trade liberalization, and also provides some implications on changes in aggregate productivity and the aggregate demand for skilled labor. Second, the paper employs the model to
quantitatively analyze the effect of trade reform on a manufacturing sector, at both firm and aggregate levels, in Indonesia, where the scarcity of skills is more apparent. This adds to the existing theory and evidence on trade liberalization among developing countries [e.g., Bustos (2011); Bas (2012); Amiti and Cameron (2012); Kugler and Verhoogen (2012)].

The paper is organized as follows. Section 2.2 presents the comparative advantage model with heterogeneous firms and endogenous technology choices. Section 2.3 presents analytical results on the specialization pattern and the impact of trade liberalization on firms’ decisions for the model with two technology choices, along with the small open economy application. In Section 2.4, a quantitative analysis and a counterfactual trade reform are undertaken using Indonesian manufacturing data. Section 2.5 revisits the model with a counterfactual analysis on skill upgrading and a shift in Indonesia’s comparative advantage. Section 2.6 presents concluding remarks.

2.2 The Model

Consider a world of two countries, two industries, two factors, and a continuum of heterogeneous firms. The model extends Bernard et al. (2007b) by incorporating endogenous technology choices. Technology choices are introduced with two important features: skill-biased technical change and sector bias of skill-biased technical change. That is, technological progress improves productivity but is skill-biased. The bias is more prominent in a skill-intensive sector. This setup is guided by an empirical application.

Two countries, Home and Foreign, are identical and differ only in terms of skilled labor supply. As the focus is on developing countries, assume that Home is skill scarce, \( \frac{S^*}{U} > \frac{S}{U} \). For the rest of the paper, an asterisk is attached to Foreign variables. Each country consists of two monopolistically competitive industries indexed by \( j \): a low-tech industry, \( j = l \), and a high-tech industry, \( j = h \), where the latter is more skill intensive.\(^6\) Heterogeneous firms

\(^6\)Manufacturing data show that R&D intensity and skill intensity are closely related when firms are
in each industry, indexed by $i$, produce differentiated goods using skilled and unskilled labor. A representative household acquires utility from consumption of the output from both industries. The household also supplies skilled and unskilled labor to firms.

### 2.2.1 Household and Demand

The representative household supplies a unit of labor with a fraction of skilled labor $S$ and a fraction of unskilled labor $U$ at wage rates $w^s$ and $w^u$. The representative household’s utility depends on the output of two industries, each of which contains a large number of differentiated varieties produced by heterogeneous firms $i \in [0,1]$ where

$$U = Q^h_1 Q^1 - \eta,$$  \hfill (2.1)

where $Q_j$ is a consumption index defined over consumption of individual varieties, $q_{ij}$, with the price index, $P_j$, defined over prices of varieties, $p_{ij}$,

$$Q_j = \left[ \int_0^1 q_{ij}^\rho \, di \right]^{\frac{1}{\rho}}, \quad P_j = \left[ \int_0^1 p_{ij}^{1-\sigma} \, di \right]^{\frac{1}{1-\sigma}}$$ \hfill (2.2)

where $\sigma = \frac{1}{(1-\rho)} > 1$ is the constant elasticity of substitution across varieties. For simplicity, assume that the elasticity of substitution between varieties is the same in both industries.

Given aggregate expenditure $R$, household expenditure on each variety $i$ is

$$r_{ij} = \eta_j R \left[ \frac{p_{ij}}{P_j} \right]^{1-\sigma}. \hfill (2.3)$$

classified according to the International Standard Industrial Classification (ISIC). Thus, in this paper, the concepts low-tech/high-tech and unskilled-intensive/skill-intensive are used interchangeably.
2.2.2 Production and Technology

For each sector, each differentiated good is produced by a monopolistically competitive firm. Production requires unskilled \((u)\) and skilled \((s)\) workers. Prior to entry, all firms are identical and face a sunk entry cost \(f_e\). Once the sunk entry cost is paid, firms draw inherited productivity, \(\varphi\), from a distribution \(G(\varphi)\) with the support \([\varphi_{\min}, \infty)\). This inherited productivity remains fixed after entry. This setting is the same as in the standard heterogeneous-firm model of Melitz (2003). At this point, all firms are endowed with the same technology level \(z = 0\). Firms can invest \(f_z(z)\) to choose a technology level \(z \in (-\infty, \infty)\) which will improve or decrease their productivity. This is the extension of technology upgrading introduced by Bustos (2011). Assume \(f_z\) is increasing and convex in the technology level \(z\).

To produce, firms pay a fixed overhead cost \(f\) each period which causes some firms to exit the market. After paying this cost, a firm with inherited productivity \(\varphi\) and a technology level \(z\) produces output \(y\) according to the following constant returns to scale production function:

\[
y_j(\varphi, z, s, u) = \varphi \left[ \beta_j \frac{1}{\alpha} (a^s_j(z)s)^{\alpha-1} + (1 - \beta_j) \frac{1}{\alpha} (a^u_j(z)u)^{\alpha-1} \right]^{\frac{1}{\alpha-1}}, \tag{2.4}
\]

where \(s\) and \(u\) are units of skilled and unskilled labor, with \(\alpha > 0\) representing the elasticity of substitution. \(\beta_j\) determines the relative importance of skilled labor in industry \(j\), so \(\beta_h > \beta_l\). \(a_j(z)\) captures productivity improvements from technological progress, which are defined as

\[
a^s_j(z) = \exp(\gamma^s_j z) \quad \text{and} \quad a^u_j(z) = \exp(\gamma^u_j z).
\]

\(\gamma^s_j\) shapes the skill bias of technology and rescales the exponential firm productivity. \(\gamma^s_h - \gamma^s_l > \gamma^u_h - \gamma^u_l > 0\) implies that technological progress in a high-tech industry is more skill-biased. The key idea is that technological progress in a high-tech industry, although usually associated with high productivity and high returns to skills, is more complementary with
skilled workers. All firms in both sectors share the same fixed entry and overhead costs, as well as the same technology cost function. These costs use both skilled and unskilled labor whose intensity of use depends only on $\beta_j$, independent of the firm’s technology level, $z$. It can be seen that industries differ only in their skill intensity and skill bias of technological progress.

### 2.2.3 International Trade

International trade is subject to both fixed and marginal costs of exporting. Firms decide whether to sell only in a domestic market or in both domestic and foreign markets in which they have to pay a fixed cost of exporting $f_x$. This fixed cost is produced in a similar way to other fixed costs using both skilled and unskilled labor. To deliver a unit of industry $j$’s good from Home (Foreign) to Foreign (Home), firms must export $\tau_j (\tau_j^*)$ units of the good.

### 2.2.4 Firms’ Problems: Exit, Export and Technology

Given wages $w^s$ and $w^u$, a firm from industry $j$ with inherited productivity $\varphi$ and technology level $z$ minimizes its cost by employing skilled and unskilled labor with the ratio

$$\frac{s_j(\varphi, z)}{u_j(\varphi, z)} = \left( \frac{w^u}{w^s} \right)^\alpha \frac{\beta_j}{1 - \beta_j} e^{(\alpha-1)\gamma_j^s - \gamma_j^u}.$$  \hspace{1cm} (2.5)

The demand for skilled labor is positively correlated with two sector-specific skill characteristics: the skill intensity $\beta_j$ and the skill bias of technology $\gamma_j^s - \gamma_j^u$, while it is negatively related to the skill premium. Therefore, for firm $(\varphi, z)$, the cost of producing one unit of

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7Hollanders and Weel (2002) find a stronger and significant relationship between R&D intensity and the employment shares of higher-skilled workers in high-tech industries.
output can be expressed by

$$c_j(\varphi, z) = \frac{1}{\varphi} \left[ \beta_j (w^s)^{1-\alpha} \exp \left( (\alpha - 1) \gamma_j^s z \right) + (1 - \beta_j)(w^u)^{1-\alpha} \exp \left( (\alpha - 1) \gamma_j^u z \right) \right]^{\frac{1}{1-\alpha}}. \quad (2.6)$$

Profit maximization implies that equilibrium prices are a constant mark-up over marginal costs. Export prices are a constant multiple of domestic prices due to the marginal costs of exporting:

$$p_{dj}(\varphi, z) = \frac{c_j(\varphi, z)}{\rho} \quad \text{and} \quad p_{xj}(\varphi, z) = \frac{\tau_j c_j(\varphi, z)}{\rho}. \quad (2.7)$$

Given the demand from Home and Foreign derived in equation (2.3), a firm’s profit from the domestic market, $\pi_{dj}(\varphi, z)$, and an additional profit from exporting to the foreign market, $\pi_{xj}(\varphi, z)$ are:

$$\pi_{dj}(\varphi, z) = \eta_j R \left[ \frac{\rho P_j}{c_j(\varphi, z)} \right]^{\sigma-1} - fc_{0j} \quad \text{and} \quad \pi_{xj}(\varphi, z) = \eta_j R^* \left[ \frac{\rho P^*_{j}}{\tau_j c_j(\varphi, z)} \right]^{\sigma-1} - f_x c_{0j} \quad (2.8)$$

where $c_{0j} = \left[ \beta_j (w^s)^{1-\alpha} + (1 - \beta_j)(w^u)^{1-\alpha} \right]^{\frac{1}{1-\alpha}}$. That is, all firms in the same industry share the same fixed costs regardless of their inherited productivity or technology level.

A firm with inherited productivity $\varphi$ chooses exit status $e$, export status $x$ and technology $z$ to maximize profit:

$$\pi_j(\varphi) = \max_{e \in \{0,1\}, x \in \{0,1\}, z} \{ (1 - e) \{ \pi_{dj}(\varphi, z) + x \pi_{xj}(\varphi, z) - f_z(z)c_{0j} \} \}. \quad (2.9)$$

Denote $E(\varphi)$, $X(\varphi)$, and $Z(\varphi)$ firm $\varphi$’s optimal choices. A firm’s benefit from advanced technology is proportional to its inherited productivity $\varphi$, so more productive firms choose a higher technology level. Because the profits $\pi_{dj}(\varphi, Z_j(\varphi))$ and $\pi_{xj}(\varphi, Z_j(\varphi))$ are increasing in firms’ inherited productivity, firms’ exit and export decisions can be characterized by inherited productivity cutoffs, $\bar{\varphi}_j$ and $\bar{\varphi}_{xj}$. In particular, $E(\varphi) = 0$ if $\varphi \geq \bar{\varphi}_j$ and $X(\varphi) = 1$ if $\varphi \geq \bar{\varphi}_{xj}$. 

55
2.2.5 Determining the Technology Choice

To see how the optimal technology choice is determined, firms’ optimization implies that the optimal technology rule can be explained by equating the marginal benefit and the marginal cost of the technology choice: 

\[
\varphi^{\sigma-1} (c_j(1,z)^{1-\sigma} + \epsilon) \left[ 1 + x(\varphi,z) \left( \frac{P^*_j}{P_j} \right)^{\sigma-1} \frac{R^*_j}{R} \tau_j^{1-\sigma} \right] = c_0 f'_z(z) \quad (2.10)
\]

given an export decision, \( x(\varphi,z) \), if the firm has inherited productivity \( \varphi \) and chooses technology level \( z \). The marginal benefit consists of three components: inherited productivity, technology cost saving, and sources of revenue. Firms with high inherited productivity and an additional revenue source will benefit more from a productivity improvement when upgrading their technology. The optimal technology choice \( Z(\varphi) \) is, therefore, increasing in a firm’s inherited productivity \( \varphi \). However, to what extent a higher level of technology can save costs depends on its productivity improvement, its skill bias and the country’s skill premium. Advanced technology improves firm productivity but changes its skill structure. That is, although a productivity improvement undoubtedly reduces the unit cost of production, a change in the skill structure has an ambiguous effect on the unit cost, depending on the skill premium. A skill-biased technology upgrading may increase the unit cost if the skill premium is high. The firm also incurs additional costs of investing in technology development. The more advanced the technology level is, the higher the fixed cost that the firm has to pay. Thus, it is not surprising to see some firms downgrade their technology.

\footnote{Both the marginal cost and marginal benefit of technology upgrading are strictly increasing in \( z \), so some restriction must be imposed on the technology cost function to ensure the existence of optimal technologies.}
2.2.6 Equilibrium

In each industry $j$, there is a mass of prospective entrants. These entrants are forward looking and correctly anticipate their future expected profits and exogenous exit rate of $\delta$. After paying a sunk entry cost, an entrant realizes initial productivity $\varphi$ drawn from a known distribution $G(\varphi)$. The entrant then makes an exit decision. In an equilibrium with positive firm entry, the free entry condition must hold. This requires the expected value of entry to equal the sunk entry cost in each industry:

$$\frac{1}{\delta} \int_{\bar{\varphi}_j}^{\infty} \pi_j(\varphi)dG(\varphi) = f_e c_{0j}. \quad (2.11)$$

The steady state equilibrium is characterized by constant masses of firms entering, producing and exporting in each industry. This requires that the mass of successful entrants equal the mass of incumbents who exit the market in each industry:

$$[1 - G(\bar{\varphi}_j)] M_{ej} = \delta M_j \quad (2.12)$$

where $M_e$ denotes the mass of entrants and $M$ denotes the mass of producing firms. Using the equilibrium pricing rules (2.7) and the optimal decisions (2.9), the equilibrium price indices can be expressed by

$$P_j = \left[ M_j \int_{\bar{\varphi}_j}^{\infty} p_{d_j}(\varphi, Z_j(\varphi))^{1-\sigma} \mu_j(\varphi) d\varphi + M_j^* \int_{\bar{\varphi}_{xj}}^{\infty} p_{x_j}^*(\varphi, Z_j^*(\varphi))^{1-\sigma} \mu_j^*(\varphi) d\varphi \right]^{1/1-\sigma} \quad (2.13)$$

where

$$\mu_j(\varphi) = \begin{cases} \frac{g(\varphi)}{1-G(\varphi)} & , \varphi \geq \bar{\varphi}_j \\ 0 & , \text{otherwise} \end{cases} \quad (2.14)$$

is the ex post distribution of inherited productivity among producing firms.

To close the model, labor markets and goods markets must clear. Using the relative
demand for skilled and unskilled labor (2.5), the demand for varieties of the good (2.3) and firms’ optimal decisions (2.9), firm \( \varphi \)'s demands for skilled and unskilled labor used for production can be derived:

\[
\begin{align*}
    u_j^p(\varphi) &= \eta_j \rho^s (RP_j^a)^{1-\sigma} c_j(\varphi, Z(\varphi))^{\alpha-\sigma} \left( \frac{1-\beta_j}{\varphi^{1-\alpha} (w^s)^{\alpha}} \right), \\
    s_j^p(\varphi) &= \eta_j \rho^s (RP_j^a)^{1-\sigma} c_j(\varphi, Z(\varphi))^{\alpha-\sigma} \left( \frac{\beta_j}{\varphi^{1-\alpha} (w^s)^{\alpha}} \right). \tag{2.15}
\end{align*}
\]

Firms also hire labor to produce all fixed costs: overhead, export, technology, and entry. The demands for skilled and unskilled labor to produce one unit of fixed costs are

\[
\begin{align*}
    s_j^f &= c_0 \alpha \frac{\beta_j}{(w^s)^{\alpha}}, \text{ and } u_j^f = c_0 \alpha \frac{1-\beta_j}{(w^u)^{\alpha}}. \tag{2.16}
\end{align*}
\]

The labor market clearing conditions require that the aggregate demand for labor used for the production process and fixed costs equals the aggregate labor supply:

\[
\begin{align*}
    \sum_{j=1,2} \left[ M_j \int s_j^p(\varphi) + (f + f_z(Z_j(\varphi))) f_x s_j^f \mu_j(\varphi) d\varphi + M_{ej} f e s_j^f \right] &= S \tag{2.17}
\end{align*}
\]

and

\[
\begin{align*}
    \sum_{j=1,2} \left[ M_j \int u_j^p(\varphi) + (f + f_z(Z_j(\varphi))) f_x u_j^f \mu_j(\varphi) d\varphi + M_{ej} f e u_j^f \right] &= U. \tag{2.18}
\end{align*}
\]

Lastly, the goods market clearing conditions require that the world’s demand equals the world’s supply for all countries and industries. In particular, the sum of domestic and foreign expenditures on domestic goods is equal to the total industry revenue which, by the free entry condition, equals the total amount of wages paid to workers for each industry:

\[
\begin{align*}
    \eta_j M_j \left[ \int R \left( \frac{p_j(\varphi, Z_j(\varphi))}{P_j} \right)^{1-\sigma} \left( 1 + 1 \{ \varphi \geq \bar{\varphi}_{xj} \} \frac{R^*}{R} \left( \frac{\tau P_j^*}{P_j^*} \right)^{1-\sigma} \right) \mu_j(\varphi) d\varphi \right] &= w^s S_j + w^u U_j. \tag{2.19}
\end{align*}
\]
Definition 2. An equilibrium is a collection of aggregate prices and wages \( \{ P_l, P_h, w^s, w^u \} \), firms’ decisions \( \{ \bar{\varphi}_j, \bar{\varphi}_{xj}, Z_j(\varphi), p_j(\varphi, z), p_{xj}(\varphi, z), s^P_j(\varphi), u^P_j(\varphi), s^f_j, u^f_j \}_{j=l,h} \), aggregate quantity \( \{ R, Q_l, Q_h \} \) and allocation of labor \( \{ S_j, U_j \}_{j=l,h} \) in Home and Foreign such that the following equilibrium conditions are satisfied for each country: (i) firms’ pricing rules (equation (2.7) for each industry and for the domestic and export markets separately), (ii) firms’ exit, export and technology decisions (equation (2.9) for each industry), (iii) firms’ labor demand to produce variable and fixed costs (equation (2.15) and (2.16) for each industry) (iv) free entry (equation (2.11) for each industry), (v) household optimization (equation (2.3)), (vi) labor market clearing (equation (2.17) and (2.18)), (vii) the values for the equilibrium price indices implied by household and firm optimization (equation (2.13) for each industry), and (viii) world expenditure on a country’s varieties equals the value of their production (equation (2.19) for each industry).

2.3 Analytical Results: A Case of Two Technology Choices

Once the economy moves from autarky to costly trade, firms adjust their behavior. This section analyzes how a reduction in trade costs from \( \tau = \infty \) to \( \tau < c \) affects firm decisions both within and across sectors. To establish the analytical results, a technology choice is assumed to be discrete. In particular, following the setting in Bustos (2011), there are two technology choices \( z_0 = 0 \) and \( z_1 = \Delta \) where \( f_z(z_0) = 0 \) and \( f_z(z_1) = f_\Delta \). The focus of this analysis is on the equilibrium where \( f_\Delta \) is high enough such that there are three groups of firms: (1) the least productive firms selling domestically and using \( z_0 \) technology, (2) exporters using \( z_0 \) technology, and (3) exporters using \( z_1 \) technology. In addition, assume that inherited productivity distribution \( G(\varphi) \) is a Pareto distribution \( 1 - \varphi^{-k} \) with the support \([1, \infty)\). The condition that \( k > \sigma - 1 \) is then needed to ensure that the variance of log productivity is finite. Apart from the tractability reason, this distribution also provides
a reasonable approximation of the observed variation in firm productivity. Although there are no longer closed-form solutions for several key endogenous variables of the model, a number of analytical results concerning the impacts of trade can still be derived. The results are first obtained for the case of two large countries with a difference in the supply of skilled labor supply. Then, they are extended to the case of a small open economy.

2.3.1 Two Large Countries

First, consider two countries of the same size. They are identical and only differ in terms of skilled labor supply. By assumption, the exit, export, and technology decisions can be summarized by three productivity cutoffs. This is because the fixed costs of exporting and technology upgrading are the same for all firms while the extra benefit is increasing in inherited productivity. In particular, firms with inherited productivity $\varphi$ higher than $\bar{\varphi}_j, \bar{\varphi}_{xzj}$, and $\bar{\varphi}_{zj}$ will produce for the domestic market, produce for the foreign market, and upgrade their technology to $\Delta$, respectively.

To separately examine the effect of inherited productivity and the technology choice, redefine the production cost function as $c(\varphi, z_0) = \frac{c_{0j}}{\varphi}$ and $c(\varphi, z_1) = \frac{c_{\Delta j}}{\varphi}$, where $c_{0j} = c(1, 0)$ and $c_{\Delta j} = c(1, \Delta)$ as characterized by equation (2.6). Solving the zero profit conditions, the relationship between the export cutoff and the exit cutoff can be characterized by:

$$\frac{\bar{\varphi}_{xzj}}{\bar{\varphi}_j} = \Lambda_{xzj} = \tau_j \left( \frac{f_x R}{f R^*} \right)^{\frac{1}{\sigma-1}} \frac{P_j}{P^*_j},$$

while the relationship between the technology cutoff and the exit cutoff can be characterized by

$$\frac{\bar{\varphi}_{zj}}{\bar{\varphi}_j} = \left[ \frac{f + f_x \Lambda_{xzj}}{f_{\Delta}} \left( \frac{c_{0j}}{c_{\Delta j}} \right)^{\sigma-1} - 1 \right]^{1-\sigma}. \tag{2.21}$$

It can be seen that two factors that determine industrial productivity and skill in-

---

$^9$See Appendix B.3.
tensity are firm selection and firms’ technology choices. Firm selection – the selection of high-productivity firms into the market and the drop-off of low-productivity firms from the market – affects the inherited productivity distribution of firms operating in the market. Given the inherited productivity distribution, firms’ technology choices then shape the actual productivity and skill intensity distribution of firms operating in the market. Therefore, in what follows, the focus will be on the effect of a trade cost reduction on these two productivity cutoffs, $\bar{\phi}_j$ and $\bar{\phi}_{zj}$. To ensure that the skill-biased technical change and the sector bias of skill-biased technical change play a significant role in the results, the following condition is imposed on the production function parameters.

**Assumption 2.** Differences in the relative skill intensity and the skill bias of technical change between a high-tech industry and a low-tech industry are large enough such that
\[
\frac{(\bar{\phi}_h)}{(\bar{\phi}_l)}\frac{\sigma-1}{\sigma-1} - 1 \quad \text{is decreasing in} \quad \frac{u^w}{w^s}.
\]

An increasing skill premium decreases the cost-saving benefits from technology upgrading. Because a high-tech industry relies heavily on skilled labor, this assumption assures that a gain from technology upgrading increases by more in a high-tech industry when the skill premium decreases. To obtain the analysis on firm selection and technology choices, it is necessary to establish the export decisions by firms.

**Lemma 3** (Export decisions). The export cutoff is closer to the exit cutoff in a country’s comparative advantage industry, $\bar{\phi}_{xh} > \bar{\phi}_{xl}$ and $\bar{\phi}^*_x > \bar{\phi}^*_h$. Therefore, the fraction of surviving firms that export is higher in a country’s comparative advantage industry,
\[
\frac{1-G(\bar{\phi}_{xl})}{1-G(\bar{\phi})} > \frac{1-G(\bar{\phi}_{xh})}{1-G(\bar{\phi}_h)} \quad \text{and} \quad \frac{1-G(\bar{\phi}^*_xl)}{1-G(\bar{\phi}_l)} > \frac{1-G(\bar{\phi}^*_xh)}{1-G(\bar{\phi}^*_h)}.
\]

**Proof.** See Appendix B.3.1. \hfill \square

When trade is costly, only a subset of firms find it profitable to export. Profits from export sales relative to domestic sales are larger in a comparative advantage industry, so
more firms find it profitable to export and the export cutoff lies closer to the exit cutoff. The Pareto distribution of inherited productivity implies that there is a higher fraction of exporting firms in the country’s comparative advantage industry.

The effect of trade opening on technology decisions works through two channels. First, a reduction in trade costs affects domestic and export revenues. This causes production to shift toward a comparative advantage industry and causes firms to change their technology choices. This is called the direct effect of costly trade, which is the first-order effect. Second, because the direct effect leads to a shift in the relative demand for skilled labor, the skill premium changes. This skill premium change affects firms differently depending on their factor intensity. This is called the indirect effect of costly trade, which is the second-order effect. In other words, the direct effect is thus the change in productivity cutoffs due to the reduction in trade costs, with the skill premium held fixed. The indirect effect is the change in productivity cutoffs in response to the skill premium change. Propositions 1-4 show the direct and indirect effects of costly trade on firms’ technology choices and firm selection. Proposition 5 then summarizes how costly trade can affect industrial productivity and aggregate productivity.

**Proposition 5** (Direct effect of costly trade on firms’ technology choices). *If the relative supply of skilled labor is perfectly elastic, a move from autarky to costly trade moves the technology upgrading cutoff closer to the exit cutoff by a larger percentage in a country’s comparative advantage industry.*

*Proof.* See Appendix B.3.1.

Within an industry, additional revenues obtained from the foreign market following a reduction in marginal trade costs induce exporters to opt for more advanced technology. This affects all firms proportionally according to their inherited productivity. Across industries, revenue from the foreign market relative to the domestic market is larger in a
comparative advantage industry. If the relative supply of skilled labor is perfectly elas-
tic, the skill premium is held fixed. The revenue of more productive exporting firms rises
by more in a comparative advantage industry. Therefore, the technology upgrading cutoff
moves closer to the exit cutoff to a larger extent in a comparative advantage industry. The
Pareto distribution implies that the fraction of technology upgrading firms increases by a
larger percentage in a country’s comparative advantage industry.

**Proposition 6** (Direct effect of costly trade on firm selection). *If the relative supply of
skilled labor is perfectly elastic, a move from autarky to costly trade induces more intensive
selection of high-productivity firms with a larger percentage in a country’s comparative
advantage industry.*

*Proof.* See Appendix B.3.1.

As in Melitz’s model, trade opening raises profits of high-productivity firms that become
exporters, increasing the expected value of entry in each industry. The industry becomes
more competitive, driving the low-productivity firms out of the market because they no
longer receive enough revenue to cover fixed production costs. The model presented here
introduces another channel through which technology choices operate. From Proposition
(5), trade not only increases profits of exporting firms but also induces technology upgrading
among these firms. These two forces together increase the expected value of entry, and so
the exit productivity cutoff. The increase is larger in a comparative advantage industry, as
the positive direct effect on profits of exporting firms and technology upgrading decisions
is larger in a comparative advantage industry.

Moving on to the indirect effect of a reduction in trade costs, this is the second-order
effect arising from a change in the skill premium. As discussed, the direct effect shifts pro-
duction toward a comparative advantage industry and encourages firms to upgrade their
technology. Because industries have different factor intensity, a shift in production changes
the relative demand for skilled labor and, thus the skill premium. This channel is referred to as a *specialization channel*.\textsuperscript{10} Technology upgrading is skill-biased, so it shifts demand toward skilled labor and raises the skill premium. This channel is referred to as a *skill-biased technical change channel*.

**Proposition 7** (Indirect effect of costly trade on firms’ technology choices).

1. *The specialization channel drives down the skill premium in Home, moving the technology cutoff closer to the exit cutoff. The opposite occurs in Foreign.*

2. *The skill-biased technical change channel raises the skill premium, moving the technology cutoff further from the exit cutoff in both countries.*

**Proof.** See Appendix B.3.1.

Specialization causes production to shift toward a low-tech sector in Home, decreasing the relative demand for skilled labor and thus the skill premium. This induces firms to choose to upgrade their skill-biased technology. The opposite occurs in Foreign, where production shifts toward a high-tech sector, raising the skill premium and, as a second-order effect, discouraging firms from upgrading their technology. The direct effect of trade opening also increases the number of firms using skill-biased advanced technology. As a result, the relative demand for skilled labor and the skill premium increase, dampening the positive effect on technology upgrading in both countries.

**Proposition 8** (Indirect effect of costly trade on firm selection).

1. *The specialization channel drives down the skill premium in Home, inducing more intensive selection of high-productivity firms. The opposite occurs in Foreign.*

2. *The skill-biased technical change channel raises the skill premium, inducing less intensive selection of high-productivity firms.*

\textsuperscript{10}This is the Stolper-Samuelson effect that trade opening raises the relative return to the factor that is used intensively in a country’s comparative advantage industries.
tensive selection of high-productivity firms in both countries.

Proof. See Appendix B.3.1.

The change in the skill premium, occurring through the specialization channel, creates a stronger incentive for firms in Home to upgrade their technology, increasing the expected value of entry and the exit cutoffs. The opposite occurs in Foreign, causing a decrease in the exit cutoff. By the same reasoning as that for Proposition 7, the indirect effect, through the skill-biased technical change channel, dampens the positive effect on technology upgrading and the exit cutoffs in both countries.

How might costly trade affect industrial productivity and aggregate productivity? Define an index of industrial productivity as an industrial average of firm productivity:

\[
\Phi_j = \int \frac{y_j(\varphi, Z_j(\varphi), s^p_j(\varphi), u^p_j(\varphi))}{y_j(0,0, s^p_j(\varphi), u^p_j(\varphi))} \mu_j(\varphi) d\varphi
\]  

(2.22)

where \(s^p_j(\varphi)\) and \(u^p_j(\varphi)\) are determined by (2.15) and \(Z_j(\varphi) = \Delta\) if \(\varphi \geq \tilde{\varphi}_{zj}\) and 0 otherwise. This measure is similar to that in Melitz (2003) but allows both inherited productivity and productivity improvement from technology upgrading to be captured. Aggregate productivity, \(\Phi\), is then defined as a weighted average of industrial productivity:

\[
\Phi = \frac{\sum M_j \Phi_j}{\sum M_j}.
\]  

(2.23)

Proposition 9 (Effect of costly trade on aggregate productivity in Home). If the specialization channel dominates, trade opening has two sets of effects on aggregate productivity in Home:

1. (Mass Effect) The relative equilibrium mass of firms in a low-tech industry increases.

2. (Industrial Productivity Effect) Industrial productivity increases in both industries due to technology upgrading and intensive firm selection.
The impact of trade cost reduction on aggregate productivity can be decomposed into two sets of effects: the industrial productivity effect and the mass effect. The specialization channel causes a fall in the skill premium in Home. The direct effect and the indirect effect, thus, move the technology upgrading cutoff closer to the exit cutoff and also raise the exit cutoff in both industries. Some low-productivity firms drop out of the market. Among those staying in the market, a larger fraction of firms upgrade their technology. Industrial productivity then increases in both industries. However, trade opening changes the composition of firms, namely, the mass effect. As Home specializes according to comparative advantage, an increasing share of resources is allocated to a comparative advantage industry. The mass of firms in a low-tech industry increases relative to those in a high-tech industry.

The effect of trade opening on aggregate productivity can be ambiguous if a productivity gain from technology upgrading is allowed to vary across industries. Specifically, if a high-tech industry has a higher productivity gain from technology upgrading, as is usually the case, a reduction in trade cost may lead to a fall in aggregate productivity if resources are re-allocated away from a high-tech industry. This can occur even though trade opening is productivity-improving in both industries.

2.3.2 Small Open Economy

Because the focus is on a developing country, it is interesting to consider Home as a small open economy. The analysis considered here is thus a unilateral trade opening by Home which involves a reduction in trade barriers from $\tau^* = \infty$ to $\tau^* < c$ and a fixed export cost from $f_x = \infty$ to $f_x < c$. Foreign can then be referred to as the rest of the world which already has some degree of trade openness. The key assumption is that some Foreign variables are not affected by any changes in Home. These variables include the exit cutoffs, the technology cutoffs, the mass of firms, the skill premium, the total expenditures, and
the price indices. The export cutoffs and the measure of exporters, however, respond to a reduction in trade barriers. Intuitively, one can think of Foreign as a very large country or a country that trades with many countries. Additional revenues from exporting to one small economy is thus so negligible that it has no effect on an individual firm’s exit and technology decisions. Nevertheless, when each individual firm decides whether to export to one small country, the trade barrier of that country does matter.

The small open economy analysis requires a few changes in the equilibrium characterization. First, \( R^* \) and \( P^*_j \) are exogenous, with \( \frac{P^*_j}{P^*_h} > \frac{P^{aut}_h}{P^{aut}_n} \). This condition assures that the relative ability to supply skilled labor is reflected in the relative price index. Second, \( \frac{w^{s,aut}}{w^{u,aut}} > \frac{w^{s,*}}{w^{u,*}} \). This condition assures that the relative ability to supply skilled labor is reflected in the skill premium. Finally, conditions (2.11) to (2.19) are only required for Home. Under these conditions, the results for Home from the previous section can be applied to the small open economy. Appendix B.3.2 formally shows how those propositions remain true when Home, as a small open economy, moves from autarky to costly trade.

### 2.4 Quantitative Exercise: Evidence from Indonesia

This section applies a small open economy variant of the continuous technology choice model formulated in Section 2.2 to Indonesian data. First, a description of Indonesian reforms and manufacturing data is given. The model is then calibrated to the pre-liberalization period by matching some stylized facts about the Indonesian economy and its manufacturing sector. Lastly, the counterfactual experiment is performed on a change between pre- and post-liberalization periods.
2.4.1 Indonesia: Trade and Skills

Indonesia is a lower-middle-income economy, as classified by World Bank, which engages intensively in international trade. Over the last four decades, Indonesia has undergone comprehensive trade liberalization, by participating in multilateral and regional trade arrangements and by conducting unilateral liberalization. There are three comprehensive trade reform periods documented in the literature. The first period is a change from an import substitution strategy to a limited liberalization in 1970. This period is documented by Sachs and Warner (1995) and later confirmed by Wacziarg and Welch (2008). Later on, in the mid 1980s, Indonesia underwent unilateral liberalization. In this second period, tariffs were rationalized and reduced across the board, and some non-tariff barriers (NTBs) were removed. The progress on unilateral liberalization slowed by 1991. However, a comprehensive program of tariff reductions became active again in the third period, 1995. This followed from the Uruguay Round Agreement and creation of the WTO at the end of 1994. Figure (11) shows the evolution of the measure of cross-sector labor shifts. This is measured by the average value of changes in sector shares in manufacturing employment, as in Wacziarg and Wallack (2004). The average change in sector shares over three years increased during each liberalization period.

At the firm-level, the Statistik Industri (SI) provides a firm-level panel data set for a survey of manufacturing firms with twenty or more employees. This is published by the Indonesia Central Bureau of Statistics (BPS). The surveys cover the period from 1990 to 2005. There were roughly 14,000 manufacturing establishments in 1990 and this number increases to around 20,000 establishments in 2005. The series of inputs (capital, labor and materials), output (total gross output), expenditure (wage, rental and others) and export status for each establishment are collected and categorized based on the three-digit industry classification.\footnote{Indonesian Standard Industrial Classification Codes (KBLI) employed in the survey follow the International Standard Industrial Classification (ISIC), with some modifications to suit Indonesian conditions.} The employment-related data include information on wages and
employment of production and nonproduction workers. The SI collected information on a fraction of workers by education category for production and nonproduction workers for a sub-sample of years, 1995 and 1997.

Because the firm-level data cover the period of 1990-2005, the analysis here will focus on the third period of trade reform or the WTO wave. To make sure that a change in the country’s ability to supply skilled labor and comparative advantage is taken into consideration, Figure (12) shows the weighted manufacturing tariff and the fraction of the labor force with at least a secondary education during this period. At the aggregate level, the weighted manufacturing tariff has been declining from 16% in 1990 to less than 5% in 2005, with a large drop in 1995 when a comprehensive program of tariff reductions was announced. The country’s ability to supply skilled labor improved after 2000. Although skill supply in Indonesia decreased slightly during 1990-1995, it has been increasing since 1995, with rapid growth after 2000.\footnote{This is consistent with the fact that total public spending on education as a percentage of GDP was stagnant at around 1% during 1988-1997, then more than doubled in 1998-2000 and reached 3% in 2005.} This observation is supported by the work of Damuri et al. (2006), who estimated the Indonesian trade specialization index based on technology intensity for the periods 1990-1992 and 2001-2003. The indices suggest that Indonesia had
trade specialization in low-tech industries during the 1990s, while the specialization shifts toward high-tech industries after 2000.\textsuperscript{13}

![Figure 12: Indonesia's Weighted Tariffs and Secondary Level Education, 1990-2005](image)

Major shifts are observed in 1995 and 2000. It is therefore interesting to explore changes in firm behavior over three subperiods: (i) 1990 - 1995, (ii) 1996 - 1999, and (iii) 2000 - 2005. The effect of a reduction in trade costs can be observed from changes in firm behavior from subperiod 1 to subperiod 2, when the country’s skill supply is relatively constant. The effect of an improvement in the ability to supply skilled labor can be observed from changes in firm behavior between subperiod 2 and subperiod 3. The exporter skill-intensity premium and the exporter productivity premium are estimated separately for high-tech industries and low-tech industries. This suggests how decisions of exporting firms change relative to those of domestic firms for different industries. Moreover, by assumption of a sector bias of skill-biased technical change, these exporter premia can summarize the relative change in firms’ technology decisions in response to a reduction in trade cost and an increase in the skilled labor supply.

\textsuperscript{13}For low-tech to low-medium-tech industries, the specialization indices were 13.94 and 2.79 in 1990-1992, but decreased to 11.57 and -1.01 in 2001-2003. For medium-high-tech to high-tech industries, the specialization indices were -24.18 and -2.10 in 1990-1992, but increased to -12.31 and 2.62 in 2001-2003.
From the data set, firms are classified into different industries according to the ISIC Rev.2. To group industries into a high-tech skill-intensive industry and a low-tech unskilled-intensive industry, industries are categorized according to two indices: the skill intensity and the technology intensity. The technology intensity definition is taken from an OECD classification based on R&D intensities. The skill intensity of each manufacturing industry is computed using the NBER-CES Manufacturing Industry Database. It is the ratio of non-production workers to the total number of workers by industry. That is, Indonesian industries will be categorized as a high-tech industry or a low-tech industry using these criteria, regardless of their actual skill intensity and technology intensity.\textsuperscript{14}

The exporter skill-intensity premium and the exporter productivity premium are estimated by running the following regressions at the firm-level;

\[
\ln \left( \frac{s_{ij}}{s_{ij} + u_{ij}} \right) = \phi_{0j} + \phi_{1j} \text{exporter}_{ij} + \epsilon_{ij}, \text{ for } j = l, h \\
\ln \left( \text{tfp}_{ij} \right) = \phi_{0j} + \phi_{1j} \text{exporter}_{ij} + \epsilon_{ij} \text{ for, } j = l, h
\]

(2.24)  
(2.25)

where \(\frac{s_{ij}}{s_{ij} + u_{ij}}\) is the fraction of workers who have completed a secondary degree\textsuperscript{15}, \(\text{tfp}_{ij}\) is obtained using the Olley-Pakes method [Olley and Pakes (1996)], and \(\text{exporter}_{i}\) is a firm-level exporter dummy variable. Year dummies and 3-digit industry dummies are also added. Table (8) shows estimated exporter premia from each subperiod.

During the 1990s, Indonesia trade specialization was in low-tech industries. Thereafter, following the WTO wave of trade reform, among low-tech industries there was a significant difference between technology levels chosen by exporting firms and domestic firms, with exporters choosing a higher technology level. This is reflected in an increase in the exporter productivity premium. The exporter skill-intensity premium, however, did not increase significantly, suggesting that technology upgrading in low-tech industries is not strongly

\textsuperscript{14}The category is shown in Appendix B.4.1.
\textsuperscript{15}A skilled worker is defined as a worker with at least secondary education. Because the data on workers’ education are not provided every year, the number of workers with at least secondary education is approximated using the fractions of workers with at least secondary education in production and nonproduction for each 3-digit industry obtained from the 1995 and 1997 survey.
Table 8: Exporter Premia Estimated from Indonesian Manufacturing Data, 1990-2005

<table>
<thead>
<tr>
<th></th>
<th>Low-Tech Industry</th>
<th>High-Tech Industry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Skill Intensity</td>
<td>Productivity</td>
</tr>
<tr>
<td><strong>Tariff reduction</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subperiod 1 (1990-1995)</td>
<td>0.37%</td>
<td>25.96%</td>
</tr>
<tr>
<td>Subperiod 2 (1996-1999)</td>
<td>0.37%</td>
<td>31.76%</td>
</tr>
<tr>
<td>Δ = Subperiod 2 − 1</td>
<td>0.00%</td>
<td>5.81%</td>
</tr>
<tr>
<td><strong>Skill Upgrading</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subperiod 2 (1996-1999)</td>
<td>0.37%</td>
<td>31.76%</td>
</tr>
<tr>
<td>Subperiod 3 (2000-2005)</td>
<td>0.00%</td>
<td>17.60%</td>
</tr>
<tr>
<td>Δ = Subperiod 3 − 2</td>
<td>-0.37%</td>
<td>-14.16%</td>
</tr>
</tbody>
</table>

1 Full estimation results are reported in Appendix B.4.2.
2 Because the dependent variables are expressed in log terms, the coefficient on the exporter dummy can be interpreted as a percentage. For example, the skill intensity of exporters in low-tech industries was, on average, 0.37% higher than that of non-exporters.

skill-biased. Because the country did not specialize in high-tech industries, technology levels chosen by exporting firms and domestic firms were not significantly different. Changes in both exporter skill-intensity and productivity premia, as a result, were insignificant. After 2000, Indonesia’s trade specialization shifted toward high-tech industries, and the difference between technology levels chosen by exporting firms and domestic firms in these industries became larger. Exporters chose more advanced technology which, for high-tech industries, is more skill-biased, so there was an increase in both exporter skill-intensity and productivity premia in high-tech industries. At the same time, trade specialization was shifted away from low-tech industries. Exporters in these industries enjoyed less advantage from trade, so the relative technology level between exporting firms and domestic firms became smaller. The exporter productivity premium, thus, decreased.

2.4.2 Parameterization to Pre-reform Period

A small open economy variant of the model formulated in Section 2.2 is parameterized to match some salient features of Indonesian firm-level data in 1990, a period before Indonesia began to adopt WTO’s trade policy. During this period, exports to and imports from high-
income countries accounted for 90% and 85% of total exports and total imports, respectively, with Japan, the US, Singapore, Korea and Germany accounting for 60% of total trade values. Before proceeding to the parameterization, first assume a functional form for the technology cost function:

\[ f_z(z) = h \exp(bz) \]  

(2.26)

where \( b \) determines the curvature of the function. This function allows the closed-form derivation of the sufficient condition for the existence of an optimal technology choice.\(^{16}\) The economy size \( S + U \) is normalized to 1. The relative supply of skilled labor, \( S \), is assumed to be inelastic and is set to 0.46 to match the fraction of workers with at least secondary education, based on Indonesian manufacturing data.

Parameters are grouped into two categories. The first category includes parameters of which the values are either taken from other literature or directly obtained from the data using the equilibrium conditions. The second category includes parameters chosen so that endogenous outcomes from the model match salient features of the data.

The preference parameters are the share of each good in consumer expenditure, \( \eta \), and the elasticity of substitution \( \sigma \). \( \eta \) is set to 0.45 to match low-tech industries’ share of the gross output of Indonesia and five major trading partners. The US estimate is used for \( \sigma \), as in Burstein and Vogel (2012); here, \( \sigma = 2.7 \). Marginal trade costs are the weighted average tariff rates calculated using the data from UN Comtrade and the UNCTAD TRAINS database. Average tariff rates imposed by Indonesia’s major trading partners in low-tech and high-tech industries are 4% and 1%, respectively. Using the same approach, average tariff rates faced by foreign firms in low-tech and high-tech industries are 25% and 15% respectively. The values of production parameters \( \beta_1, \beta_2 \) and \( \alpha \) are assigned using the equilibrium condition (2.5). The industry aggregate statistics are matched to the homogeneous technology case, with \( z = 0 \). \( \alpha \) is set to 1.6, as in Acemoglu and Autor (2011), for the

\(^{16}\) Equation (2.10) implies that the sufficient condition for the existence of optimal technology choices is \( \frac{k}{\sigma - 1} \geq \gamma^a \).
homogeneous technology case. The shares of workers with at least secondary education employed in low-tech industries and high-tech industries, obtained from Indonesian manufacturing data, are 0.39 and 0.58. Using the observed skill premium of 2.37 in Indonesia from Lee and Wie (2013), $\beta_1 = 0.73$ and $\beta_2 = 0.85$.

Table 9: Parameter Values

<table>
<thead>
<tr>
<th>Value</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\eta$</td>
<td>0.45</td>
<td>Share of low-tech goods</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>2.7</td>
<td>Elasticity of substitution</td>
</tr>
<tr>
<td>$(\beta_l, \beta_h)$</td>
<td>(0.73, 0.85)</td>
<td>Production parameter</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>1.6</td>
<td>Production parameter</td>
</tr>
<tr>
<td>$(\tau_l, \tau_h)$</td>
<td>(4%, 1%)</td>
<td>Tariffs faced by Home</td>
</tr>
<tr>
<td>$(\tau^<em>_l, \tau^</em>_h)$</td>
<td>(25%, 15%)</td>
<td>Tariffs faced by Foreign</td>
</tr>
<tr>
<td>$f_e$</td>
<td>1</td>
<td>Fixed entry cost</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.04</td>
<td>Exogenous exit rate</td>
</tr>
<tr>
<td>$S$</td>
<td>0.46</td>
<td>Skilled labor supply</td>
</tr>
</tbody>
</table>

Calibrated Parameters

<table>
<thead>
<tr>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(\gamma^s_l, \gamma^s_h)$</td>
<td>(1.10, 1.57)</td>
</tr>
<tr>
<td>$(\gamma^u_l, \gamma^u_h)$</td>
<td>(0.58, 0.42)</td>
</tr>
<tr>
<td>$b$</td>
<td>6.05</td>
</tr>
<tr>
<td>$h$</td>
<td>0.02</td>
</tr>
<tr>
<td>$f_x$</td>
<td>0.25</td>
</tr>
<tr>
<td>$f$</td>
<td>0.01</td>
</tr>
<tr>
<td>$k$</td>
<td>3.61</td>
</tr>
<tr>
<td>${R^<em>_iP^</em>_i}^\sigma^{-1}$</td>
<td>(3.75, 1.92)</td>
</tr>
</tbody>
</table>

† With support [0.1, 2].

The exogenous exit rate $\delta = 0.04$ is set to capture the exit rate of large firms in Indonesian manufacturing. This is in the range of those used in the US data, 3% – 6%. The fixed entry cost $f_e$ is normalized to 1. The rest of the parameters are selected so that the model matches: (i) the exports share of total absorption for each sector; (ii) the imports share of total absorption for each sector; (iii) the fraction of the total sales of each sales quartile for each sector; (iv) the mean skill intensity of firms in each sales quartile for each sector; (v) the skill premium; and (vi) the standard deviation of firm size (log employment). The parameter values are illustrated in Table (9).

The model matches very well with the targeted moments shown in Table (10). For high tech industries only, the model slightly overestimates the skill intensity of firms in the
middle quartiles. As in other developing countries, Indonesia imports more high-tech goods and exports more low-tech goods. Firms in the upper quartiles of sales are more likely to be exporters and thus earn additional revenues from the foreign market. They have higher skill intensity because larger sales encourage them to choose more advanced technology.

Figure (13) illustrates technology, export and exit decisions of firms from both high-

<table>
<thead>
<tr>
<th>Targeted moments</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exports to total absorption, $j = l, h$†</td>
<td>(17.9%, 5.3%)</td>
<td>(18.1%, 5.8%)</td>
</tr>
<tr>
<td>Imports to total absorption, $j = l, h$††</td>
<td>(4.5%, 15.2%)</td>
<td>(4.5%, 15.2%)</td>
</tr>
<tr>
<td>Fraction of sales by each quartile, $j = l$</td>
<td>(0.02, 0.05, 0.15, 0.78)</td>
<td>(0.03, 0.05, 0.13, 0.79)</td>
</tr>
<tr>
<td>Fraction of sales by each quartile, $j = h$</td>
<td>(0.02, 0.05, 0.14, 0.79)</td>
<td>(0.03, 0.05, 0.13, 0.79)</td>
</tr>
<tr>
<td>Mean skill intensity of each sales quartile, $j = l$</td>
<td>(0.62, 0.65, 0.67, 0.71)</td>
<td>(0.62, 0.64, 0.66, 0.70)</td>
</tr>
<tr>
<td>Mean skill intensity of each sales quartile, $j = h$</td>
<td>(1.31, 1.49, 1.64, 1.68)</td>
<td>(1.31, 1.40, 1.51, 1.70)</td>
</tr>
<tr>
<td>Skill premium</td>
<td>2.37</td>
<td>2.37</td>
</tr>
<tr>
<td>Standard deviation of log employment</td>
<td>1.20</td>
<td>1.17</td>
</tr>
</tbody>
</table>

†, †† These are merchandise exports and imports as a percentage of total absorption. Imports and exports of high-tech and low-tech industries are obtained from UN Commodity trade statistics (UN Comtrade). Total absorption is total income plus merchandise imports minus exports.

Figure 13: Technology Choices and Productivity Cutoffs
tech and low-tech industries. An optimal technology choice is increasing in the inherited productivity, with a discontinuous jump at the export cutoffs. Some firms downgrade their technology from the initial level \( z = 0 \). For the least productive firms, it is optimal to give up productivity gains in exchange for facing less skill bias due to the extremely high skill premium in Indonesia.

Now, compare the optimal technology choice for each inherited productivity across industries. Among domestic firms, the technology choice function is steeper in a high-tech industry. From equation (2.10), this is because, when inherited productivity is low, the cost saving component dominates the inherited productivity component. Although technology upgrading reduces costs by improving productivity, the upgrading also shifts the composition of labor demand toward skilled labor. In a country such as Indonesia that has high skill premia, the skill-biased technical change has a negative effect on cost savings, which is more severe in a high-tech industry. Therefore, in a high-tech industry, firms with low inherited productivity will choose relatively low levels of technology compared to firms with high inherited productivity. This effect is less prominent in a low-tech industry, in which the technical change is less skill-biased. As a result, a steeper technology choice function can be observed in a high-tech industry.

A bigger jump observed in a technology choice function in a low-tech industry can be explained by comparative advantage. Additional revenue from exporting is relatively higher in a comparative advantage industry, resulting in a stronger incentive to use more advanced technology. Comparative advantage also explains why the export cutoff is lower and lies closer to the exit cutoff in a low-tech industry.

### 2.4.3 Pre- and Post-reform Periods

What are the effects of Indonesia joining the WTO in 1995? Although Indonesia was allowed to gain greater access in world markets, it was also obliged to reduce tariff rates. To
see how well the model can predict the effect from these exogenous changes, some parameter
values are reassigned. First, tariffs are exogenously decreased to match the Indonesian
average in 1990 and 1998. Indonesia’s tariff rates were reduced from 25% to 7.3% in low-
techn industries and from 15% to 6.5% in high-tech industries, according to UN Comtrade
and the UNCTAD TRAINS database. Second, to allow for the expansion of access in world
markets, foreign demands are allowed to change to exactly match the aggregate change in
imports and exports. To be specific, between 1990 and 1998, low-tech imports expanded
from 4.5% to 7.1% of total absorption, and exports expanded from 17.9% to 28.5%. There
were changes in trade flows for high-tech industries, where imports expanded from 15.2%
to 20.2% of absorption, and exports expanded from 5.3% to 13.4% of absorption.\footnote{Exports expanded by a larger percentage in high-tech industries due in part to a change in Indonesia’s trading partners. In 1990, exports to high-income countries accounted for 90% of total exports. This number decreased to 80% in 1998.}

Table 11: Changes in Skill Premium – Trade Reform

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>2.37</td>
<td>2.37</td>
</tr>
<tr>
<td>1998</td>
<td>2.09</td>
<td>2.25</td>
</tr>
<tr>
<td>$\Delta = 1998 - 1990$</td>
<td>-0.28</td>
<td>-0.12</td>
</tr>
</tbody>
</table>

Table (11) shows that, consistent with the data, the model qualitatively and quantita-
tively predicts a decrease in the skill premium. Unlike middle-income countries, low-income
countries such as Indonesia experience a fall in the skill premium after trade reform. Fol-
lowing trade reform, specialization according to comparative advantage causes production
to shift toward a low-tech sector. At the same time, more competition from foreign firms
reduces the profits of non-exporters and discourages them from investing in skill-biased ad-
vanced technology, as shown in Figure (14). These two forces raise the relative demand for
unskilled labor, bidding up the wage for unskilled labor. In Indonesia, this effect outweighs
an increase in the relative demand for skilled labor resulting from exporters choosing more
skill-biased advanced technology, and thus the skill premium falls.

After trade reform, firms change their exit, export and technology choices. Figure (14)
Figure 14: Changes in Technology Choices and Productivity Cutoffs – Trade Reform

shows the model results of firms’ optimal decisions for the pre- and post-reform periods. Non-exporters downgrade their technology due to competition from foreign firms, while exporters upgrade their technology, thanks to an expansion of access to world markets. The downgrading among non-exporters is larger in a low-tech industry, as the tariff rate was reduced by more. The upgrading among exporters is larger in a high-tech industry due to a larger expansion in foreign demand and a fall in the skill premium, which make technology upgrading more attractive. For the same reason, the export cutoff decreases by more in a high-tech industry. Nevertheless, comparative advantage is still in a low-tech industry, in which the export cutoff lies closer to the exit cutoff.

These changes in firms’ decisions, then, have some implication for changes in both skill intensity and productivity among exporters and non-exporters across industries. Table (12) reports the effect of trade reform on exporter premia in each industry, for those premia obtained from the data and predicted by the model. Exporter premia measure the extent to which exporters are more skill intensive or more productive than non-exporters. The
goal is to explore the relative change between exporters and non-exporters across industries due to trade reform in 1995. The model matches reasonably well with the exporter premia in 1990, which are non-targeted moments in the parameterization procedure. Consistent with the data, the model predicts that the exporter skill-intensity premium increases in a low-tech industry and decreases in a high-tech industry, although it underestimates the magnitude. Log value added per worker measures labor productivity, which is the most common measure of productivity. Similarly, the exporter productivity premium increases in a low-tech industry and decreases in a high-tech industry. This is because technology upgrading raises both a firm’s skill intensity and its productivity. The model does fairly well in predicting these changes.

Table 12: Changes in Exporter Premia – Trade Reform

<table>
<thead>
<tr>
<th></th>
<th>Low-Tech Sector</th>
<th>High-Tech Sector</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Exporter – Non-Exporter (%)†</strong></td>
<td>Data</td>
<td>Model</td>
</tr>
<tr>
<td><strong>Skill Intensity (s/u)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990</td>
<td>9.82</td>
<td>9.90</td>
</tr>
<tr>
<td>1998</td>
<td>10.95</td>
<td>10.49</td>
</tr>
<tr>
<td>Δ = 1998 – 1990</td>
<td>1.13</td>
<td>0.59</td>
</tr>
<tr>
<td><strong>Log Value Added per Worker (log(r/(s + u)))</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990</td>
<td>7.83</td>
<td>6.76</td>
</tr>
<tr>
<td>1998</td>
<td>10.25</td>
<td>8.72</td>
</tr>
<tr>
<td>Δ = 1998 – 1990</td>
<td>2.42</td>
<td>1.96</td>
</tr>
</tbody>
</table>

†Exporter premium is the mean difference between exporters and non-exporters in percentage terms. For example, in 1990, exporters in low-tech industries, on average, were 8.89% more skill intensive than non-exporters.

In a low-tech industry, an increase in the exporter premia is due to a greater technology difference between exporters and non-exporters. Comparative advantage makes exporters significantly more profitable than non-exporters. A large reduction in the tariff rate also causes extensive technology downgrading among non-exporters. This enlarges the gap between exporters and non-exporters in a low-tech industry. The opposite occurs in a high-tech industry. Comparative disadvantage makes exporters slightly more profitable than non-exporters. An increase in foreign demand and a fall in the skill premium induce firms that are less productive, and thus less skill intensive, to become exporters. The gap
between exporters and non-exporters in a high-tech industry is then reduced.

Table 13: Changes in Productivity and Mass of Firms – Trade Reform

<table>
<thead>
<tr>
<th></th>
<th>Industrial Productivity</th>
<th>Relative Mass</th>
<th>Aggregate Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>0.73,0.94</td>
<td>1.67</td>
<td>0.81</td>
</tr>
<tr>
<td>1998</td>
<td>0.83,1.03</td>
<td>2.07</td>
<td>0.89</td>
</tr>
<tr>
<td>$\Delta = 1998 - 1990$</td>
<td>0.10,0.09</td>
<td>0.40</td>
<td>0.09</td>
</tr>
</tbody>
</table>

As discussed in Proposition 9 of Section 2.3, changes in firms’ decisions can affect industrial and aggregate productivity. Although measures of the relative mass of firms and productivity cannot be directly observed from the data, it is interesting to see how the model predicts their changes in response to the trade reform. Table (13) shows that industrial productivity increases in both industries because more firms become exporters and upgrade their technology, and because the least productive firms are driven out of the market by stronger competition. Trade reform also reallocates labor toward a comparative advantage industry, which raises the relative mass of firms in a low-tech industry. These results are in line with those proposed in Proposition 9. Aggregate productivity is determined by two effects: the industrial productivity effect and the mass effect. In this quantitative exercise, despite experiencing a larger increase in industrial productivity, a low-tech sector, on average, has lower productivity. The two effects, thus, work in opposing directions. Quantitatively, the industrial productivity effect dominates and the trade reform increases aggregate productivity, although the aggregate effect is slightly dampened.

2.5 Model Revisit: Skill Upgrading

The counterfactual trade reform in the previous section predicts the effects of Indonesia’s trade reform in 1995 on the skill premium, the exporter premia, and productivity. Indonesian time series data in Figure (12) and its pattern of comparative advantage suggest another interesting structural change in 2000, when the country’s ability to supply skilled
labor improved and comparative advantage shifted toward medium-high-tech to high-tech industries. Exporter premia reported in Table (8) also show the relative change in firms’ decisions. This section, therefore, performs a counterfactual to see how well the model can qualitatively predict the change in the skill premium and the exporter premia.\textsuperscript{18} Some parameter values are reassigned. First, the relative supply of skilled labor, $S$, increased by 5\% from 1998 to 2005, based on the fraction of workers with at least secondary education, from Indonesian manufacturing data. Second, to allow for the change in comparative advantage, foreign demands are allowed to change to exactly match the aggregate change in Indonesia’s imports and exports. To be specific, between 1998 and 2005, low-tech imports decreased from 7.1\% to 6.3\% of total absorption, and exports decreased from 28.5\% to 13.3\%. There were changes in trade flows for high-tech industries, where imports expanded from 20.2\% to 21.2\% of total absorption, and exports expanded from 13.4\% to 18.3\% of total absorption.

Table 14: Changes in Skill Premium – Skill Upgrading

<table>
<thead>
<tr>
<th>Skill Premium ($w^s/w^u$)</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td>2.09</td>
<td>2.25</td>
</tr>
<tr>
<td>2005</td>
<td>2.13</td>
<td>2.28</td>
</tr>
<tr>
<td>$\Delta = 2005 - 1998$</td>
<td>0.04</td>
<td>0.03</td>
</tr>
</tbody>
</table>

According to the National Labor Force Survey of Indonesia, the skill premium increased significantly over 2003-2009 for overall industry and across the region. Table (14) shows that, consistent with the data, the model predicts an increase in the skill premium. Changes in Indonesia’s comparative advantage cause production to shift away from the low-tech sector, raising the relative demand for skilled labor. Even though the relative supply of skills increases, a shift in the demand causes the skill premium to rise.

Figure (15) shows how firms change their optimal decisions. In a low-tech sector, an increase in the skill premium leads to an upgrading among non-exporters. For exporters, however, this not enough to outweigh the effect of a contraction in foreign demand, which

\textsuperscript{18}As many calibrated parameter values could have changed between 1990 and 2005, predicting magnitude is difficult.
causes them to downgrade their technology levels. For the same reason, the fraction of exporting firms decreases. The opposite occurs in a high-tech sector. Exporters upgrade their technology thanks to an expansion of foreign demand, although a higher skill premium might discourage them from adopting advanced technology, which is too skill biased. Non-exporters downgrade their technology due to competition from foreign firms and a rise in the skill premium. It is obvious that the export cutoff now lies closer to the exit cutoff in a high-tech industry, as a result of the shift in comparative advantage.

The implication of changes in firms’ decisions on changes in both skill intensity and productivity among exporters and non-exporters across industries is shown in Table (15). As mentioned, the goal is to see how the model can qualitatively predict the direction of changes. Consistent with the data, the model predicts that the exporter skill intensity and productivity premia decrease in a low-tech industry. This is due to technology upgrading among non-exporters and technology downgrading among exporters. Because the reverse occurs in a high-tech industry, a greater technology difference between exporters and non-
Table 15: Changes in Exporter Premia – Skill Upgrading

<table>
<thead>
<tr>
<th></th>
<th>Exporter Non-Exporter (%)</th>
<th>Low-Tech Sector</th>
<th>High-Tech Sector</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Data</td>
<td>Model</td>
</tr>
<tr>
<td>Skill Intensity ((s/u))</td>
<td>1998</td>
<td>10.95</td>
<td>10.49</td>
</tr>
<tr>
<td>(\Delta = 2005 - 1998)</td>
<td></td>
<td>-15.16</td>
<td>-0.96</td>
</tr>
<tr>
<td>Log Value Added per Worker (\log(r/(s+u)))</td>
<td>1998</td>
<td>10.25</td>
<td>8.72</td>
</tr>
<tr>
<td></td>
<td>2005</td>
<td>1.01</td>
<td>6.96</td>
</tr>
<tr>
<td>(\Delta = 2005 - 1998)</td>
<td></td>
<td>-9.24</td>
<td>-1.76</td>
</tr>
</tbody>
</table>

† Exporter premium is the mean difference between exporters and non-exporters in percentage terms. For example, in 1998, exporters in low-tech industries, on average, are 10.95% more skill intensive than non-exporters.

Table 15: Changes in Exporter Premia – Skill Upgrading

Changes in the relative mass of firms and productivity are shown in Table (16). Industrial productivity decreases in a low-tech industry. Mainly, this is because firms that were once exporters downgrade their technology as their foreign profits fall and some of them switch to the domestic market only. In a high-tech sector, more firms become exporters and upgrade their technology, and the least productive firms are driven out of the market by stronger competition. Industrial productivity, thus, increases. A shift in comparative advantage also reallocates labor toward a high-tech industry. In this quantitative exercise,

Table 16: Productivity and Mass of Firms – Skill Upgrading

<table>
<thead>
<tr>
<th></th>
<th>Industrial Productivity</th>
<th>Relative Mass</th>
<th>Aggregate Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(\Phi_l, \Phi_h)</td>
<td>(M_l/M_h)</td>
<td>(\Phi)</td>
</tr>
<tr>
<td>1998</td>
<td>0.83, 1.03</td>
<td>2.07</td>
<td>0.89</td>
</tr>
<tr>
<td>2005</td>
<td>0.72, 1.06</td>
<td>1.84</td>
<td>0.84</td>
</tr>
<tr>
<td>(\Delta = 2005 - 1998)</td>
<td>-0.11, 0.03</td>
<td>-0.23</td>
<td>-0.05</td>
</tr>
</tbody>
</table>

The exporter productivity premium estimated using the Olley-Pakes method reported in Table (8), however, increased from subperiod 2 to subperiod 3. This might be due to a discrepancy between the firm total factor productivity based on the Olley-Pakes method and log value added per worker as measured productivity. The counterfactual experiments focus on log value added per worker because this has a direct mapping from the model.
industrial productivity substantially falls in a low-tech sector but hardly rises in a high-tech sector. Therefore, despite a fall in the relative mass of firms in a low-tech industry, which on average has lower productivity, aggregate productivity decreases. Similar to the counterfactual reform presented in the previous section, the industrial productivity effect dominates the mass effect. Nevertheless, the mass effect does dampen the negative impact on aggregate productivity.

2.6 Conclusion

How does trade liberalization affect productivity and the demand for skills, at both firm and aggregate levels, in developing countries? Empirical evidence suggests that cross-sectoral labor reallocation following trade liberalization should not be ignored, especially in low-income countries. This paper proposes a unified model of international trade with multiple sectors, heterogeneous firms, and endogenous technology choices. The model provides a rich setting for explaining how productivity and skill intensity of firms in different industries respond to trade liberalization. This, in turn, shows some implications of trade liberalization for changes in aggregate productivity and the aggregate demand for skilled labor.

Analytical results show that, within industry, more firms adopt advanced technology and become more skill intensive, but, between industries, labor is reallocated toward a low-tech industry. If a high-tech industry has a higher productivity gain from technology upgrading, within- and between-industry effects work in opposite directions in determining aggregate productivity and the demand for skill, resulting in an ambiguous impact of trade liberalization. To quantify this aggregate impact, the model is parameterized using Indonesian manufacturing data during the pre-trade reform period. The counterfactual reform matches the data qualitatively well. In Indonesia, the skill premium falls, implying a decrease in the aggregate demand for skill. An increase in industrial productivity
is large enough that aggregate productivity increases, although slightly dampened due to between-sector reallocation.
Chapter 3

Capital-Based Corporate Tax Benefits: Endogenous Misallocation through Lobbying

This chapter is co-authored with Felipe E. Saffie and Minchul Shin.

Abstract

The dominant issue of corporate lobbying in the U.S. is taxation. Firms that lobby are granted tax benefits and enjoy systematically lower effective tax rates than non-politically active firms, even after controlling by firm characteristics. Because most of these tax benefits are tied to capital holding, corporate lobbying could distort the allocation of capital in the economy. A heterogeneous firm dynamics model with endogenous lobbying decisions is presented to study the macroeconomic effects of capital-based tax benefits and their interaction with endogenous corporate lobbying behavior. The model is calibrated to U.S. firm-level data. The model suggests that the increase in corporate lobbying and the decrease in effective corporate tax rates between 1998-99 and 2010-11 are mostly due to the increase in the availability of political rents. Moreover, rent-seeking by firms explains more than 20% of the dispersion in the marginal product of capital, the main measure used in the literature to quantify the misallocation of capital.
3.1 Introduction

The current U.S. tax system taxes corporate income at a statutory rate of 35%, the highest rate among the Organization for Economic Co-operation and Development (OECD) nations.\textsuperscript{1,2} The system, however, contains a number of deductions, exemptions, deferrals, and tax credits. The largest part of corporate tax benefits - also referred to as corporate tax expenditures - includes accelerated depreciation, the domestic production activities deduction, the deferral of income earned abroad, and credit for increasing research activities.\textsuperscript{3} These benefits affect firms unequally. For instance, the largest tax deduction is associated with depreciation of capital, and one of the most important tax credits is the Research and Experimentation Tax Credit, heavily used by large and capital intensive companies. These tax provisions imply that the effective tax rate paid by U.S. corporations is highly heterogeneous and well below 35% on average.\textsuperscript{4} Figure (16) illustrates the distribution of effective tax rates paid by U.S. corporations over the past decade. Effective tax rates vary significantly across firms, with the average fluctuating around 21.8%.

Nevertheless, the nature and extension of these tax benefits is not completely exogenous to the companies. In fact, some of those benefits are applicable to a very restrictive set of firms.\textsuperscript{5} This leaves room for corporate pressure by lobbying activity. While tax benefits cannot be negotiated on a case-by-case basis with companies because they must be incorporated into a tax code, many companies successfully lobby for the creation of tax benefits

\textsuperscript{1}According to the law, the tax starts at 15% for income below $50,000. It reaches 34% gradually for incomes between $335,000 and $10m, then it gradually increases to 35% for incomes above $18.33m.

\textsuperscript{2}See Appendix C.1 for corporate income tax rates in OECD countries.

\textsuperscript{3}Tax expenditures - special exemptions and exclusions, credits, deductions, deferrals, and preferential tax rates claimed by corporations - support federal policy goals to encourage certain types of behaviors and assist certain businesses but result in revenue forgone by the federal government. Source: U.S. Government Accountability Office.

\textsuperscript{4}The effective tax rate for a corporation is the average rate at which its pre-tax profits are taxed. It is computed by dividing total tax expenses by the firm’s earnings before taxes. In fact, the U.S. average effective tax rate is similar to the OECD weighted average, as reported in Gravelle and Marples (2014).

\textsuperscript{5}For example, according to the Government Accountability Office (\textit{GAO}, 2013), “in 2010 almost 12,000 organizations claimed the tax exemption for certain insurance companies owned by tax-exempt organizations ($200 million in corporate tax revenue losses in 2011) while 5 corporations claimed the credit for energy efficient appliances ($280 million in corporate tax revenue losses in 2011).”
Source: Authors’ calculation. 5%, 10%, 25%, 50%, 75%, 90%, and 95% quantiles of effective tax rate among all firms over time.

Figure 16: Effective Tax Rate Distribution

tailored to their profiles. Not surprisingly, lobbying expenditures for taxation purposes are among the top two issues of corporate lobbying every single year in the U.S. The tax benefits of firms that lobby can be seen even in the raw data. As Figure (17a) shows, lobbying firms face consistently lower effective tax rates than non-lobbying firms, and this gap is particularly important when corporate lobbying expenditure for taxation, Figure (17b), increases sharply.

This paper, thus, aims to study the macroeconomic effects of capital-based tax benefits and their interaction with endogenous corporate lobbying behavior. In particular, as this class of benefits distorts the marginal cost of capital differently across firms, it can potentially generate substantial capital misallocation in the economy. In a nutshell, if two firms face different costs of capital, the marginal productivity of capital between these firms will not be equalized, and, hence, a redistribution of the total existing capital from this distorted

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6Case studies and journal articles are full of examples. See, for instance, Kocieniewski (2011) for “GE’s strategies let it avoid taxes altogether,” and McIntyre et al. (2011) for “Corporate taxpayers and corporate tax dodgers.”

7For the rest of the paper, the terms “lobbying firm” and “non-lobbying firm” are used to describe a firm’s lobbying status. For example, firm A is a lobbying firm in 2000 if it spent money on lobbying in 2000.
situation could potentially increase output in the economy. Moreover, the presence of political rents tied to lobbying can substantially amplify the gaps in the marginal product of capital among firms and, therefore, exacerbate the misallocation in the economy.

To support the link between tax benefits and firms’ political influence, which will be the central mechanism of interest, some empirical regularities on effective corporate taxation and lobbying behavior in the U.S. economy are documented. The lobbying data from the Center for Responsive Politics is matched with Compustat to obtain the firm characteristics that are necessary for calculating effective corporate tax rates.\footnote{The Center for Responsive Politics data set is available starting in 1998.} We first document that taxation is the dominant issue for corporate lobbying, and that, although less than 12% of the sample lobbies every year, these firms account for more than 50% of the capital holding in the sample. Then, we document three empirical regularities that motivate our model: i) capital intensity is associated with lower effective tax rates; ii) lobbying firms are large and capital intensive; iii) lobbying firms, on average, have lower effective tax rates.

To identify the mechanisms that link tax benefits and firms’ lobbying activities to resource misallocation, we develop a dynamic model of heterogeneous firms with endogenous
lobbying decisions. The framework is adapted from Hopenhayn (1992). In the model economy, firms use a decreasing returns to scale technology to transform capital and labor into output, and they face idiosyncratic productivity shocks. Firms decide on the level of inputs and on lobbying spending. In addition, there is a government, which grants tax benefits to firms as tax deductions associated with their capital holdings. A first component of these benefits is applied to all firms, while a second component can be influenced by lobbying activity, namely, a preferential tax treatment. However, because the government has limited resources for tax expenditures, the benefits are allocated sequentially, starting with the firms that value them the most. Hence, only a subset of the firms lobby in equilibrium.

In order to quantify the macroeconomic impact of tax benefits and corporate lobbying on capital allocation, we calibrate the model to the U.S. economy during 2010-11. The benchmark calibration is able to successfully match every targeted moment. We evaluate the model calibration using a set of non-targeted moments. The model is able to mimic closely the empirical distribution of the marginal product of capital, for both lobbying and non-lobbying firms. Moreover, it generates 70% of the persistence in lobbying status observed in the data, as well as the signs of all conditional correlations between lobbying activities and effective tax rates documented in the empirical section. The success of the model relies on the fact that highly productive firms with low capital that decide optimally not to participate in lobbying face a higher effective tax rate than low-productivity firms that over-accumulate capital in order to maximize their tax benefits from lobbying.

After validating the calibrated model, we conduct two counterfactual exercises. First, we examine whether an increase in the fraction of revenue losses from tax expenditures can explain the differences between 1998-99 and 2010-11. To this end, we compare the benchmark to a counterfactual calibration, where the only change is that the fraction of revenue losses from tax expenditures is set to 1998-99. In the model, the increase in the proportion of tax benefits generates a decrease in the effective tax rate of lobbying and
non-lobbying firms, with lobbying firms experiencing a larger decrease. It also increases the fraction of lobbying firms and the amount of capital held by them. All these trends are present in the data. Moreover, the model captures fairly well the magnitudes of these changes. It generates 76% of the observed decrease in the average effective tax rate of the U.S. economy. The second exercise studies the effect of capital-based tax benefits and corporate lobbying on capital misallocation. To this end, we compare the benchmark model to two counterfactuals, one where tax benefits are tied to capital but lobbying does not generate additional rents, and the other where there are neither standard capital-based benefits nor rents to be extracted by lobbying. Because, in an undistorted world, the marginal product of capital should be equalized among firms, the dispersion of the marginal product of capital reflects an inefficiency in allocation of resources. The impact of corporate lobbying on misallocation is substantial. Firms’ political activity accounts for at least 20% and up to 70% of the dispersion. The remaining fraction is due to the standard tax benefits that apply evenly across firms. Therefore, the calibrated model suggests that an increase in the fraction of tax expenditures can explain a decrease in effective tax rates and an increase in corporate lobbying at both the extensive and intensive margins. This, in turn, worsens capital misallocation in the economy.

The paper is organized as follows. Section 3.2 summarizes some of the related literature on firms’ political activity and corporate taxation. Section 3.3 presents our database and the main empirical findings of the paper. A dynamic model of heterogeneous firms with endogenous lobbying decisions is introduced in Section 3.4. Section 3.5 presents the quantitative exercises, including the model calibration and quantitative experiment. Finally, Section 3.6 concludes the paper.
3.2 Literature Review

The paper contributes to two strands of literature: corporate lobbying and resource misallocation. Firm-level empirical work on corporate lobbying has been done in several dimensions. Igan et al. (2012) find that lobbying was associated with more risk-taking during 2000-07. Kerr et al. (2014) explore lobbying behavior toward immigration-specific issues and document the persistence in lobbying status. Several accounting and finance papers have explored the link between lobbying expenditure and tax benefits. Birnbaum and Murray (2010) provide evidence of the pressure exerted by lobbyists in the Tax Reform Act of 1986 in the United States in order to grant specific benefits and exemptions to their clients. Kang (2013) quantifies the effect of lobbying expenditures on policy enactment in the energy sector. Among others, Richter et al. (2009), Meade and Li (2012), Cooper et al. (2010), and Brown et al. (2013) find that political action by firms is positively correlated with firms’ preferential treatment and profit. However, theoretical work is considerably less developed. The only area of study that is theoretically and empirically well developed is the literature on the influence of lobbying activity on trade policy by Grossman and Helpman (1994), Mitra (1999), Gawande and Bandyopadhyay (2000), Bombardini (2008), Bombardini and Trebbi (2012), and Kim (2012). Less attention has been drawn to tax lobbying, which accumulates more expenditure than trade issues for every single year in the data. Even so, little work has been done in looking at lobbying effort as an endogenously determined decision.

Recent literature emphasizes that input misallocation across firms is one of the main sources of aggregate total factor productivity (TFP) loss. Many factors are thought to be important sources of misallocation. Hopenhayn and Rogerson (1993) and Lagos (2006) and Guner et al. (2008) study the distortion created by taxes and government policy, which leads to resource misallocation and aggregate TFP loss. Another interesting factor is trade barriers as a source of misallocation, studied by Waugh (2010) and Epifani and Gancia
(2011). However, the most studied source of misallocation is credit market imperfections. Erosa (2001), Amaral and Quintin (2010), Buera et al. (2011), and Midrigan and Xu (2010) have all estimated the effects of credit market imperfections on TFP through various channels. However, one key issue in this literature is that productivity differentials usually disappear once the establishments can overcome credit market constraints through self-financing. Instead of focusing on the channel which creates misallocation, Restuccia and Rogerson (2008) exogenously introduce idiosyncratic tax rates and examine the conditions under which the misallocation caused by these generic distortions leads to larger effects on aggregate TFP. In our paper, we propose a new source of misallocation which, to our knowledge, has not been explored. The distortion in our model is endogenously driven by capital-based tax benefits and firms’ rent-seeking behavior, creating resource misallocation.

### 3.3 Data and Empirical Regularities

This section introduces the database used in this paper. We first document that tax-ation is the dominant issue in corporate lobbying. Then we document an expansion in lobbying activities, at both the intensive and extensive margins, during the 1998-2011 period. Finally, we document the main empirical regularities that motivate our modelling strategy.

#### 3.3.1 Data: Lobbying for Taxation

The empirical analysis relies on two sources of data. Lobbying behavior data is obtained from the Center for Responsive Politics (CRP). This data is available due to the Lobbying Disclosure Act of 1995. This Act requires filers to disclose detailed information about

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9This Act was strengthened by the Honest Leadership and Open Government Act of 2011. Because the law did not change the mandatory disclosure, we decided to use the complete data for this analysis. Nevertheless, our empirical analysis is robust to the exclusion of this part of the data.
lobbying expenditures above $3,000 during a quarter. Lobbying activity is reported under
one of 78 issue areas and the expenditure allocated to lobbying on a particular bill must be
declared. The information on firm’s characteristics comes from Compustat. This database
contains detailed information on sales, employment, assets, and tax expenditures, among
other variables, for publicly traded companies in the U.S. economy. Table (17) summarizes
the raw data for the period spanning 1998 - 2011.

Table 17: Lobbying Data and Compustat

<table>
<thead>
<tr>
<th></th>
<th>Lobbying data</th>
<th>Compustat</th>
<th>Lobbying in Compustat</th>
</tr>
</thead>
<tbody>
<tr>
<td># of obs. (firm-year)</td>
<td>72,110</td>
<td>159,111</td>
<td>4,978</td>
</tr>
<tr>
<td>Lobbying Expenditure ($ million)</td>
<td>14,130</td>
<td>N/A</td>
<td>6,674 (47.2%)</td>
</tr>
<tr>
<td>Total Asset ($ million)</td>
<td>N/A</td>
<td>873,200,000</td>
<td>289,000,000 (33.1%)</td>
</tr>
</tbody>
</table>

Although the CRP data contains not only corporate lobbying but also lobbying by
organizations, individuals, and even foreign governments, lobbying firms account for 47%
of the total lobbying expenditures in CRP. Therefore, most corporate lobbying activity is
likely to be reflected in our sample. In addition, lobbying firms account for 33% of the total
asset values in Compustat. Therefore, given the relevance of actors involved in lobbying,
lobbying behavior is likely to have a sizable impact on the aggregate economy. Moreover,
the data shows that the primary purpose of lobbying is taxation.

As shown in Table (18), the percentage of total lobbying expenditures spent on taxation
issues over the period of 1998-2011 is well above every other issue. Appendix C.2 presents
this analysis for each year. Taxation ranks first every year except 2009.

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10Firms with in-house lobbying activities are also required to report the relevant information. However,
the CRP data do not include bribes, other under-the-table payments or firms’ illegal expenditures aiming
to influence policy outcomes.

11Each bill might contain multiple issues, so we discount the dollar amount by the number of issues. Then
we build the total amount for every issue during the period and rank them accordingly. Ranking is based
on the matched data set before sample selection.

12The health care reform in 2009 placed health issues at the top.
Table 18: Percentage of Aggregate Expenditures by Issues (Top 10, 1998 – 2011)

<table>
<thead>
<tr>
<th>Issue</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taxes</td>
<td>10.68</td>
</tr>
<tr>
<td>Health Issues</td>
<td>7.47</td>
</tr>
<tr>
<td>Energy/Nuclear</td>
<td>5.30</td>
</tr>
<tr>
<td>Budget/Appropriations</td>
<td>5.22</td>
</tr>
<tr>
<td>Medicare/Medicaid</td>
<td>5.02</td>
</tr>
<tr>
<td>Trade (Domestic &amp; Foreign)</td>
<td>4.93</td>
</tr>
<tr>
<td>Defense</td>
<td>4.15</td>
</tr>
<tr>
<td>Telecommunications</td>
<td>3.81</td>
</tr>
<tr>
<td>Environmental/Superfund</td>
<td>3.77</td>
</tr>
<tr>
<td>Financial Institutions/Investments/Securities</td>
<td>3.53</td>
</tr>
</tbody>
</table>

3.3.2 Lobbying at the Extensive and Intensive Margin

Table (19) and Figure (18) show descriptive statistics for lobby data. In our sample, the number of lobbying firms has increased over the years. In particular, the number of lobbying firms was practically constant at around 80 firms for the first five years, and then it has been increasing steadily, and double the number in the last year of the sample. This implies that lobbying participation increased by more than double during the past decade. The intensive margin also follows a similar pattern, i.e., the average lobbying expenditure almost doubled during the period. Introducing the median into the analysis, we see considerable inequality among lobbying expenditures, where few firms account for most of the expenditures. This inequality grows steadily over time. Finally, the dispersion in lobbying expenditure essentially doubles during the period. Figure (18) illustrates the trends in lobbying activities at both the intensive and extensive margins over time. The increasing trend is obvious for all variables: the total lobbying expenditure, the proportion of lobbying firms, the average lobbying expenditure, and the standard deviation of lobbying expenditure. In addition, each variable more than doubles over the period of 1998-2011.

13Hereafter, we focus on lobby invoices that are issued for tax subjects. Appendix C.3 describes the sample selection procedure, the removal of outliers and the basic variables of the data set used for the rest of this section.
Table 19: Descriptive Statistics for Lobby Data

<table>
<thead>
<tr>
<th>year</th>
<th># of firms</th>
<th># of lob firms</th>
<th>% lob firms</th>
<th>lob exp per firm</th>
<th>median (lob exp)</th>
<th>SD(lob exp)</th>
<th>total exp</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td>2146</td>
<td>78</td>
<td>3.63</td>
<td>1.09</td>
<td>0.2</td>
<td>1.83</td>
<td>85.35</td>
</tr>
<tr>
<td>1999</td>
<td>1952</td>
<td>83</td>
<td>4.25</td>
<td>0.92</td>
<td>0.24</td>
<td>1.46</td>
<td>76.23</td>
</tr>
<tr>
<td>2000</td>
<td>1748</td>
<td>84</td>
<td>4.81</td>
<td>1.13</td>
<td>0.22</td>
<td>1.76</td>
<td>94.65</td>
</tr>
<tr>
<td>2001</td>
<td>1480</td>
<td>69</td>
<td>4.66</td>
<td>1.1</td>
<td>0.19</td>
<td>1.93</td>
<td>75.83</td>
</tr>
<tr>
<td>2002</td>
<td>1433</td>
<td>63</td>
<td>4.4</td>
<td>1.17</td>
<td>0.15</td>
<td>2.02</td>
<td>73.72</td>
</tr>
<tr>
<td>2003</td>
<td>1592</td>
<td>85</td>
<td>5.34</td>
<td>1.02</td>
<td>0.35</td>
<td>1.71</td>
<td>86.99</td>
</tr>
<tr>
<td>2004</td>
<td>1768</td>
<td>102</td>
<td>5.77</td>
<td>1.21</td>
<td>0.38</td>
<td>1.84</td>
<td>123.22</td>
</tr>
<tr>
<td>2005</td>
<td>1801</td>
<td>115</td>
<td>6.39</td>
<td>1.35</td>
<td>0.34</td>
<td>2.66</td>
<td>154.71</td>
</tr>
<tr>
<td>2006</td>
<td>1766</td>
<td>124</td>
<td>7.02</td>
<td>1.23</td>
<td>0.4</td>
<td>2.03</td>
<td>153.12</td>
</tr>
<tr>
<td>2007</td>
<td>1657</td>
<td>132</td>
<td>7.97</td>
<td>1.34</td>
<td>0.45</td>
<td>2.28</td>
<td>176.48</td>
</tr>
<tr>
<td>2008</td>
<td>1353</td>
<td>127</td>
<td>9.39</td>
<td>1.73</td>
<td>0.57</td>
<td>3.2</td>
<td>219.46</td>
</tr>
<tr>
<td>2009</td>
<td>1236</td>
<td>127</td>
<td>10.28</td>
<td>1.68</td>
<td>0.39</td>
<td>2.92</td>
<td>213.99</td>
</tr>
<tr>
<td>2010</td>
<td>1402</td>
<td>160</td>
<td>11.41</td>
<td>2.22</td>
<td>0.61</td>
<td>4.41</td>
<td>355.81</td>
</tr>
<tr>
<td>2011</td>
<td>1479</td>
<td>153</td>
<td>10.34</td>
<td>1.99</td>
<td>0.64</td>
<td>3.29</td>
<td>304.57</td>
</tr>
</tbody>
</table>

average: 1629.5 107.29 6.83 1.37 0.37 2.38 156.72
sum: 22813 - - - - - 2194.13
98-99 avg: 2049 80.5 3.94 1.01 0.22 1.65 80.79
10-11 avg: 1440.5 156.5 10.88 2.11 0.63 3.85 330.19

1 Lobbying expenditure (million dollars) is deflated by the GDP deflator (index=100 at 1998).
2 Lobbying expenditure per firm is the average lobbying expenditure among lobbying firms.
3 Lobbying statistics are based on bills that are issued for tax. Appendix C.3 describes the sample selection procedure.

3.3.3 Conditional Correlations: Effective Tax Rate, Capital Intensity, and Lobbying Activity

The statutory corporate tax rate is generally flat at 35% in the U.S. economy for our sample. This is the highest corporate tax rate among the O.E.C.D. countries. Nevertheless, the effective tax rates actually paid by U.S. companies are well below this rate. We calculate effective tax rates in our sample following the definition of Richter et al. (2009). In a nutshell, the effective tax rate is taxes paid divided by taxable income reported to stockholders. Each company’s effective tax rate is computed using entries from Compustat as follows:

\[
ETR = \frac{\text{Income Taxes Total} - \text{Deferred Taxes}}{\text{Pre-Tax Income} - \text{Equity in Earnings} - \text{Special Items} + \text{Interest Expense}}
\]

As mentioned above, firms in our sample on average pay an effective tax rate of 21.8%, considerably lower than the statutory tax rate. Moreover, there is considerable hetero-
Figure 18: Lobbying Data Statistics

geneity across firms with respect to their effective tax rate. Lobby data suggests that corporate lobbying seems to influence a potential pattern for this heterogeneity. In particular, the time-series of ETR conditional on lobbying activity suggests that lobbying firms face consistently lower effective tax rates than their non-lobbying counterparts. This section provides more compelling evidence of the correlation between corporate lobbying activity and effective tax rates. Table (20) presents the results of five panel regressions estimated using random effects. The dependent variable in every specification is the effective tax rate. More details on variables can be found in Appendix C.4.

Reg (1) and Reg (2) provide evidence on the correlation between effective tax rates and corporate lobbying activity at the extensive margin. Reg (1) confirms that the effective tax rate differential between lobbying firms and non-lobbying firms is significant even after
Table 20: Effective Tax Rate Panel Regression

<table>
<thead>
<tr>
<th></th>
<th>Reg (1)</th>
<th>Reg (2)</th>
<th>Reg (3)</th>
<th>Reg (4)</th>
<th>Reg (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i_f$lob$_{t-1}$</td>
<td>-0.014***</td>
<td>-0.010***</td>
<td>-0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>log$lob_{t-1}$</td>
<td></td>
<td>-0.020***</td>
<td>-0.018***</td>
<td>-0.014*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>cap$_{int}$</td>
<td>-0.575***</td>
<td>-0.354***</td>
<td>-0.572***</td>
<td>-0.359***</td>
<td>-0.360***</td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td>(0.045)</td>
<td>(0.067)</td>
<td>(0.045)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>log$lob_{t-1}$ $\times$ cap$_{int}$</td>
<td>0.109</td>
<td>0.105</td>
<td>0.109</td>
<td>0.105</td>
<td>0.105</td>
</tr>
<tr>
<td>ETR$_{t-1}$</td>
<td>0.343***</td>
<td>0.343***</td>
<td>0.343***</td>
<td>0.343***</td>
<td>0.343***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>lev</td>
<td>-0.196***</td>
<td>-0.142***</td>
<td>-0.195***</td>
<td>-0.142***</td>
<td>-0.142***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.008)</td>
<td>(0.010)</td>
<td>(0.008)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>inv$_{int}$</td>
<td>1.432**</td>
<td>1.165**</td>
<td>1.447**</td>
<td>1.162**</td>
<td>1.159**</td>
</tr>
<tr>
<td></td>
<td>(0.655)</td>
<td>(0.466)</td>
<td>(0.656)</td>
<td>(0.466)</td>
<td>(0.466)</td>
</tr>
<tr>
<td>R&amp;D$_{int}$</td>
<td>-0.675</td>
<td>0.346</td>
<td>-0.547</td>
<td>0.522</td>
<td>0.569</td>
</tr>
<tr>
<td></td>
<td>(3.055)</td>
<td>(2.194)</td>
<td>(3.063)</td>
<td>(2.206)</td>
<td>(2.207)</td>
</tr>
<tr>
<td>size</td>
<td>0.009***</td>
<td>0.005***</td>
<td>0.009***</td>
<td>0.005***</td>
<td>0.005***</td>
</tr>
<tr>
<td></td>
<td>(.001)</td>
<td>(.001)</td>
<td>(.001)</td>
<td>(.001)</td>
<td>(.001)</td>
</tr>
<tr>
<td>Year dummy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry dummy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Random effect model</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R2</td>
<td>0.140</td>
<td>0.344</td>
<td>0.140</td>
<td>0.344</td>
<td>0.344</td>
</tr>
<tr>
<td># of observations</td>
<td>15743</td>
<td>15743</td>
<td>15743</td>
<td>15743</td>
<td>15743</td>
</tr>
</tbody>
</table>

1 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.01$.
2 † Variable descriptions are provided in Appendix C.4.

controlling by capital intensity, leverage, investment intensity, R&D intensity, size, year and industry dummies. In particular, just controlling for the extensive margin, we see that, on average, lobbying firms face effective tax rates 1.4% lower. As Reg (2) shows, this result is robust when the lagged effective tax rate is included in the regression. This result also holds at the intensive margin, as shown in Reg (3) and Reg (4). Firms that lobby more face lower effective tax rates. When including both extensive and intensive margins, Reg (5) shows that both effects maintain their signs, but only the intensive margin is statistically significant. Interestingly, capital intensity is associated with a lower effective tax rate in every specification. This points to the capital-based tax benefits that constitute most of
the tax expenditures in the U.S. These results are in line with those of Richter et al. (2009) and Meade and Li (2012).

### 3.4 Model Economy

To study the mechanism that links tax benefits and firms’ lobbying activities and its effect on resource misallocation, this section presents a dynamic model of heterogeneous firms with endogenous lobbying decisions to obtain tax preferential treatment. The model is adapted from Hopenhayn (1992). In the model, the industry is composed of a continuum of firms which produce a homogeneous product. Firms behave competitively, taking prices as given. They decide on the level of capital and lobbying spending. In addition, there is a government, which grants tax benefits to firms in the form of tax deductions or tax credits. A part of tax benefits is standard, applied to all firms, while the other part can be influenced by lobbying activity, namely, preferential tax treatment. However, the government has limited resources for tax expenditures. In the model, the benefits are allocated sequentially, starting with the firms that value them the most, until the total amount of funds available for tax benefits is reached. Therefore, in equilibrium, only a subset of the firms lobby.

#### 3.4.1 Firms

An operating firm starts the period with capital $k$ and debt $b$. It produces output using a production function that combines productivity $z$, capital $k$, and labor $n$. The production function has a decreasing return to scale:

$$y = f(z, k, n) = z^\alpha k^\alpha n^\eta,$$  \hfill (3.1)
where \(0 < \alpha + \eta < 1\) and \(\alpha, \eta \in (0, 1)\). The productivity \(z\) follows

\[
\ln(z_{t+1}) = (1 - \rho) \ln(\mu) + \rho \ln(z_t) + \epsilon_{t+1}, \quad \epsilon_{t+1} \sim \mathcal{N}(0, \sigma^2)
\]  

(3.2)

After producing and selling the output, the firm is subject to the statutory tax of \(\tau\) on its net income. However, the government grants tax benefits to firms in the form of tax deductions or tax credits associated with the firm’s capital stock. A part of tax benefits is standard, applying to all firms, while the other part can be influenced by lobbying activity. Because the government has limited resource to spend on tax credits, not every firm is granted those additional tax benefits in equilibrium. We assume that standard benefits are granted to every firm first. Then, if there are still resources to be allocated, those lobby-dependent tax benefits are granted. In particular, we assume that lobby-induced benefits are allocated sequentially, starting with the firms that are willing to lobby the most.\(^{14}\) Note that, because the information is perfect, every agent knows in equilibrium what the order is. In the firm’s problem, this is equivalent to the existence of a threshold of lobbying effort, \(l\), above which the firm receives preferential tax treatment. Therefore, the firm lobbies if and only if its non-strategic lobbying decision is above the threshold \(l\). In addition, the firm can accumulate capital over time. It finances the new capital \(k'\) and dividends \(d\) with after-tax profits net of debt payment and a new loan \(b'\). However, the loan is subject to the collateral constraint such that there is no default.

The timing of the decision for an operating firm within each period is as follows. At the beginning of the period \(\upsilon\), a fraction of firms exogenously exit. All surviving firms realize their idiosyncratic productivity \(z\). A firm with capital \(k\), debt \(b\) and productivity \(z\) makes the decision on labor and lobbying spending. It then chooses a new loan, capital for the following period, and dividends. At the end of each period, firms with negative values exit.\(^{14}\) This assumption is for tractability, as it allows us to have a single equilibrium associated with lobbying. It mimics the case that big corporations are allowed to negotiate before small companies.
The firm value function is given by

\[ V(k, b, z; l) = \max \left\{ V^l(k, b, z; l), V^{nl}(k, b, z; l), 0 \right\}, \]  

(3.3)

where

\[ V^l(k, b, z; l) = \max_{n,k',b'} d^l + \frac{1 - \nu}{1 + r} \mathbb{E}_{z'|z}[V(k', b', z'; l')], \]  

(3.4)

\[ V^{nl}(k, b, z; l) = \max_{n,k',b'} d^{nl} + \frac{1 - \nu}{1 + r} \mathbb{E}_{z'|z}[V(k', b', z'; l')], \]  

(3.5)

subject to a non-negative dividend condition given by

\[ d^l = (1 - \tau)\pi + \tau R(l, b, k) + (1 - \delta)k - k' - b + \frac{1}{1 + r} b' - \Gamma(l) \geq 0, \]  

(3.6)

\[ d^{nl} = (1 - \tau)\pi + \tau R(0, b, k) + (1 - \delta)k - k' - b + \frac{1}{1 + r} b' \geq 0, \]  

(3.7)

\[ \pi = zk^n n^\eta - wn. \]  

(3.8)

\( R(l, b, k) \) is the firm-specific tax deduction, which depends on the standard tax benefits \( b \), lobbying effort \( l \), and capital \( k \). Tax benefits reduce net income that is subject to tax. This function will be specified in the next section. Even though the firm decides not to lobby, it can still get the standard tax benefits. By making lobbying effort \( l \), the firm receives extra tax benefits but incurs the cost of \( \Gamma(l) = \frac{\gamma}{2}l^2 \). Flows are discounted at the interest rate \( 1 + r \).\(^{15}\)

3.4.2 Government and Tax Policy

The government grants corporate tax benefits to reduce a tax burden. Mostly, firms obtain tax benefits, notably through research and experimentation credits and accelerated depreciation schedules tailored to specific types of capital equipment.\(^{16}\) As stated in the

\(^{15}\)In this model, there is no aggregated risk; therefore, we can think of \( r \) as the long-run interest rate implied by the discount factor of a representative household owning every firm.

\(^{16}\)See Bartlett and Steele (1988), McIntyre and Nguyen (2000, 2004), and Richter et al. (2009).
previous section, a firm-specific tax deduction follows the function \( R(l, \Omega, k) \), where

\[
R(l, \Omega, k) = \min \left\{ (\psi l^\varphi + \Omega) k^\phi, \chi \pi \right\} \quad 0 < \varphi, \phi < 1
\]  

(3.9)

How much a firm can reap tax benefits depends on its capital \( k \), in line with the fact that most tax benefits are tied to capital, either in the form of research activities or accelerated depreciation of machinery and equipment.\(^{17}\) Without any effort in lobbying, the tax burden decreases by \( \tau \Omega k^\phi \). If a firm lobbies, it obtains preferential tax treatment, where the additional tax benefit is increasing in the lobbying effort. To ensure that, at least, a minimum amount of income tax is paid in spite of the legitimate use of deductions, the maximum tax deduction is limited by a firm’s profit, \( \chi \pi \).

Finally, the government can only forgo a limited fraction of its revenue on corporate tax expenditures.\(^ {18}\) Because the amount of tax expenditures is limited, the government only grants preferential tax treatment to firms that put in more lobbying efforts, until it runs out of resources. Tax benefits, therefore, are partly determined by other firms’ lobbying spending and the total amount of tax expenditures. There is a threshold \( l \) such that firms receive preferential tax treatment according to their lobbying effort only if their lobbying effort is higher than this threshold. The government tax expenditure constraint is

\[
\tau \int R(l(k, b, z) \times 1\{l(k, b, z) \geq l\}, \Omega, k) d\Psi(k, b, z) = \theta \tau \int (zk^\alpha n^\beta - wn)d\Psi(k, b, z). 
\]  

(3.10)

That is, the government is willing to lose a \( \theta \) fraction of its revenue on corporate tax expenditures.

\(^{17}\)In 2011, accelerated depreciation of machinery and equipment and credit for increasing research activities accounted for 48% of corporate tax revenue losses.

\(^{18}\)A corporate tax expenditure is a debatable issue for policymakers. Although it supports federal policy goals to provide incentives and assist certain businesses, estimated revenue loss due to corporate tax expenditures is relatively large.
3.4.3 Entrants

The problem for a potential entrant is simple in this model. All entrants enter with no debt. Capital collected from exiting firms is distributed equally among entrants, and their initial productivity is drawn from the ergodic distribution associated with Equation (3.2). Thus, the value for a potential entrant is given by

\[ V^e(z) = V(\bar{k}_0, 0, z; \bar{l}), \]  

(3.11)

where \( \bar{k}_0 \) is the capital distributed equally among entrants. To ensure that the mass of firms does not change, the mass of entrants must be the same as the mass of firms that exit, either exogenously or voluntarily.

3.4.4 Definition of Equilibrium

**Definition 3.** Given a wage rate \( w \) and interest rate \( r \), a stationary partial equilibrium under the tax policy rule \( \mathcal{R} \) is a set of value functions \( \{V, V^d, V^{nd}, V^e\} \), decision rules \( \{n(k, b, z), k'(k, b, z), b'(k, b, z), l(k, b, z)\} \), an exit decision, a threshold \( \bar{l} \), and a distribution \( \Psi(k, b, z) \) such that, given prices, the following conditions are satisfied:

1. Firms’ value functions, their decision rules and exit decisions are consistent with (3.3)-(3.8), and (3.11).

2. A stationary distribution \( \Psi \).

3. The government tax expenditure constraint (3.10) holds.
3.5 Quantitative Exercise

In this section, we perform a quantitative exploration of the model introduced in Section 3.4 to assess the impact of capital-based tax benefits on resource misallocation in the economy and their interaction with firms’ rent-seeking behavior. In particular, we calibrate the model to the firm level data presented in Section 3.3 for the period 2010-11. We evaluate the calibrated model using two sets of non-targeted moments. The first test is to compare the distribution of the marginal product of capital that is implied by the model to its data counterpart. Despite its parsimony, the model is able to match the shape and the first two moments of the data-generated distribution fairly well. The second challenge faced by the model tests its ability to replicate the conditional correlation analysis in Section 3.3. The model-generated data, like the U.S. data, suggest that effective tax rates are negatively correlated with a firm’s lobbying activities and capital intensity, and positively correlated with a firm’s values. Moreover, we show that the empirically observed persistence in the lobbying status of the firms can be generated by the model through the interaction between tax benefits and capital holdings. In particular, because capital stock is endogenously persistent, it imparts this property to the lobby participation margin.

We then use the calibrated model to learn more about the lobbying process and its implications for the allocation of capital in the economy. In the first experiment, we show that an increase in the fraction of revenue loss from tax expenditures between 1998-99 and 2010-11 can explain a decrease in the overall effective tax rate and also can explain an increase in both the intensive and extensive margin of lobbying during the period. In the second experiment, we use the calibrated model to study the impact of lobbying and capital-based tax benefits on resource misallocation in the U.S. economy. We document that lobbying can account for at least 20% of capital misallocation, measured as the variance of the marginal product of capital.
3.5.1 Calibration

We calibrate our model to the U.S. economy. Parameters are grouped into two categories. The first category includes parameters for which the values are either taken from other literature or directly obtained from the data. The second category includes parameters chosen so that endogenous outcomes from the model match salient features of the U.S. firm-level data in 2010-11.

The productivity process is discretized following the method in Tauchen (1986). The number of grid points for $z$ is set to 20. The productivity distribution of entrants is assumed to be the ergodic distribution obtained from the transition matrix. The parameters governing the productivity process are set to those estimated for the U.S. manufacturing sector by Cooper and Haltiwanger (2006). In particular, $\rho = 0.885$, $\mu = 1$, and $\sigma = 0.2$. The return to scale $\alpha + \eta$ is set to 0.85, as in Restuccia and Rogerson (2008). A standard value of the income share of labor is 0.64, implying $\alpha = 0.31$ and $\eta = 0.54$. The depreciation rate $\delta$ is taken from D’Erasmo and Moscoso Boedo (2012) in their firm dynamics model for the formal sector of the U.S. economy. The exogenous exit probability, $\nu$, is in the range used in the U.S. data, 3% – 6%.\footnote{Its only role is to ensure the existence of a stationary distribution by preventing firms from accumulating capital without bounds.} The maximum bound on tax benefits, $\chi$, ensures that, at least, a minimum amount of income tax is paid in spite of the legitimate use of tax credits.\footnote{This rules out highly negative effective tax rates. In the baseline calibration, this constraint binds for 10% of firms.} Finally, the taxation parameters, $\tau$ and $\theta$, are taken directly from the statutory tax rate and tax credits in the U.S. In particular, the statutory corporate tax rate is 35% and the tax expenditure ratio is calculated from the IRS corporate income tax returns balance sheet.

Five internally calibrated parameters are those governing tax benefits and lobby spending: $\Omega$, $\phi$, $\varphi$, $\psi$, and $\gamma$. Although these parameters are calibrated jointly to match six targeted moments, each parameter value is mostly related to a particular moment. The base tax deduction that is independent of lobbying expenditure, $\Omega$, pins down the average
Table 21: Parameter Values

<table>
<thead>
<tr>
<th>Value</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>θ</td>
<td>Revenue loss by tax expenditure</td>
<td>IRS corporate tax returns balance sheet</td>
</tr>
<tr>
<td>α</td>
<td>Production function, capital</td>
<td>Income share, Restuccia and Rogerson (2008)</td>
</tr>
<tr>
<td>η</td>
<td>Production function, labor</td>
<td>Income share, Restuccia and Rogerson (2008)</td>
</tr>
<tr>
<td>δ</td>
<td>Depreciation of capital</td>
<td>D’Erasmo and Moscoso Boedo (2012)</td>
</tr>
<tr>
<td>τ</td>
<td>Statutory tax rate</td>
<td>U.S. statutory corporate tax rate</td>
</tr>
<tr>
<td>r</td>
<td>Interest rate</td>
<td>D’Erasmo and Moscoso Boedo (2012)</td>
</tr>
<tr>
<td>υ</td>
<td>Exogenous exit rate</td>
<td>Restuccia and Rogerson (2008)</td>
</tr>
<tr>
<td>χ</td>
<td>Maximum benefit</td>
<td>Minimum ETR = 1st percentile ETR samples</td>
</tr>
<tr>
<td>ρ</td>
<td>Autocorrelation</td>
<td>Cooper and Haltiwanger (2006)</td>
</tr>
<tr>
<td>μ</td>
<td>Mean of productivity</td>
<td>Cooper and Haltiwanger (2006)</td>
</tr>
<tr>
<td>σ</td>
<td>Std Dev of stochastic component</td>
<td>Cooper and Haltiwanger (2006)</td>
</tr>
<tr>
<td>b</td>
<td>Tax benefit, base deduction</td>
<td>Mean ETR of non-lobbying firms</td>
</tr>
<tr>
<td>φ</td>
<td>Tax benefit, capital exponent</td>
<td>Fraction of capital held by lobbying firms</td>
</tr>
<tr>
<td>ϕ</td>
<td>Tax benefit, lobby exponent</td>
<td>Mean ETR of lobbying firms</td>
</tr>
<tr>
<td>ψ</td>
<td>Tax benefit, lobby scale</td>
<td>Fraction of lobbying firm</td>
</tr>
<tr>
<td>γ</td>
<td>Lobby cost, scale</td>
<td>Lobbying expenditure to sales</td>
</tr>
</tbody>
</table>

The model-based counterpart of the data is based on the stationary distribution of the economy. Despite its parsimony, the model is able to successfully match the targets. The model does a good job of generating the small fraction of lobbying firms, which own more than half of the total capital. In particular, approximately 60% of capital is owned by
Table 22: Targeted Moments

<table>
<thead>
<tr>
<th></th>
<th>Moments</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average effective tax rate (%)</td>
<td>All firms</td>
<td>18.7</td>
<td>18.0</td>
</tr>
<tr>
<td></td>
<td>Lobbying firms</td>
<td>15.5</td>
<td>10.8</td>
</tr>
<tr>
<td></td>
<td>Non-lobbying firms</td>
<td>19.1</td>
<td>19.2</td>
</tr>
<tr>
<td>Lobbying firms (%)</td>
<td></td>
<td>10.9</td>
<td>13.5</td>
</tr>
<tr>
<td>Capital owned by lobbying firms (%)</td>
<td></td>
<td>60</td>
<td>64</td>
</tr>
<tr>
<td>Lobby expenditure over sales (%)</td>
<td></td>
<td>0.06</td>
<td>0.11</td>
</tr>
</tbody>
</table>

lobbying firms, which only account for 10% of firms. The model also generates the result that lobbying firms, on average, pay lower effective tax rates. Although matching well the average effective tax rate of non-lobbying firms, the model underestimates the effective tax rate of lobbying firms.

### 3.5.2 Results and Non-Targeted Moments

Lobbying firms, on average, pay lower effective tax rates. This is mainly due to preferential tax treatment granted when they exert lobbying efforts. The right panel of Figure (19) shows that, without lobbying benefits, the effective tax rate is increasing in productivity and capital. This is because the standard deductions are tied only to capital, and with a decreasing return. Once lobbying benefits are introduced to the policy function, i.e. $\psi > 0$, large firms find it profitable to lobby and become entitled to additional deductions. The left panel of Figure (19) illustrates how lobbying effort can change the relative effective tax rate for lobbying firms and non-lobbying firms. For firms with the same level of productivity, large firms enjoy significantly lower effective tax rates when they decide to exert lobbying effort, compared to small, non-lobbying firms. However, lobbying benefits, measured by effective tax rates, seem to be less prominent for highly productive firms because the benefits are only tied to capital.

To make it clearer, the black dots in Figure (19) show two firms with the same amount
Effective tax rates faced by large, unproductive firms are substantially lower than those faced by small, productive firms in the baseline model, while the difference is less noticeable in the model without lobbying benefits. This obviously has implications for resource misallocation issues. On the one hand, large, unproductive firms enjoy tax benefits, encouraging them to accumulate more capital. On the other hand, small, productive firms face high effective tax rates, reducing their after-tax profit and preventing them from accumulating capital.

### Marginal Product of Capital, Non-Targeted Moments

Because the model has a clear implication for resource misallocation and because further analyses will be conducted in Section 3.5.4 to explore how tax benefits and lobbying activities distort the allocation of capital, it is crucial to see how well the model can match the most common measure of resource misallocation, i.e., a dispersion of the marginal product of capital (MPK).

Table (23) reports four non-targeted moments: the relative mean and standard devi-
Table 23: Marginal Product of Capital (MPK), Non-Targeted Moments

<table>
<thead>
<tr>
<th>Moments</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean(MPK)</td>
<td>(Lobbying firms)/(All firms)</td>
<td>0.71</td>
</tr>
<tr>
<td></td>
<td>(Non-lobbying firms)/(All firms)</td>
<td>1.04</td>
</tr>
<tr>
<td>std. dev.(MPK)</td>
<td>(Lobbying firms)/(All firms)</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>(Non-lobbying firms)/(All firms)</td>
<td>1.04</td>
</tr>
</tbody>
</table>

The data show that lobbying firms have, on average, lower marginal product of capital than the average firm, and that non-lobbying firms have, on average, higher marginal product of capital. The data also suggest that the marginal product of capital is two times less dispersed among lobbying firms than non-lobbying firms. Most of these facts are captured well by the model.

In the model, as suggested by the policy functions in Figure (19), lobbying firms hold large amounts of capital. The average amount of capital is even larger for less productive firms. The model, thus, naturally delivers the low average marginal product of capital among lobbying firms.

Figure (20) compares the model-implied distribution of the logarithmic marginal product of capital, in the top panel, to the actual distribution from the data for the period 2010-11, in the bottom panel. Note that the model is able to replicate the distribution of the marginal product of capital of both groups of firms. In fact, the support of model-implied demeaned distribution is very similar to the support of the demeaned distribution in the data. Moreover, just as in the data, the distribution of non-lobbying firms (left panel) is significantly more dispersed than the distribution of lobbying firms (right panel). Finally, the shapes of the distributions are also very similar; in fact, the only difference is in the non-lobbying distribution, where, in the model, there are some signs of a bimodal distribution. Therefore, because the model is able to capture the main features of the distribution of the marginal product of capital, it is well suited to study the misallocation of capital in
Lobbying and Effective Tax Rates, Non-Targeted Moments

When calibrating the model, the targeted moments are the average effective tax rates of lobbying firms and non-lobbying firms. To check the model performance, a conditional correlation between lobbying activities and effective tax rates from the model’s predictions can be compared with the correlation from the data. In particular, the panel regressions (1)
Table 24: ETR Regressions, Non-Targeted Moments

<table>
<thead>
<tr>
<th>Variables</th>
<th>Data†</th>
<th>Model</th>
<th>Data</th>
<th>Model</th>
<th>Same Sign</th>
<th>Data</th>
<th>Model</th>
<th>Same Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>if lobₜ₋₁</td>
<td>1(ₜ₋₁ &gt; 0)</td>
<td>-0.014**</td>
<td>-0.136 yes</td>
<td></td>
<td></td>
<td>-0.020**</td>
<td>-0.022 yes</td>
<td></td>
</tr>
<tr>
<td>log lobₜ₋₁</td>
<td>log(ₜ₋₁ + 1)</td>
<td>-0.020**</td>
<td>-0.022 yes</td>
<td></td>
<td></td>
<td>-0.020**</td>
<td>-0.022 yes</td>
<td></td>
</tr>
<tr>
<td>cap int</td>
<td>k/n</td>
<td>-0.575***</td>
<td>-0.003 yes</td>
<td>-0.572***</td>
<td>-0.003 yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>lev</td>
<td>b/k</td>
<td>-0.196***</td>
<td>-0.270 yes</td>
<td>-0.195***</td>
<td>-0.267 yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>size</td>
<td>log(V)</td>
<td>0.009***</td>
<td>0.306 yes</td>
<td>0.009***</td>
<td>0.308 yes</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

† Variable descriptions are provided in Appendix C.4.

**p < 0.01, ***p < 0.05, *p < 0.01.

See Table (20) for regressions with data.

Table (24) reports the regression results from model-simulated observations along with those from the data for the period 1998-2011.

Although the model is calibrated to 2010-11 data, it yields correct predictions of the sign of all regression coefficients, including lobbying activities, capital intensity, leverage ratio, and total assets. Regression 1 shows the effect of lobbying at the extensive margin. Firms that engage in lobbying activity have, on average, lower effective tax rates. Regression 2 shows the effect of lobbying at the intensive margin. By spending a larger amount on lobbying activity, firms enjoy lower effective tax rates. The higher capital intensity and leverage ratio the firm has, the lower effective tax rate the firm pays. This is because tax benefits are tied to capital. Capital intensive firms can claim higher tax benefits. The negative coefficient for the leverage ratio is influenced by small, unproductive firms that are highly leveraged but take large benefits from base deductions. These firms pay very low effective tax rates. Lastly, a proxy for the volume of assets is the firm’s value. Firms with large volumes of assets pay higher effective tax rates. This prediction arises in the model from the fact that tax benefits are tied to capital with a decreasing return. Large firms, and, particularly, productive large firms, can then possibly face higher effective tax rates because of their large sales volume. Those that pay low effective tax rates are unproductive

Because there are no model counterparts for R&D intensity and inventories, these variables are dropped from the analysis.
firms, which generally have lower values.

### 3.5.3 The Persistence of Lobbying

A resilient fact of corporate lobbying documented by Kerr et al. (2014) is that lobby status is highly persistent at the firm level. Before proceeding to the analysis of the calibrated model, it is interesting to see this moment delivered by the model. Tables (25a) to (25c) show the average transition probabilities in the data between lobbying and non-lobbying firms for three different periods. In line with the results from Kerr et al. (2014), lobbying decisions are highly persistent states. They suggest that this persistence is due mainly to the option value generated by the interaction between entry cost to lobby and returns to experience in lobbying.

Table (25d) shows the model-implied transition probability for the baseline calibration. The baseline model captures more than 70% of the persistence in lobby status without fixed entry cost to lobby or returns to political experience. The fact that tax benefits are tied to capital holdings and that capital is highly persistent implies that benefits from lobbying are also persistent. Therefore, at least for tax-related lobbying, this paper provides an alternative mechanism that can explain the persistence in firms’ political activism.

Table 25: Transition Matrix of Lobbying Decision

<table>
<thead>
<tr>
<th></th>
<th>lob$_t$ = 0</th>
<th>lob$_t$ = 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>lob$_{t-1}$ = 0</td>
<td>98.74</td>
<td>1.26</td>
</tr>
<tr>
<td>lob$_{t-1}$ = 1</td>
<td>20.31</td>
<td>79.69</td>
</tr>
</tbody>
</table>

(a) Data (1998 − 1999)

<table>
<thead>
<tr>
<th></th>
<th>lob$_t$ = 0</th>
<th>lob$_t$ = 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>lob$_{t-1}$ = 0</td>
<td>98.23</td>
<td>1.77</td>
</tr>
<tr>
<td>lob$_{t-1}$ = 1</td>
<td>14.29</td>
<td>85.71</td>
</tr>
</tbody>
</table>

(b) Data (2010 − 11)

<table>
<thead>
<tr>
<th></th>
<th>lob$_t$ = 0</th>
<th>lob$_t$ = 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>lob$_{t-1}$ = 0</td>
<td>98.45</td>
<td>1.55</td>
</tr>
<tr>
<td>lob$_{t-1}$ = 1</td>
<td>14.59</td>
<td>85.41</td>
</tr>
</tbody>
</table>

(c) Data (1998 − 2011)

<table>
<thead>
<tr>
<th></th>
<th>lob$_t$ = 0</th>
<th>lob$_t$ = 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>lob$_{t-1}$ = 0</td>
<td>92.67</td>
<td>7.33</td>
</tr>
<tr>
<td>lob$_{t-1}$ = 1</td>
<td>38.1</td>
<td>61.9</td>
</tr>
</tbody>
</table>

(d) Model (Baseline Calibration)
3.5.4 Quantitative Experiment


The first experiment is to see how well the model can capture changes in lobbying activities and effective tax rates between 1998-1999 and 2010-11, the first and the final two years of the data set. Because the level of tax expenditures determined by the government is observed directly in the data, the only change to the baseline calibration is in $\theta$. In 1998-1999, revenue losses from tax expenditures are 23%, compared to 33% in 2010-11.\textsuperscript{22} In particular, all targeted moments in the benchmark calibration are obtained for the model with benchmark parameters but with $\theta = 0.23$.

Table 26: Lobbying and Effective Tax Rate Moments in 1998-1990 and 2010-11

<table>
<thead>
<tr>
<th></th>
<th>1998-1999</th>
<th>2010-11</th>
<th>Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data</td>
<td>Model</td>
<td>Data</td>
</tr>
<tr>
<td>Effective tax rate (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All firms</td>
<td>24.4</td>
<td>21.9</td>
<td>18.7</td>
</tr>
<tr>
<td>Lobbying firms</td>
<td>21.2</td>
<td>16.7</td>
<td>15.5</td>
</tr>
<tr>
<td>Non-lobbying firms</td>
<td>24.6</td>
<td>22.3</td>
<td>19.1</td>
</tr>
<tr>
<td>lobbying firms (%)</td>
<td>4.0</td>
<td>7.0</td>
<td>10.9</td>
</tr>
<tr>
<td>Capital owned by lobbying firms (%)</td>
<td>28</td>
<td>59</td>
<td>60</td>
</tr>
<tr>
<td>Lobbying expenditures to sales (%)</td>
<td>0.07</td>
<td>0.09</td>
<td>0.06</td>
</tr>
</tbody>
</table>

1 Numbers in bold are targeted. They are reported in Table (22).
2 All parameters but $\theta$ are common. $\theta = 0.23$ for the model replicating 1998-99.

The first column of Table (26) shows the data moments from the period of 1998-99. Although several other parameters might have changed over the past decade, by adjusting only the fraction of tax expenditures, the model is able to qualitatively predict all changes observed in the data except the ratio of lobbying expenditures to sales. The last column of Table (26) compares the percentage changes observed in the data and those predicted by the model. In fact, other than under-predicting the change in capital owned by lobbying firms and over-predicting the change in lobbying expenditures over sales, the model quantitatively

\textsuperscript{22}IRS corporate tax returns balance sheet.
predicts all changes relatively well.

In the model, the increase in tax expenditures reduces the average effective tax rate for every group of firms, with lobbying firms experiencing a larger decrease. The rise in tax expenditures allows more firms to benefit from lobbying activities, resulting in a larger fraction of lobbying firms. Most of these new lobbying firms have low productivity but not high enough capital, so they were not able to spend a large enough amount on lobbying activities when preferential tax treatment was more limited. These firms’ optimal lobbying spending is relatively lower but, once they are granted preferential treatment, their effective tax rates become substantially lower than those of existing lobbying firms, which generally have higher productivity and greater capital. As a result, the ratio of lobbying expenditures to sales decreases, and the average effective tax rate of lobbying firms falls substantially. For the group of non-lobbying firms, the only effect is that there is a lower proportion of firms with a large amount of capital, which, in general, have slightly higher effective tax rates, as discussed above. As a result, the average effective tax rate falls by a smaller percentage. Lastly, the share of the total capital owned by lobbying firms increases. This is mainly due to a larger fraction of lobbying firms in the economy. All these predictions are confirmed in the data, with considerable success even at the quantitative level.

**Resource Misallocation**

The effective tax rate functions shown in Figure (19) suggest that a non-negligible distortion is created by the presence of lobbying activities on top of a distortion from the standard tax benefits, which are applied evenly across firms. Hsieh and Klenow (2009) point out that the more dispersed is the marginal product of capital, the more severe is the resource misallocation in the economy. This is because capital can be reallocated across firms to achieve a higher level of output.

Table (27) shows the dispersion of the marginal product of capital generated by the
model with different sets of parameter values. The model with the benchmark parameter values is reported in the first column. The second column is the model without tax benefits. The last two columns are the models without lobbying benefits, one with the same base deduction as the benchmark and the other with the base deduction, which yields the benchmark’s fraction of tax expenditures. The benchmark parameters result in the most severe misallocation. Removing tax benefits washes out almost all of the misallocation except that created by entrants, driving down the variance of the marginal product of capital practically to zero.23 Removing lobbying benefits yield intermediate results. Therefore, tax benefits, either base deductions or preferential tax treatment, endogenously generate a larger dispersion in the marginal product of capital, implying inefficiencies in the allocation of resources. When base deductions are high, there are a number of highly productive firms clustered around high levels of capital. Low-productivity firms choose to have low levels of capital because they can still enjoy very low effective tax rates. When base deductions are low, more firms, including productive firms, cluster around low levels of capital. As a result, the variance of the marginal product of capital is larger in the model with lower base deductions.

In summary, this section shows that the calibrated version of the model introduced in Section 3.4 successfully replicates the data features highlighted in Section 3.3. Moreover, the model suggests that the evolution of effective tax rates and lobbying activity in the U.S. economy between 1998-2011 can be attributed to a relative increase in the availability

\[\text{Exit firms are replaced by entrants with capital holdings equal to the total capital of exit firms; only after a period are they able to adjust their holdings.}\]

\[\text{115}\]
of corporate tax benefits tied to capital usage. Finally, the calibrated model implies that corporate rent-seeking is responsible for at least 20% of capital misallocation in the U.S. economy.

3.6 Conclusion

In this paper, we document a wide heterogeneity in the effective corporate taxation paid by U.S. corporations. In particular, firms in the U.S. pay on average an effective tax rate that is more than ten percentage points lower than the statutory tax rate, with a great dispersion among them. This is mainly due to tax benefits granted by the government. These benefits are not exogenous for every firm. In fact, large, capital-intensive firms are able to lobby for tailored benefits that fit their profiles. Because most tax provisions are tied to capital holding, different firms face different marginal benefits depending on their capital accumulation. Therefore, corporate lobbying can be an endogenous mechanism driving capital misallocation in the economy.

The heterogeneous firm dynamic model presented in this paper formalizes this mechanism and provides a framework to quantify the role of capital-based tax benefits and firms’ rent-seeking behavior in the economy. In the model, firms are granted tax benefits tied to their capital holdings, and lobbying firms are granted extra benefits depending on their lobbying expenditure. Because benefits available through lobbying are limited, only a small fraction of firms lobby in equilibrium. However, these firms are large and they can potentially hold most of the capital in the economy; therefore, the presence of capital-based tax benefits and lobbying behavior can potentially create important capital misallocation in the economy.

The calibrated model matches the targeted and non-targeted moments in the data. In particular, it is accurate when replicating the non-targeted moments, such as the first two moments of the marginal product of capital for a group of lobbying and non-lobbying firms.
The two main quantitative results of the paper can be summarized as follow. First, the increase in the availability of tax benefits in the U.S. economy between 1998-99 and 2010-11 can explain most of the decrease in the effective tax rate, and can also explain the increase in lobbying activity at both the intensive and extensive margins. Second, corporate lobbying accounts for more than 20% of the variance in the marginal product of capital in the U.S. economy, which measures the degree of misallocation.

This paper provides a new mechanism that can endogenously generate misallocation of resources in the economy. The main alternative channel in the literature to endogenize capital misallocation is the existence of credit-constrained firms that cannot achieve their optimal scale. Future research should contrast the two channels and quantify the contribution of each channel to the misallocation of capital. For this particular sample, the credit constraint channel does not seem to be particularly important. In fact, credit access has not been an issue for large and publicly-held firms in the U.S., even during the Great Recession. Nevertheless, in a developing economy where small firms are likely to be constrained, and weak institutions give wide access to rent-seeking behavior, the distinction of the two channels is fundamental for the efficient design of public policy.
Appendix A

Appendix to Chapter 1

A.1 Data

1. World Bank Enterprise Surveys (WBES) A cross-country firm-level data set collected by the World Bank as a second data source. The data set combines surveys of 130,000 firms in 125 countries, most of which are developing and emerging countries. The surveys cover a broad range of topics, with in-depth data on firms’ characteristics, ownership structure, technology usage, financial constraints, human capital and productivity. In particular, the surveys collect information on technology adoption, assets, liabilities, sales, raw materials, investments, labor composition, capital composition and credits. The firms were asked whether they use technology licensed from a foreign-owned company. This will be used as a proxy for a firm’s adoption decision. The analysis is based on the standardized survey conducted between 2002-2005, a common questionnaire across countries allowing for cross-country comparison. Government-owned firms are excluded from the samples.

Regression Variables Firm characteristics include size, human capital, foreign ownership and foreign activity. $size_j$ is the total number of employees. $human\ capital_j$
corresponds to the fraction of skilled workers. \(foreign\ own_j\) is a dummy taking the value of 1 if more than 40% of the firm’s shares are owned by foreign entities. \(Imp_j\) takes the value of 1 if more than 40% of the firm’s inputs and supplies are imported directly or indirectly. \(Industry_k\) are 11 dummies taking the value of 1 if the firm’s main production activity is categorized into that particular industry. \(Country_c\) is a matrix including GDP per capita, regulation environments and country dummies. Regulation environments are proxied by one index, the Ease of Doing Business Rank. The rank is taken from The World Bank’s Doing Business, where a high ranking on the ease of doing business index means the regulatory environment is more conducive to the starting and operation of a local firm. \(Loan\ recovery\ rate\) measures the cents on the dollar recovered by creditors through reorganization, liquidation or debt enforcement proceedings. \(Interest\ rate\ spread\) is the interest rate charged by banks on loans to prime customers minus the interest rate paid by commercial banks for deposits or minus the ”risk free” treasury bill interest rate. \(Credit\ depth\ of\ information\ index\) measures rules affecting the scope, accessibility, and quality of credit information available through public or private credit registries. The index ranges from 0 to 6, with higher values indicating the availability of more credit information, from either a public registry or a private bureau, to facilitate lending decisions. These three measures are country-specific. \(Firm-specific\ interest\ rate\) is the loan’s approximate rate of interest reported by each firm.

**Industries** The sample is restricted to firms in manufacturing and agroindustry sectors, which can be categorized into 12 industries: textiles and garments, food and beverage, electronics, leather, chemicals and pharmaceutics, metals and machinery, non-metallic and plastic materials, wood and furniture, papers, agroindustry, auto and auto components, and other manufacturing.

2. **Historical Cross-Country Technological Adoption (HCCTA)** An unbalanced panel data set with information on adoption decisions of about 104 technologies in 161 countries since 1800. As the focus is on the speed of technology diffusion, the U.S.
data is truncated to a time before the intensity of technology usage becomes stable or decreasing. To calculate technology usage lags, first compute the usage intensity of a given technology in sampled countries at time \( t \). Then, compare these numbers with the historical U.S. time series to find the last time the U.S. had the same usage intensity. If the usage intensity of the sampled countries is not exactly equal to the intensity values observed in the U.S. time series, linear interpolation is employed to get the result. However, it can be the case that the U.S. historical time series is not long enough to obtain a rich observation of technology usage lags. To circumvent this issue, the U.S. time series is initialized by setting the usage intensity observed in the U.S. equal to 0 at the year of invention.

3. **Chilean Annual Manufacturing Survey (ENIA)** An unbalanced panel data set, which is an annual manufacturing survey of Chilean firms with more than 10 employees collected by the National Statistics Institute of Chile (INE). The survey collects firm-level information on sales, employment, raw materials and investments. Unlike other manufacturing survey data, the Chilean Manufacturing Survey also collects information on firm-level expenditures on licenses and foreign technical assistance, which is used as a proxy for foreign technology usage intensity, along with the data on imported inputs. All nominal variables are expressed in real terms using the deflator.

4. **World Productivity Database (WPD)** A data set provides the measure of TFP computed relative to the TFP level of the United States for as many as 112 countries, from 1960 to 2000. The measurement method is a standard Cobb-Douglas, in logarithmic form, with Hicks neutral technical change being assumed. The capital is assumed to depreciate at 6 percent annually and labor is adjusted by schooling where possible.
A.2 Proofs for Propositions and Lemmas

A.2.1 Proposition 1

Proof for Proposition 1. First, show in Lemma A.2.1 that the distribution of new technology productivity is monotonic in \( \lambda \) in a first order stochastic dominance sense.

Lemma A.2.1. Denote \( \Psi_\lambda \) the distribution \( \lambda \Psi^h(\cdot) + (1 - \lambda) \Psi^l(\cdot) \) and \( \psi_\lambda \) the density function \( \lambda \psi^h(\cdot) + (1 - \lambda) \psi^l(\cdot) \).

(i) If \( \psi^h \) and \( \psi^l \) satisfy MLRP with \( \psi^h(x_1) \geq \psi^h(x_0) \) for \( x_0 < x_1 \), \( \frac{\psi_{\lambda_1}(x_1)}{\psi_{\lambda_2}(x_1)} \geq \frac{\psi_{\lambda_1}(x_0)}{\psi_{\lambda_2}(x_0)} \) for \( \lambda_1 > \lambda_2 \).

(ii) If \( \lambda_1 > \lambda_2 \), \( \Psi_{\lambda_1} \) first order stochastically dominates \( \Psi_{\lambda_2} \) on the support \([z^n, \bar{z}^n] \).

Proof for Lemma A.2.1. For (i), \( \frac{\psi_{\lambda_1}(x)}{\psi_{\lambda_2}(x)} = \frac{\lambda_1 \psi^h(x) + (1 - \lambda_1) \psi^l(x)}{\lambda_2 \psi^h(x) + (1 - \lambda_2) \psi^l(x)} \). This is increasing in \( \frac{\psi^h(x)}{\psi^l(x)} \). As \( \frac{\psi^h(x_1)}{\psi^l(x_1)} \geq \frac{\psi^h(x_0)}{\psi^l(x_0)} \) for \( x_0 < x_1 \), \( \frac{\psi_{\lambda_1}(x_1)}{\psi_{\lambda_2}(x_1)} \geq \frac{\psi_{\lambda_1}(x_0)}{\psi_{\lambda_2}(x_0)} \) for \( \lambda_1 > \lambda_2 \). For (ii), \( \Psi^h(\cdot) \) first order stochastically dominates \( \Psi^l(\cdot) \) on the support \([z^n, \bar{z}^n] \) by assumption. Then, \( \Psi^h(\cdot) \leq \Psi^l(\cdot) \). Since \( \lambda_1 > \lambda_2 \), it follows that \( \lambda_1 \Psi^h(\cdot) + (1 - \lambda_1) \Psi^l(\cdot) \leq \lambda_2 \Psi^h(\cdot) + (1 - \lambda_2) \Psi^l(\cdot) \) for all \( z^n \in [z^n, \bar{z}^n] \).

First, to prove the first property of the interest rate schedule, fix loan size \( k \). The associated interest rate offered to a firm when the belief is \( \lambda \) is

\[
\left\{ i \mid 1 + r = (1 + i) \left( 1 - \Psi^\lambda \left( \frac{(1+i)k}{k^n} \right) \right) + \xi k \alpha - 1 \int_0^{(1+i)k \over k^n} z^n d\Psi^\lambda(z^n) \right\}
\]

The solution to this problem is not necessary unique. If not, only the lowest offered interest rate will be observed in equilibrium. This is because it is not optimal for a firm to choose the contract that offers the same loan amount at a higher interest rate. The analysis is restricted only in the region of nonnegative interest rates. Rewrite the expected zero profit
condition as

\[(i - r) = \Psi^\lambda \left( \frac{(1 + i)k}{\alpha} \right) \left( (1 + i) - k^{\alpha-1}E_{\Psi^\lambda} \left[ z^n \mid 0 \leq z^n \leq \frac{(1 + i)k}{\alpha} \right] \right). \quad (A.1)\]

The first step is to show that the right-hand side is nonnegative and decreasing in \(\lambda\). Let

\[g(i, \lambda) = \left( (1 + i) - k^{\alpha-1}E_{\Psi^\lambda} \left[ z^n \mid 0 \leq z^n \leq \frac{(1 + i)k}{\alpha} \right] \right) \cdot \xi k^{\alpha-1}E_{\Psi^\lambda} \left[ z^n \mid 0 \leq z^n \leq \frac{(1 + i)k}{\alpha} \right] \leq \xi k^{\alpha-1}\frac{(1 + i)k}{\alpha} = \xi(1 + i)\] 

implies that \(g(i, \lambda) \geq 0 \forall i \geq 0\). As \(k > 0\), it follows that \(\Psi^\lambda \left( \frac{(1 + i)k}{\alpha} \right)\) is positive and increasing in \(i\). Let \(m(i, \lambda) = \Psi^\lambda \left( \frac{(1 + i)k}{\alpha} \right) g(i, \lambda)\), it is trivial to show that \(m(i, \lambda) \geq 0\). From LEMMA 2.1, the conditional distribution \(\Omega_\lambda(x) = \frac{\psi^\lambda(x)}{\Psi^\lambda \left( \frac{(1 + i)k}{\alpha} \right)}\) also satisfies MLRP and FOSD. Thus, \(E_{\Psi^\lambda} \left[ z^n \mid 0 \leq z^n \leq \frac{(1 + i)k}{\alpha} \right]\) is increasing in \(\lambda\) and \(g(i, \lambda)\) is decreasing in \(\lambda\). Because \(\Psi^\lambda \left( \frac{(1 + i)k}{\alpha} \right)\) is decreasing in \(\lambda\), \(m(i, \lambda)\) is decreasing in \(\lambda\). Then, let \(f(i) = i - r\). It is trivial to show that \(f(i)\) is continuous and increasing in \(i\), \(f(0) < 0\), and \(f(0) = 0\).

Now, let \(h(i, \lambda) = m(i, \lambda) - f(i)\), then \(h(0, \lambda) > 0\), and \(h(i, \lambda_1) \leq h(i, \lambda_2)\) for \(\lambda_1 > \lambda_2\). There are two possible cases. First, consider the case where there exists \(i^*(\lambda) = \min \{ i \mid h(i, \lambda) = 0 \} \). Then, for any \(\lambda' < \lambda\), \(h(i^*(\lambda), \lambda') \geq 0\) and \(h(i, \lambda') \geq h(i, \lambda) > 0 \forall i < i^*(\lambda)\). By continuity, \(i^*(\lambda') \geq i^*(\lambda)\). Second, consider the case where there does not exist a solution to \(h(i, \lambda) = 0\). The same argument can be applied. If a financial intermediary charges an infinite interest rate to the \(\lambda\)-type firm, (which is equivalent to not issuing any loan contract to that firm, they must charge infinite interest rate to the \(\lambda\)-type firm for any \(\lambda' < \lambda\) as well. As a result, given loan size \(k\),

\[\min \left\{ i \mid (1 + i)k \left( 1 - \Psi^\lambda \left( \frac{(1 + i)k}{\alpha} \right) \right) + \xi k^{\alpha} \int_0^{\frac{(1 + i)k}{\alpha}} z^n d\Psi^\lambda(z^n) = (1 + r) \right\}\]

is nonincreasing in \(\lambda\).

Second, to prove the second property of the interest rate schedule, fix a belief \(\lambda\). Let \(m(i, k) = \Psi^\lambda \left( \frac{(1 + i)k}{\alpha} \right) \left( (1 + i) - k^{\alpha-1}E_{\Psi^\lambda} \left[ z^n \mid 0 \leq z^n \leq \frac{(1 + i)k}{\alpha} \right] \right)\). Taking the partial derivative, it can be shown that \(m(i, k)\) is increasing in \(k\). Follow the same steps of proof
with $k$ as the variable of interest and $\lambda$ treated as exogenous. The result shows that
\[
\min \left\{ i \left| (1 + i)k \left( 1 - \Psi^{\lambda} \left( \frac{(1+i)k}{k-1} \right) \right) + \xi k^\alpha \int_0^{(1+i)k} z^n d\Psi^{\lambda}(z^n) = (1 + r) \right. \right\}
\]
is nondecreasing in $k$.

Third, to prove that the maximum loan size is increasing in $\lambda$, suppose $\bar{k}(\lambda_1) > \bar{k}(\lambda_2)$ for $\lambda_2 > \lambda_1$. The equilibrium interest rate is decreasing in $\lambda$ for a given $k$ and increasing in $k$ for a given $\lambda$. There exists $k'$ such that $\bar{k}(\lambda_1) > k' > \bar{k}(\lambda_2)$ and $i(k', \lambda_2) < i(k', \lambda_1) < \infty$ as the equilibrium interest rate is decreasing in $\lambda$ given a given $k$. However, this implies that $\bar{k}(\lambda_2, \lambda_2) = \infty$ where $k' > \bar{k}(\lambda_2)$. This contradicts the fact that the equilibrium interest rate is increasing in $k$ for a given $\lambda$.

Lastly, to show the comparative statics with respect to $\xi$, it is sufficient to show that the right-hand side of equation (A.1) is decreasing in $\xi$ for given $\lambda$ and $k$. This is trivial.

A.2.2 Proposition 2

Proof for Lemma 1

1. Proof for Lemma 1(i). It is straightforward that $\pi^{o*}(z^{o}, \lambda)$ is constant in $\lambda$.

$\pi^n(z^n, k, i)$ is increasing in $z^n$. From Lemma A.2.1, $\Psi_{\lambda_1}$ first order stochastically dominates $\Psi_{\lambda_2}$ when $\lambda_1 > \lambda_2$. Then, $\mathbb{E}_{\Psi_{\lambda_1}} [\pi^n(z^n, k, i)] \geq \mathbb{E}_{\Psi_{\lambda_2}} [\pi^n(z^n, k, i)]$. Because $\pi^n(z^n, k, i)$ is decreasing in $i$, $\mathbb{E}_{\Psi_{\lambda}} [\pi^n(z^n, k, i)]$ is decreasing in $i$. From Proposition 1, if $\lambda_1 > \lambda_2$, $\mathcal{D}^n(z^{o}, \lambda_1)$ weakly dominates $\mathcal{D}^n(z^{o}, \lambda_2)$ in the sense that $\mathcal{D}^n(\lambda_1)$ offers the same set of $k$ at a lower interest rate. Hence,

\[
\mathbb{E}_{\pi^{n*}(z^{o}, \lambda)} = \max_{(k, i) \in \mathcal{D}^n(z^{o}, \lambda)} \mathbb{E}_{\Psi_{\lambda}} [\pi^n(z^n, k, i)]
\]
is nondecreasing in $\lambda$. Boundedness follows from the fact that $z^{o}$ and $z^n$ are bounded. 

\[\square\]
2. **Proof for Lemma 1(ii)**. Rewrite the firm’s problem by adding the state variable $c$ indicating the technology choice last period:

$$V(z^o, \lambda, c) = \max_{e \in \{0, 1\}} \left\{ (1 - e) \left[ \pi^{o*}(z^o, \lambda, c) + \beta E V(z^o, \Lambda(\lambda, 0, z^n), 0) \right] \\ + e \left[ E \pi^{n*}(z^o, \lambda, c) + \beta E V(z^o, \Lambda(\lambda, 1, z^n), 1) \right] \right\}$$

where $c = \{0, 1\}$, $\pi^{o*}(z^o, \lambda, c) = \pi^{o*}(z^o, \lambda)$ and $E \pi^{n*}(z^o, \lambda, c) = E \pi^{n*}(z^o, \lambda)$.

$$E V(z^o, \Lambda(\lambda, 1, z^n), 1) = \int V(z^o, \Lambda(\lambda, 1, z^n)) d\Psi^\lambda(z^n)$$

Let $X \subseteq \mathbb{R}_+ \times [0, 1] \times \{0, 1\}$ and $B(X)$ represent a space of bounded function $\varphi : X \to \mathbb{R}$ with the sup-norm $d$. Let $T : B(X) \to B(X)$ be an operator

$$TV(z^o, \lambda, c) = \max_{e \in \{0, 1\}} \left\{ (1 - e) \left[ \pi^{o*}(z^o, \lambda, c) + \beta E V(z^o, \Lambda(\lambda, 0, z^n), 0) \right] \\ + e \left[ E \pi^{n*}(z^o, \lambda, c) + \beta E V(z^o, \Lambda(\lambda, 1, z^n), 1) \right] \right\}$$

$\varphi$ is bounded below by 0 and bounded above by the perpetuity value of profit from the realization of $z^n$. To guarantee that there is a unique solution to the recursive equation, we show that $\varphi$ satisfies Blackwell’s sufficient conditions for a contraction;

(a) (Monotonicity) Take $\varphi_1 \geq \varphi_2$ for all $(z^o, \lambda, c) \in \mathbb{R}_+ \times [0, 1] \times \{0, 1\}$. Then it is trivial that $T\varphi_1(z^o, \lambda, c) \geq T\varphi_2(z^o, \lambda, c)$.

(b) (Discounting) For any function $\varphi$, a positive real number $a > 0$ and $\beta \in (0, 1)$;

$$T(\varphi + a) = T\varphi + \beta a$$

3. **Proof for Lemma 1(iii)-(iv)**. Given the recursive structure of the model, the proof is to show that the limiting form of the value function is weakly increasing and convex in the state variable, $\lambda$. The proof consists of two steps. The first step is to show,
by induction, that the value function for the finite-horizon problem is weakly increasing and convex. Then, the finite horizon problem is extended to the infinite horizon problem.

Consider the T-period finite problem. Denote $V_t(z^o, \lambda)$ the value function in period $t$. The value function for the last period $T$ is $V_T(z^o, \lambda) = \max\{\pi^o(z^o, \lambda), \mathbb{E}\pi^o(z^o, \lambda)\}$. $\mathbb{E}\pi^o(z^o, \lambda)$ is weakly increasing in $\lambda$ by Lemma 1(i) and it is convex in $\lambda$ by assumption. Therefore, $V_T(z^o, \lambda)$ is weakly increasing and convex in $\lambda$ as it is the maximum of a constant and a weakly increasing, convex function. Now, suppose $V_t(z^o, \lambda)$ is weakly increasing and convex in the second argument. $W_{t-1}^o(z^o, \lambda)$ is a linear transformation of $V_t(z^o, \lambda)$, so it is also weakly increasing and convex. To show that $W_{t-1}^n(z^o, \lambda)$ is weakly increasing and convex in the second argument, rewrite the continuation value as $V_t(z^o, \Lambda(\lambda, 1, z^n))$. Denote

$$U_t(\Lambda(\lambda, 1, z^n)) = \int V_t(z^o, \Lambda(\lambda, 1, z^n))d\Psi(\lambda) = \int V_t(z^o, \lambda \frac{\psi^h(z^n)}{\psi^\lambda})\psi^\lambda dz^n.$$

From the monotone likelihood ratio property, $\Lambda(\lambda, 1, z^n)$ is increasing in $z^n$. Because $\Lambda(\lambda, 1, z^n)$ is increasing in $\lambda$, it follows from Lemma A.2.1 that $U_t(\Lambda(\lambda, 1, z^n))$ is weakly increasing. Moreover, by convexity of $V_t$;

$$\int U_t(\Lambda(\lambda, 1, z^n))\psi^\lambda dz^n \geq \int V_t(z^o, \lambda)\psi^\lambda dz^n = U_t(\int \Lambda(\lambda, 1, z^n)\psi^\lambda dz^n)$$

$W_{t-1}^n(z^o, \lambda)$ is the summation of two weakly increasing, convex functions of $\lambda$. Therefore, it possesses the properties of weak monotonicity and convexity. $V_{t-1}(z^o, \lambda)$ as the maximum of two weakly increasing, convex functions is thus weakly increasing and convex in the second argument. It follows that $V_t(z^o, \lambda)$ is weakly increasing and convex for $t = 0, 1, 2, 3, ..., T$ by induction. Denote $\hat{V}^T(z^o, \lambda)$ the value of T-period finite problem. $\hat{V}^T(z^o, \lambda)$ is then weakly increasing and convex.
To prove the monotonicity and convexity of the infinite-time problem, it is sufficient to show that $V(z^o, \lambda) = \lim_{T \to \infty} \hat{V}_T(z^o, \lambda)$ exists and is weakly increasing and convex. Because the reward functions are bounded and $\beta \in (0, 1)$, the sequence $\hat{V}_T(z^o, \lambda)$ is Cauchy and hence converges to finite value $V(z^o, \lambda)$. Weak monotonicity and convexity is preserved under pointwise convergence.

**Proof for Proposition 2.** This proof is done by considering the following 3 cases;

1. Suppose $\pi^o(z^o, 0) < \mathbb{E}\pi^{n*}(z^o, 0)$, then $\pi^o(z^o, \lambda) < \mathbb{E}\pi^{n*}(z^o, \lambda) \ \forall \lambda$;

$$
W^o(z^o, \lambda) = \pi^o(z^o, \lambda) + \beta V(z^o, \lambda) \\
= \pi^o(z^o, \lambda) + \beta \int z^o \frac{\psi^h(z_n)}{\psi^\lambda(z_n)} d\Psi^\lambda(z_n) \\
< \mathbb{E}\pi^{n*}(z^o, \lambda) + \beta \int V(z^o, \lambda) \frac{\psi^h(z_n)}{\psi^\lambda(z_n)} \psi^\lambda dz^o \\
< W^n(z^o, \lambda) \ \forall \lambda.
$$

where inequality comes from the facts that $\pi^o(z^o, 0) < \mathbb{E}\pi^{n*}(z^o, \lambda)$ by assumption and $V(z^o, \lambda) \leq \int V(z^o, \lambda) \frac{\psi^h(z_n)}{\psi^\lambda(z_n)} \psi^\lambda dz^o$ by Jensen’s inequality. Recall that $V(\cdot)$ is a convex function. In this case, $\lambda(z^o) = 0$ and all firms with $z^o$ adopt new technology.

2. If $\pi^o(z^o, 1) > \mathbb{E}\pi^{n*}(z^o, 1)$, it is trivial that $\lambda(z^o) = 1$. Firms with $z^o$ do not adopt new technology.

3. Now considering the intermediate case: $\pi^o(z^o, 0) > \mathbb{E}\pi^{n*}(z^o, 0)$ and $\pi^o(z^o, 1) < \mathbb{E}\pi^{n*}(z^o, 1)$.

$$
W^o(z^o, 0) = \pi^o(z^o, 0) + \beta V(z^o, 0) > \mathbb{E}\pi^{n*}(z^o, 0) + \beta V(z^o, 0) = W^n(z^o, 0) \\
W^o(z^o, 1) = \pi^o(z^o, 1) + \beta V(z^o, 1) < \mathbb{E}\pi^{n*}(z^o, 1) + \beta V(z^o, 1) = W^n(z^o, 1)
$$

As it has been shown that $W^o(z^o, \lambda)$ and $W^n(z^o, \lambda)$ are increasing and convex in $\lambda$, there exists $\lambda(z^o)$ such that $W^o(z^o, \lambda) < W^n(z^o, \lambda) \ \forall \lambda \in [\lambda(z^o), 1]$. 

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Follow the proof by Copeland (2007), but adjusted for the infinite horizon case. Denote 
\[ D(z^o, \lambda) = W^n(z^o, \lambda) - W^o(z^o, \lambda), \] 
it is suffice to show that \( D(z^o, \lambda) \) is increasing in \( \lambda \). Rewrite \( D(z^o, \lambda) \) as

\[
D(z^o, \lambda) = \beta \left[ \mathbb{E} \pi^{n*}(z^o, \lambda) + \beta \mathbb{E} \left[ V(z^o, \lambda') \mid \lambda \right] - V(z^o, \lambda) \right] \\
- \beta \left[ \pi^{o*}(z^o, \lambda) + (\beta - 1) \mathbb{E} \left[ V(z^o, \lambda') \mid \lambda \right] \right] \\
+ (1 - \beta) \left[ \mathbb{E} \pi^{n*}(z^o, \lambda) - \pi^{o*}(z^o, \lambda) \right].
\]

The last term is increasing in \( \lambda \) by Lemma 1(i). From Lemma 1(iii), \( \mathbb{E} \left[ V(z^o, \lambda') \mid \lambda \right] \) is increasing in \( \lambda \). The second term is then decreasing in \( \lambda \). The first term is \( W^n(z^o, \lambda) - V(z^o, \lambda) \) which equals either 0 or \( \beta(W^n(z^o, \lambda) - W^o(z^o, \lambda)) \). Hence, \( D(z^o, \lambda) \) is increasing in \( \lambda \).

\[ \square \]

A.2.3 Proposition 3

**Proof for Proposition 3.** The proof is completed by showing that \( \lambda(z^o) \) is decreasing in \( \xi \) for all \( z^o \). As the focus is on the effect of \( \xi \), all notations are expressed as a function of \( \xi \). From the equilibrium debt contract characterization (1.11), the interest rate charged on a loan \( k \) is decreasing in \( \xi \) for a particular firm \( (z^o, \lambda) \). This implies that \( \mathbb{E} \pi^{n*}(z^o, \lambda, \xi) \) and \( W^n(z^o, \lambda, \xi) \) are increasing in \( \xi \). Suppose \( \xi_2 > \xi_1 \). By solving \( \lambda(z^o, \xi_1) = \max \{ \lambda \mid W^n(z^o, \lambda, \xi_1) \leq W^o(z^o, \lambda) \} \) and \( \lambda(z^o, \xi_2) = \max \{ \lambda \mid W^n(z^o, \lambda, \xi_2) \leq W^o(z^o, \lambda) \} \), it follows that \( \lambda(z^o, \xi_1) \geq \lambda(z^o, \xi_2) \). \[ \square \]

A.2.4 Proposition 4

**Proof for Lemma 2.** As the belief updating in this setting is a Markovian process,

\[
\mathbb{E} [\lambda_t \mid \lambda_{t-1}, \lambda_{t-2}, \ldots] = \mathbb{E} [\lambda_t \mid \lambda_{t-1}].
\]

If the true type is \( h \), the expected belief next period is
given by

$$
\mathbb{E}[\lambda_t | \lambda_{t-1}] = \begin{cases} 
\int \Lambda(\lambda_{t-1}, 1, z^n_t) d\Psi^h(z^n) & \text{if } e_t = 1 \\
\lambda_{t-1} & \text{if } e_t = 0 
\end{cases}
$$

Thus, \( \mathbb{E}[\lambda_t | \lambda_{t-1}] \geq \lambda_{t-1} \) and a sequence of beliefs \((\lambda_0, \lambda_1, \ldots)\) is submartingale. Analogously, if the true type is \( l \), the expected belief next period is given by

$$
\mathbb{E}[\lambda_t | \lambda_{t-1}] = \begin{cases} 
\int \Lambda(\lambda_{t-1}, 1, z^n_t) d\Psi^l(z^n) & \text{if } e_t = 1 \\
\lambda_{t-1} & \text{if } e_t = 0 
\end{cases}
$$

Thus, \( \mathbb{E}[\lambda_t | \lambda_{t-1}] \leq \lambda_{t-1} \) and a sequence of beliefs \((\lambda_0, \lambda_1, \ldots)\) is supermartingale.

\( \Box \)

**Proof for Proposition 4.** The convergence is trivial if \( \lambda_0 = 1 \) or \( \lambda_0 = 0 \). For \( \lambda_0 \in (0, 1) \), suppose a firm chooses to adopt only new technology, i.e., \( e_t = 1 \ \forall t \). From Lemma 2 and Martingale Convergence Theorem, the posterior belief \{\lambda_t\} converges to a limit belief almost surely as \( t \to \infty \).

$$
P_0\{\lambda_t \to 0\} = P_1\{\lambda_t \to 1\} = 1
$$

However, when the firm can make its own technology choice, the model has two absorbing states: \( \lambda = 1 \) and \( \lambda_0 \leq \Delta(z^o) \). Let \( e_t \) be the technology choice at time \( t \). Proposition 2 shows that, if the firm starts period 1 with \((z^o, \lambda_0)\) where \( \lambda_0 \leq \Delta(z^o) \), \( e_t = 0 \) and \( \lambda_t = \lambda_0 \) \( \forall t \) regardless of the realization path \{\(z^n_t\)\}_{t=1}^\infty. If the firm starts period 1 with \((z^o, \lambda_0)\) where \( \lambda_0 \geq \Delta(z^o) \), the belief convergence will depend on the realization path \{\(z^n_t\)\}_{t=1}^\infty. Given \{\(z^n_t\)\}_{t=1}^\infty, there are two possible outcomes. If \{\(z^n_t\)\}_{t=1}^\infty induces the choice of \( e_t = 1 \ \forall t \), \( \lambda_t \to 1 \) a.s. Contrarily, if \{\(z^n_t\)\}_{t=1}^\infty induces the choice of \( e_t = 0 \ \forall t \geq T \) (Recall that \( e_{T-1} = 1 \) and \( e_T = 0 \), then \( e_t = 0 \ \forall t \geq T \), \( \lambda_t \to \lambda_T \in [0, \Delta(z^o)] \).

\( \Box \)
Appendix B

Appendix to Chapter 2

B.1 Labor Reallocation During Trade Liberalization

Figure (21) shows the measure of cross-sector labor shifts around the trade liberalization period for each income group: middle-income countries and low-income countries. The measure of cross-sector labor shifts is calculated using the approach proposed by Wacziarg and Wallack (2004). The first step is to compute the absolute value of changes in the share \( S_{sc}^t \) of each sector \( s \) in total employment for country \( c \) in any given year \( t \). Denote \( CH_{sc}^t(\tau) = |S_{sc}^t - S_{sc}^{t-\tau}| \) as the absolute value of changes in shares over \( \tau \) years. To compute this, the sectoral employment data are obtained from the United Nations Industrial Development Organization (UNIDO), which provides the 3-digit data covering a maximum of 28 sectors. The period \( t \) considered is 5 years before and after each country’s trade liberalization year. For robustness, differences in shares over 2 years, 3 years, 4 years and 5 years are considered. Then, the average value of a difference in shares over sectors \( CH_{sc}^t(\tau) \) is computed for each country. To aggregate this measure for each group of countries, \( CH_{sc}^t(\tau) \) is normalized by its average value over 11 years of the periods considered. Averaging over countries in each income group yields the measure of cross-sector labor shifts of each group five years before.
and after the liberalization year. The average change in a sector’s share of employment increases around the trade liberalization period in the group of low-income countries. This result is robust for all choices of \( \tau \). The pattern, however, is not the case in middle-income countries.

![Graph showing the average x-year change in a sector’s share of employment for low and middle-income countries.]

Note: Period 0 = trade liberalization period.

**Figure 21:** Average X-Year Change in a Sector’s Share of Employment
B.2 Exporters, Skills and Technology Upgrading: Firm-Level Evidence

This section explores the effect of skill supply on domestic and exporting firms’ decisions. Because the model focuses on skill-biased technology upgrading, firms’ technology usage and skill intensity are particularly examined. Firm-level data are obtained from the World Bank Enterprise Survey, which covers a broad range of topics with in-depth data of firm’s characteristics, ownership structure, technology usage, foreign activities, skill intensity, and productivity. In particular, the surveys collect information on technology adoption, assets, liabilities, sales, raw materials, investments, export status and labor composition. \( x_{ijc} \) is a variable of firm \( i \) in an industry \( j \) from country \( c \). Skill intensity \( y_{ijc} \) is defined as the fraction of skilled labor, including professional, management and skilled production workers. Technology upgrading \( u_{ijc} \) is a binary variable which equals 1 if the firm uses technology licensed from a foreign-owned company. \( Exp_{ijc} \) is a dummy variable taking the value of 1 if the firm has its product sold in a foreign market. Skill supply is proxied by the fraction of workers with at least a secondary level education \( (Secondary_c) \) and average years of schooling \( (AvgSchYr_c) \), obtained from Barro and Lee (2010). Firm controls include firms’ capital to labor ratio, size, ownership and sales. The regression specification controls for industry-specific effects and country-specific effects using industry dummy variables and GDP per capita.

The estimated coefficients reported in Table (28) confirm that human capital plays an important role in determining the firm’s hiring decision and technology choice. As shown in the left panel, firms in the country with the higher supply of skilled labor are more skill-intensive. The effect of skill supply on firms’ skill intensity is also more prominent among exporters. As the technology upgrading choice is a binary variable, the right panel shows the results from the logit regression. Firms in the country with the higher supply of skilled labor are more likely to adopt foreign technology. The effect is also larger among exporters.
Table 28: Heterogeneous Firms-Skill Upgrading-Technology Upgrading

<table>
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<tr>
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<th>Skill intensity&lt;sub&gt;ijc&lt;/sub&gt;</th>
<th>Technology upgrading&lt;sub&gt;ijc&lt;/sub&gt;</th>
</tr>
</thead>
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<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Secondary&lt;sub&gt;c&lt;/sub&gt;</td>
<td>-0.049</td>
<td>0.009***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Secondary&lt;sub&gt;c&lt;/sub&gt; × Exp&lt;sub&gt;ijc&lt;/sub&gt;</td>
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<td>0.017***</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>AvgSchYr&lt;sub&gt;c&lt;/sub&gt;</td>
<td>1.061***</td>
<td>0.138***</td>
</tr>
<tr>
<td></td>
<td>(0.265)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>AvgSchYr&lt;sub&gt;c&lt;/sub&gt; × Exp&lt;sub&gt;ijc&lt;/sub&gt;</td>
<td>0.648**</td>
<td>0.077**</td>
</tr>
<tr>
<td></td>
<td>(0.349)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Exp&lt;sub&gt;ijc&lt;/sub&gt;</td>
<td>-6.107***</td>
<td>-3.916*</td>
</tr>
<tr>
<td></td>
<td>(1.157)</td>
<td>(2.223)</td>
</tr>
</tbody>
</table>

|                      | (1)                           | (2)                              |
| Firm Controls        | √                             | √                                |
| Country Control      | √                             | √                                |
| Industry Dummies     | √                             | √                                |
| # Observations       | 11461                         | 11461                            |
|                      | 10362                         | 10362                            |
| R²                   | 0.09                          | 0.009                            |
|                      | 0.13                          | 0.13                             |

1 *significant at 10 %, **significant at 5 %, ***significant at 1 %

This is not surprising, as the data also show that the firm’s technology upgrading choice is positively related with its skill intensity.

In sum, firm-level data suggest that human capital affects firms’ decisions on skill intensity and technology upgrading, with a larger effect on exporting firms. In the model, this is due to the interaction between comparative advantage and skill-biased technology upgrading.
B.3 Proofs for Propositions and Lemmas

B.3.1 Two Large Countries

With two discrete technology choices, each firm’s profit can be separated into three components: (1) profits earned from the domestic market with technology \( z_0 \), \( \pi^0_{dj} \), (2) profits earned from the foreign market with technology \( z_0 \), \( \pi^0_{xj} \), and (3) profits earned from upgrading technology to \( z_1 \), \( \pi^\Delta_j \):

\[
\pi^0_{dj} = \frac{\eta_j R}{\sigma} \left[ \varphi \rho P_j \right]^{\sigma-1} c_{0j} - f_{c0j} \quad (B.1)
\]

\[
\pi^0_{xj} = \frac{\eta_j R^*}{\sigma} \left[ \varphi \rho P_j^* \right]^{\sigma-1} c_{0j} - f_{x0j} \quad (B.2)
\]

\[
\pi^\Delta_j = \left( \frac{\eta_j R}{\sigma} \left[ \varphi \rho P_j \right]^{\sigma-1} c_{0j} + \frac{\eta_j R^*}{\sigma} \left[ \varphi \rho P_j^* \right]^{\sigma-1} c_{\Delta j} \right) \left( \frac{c_{0j}}{c_{\Delta j}} \right)^{\sigma-1} - 1 - f_{\Delta c0j} \quad (B.3)
\]

**Proof for Lemma 3**

*Proof.* First, consider the free trade equilibrium where there is neither a fixed cost of export \( f_x = 0 \) nor a trade cost \( \tau = 1 \). The relative price indices are the same in both countries, \( \frac{P_{fr,l}}{P_{fr,h}} = \frac{P_{fr,l}}{P_{fr,h}} \), where the superscript \( fr \) indicates free trade.

Now, under autarky, the relative price index is

\[
\frac{P_{aut,l}}{P_{aut,h}} = \left( \frac{M_l}{M_h} \right)^{\frac{1}{\sigma}} \frac{c_{0l}}{c_{0h}} \left[ \int_{\varphi_{zl}}^{\varphi_{zl}} \varphi^{\sigma-1} \mu_l(\varphi) d\varphi + \int_{\varphi_{zl}}^{\varphi_{hl}} \left( \frac{c_{0l}}{c_{\Delta l}} \right)^{\sigma-1} \mu_l(\varphi) d\varphi \right] \left( \frac{c_{0l}}{c_{\Delta l}} \right)^{\sigma-1} - 1 - \frac{f_{\Delta c0j}}{\varphi_{zl}} \quad (B.4)
\]

where the superscript \( aut \) indicates the autarky. Substitute for \( M_j = R_j \bar{r}_j \) with \( R_j = \eta_j R \) and equilibrium average revenue \( \bar{r}_j = \left[ \int_{\varphi_{zj}}^{\varphi_{zj}} \varphi^{\sigma-1} \mu_j(\varphi) d\varphi + \int_{\varphi_{zj}}^{\varphi_{zj}} \left( \frac{c_{0j}}{c_{\Delta j}} \right)^{\sigma-1} \mu_j(\varphi) d\varphi \right] \frac{\sigma f_{c0j}}{\varphi_{zj}} \).
Then the relative price index can be expressed as

\[
P_{l}^{\text{out}} = \left( \frac{\eta_l}{\eta_h} \right)^{\frac{1}{1 - \sigma}} \frac{\varphi_h}{\varphi_l} \left( \frac{c_{0l}}{c_{0h}} \right)^\alpha, \quad (B.5)
\]

Using the Pareto distribution of inherited productivity, the free entry condition (2.11) and the equilibrium relationship between productivity cutoffs (2.21) under autarky, the exit cutoff can be derived:

\[
\varphi_j = \left\{ \frac{\sigma - 1}{1 + k - \sigma} \right\} \left[ f + f \left( f \left( \frac{c_{0j}}{c_{0h}} \right) ^ {\frac{k+1-\sigma}{\sigma-1}} \left( \left( \frac{c_{0j}}{c_{0h}} \right) ^ {\sigma-1} - 1 \right) \right) \right]^{\frac{1}{k}}. \quad (B.6)
\]

Because Home is a skill-scarce country, \( \frac{w_h}{w} > \frac{w_l}{w} \) under autarky. Assumption 2 implies that \( \left( \frac{c_{0l}}{c_{0h}} \right)^{\frac{\sigma - 1}{1 - \sigma}} < \left( \frac{c_{0l}}{c_{0h}} \right)^{\frac{\alpha}{1 - \sigma}} \) and \( \tilde{\varphi}_h < \frac{\varphi^*_h}{\varphi^*_l} \). Therefore, in an autarkic equilibrium, \( \frac{P_{l}^{\text{out}}}{P_{h}^{\text{out}}} < \frac{P_{l}^{*, \text{out}}}{P_{h}^{*, \text{out}}} \).

From (2.13), the price index in an open economy can be written as

\[
P_{l} = \left[ M_j \left( f^\varphi_{j} \left( \frac{c_{0j}}{\varphi \rho} \right) ^{1-\sigma} \mu_j(\varphi)d\varphi + \int_{\varphi^*_j}^{\infty} \left( \frac{c_{\Delta j}}{\varphi \rho} \right) ^{1-\sigma} \mu_j(\varphi)d\varphi \right) \right]^{\frac{1}{1-\sigma}} + M_j \left( f^{\varphi^*_j} \left( \frac{c_{0j}}{\varphi^*_j \rho} \right) ^{1-\sigma} \mu_j^*(\varphi)d\varphi + \int_{\varphi^*_j}^{\infty} \left( \frac{c_{\Delta j}}{\varphi^*_j \rho} \right) ^{1-\sigma} \mu_j^*(\varphi)d\varphi \right) \right]. \quad (B.7)
\]

As \( \tau_j^*, \tau_j \rightarrow \infty \) and \( f_x \rightarrow \infty \) for \( j = l, h \), the relative price converges to its autarkic value where \( \frac{P_{l}^{\text{out}}}{P_{h}^{\text{out}}} < \frac{P_{l}^{*, \text{out}}}{P_{h}^{*, \text{out}}} \). As \( \tau_j^*, \tau_j \rightarrow 1 \) and \( f_x \rightarrow 0 \) for \( j = 1, 2 \), the relative price converges to the free trade value where \( \frac{P_{l}^{fr}}{P_{h}^{fr}} = \frac{P_{l}^{*, fr}}{P_{h}^{*, fr}} \). For intermediate fixed and variable trade costs where selection into export markets occurs, the relative price indices lie in between the autarky values and the free trade values. Therefore, with costly trade, \( \frac{P_{l}}{P_{h}} < \frac{P_{l}^{*, fr}}{P_{h}^{*, fr}} \). Equation (2.20) implies that \( \Lambda_{xl} < \Lambda_{xh} \) and \( \Lambda_{xl}^* > \Lambda_{xh}^* \). The fraction of surviving firms that export is

\[
1 - G(\varphi)_{xl} = \left( \frac{\varphi_{jxl}}{\varphi_j} \right)^{-k} = \Lambda_{xl}^{-k}, \quad \text{so} \quad 1 - G(\varphi)_{xl} > 1 - G(\varphi)_{xh} \quad \text{and} \quad 1 - G(\varphi^*_h) > 1 - G(\varphi^*_l).
\]

**Proof for Proposition 5 and 7**

Following from equation (2.21), an equilibrium relationship between the technology
cutoff and the exit cutoff under autarky is
\[
\frac{\bar{\phi}_{zj}^{\text{out}}}{\bar{\phi}_{j}^{\text{out}}} = \left[ \frac{f}{f_{\Delta}} \left( \frac{c_{0j}}{c_{\Delta j}} \right)^{\sigma-1} - 1 \right] \frac{1}{1-\sigma} \tag{B.8}
\]
Under costly trade, this equilibrium relationship becomes
\[
\frac{\bar{\phi}_{zj}}{\bar{\phi}_{j}} = \left[ \frac{f}{f_{\Delta}} \left( \frac{c_{0j}}{c_{\Delta j}} \right)^{\sigma-1} - 1 \right] + \frac{f_{x}^{1-\sigma}}{f_{\Delta}} \left( \frac{c_{0j}}{c_{\Delta j}} \right)^{\sigma-1} - 1 \] \tag{Indirect Effect Direct Effect Indirect Effect 1 \frac{1}{1-\sigma}} \tag{B.9}
\]
As stated before, the direct effect is the effect of trade opening with the skill premium held fixed. The indirect effect is the impact through a change in the skill premium following trade opening.

1. **Proof for Proposition 5**

   \textit{Proof.} In autarky, $\tau_j = \infty$, which implies $\Lambda_{xj} = \infty$. $\Lambda_{xj}$ becomes finite in an open economy. From equation (B.8) and (B.9), $\frac{\bar{\phi}_{zj}}{\bar{\phi}_{j}} < \frac{\bar{\phi}_{zj}^{\text{out}}}{\bar{\phi}_{j}^{\text{out}}}$ for all $j$. Denote $\% \Delta \frac{\bar{\phi}_{zj}}{\bar{\phi}_{j}} = \left( \frac{\bar{\phi}_{zj}}{\bar{\phi}_{j}} \right) - 1$. Because $\Lambda_{xl} < \Lambda_{xh}$ and $\Lambda_{xl}^{*} > \Lambda_{xh}^{*}$, it follows that $\% \Delta \frac{\bar{\phi}_{zj}}{\bar{\phi}_{j}} < \% \Delta \frac{\bar{\phi}_{zj}}{\bar{\phi}_{j}}$ and $\% \Delta \frac{\bar{\phi}_{zj}}{\bar{\phi}_{j}} < \% \Delta \frac{\bar{\phi}_{zj}}{\bar{\phi}_{j}}$. \hfill \Box

2. **Proof for Proposition 7**

   \textit{Proof.} Consider first the specialization channel. The skill premium under an open economy lies between the two countries’ autarkic values. It converges in each country to the autarkic value as trade costs become infinite and converges to the free trade value as trade costs approach 0. Because $\frac{w^{u}}{w^{s}} > \frac{w^{u*}}{w^{s*}}$ under autarky, the skill premium rises in Foreign and falls in Home after trade opening. By Assumption 2, $\% \Delta \left( \frac{c_{0l}}{c_{\Delta l}} \right)^{\sigma-1} > \% \Delta \left( \frac{c_{0l}}{c_{\Delta l}} \right)^{\sigma-1} > 0$ and $\% \Delta \left( \frac{c_{0l}}{c_{\Delta l}} \right)^{\sigma-1} < \% \Delta \left( \frac{c_{0l}}{c_{\Delta l}} \right)^{\sigma-1} < 0$, where $\% \Delta$ is a percentage change when the country moves from autarky to costly trade.
Therefore, \( \Delta \bar{\varphi}_{z_{j}} \bar{\varphi}_{j} = \left[ \left( 1 + \frac{f_{x} \Lambda_{x_{j}}^{1-\sigma}}{f_{j}} \right) \Delta \left( \frac{c_{0j}}{c_{x_{j}}} \right)^{\frac{1}{1-\sigma}} \right]^{\frac{1}{1-\sigma}} - 1 \). This implies that the indirect effect of trade through the specialization channel is \( \Delta \bar{\varphi}_{z_{j}} \bar{\varphi}_{j} < 0 \) and \( \Delta \bar{\varphi}_{z_{j}} \bar{\varphi}_{j} > 0 \) for \( j = 1, 2 \). To show the indirect effect of trade through the skill-biased technical change channel, it is sufficient to show that the direct effect of trade on firms’ technology choice increases the skill premium. Following the same argument, \( \Delta \bar{\varphi}_{z_{j}} \bar{\varphi}_{j} < 0 \) and \( \Delta \bar{\varphi}_{z_{j}} \bar{\varphi}_{j} < 0 \) for \( j = 1, 2 \).

**Proof for Proposition 6 and 8**

Using the Pareto distribution of inherited productivity, the free entry condition (2.11) and the equilibrium relationship between productivity cutoffs (2.21), the exit cutoff under autarky is given by

\[
\bar{\varphi}_{j}^{\text{aut}} = \left\{ 1 + \frac{1}{f_{c} \delta} \frac{\sigma - 1}{1 + k - \sigma} \left[ f + f_{\Delta} \left( \frac{f}{f_{\Delta}} \right)^{\frac{k}{\sigma-1}} \left( \left( \frac{c_{0j}}{c_{\Delta_{j}}} \right)^{\frac{1}{\sigma-1}} - 1 \right) \right]^{\frac{1}{\sigma-1}} \right\}^{\frac{1}{k}}. \tag{B.10}
\]

Once the economy opens to trade, the exit cutoff becomes

\[
\bar{\varphi}_{j} = \left\{ 1 + \frac{1}{f_{c} \delta} \frac{\sigma - 1}{1 + k - \sigma} \left[ f + f_{x} \Lambda_{x_{j}}^{1-\sigma} + f_{\Delta} \left[ \left( \frac{c_{0j}}{c_{\Delta_{j}}} \right)^{\frac{1}{\sigma-1}} - 1 \right] \right]^{\frac{1}{\sigma-1}} \right\}^{\frac{1}{k}}. \tag{B.11}
\]

1. **Proof for Proposition 6**

Proof. \((\bar{\varphi}_{j}^{\text{aut}})^{k}\) is determined by two terms: \( f \) and \( f_{\Delta} \left( \frac{f}{f_{\Delta}} \right)^{\frac{k}{\sigma-1}} \left( \left( \frac{c_{0j}}{c_{\Delta_{j}}} \right)^{\frac{1}{\sigma-1}} - 1 \right) \). Under costly trade, \( \Lambda_{x_{j}} \) becomes finite and the exit cutoffs rise in both industries. The first term becomes \( f + f_{x} \Lambda_{x_{j}}^{1-\sigma} \), while the second term becomes

\[
f_{\Delta} \left[ \left( \frac{f + f_{x} \Lambda_{x_{j}}^{1-\sigma}}{f_{\Delta}} \right) \left( \left( \frac{c_{0j}}{c_{\Delta_{j}}} \right)^{\frac{1}{\sigma-1}} - 1 \right) \right]^{\frac{k}{\sigma-1}}.
\]

Because \( \Lambda_{x_{l}} < \Lambda_{x_{h}} \) and \( \Lambda_{x_{l}}^{*} > \Lambda_{x_{h}}^{*} \), a percentage increase in both terms is larger in a country’s comparative advantage industry. It follows that \( \Delta \bar{\varphi}_{l} > \Delta \bar{\varphi}_{h} > 0 \) and

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\[
\% \Delta \bar{\phi}_h > \% \Delta \bar{\phi}_l^* > 0.
\]

2. Proof for Proposition 8

Proof. As shown in the proof of Proposition 7, through the specialization channel, the skill premium rises in Foreign and falls in Home after trade opening. Following the same step as in the proof for Proposition 7, it can be shown that the indirect effect of trade through the specialization channel is \( \% \Delta \bar{\phi}_j > 0 \) and \( \% \Delta \bar{\phi}_j^* < 0 \) for \( j = 1, 2 \). Similarly, through the skill-biased technical change channel, \( \% \Delta \bar{\phi}_j < 0 \) and \( \% \Delta \bar{\phi}_j^* < 0 \) for \( j = 1, 2 \).

Proof for Proposition 9

Proof. In this analytical setting, industrial productivity is governed by two productivity cutoffs: \( \bar{\phi}_{zj} \) and \( \bar{\phi}_j \):

\[
\Phi_j = \int_{\bar{\phi}_j}^{\bar{\phi}_{zj}} \varphi \mu_j(\varphi) d\varphi + e^{\gamma_j^* \Delta} \left( \frac{\beta_j}{1 - \beta_j} \left( \frac{w^*}{w} \right)^{1-\alpha} \exp^{(\alpha-1)(\gamma_j^*-\gamma_j^*)\Delta} + 1 \right) \int_{\bar{\phi}_j}^{\infty} \varphi \mu_j(\varphi) d\varphi \tag{B.12}
\]

1. By the labor market clearing condition, the relative supply of skilled labor must equal the relative demand for skilled labor,

\[
\frac{S}{U} = \frac{S^h_j M_j S^l_j}{M_h U^h_j M_j U^l_j} + 1 \tag{B.13}
\]

where \( S^j' \) and \( U^j' \) are aggregate demands for skilled and unskilled labor from firms of mass 1, respectively. If the specialization channel dominates, a larger fraction of firms upgrade their technology following a reduction in trade cost. The skill-biased technical change implies that \( S^h_j < U^h_j \). Because \( \frac{S^l_j}{S^h_j} < \frac{U^l_j}{U^h_j} \), \( \frac{M_j}{M_h} \) must increase so that the relative demand equals the relative supply, which is fixed at the autarky level.
2. Following from Propositions 5-8, the direct effect of trade, combined with the indirect effect through the specialization channel, not only raises the exit cutoffs but also brings the technology cutoffs closer to the exit cutoffs in Home. Thus, it has a positive effect on industrial productivity.

B.3.2 Small Open Economy

Proof. Given that \( \frac{P_{\text{aut}}^l}{P_{\text{aut}}^h} < \frac{P^*}{P^*_h} \) and \( P_j^* \) remains unchanged, to prove that the results from Lemma 3 remain valid for Home as a small open economy, it is sufficient to show that \( \frac{P^l}{P^h} < \frac{P^*_l}{P^*_h} \) after trade opening. The price index in a small open economy can also be written as in equation (B.7).

As \( \tau_j^* \to \infty \) and \( f_x \to \infty \) for \( j = 1, 2 \), the relative price converges to \( \frac{P_{\text{aut}}^l}{P_{\text{aut}}^h} < \frac{P^*}{P^*_h} \). As \( \tau_j^* \to 1 \) and \( f_x \to 0 \) for \( j = 1, 2 \), the relative price \( \frac{P^l}{P^h} \to \frac{P^*_l}{P^*_h} \). Therefore, when a small open economy moves from autarky to costly trade, the relative price index is such that \( \frac{P^l}{P^h} < \frac{P^*_l}{P^*_h} \). Following the same proof, it can be shown that \( \Lambda_{xl} < \Lambda_{xh} \) and the results from Proposition 1 remain valid for Home.

The proof for Propositions 5-8 relies upon the results from Lemma 3, i.e., \( \Lambda_{xl} < \Lambda_{xh} \) and \( \frac{P^l}{P^h} < \frac{P^*_l}{P^*_h} \). The difference in the relative price index, together with \( \frac{w_s^{\text{aut}}}{w_u^{\text{aut}}} > \frac{w_s^*}{w_u^*} \), creates the similar specialization pattern, which moves labor toward a country’s comparative advantage industry. The direct effect analysis for Home remains valid in the small open economy case. Likewise, under the small open economy assumptions, the specialization channel and the skill-biased technical change channel shift the skill premium in the same way as in the asymmetric two-country case. Therefore, the indirect effect analysis for Home can also be carried over to the small open economy case. It is obvious that Proposition 9 still holds under the small open economy assumptions, as the proof rests only on the results of Lemma 3 and Propositions 5-8. 

\[ \square \]
B.4 Indonesian Manufacturing

B.4.1 Industry Classification

Table (29) reports the classification of manufacturing industries into a high-tech industry and a low-tech industry, the definitions used in the model.

Table 29: Classification of Manufacturing Industries

<table>
<thead>
<tr>
<th>ISIC Rev 2</th>
<th>Industry</th>
<th>Skill Intensity (NBER-CES)</th>
<th>OECD classification</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>311-312</td>
<td>Food Products</td>
<td>0.25</td>
<td>Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>313</td>
<td>Beverage</td>
<td>0.39</td>
<td>Low-Tech</td>
<td>High-Tech</td>
</tr>
<tr>
<td>314</td>
<td>Tobacco</td>
<td>0.27</td>
<td>Low-Tech</td>
<td>High-Tech</td>
</tr>
<tr>
<td>321</td>
<td>Textiles</td>
<td>0.16</td>
<td>Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>322</td>
<td>Wearing apparel</td>
<td>0.20</td>
<td>Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>323</td>
<td>Leather Products</td>
<td>0.21</td>
<td>Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>324</td>
<td>Footwear</td>
<td>0.17</td>
<td>Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>331</td>
<td>Wood Products</td>
<td>0.18</td>
<td>Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>332</td>
<td>Furniture</td>
<td>0.22</td>
<td>Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>341</td>
<td>Paper and Products</td>
<td>0.22</td>
<td>Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>342</td>
<td>Printing and Publishing</td>
<td>0.34</td>
<td>Low-Tech</td>
<td>High-Tech</td>
</tr>
<tr>
<td>351</td>
<td>Industrial Chemicals</td>
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<td>Med-High-Tech</td>
<td>High-Tech</td>
</tr>
<tr>
<td>352</td>
<td>Other Chemicals</td>
<td>0.36</td>
<td>Med-High-Tech</td>
<td>High-Tech</td>
</tr>
<tr>
<td>353</td>
<td>Petroleum Refineries</td>
<td>0.30</td>
<td>Med-Low-Tech</td>
<td>High-Tech</td>
</tr>
<tr>
<td>354</td>
<td>Miscellaneous Petroleum/Coal</td>
<td>0.37</td>
<td>Med-Low-Tech</td>
<td>High-Tech</td>
</tr>
<tr>
<td>355</td>
<td>Rubber Products</td>
<td>0.22</td>
<td>Med-Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>356</td>
<td>Plastic Products</td>
<td>0.23</td>
<td>Med-Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>361</td>
<td>Pottery, China, Earthenware</td>
<td>0.20</td>
<td>Med-Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>362</td>
<td>Glass and Products</td>
<td>0.18</td>
<td>Med-Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>369</td>
<td>Non-Metallic Mineral Products</td>
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<td>Med-Low-Tech</td>
<td>High-Tech</td>
</tr>
<tr>
<td>371</td>
<td>Iron and Steel</td>
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<td>Med-Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>372</td>
<td>Non-ferrous Metals</td>
<td>0.23</td>
<td>Med-Low-Tech</td>
<td>Low-Tech</td>
</tr>
<tr>
<td>381</td>
<td>Fabricated Metal Products</td>
<td>0.27</td>
<td>Med-Low-Tech</td>
<td>High-Tech</td>
</tr>
<tr>
<td>382</td>
<td>Machinery, Except Electrical</td>
<td>0.38</td>
<td>Med-High-Tech</td>
<td>High-Tech</td>
</tr>
<tr>
<td>383</td>
<td>Electric Machinery</td>
<td>0.38</td>
<td>Med-High-Tech</td>
<td>High-Tech</td>
</tr>
<tr>
<td>384</td>
<td>Transport Equipment</td>
<td>0.34</td>
<td>Med-High-Tech</td>
<td>High-Tech</td>
</tr>
</tbody>
</table>

† Firms from ISIC 385 are dropped from the analysis. Most of them are foreign owned, with a large percentage of capital owned by foreign. They are highly technology intensive and skill intensive.
B.4.2 Estimation Results of Exporter Premia

Table (30) shows the estimation results by pooling observations from all subperiods for low-tech and high-tech industries. Different subperiods are captured by dummy variables: \(1\{year \geq 1995\}\) and \(1\{year \geq 2000\}\). Changes in exporter premia can then be directly observed from the coefficients of interaction terms.

Table 30: Estimates of Exporter Premia for Different Subperiods

<table>
<thead>
<tr>
<th></th>
<th>Low-Tech Industry</th>
<th>High-Tech Industry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Skill Intensity</td>
<td>Productivity</td>
</tr>
<tr>
<td>(Exp)</td>
<td>0.004***</td>
<td>0.260***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>(1{year \geq 1995})</td>
<td>−0.014***</td>
<td>−0.165***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>(1{year \geq 2000})</td>
<td>0.111***</td>
<td>0.164***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>(1{year \geq 1995})</td>
<td>−0.002</td>
<td>0.058***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>(1{year \geq 2000})</td>
<td>−0.004**</td>
<td>−0.142***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.016)</td>
</tr>
</tbody>
</table>

- Year Dummies: \(\checkmark\)
- ISIC Rev 2 Dummies: \(\checkmark\)
- # Observations: 183,040, 137,677, 61,327, 42,624
- R\(^2\): 0.83, 0.05, 0.91, 0.17

\(^1\) *significant at 10%, **significant at 5%, ***significant at 1%
Appendix C

Appendix to Chapter 3

C.1 Corporate Income Tax Rates in OECD Countries

Figure (22) shows that the current U.S. tax system taxes corporate income at a statutory rate of 35%, the highest rate among the Organization for Economic Co-operation and Development (OECD) nations. The Organization for Economic Cooperation and Development (OECD), however, face an average rate of 25%. Even corporations in high-tax European countries such as Belgium (34%), France (34%), and Sweden (22%) face lower statutory rates than those in the United States.
Figure 22: Central Government Statutory (Flat or Top Marginal) Corporate Income Tax Rate by OECD Nation, 2013
C.2 Ranking of Lobbying Issues Based on Expenditures

Table (31) lists the top ten lobbying issues by lobbying firms in the Compustat database, according to proportions of lobby expenditure for specific issues. Ranking is based on the matched data set before the sample selection. Because there can be multiple issues for a single bill, we discount each lobbying expenditure by dividing the total amount by the number of issues reported in each bill. During 1998-2011, taxation issues stay at the top for every single year except 2009, when the health care reform places health issues at the top.

Table 31: Top 10 Lobbying Issues Based on Aggregate Expenditures

<table>
<thead>
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<th></th>
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<th></th>
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</thead>
<tbody>
<tr>
<td>TAX</td>
<td>TAX</td>
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<td>TAX</td>
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<td>TAX</td>
<td>HCR</td>
<td>TAX</td>
<td>TAX</td>
<td>TAX</td>
</tr>
<tr>
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<td>TRD</td>
<td>TRD</td>
<td>TRD</td>
<td>TRD</td>
<td>DEF</td>
<td>BUD</td>
<td>BUD</td>
<td>BUD</td>
<td>ENG</td>
<td>ENG</td>
<td>MMM</td>
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<td>ENG</td>
</tr>
<tr>
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<td>HCR</td>
<td>HCR</td>
<td>HCR</td>
<td>HCR</td>
<td>TRD</td>
<td>HCR</td>
<td>HCR</td>
<td>TRD</td>
<td>HCR</td>
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<td>PHA</td>
<td>HCR</td>
<td>BUD</td>
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<td>TEC</td>
<td>DEF</td>
<td>HCR</td>
<td>DEF</td>
<td>TRD</td>
<td>HCR</td>
<td>TRD</td>
<td>TRD</td>
<td>TAX</td>
<td>FIN</td>
<td>ENV</td>
<td></td>
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<td>DEF</td>
<td>ENG</td>
<td>BUD</td>
<td>TRD</td>
<td>DEF</td>
<td>ENG</td>
<td>BUD</td>
<td>BUD</td>
<td>ENG</td>
<td>BUD</td>
<td>HCR</td>
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<td>BUD</td>
<td>BUD</td>
<td>BUD</td>
<td>TEC</td>
<td>TEC</td>
<td>TEC</td>
<td>DEF</td>
<td>CPT</td>
<td>DEF</td>
<td>BUD</td>
<td>ENV</td>
<td>TRA</td>
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<tr>
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<td>BUD</td>
<td>ENV</td>
<td>ENG</td>
<td>TEC</td>
<td>ENG</td>
<td>ENG</td>
<td>ENG</td>
<td>TEC</td>
<td>DEF</td>
<td>ENV</td>
<td>DEF</td>
<td>FIN</td>
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<tr>
<td>TRA</td>
<td>UTI</td>
<td>ENV</td>
<td>MMM</td>
<td>MMM</td>
<td>MMM</td>
<td>MMM</td>
<td>CPT</td>
<td>MMM</td>
<td>CPT</td>
<td>TRD</td>
<td>TRD</td>
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<td>ENG</td>
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<td>LBR</td>
<td>AVI</td>
<td>ENV</td>
<td>FIN</td>
<td>TOR</td>
<td>TRA</td>
<td>MMM</td>
<td>TEC</td>
<td>MMM</td>
<td>FIN</td>
<td>CPT</td>
<td>CPT</td>
</tr>
<tr>
<td>UTI</td>
<td>LBR</td>
<td>TRA</td>
<td>TRA</td>
<td>FIN</td>
<td>TOR</td>
<td>FIN</td>
<td>FIN</td>
<td>RET</td>
<td>FIN</td>
<td>TEC</td>
<td>CPT</td>
<td>MMM</td>
<td>SCI</td>
</tr>
</tbody>
</table>

1 See Table (34) for an explanation of abbreviation.

C.3 Data Source and Sample Selection

As explained in the main text, we link lobby data and data on firm characteristics from Compustat for the period of 1998–2011. We focus on lobby data on tax issues only and keep i) firm-year observations that have non-negative pre-tax income; ii) firms that are incorporated (or legally registered) in the U.S.; and iii) non-financial firms. Then, we further refine data by dropping extreme and missing values for variables considered in the regression. After selection, there are 28,710 firm-year observations, giving on average 2,050 firms each year. It is an unbalanced panel. Nominal variables are deflated by the GDP deflator so that they are in dollars in 1998.
Each company’s effective tax rate is computed using data from Compustat as:

\[
ETR = \frac{\text{Income Taxes Total} - \text{Deferred Taxes}}{\text{Pre Tax Income} - \text{Equity in Earnings} - \text{Special Items} + \text{Interest Expense}}.
\]  

Marginal product of capital is computed using data from Compustat as:

\[
mpk = \frac{\text{SALE}}{\text{Property, Plant and Equipment - Total (Gross)}}.
\]

### C.4 List of Variables

Table (32) provides details and sources of all variables used in the empirical analysis. Table (33) presents the variables used as regressors in this exercise and their Compustat codes.

<table>
<thead>
<tr>
<th>Code</th>
<th>Variable description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>TXT</td>
<td>Income Taxes - Total</td>
<td>Compustat</td>
</tr>
<tr>
<td>TXFO</td>
<td>Income Taxes - Foreign</td>
<td>Compustat</td>
</tr>
<tr>
<td>TXDI</td>
<td>Income Taxes - Deferred</td>
<td>Compustat</td>
</tr>
<tr>
<td>TXDFO</td>
<td>Deferred Taxes - Foreign</td>
<td>Compustat</td>
</tr>
<tr>
<td>PI</td>
<td>Pretax Income</td>
<td>Compustat</td>
</tr>
<tr>
<td>PIDOM</td>
<td>Pretax Income Domestic</td>
<td>Compustat</td>
</tr>
<tr>
<td>PIFO</td>
<td>Pretax Income Foreign</td>
<td>Compustat</td>
</tr>
<tr>
<td>ESUB</td>
<td>Equity in Earnings - Unconsolidated Subsidiaries</td>
<td>Compustat</td>
</tr>
<tr>
<td>SPI</td>
<td>Special Items</td>
<td>Compustat</td>
</tr>
<tr>
<td>XINT</td>
<td>Interest and Related Expense</td>
<td>Compustat</td>
</tr>
<tr>
<td>TXPD</td>
<td>Income Taxes Paid</td>
<td>Compustat</td>
</tr>
<tr>
<td>AT</td>
<td>Assets - Total</td>
<td>Compustat</td>
</tr>
<tr>
<td>PPEGT</td>
<td>Property, Plant and Equipment - Total (Gross)</td>
<td>Compustat</td>
</tr>
<tr>
<td>DLTT</td>
<td>Long – Term Debt - Total</td>
<td>Compustat</td>
</tr>
<tr>
<td>INVT</td>
<td>Inventories - Total</td>
<td>Compustat</td>
</tr>
<tr>
<td>XRD</td>
<td>Research and Development Expense</td>
<td>Compustat</td>
</tr>
<tr>
<td>SALE</td>
<td>Sales/Turnover (Net)</td>
<td>Compustat</td>
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<tr>
<td>LT</td>
<td>Liabilities – Total</td>
<td>Compustat</td>
</tr>
<tr>
<td>FCA</td>
<td>Foreign Exchange Income (Loss)</td>
<td>Compustat</td>
</tr>
<tr>
<td>EMP</td>
<td>Employees</td>
<td>Compustat</td>
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</tbody>
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<table>
<thead>
<tr>
<th>Deflator</th>
<th>Source</th>
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</thead>
<tbody>
<tr>
<td>GDPDEF</td>
<td>FRED</td>
</tr>
<tr>
<td>Variable name</td>
<td>Variable description</td>
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<td>---------------</td>
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<tr>
<td>$def$</td>
<td>GDP deflator</td>
</tr>
<tr>
<td>$ETR_t$</td>
<td>Effective tax rate at $t$</td>
</tr>
<tr>
<td>$if_lob_t$</td>
<td>Indicator variable takes one when firm lobbies</td>
</tr>
<tr>
<td>$lob_t$</td>
<td>Lobby expenditure in million dollar (in 1998)</td>
</tr>
<tr>
<td>$loglob_t$</td>
<td>Natural logarithm of $lob_t$</td>
</tr>
<tr>
<td>$cap_int$</td>
<td>Deflated capital over workers ($ppegt/emp/def$)</td>
</tr>
<tr>
<td>$inv_int$</td>
<td>Deflated inventories over workers ($invt/emp/def$)</td>
</tr>
<tr>
<td>$rnd_int$</td>
<td>Deflated R&amp;D over workers ($xrd/emp/def$)</td>
</tr>
<tr>
<td>$size_at$</td>
<td>Log transformation of deflated total assets</td>
</tr>
<tr>
<td>$lev$</td>
<td>Leverage (liabilities divided by total assets)</td>
</tr>
</tbody>
</table>
### C.5 List of Lobbying Issues

Table 34: List of Lobbying Issues

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full description</th>
<th>Abbreviation</th>
<th>Full description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACC</td>
<td>Accounting</td>
<td>CSP</td>
<td>Consumer Issues/Safety/Protection</td>
</tr>
<tr>
<td>HOM</td>
<td>Homeland Security</td>
<td>RET</td>
<td>Retirement</td>
</tr>
<tr>
<td>ADV</td>
<td>Advertising</td>
<td>CON</td>
<td>Constitution</td>
</tr>
<tr>
<td>HOU</td>
<td>Housing</td>
<td>ROD</td>
<td>Roads/Highway</td>
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<tr>
<td>AER</td>
<td>Aerospace</td>
<td>CPT</td>
<td>Copyright/Patent/Trademark</td>
</tr>
<tr>
<td>IMM</td>
<td>Immigration</td>
<td>SCI</td>
<td>Science/Technology</td>
</tr>
<tr>
<td>AGR</td>
<td>Agriculture</td>
<td>DEF</td>
<td>Defense</td>
</tr>
<tr>
<td>IND</td>
<td>Indian/Native American Affairs</td>
<td>SMB</td>
<td>Small Business</td>
</tr>
<tr>
<td>ALC</td>
<td>Alcohol &amp; Drug Abuse</td>
<td>DOC</td>
<td>District of Columbia</td>
</tr>
<tr>
<td>INS</td>
<td>Insurance</td>
<td>SPO</td>
<td>Sports/Athletics</td>
</tr>
<tr>
<td>ANI</td>
<td>Animals</td>
<td>DIS</td>
<td>Disaster Planning/Emergencies</td>
</tr>
<tr>
<td>INT</td>
<td>Intelligence and Surveillance</td>
<td>TAR</td>
<td>Miscellaneous Tariff Bills</td>
</tr>
<tr>
<td>APP</td>
<td>Apparel/Clothing Industry/Textiles</td>
<td>ECN</td>
<td>Economics/Economic Development</td>
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<tr>
<td>LBR</td>
<td>Labor Issues/Antitrust/Workplace</td>
<td>TAX</td>
<td>Taxation/Internal Revenue Code</td>
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<tr>
<td>ART</td>
<td>Arts/Entertainment</td>
<td>EDU</td>
<td>Education</td>
</tr>
<tr>
<td>LAW</td>
<td>Law Enforcement/Crime/Criminal Justice</td>
<td>TEC</td>
<td>Telecommunications</td>
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<tr>
<td>AUT</td>
<td>Automotive Industry</td>
<td>ENG</td>
<td>Energy/Nuclear</td>
</tr>
<tr>
<td>MAN</td>
<td>Manufacturing</td>
<td>TOB</td>
<td>Tobacco</td>
</tr>
<tr>
<td>AVI</td>
<td>Aviation/Aircraft/Airlines</td>
<td>ENV</td>
<td>Environmental/Superfund</td>
</tr>
<tr>
<td>MAR</td>
<td>Marine/Maritime/Boating/Fisheries</td>
<td>TOR</td>
<td>Torts</td>
</tr>
<tr>
<td>BAN</td>
<td>Banking</td>
<td>FAM</td>
<td>Family Issues/Abortion/Adoption</td>
</tr>
<tr>
<td>MIA</td>
<td>Media (Information/Publishing)</td>
<td>TRD</td>
<td>Trade (Domestic &amp; Foreign)</td>
</tr>
<tr>
<td>BNM</td>
<td>Bankruptcy</td>
<td>FIR</td>
<td>Firearms/Guns/Ammunition</td>
</tr>
<tr>
<td>MMD</td>
<td>Medical/Disease Research/Clinical Labs</td>
<td>TRA</td>
<td>Transportation</td>
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<tr>
<td>MIM</td>
<td>Medicare/Medicaid</td>
<td>TOU</td>
<td>Travel/Tourism</td>
</tr>
<tr>
<td>BUD</td>
<td>Budget/Appropriations</td>
<td>FOO</td>
<td>Food Industry (Safety, Labeling, etc.)</td>
</tr>
<tr>
<td>MON</td>
<td>Minting/Money/Gold Standard</td>
<td>TRU</td>
<td>Trucking/Shipping</td>
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<tr>
<td>CHM</td>
<td>Chemicals/Chemical Industry</td>
<td>FOR</td>
<td>Foreign Relations</td>
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<tr>
<td>NAT</td>
<td>Natural Resources</td>
<td>URB</td>
<td>Urban Development/Municipalities</td>
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<tr>
<td>CIV</td>
<td>Civil Rights/Civil Liberties</td>
<td>FUE</td>
<td>Fuel/Gas/Oil</td>
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<tr>
<td>PHA</td>
<td>Pharmacy</td>
<td>UNM</td>
<td>Unemployment</td>
</tr>
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<td>CAW</td>
<td>Clean Air &amp; Water (Quality)</td>
<td>GAM</td>
<td>Gaming/Gambling/Casino</td>
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<tr>
<td>POS</td>
<td>Postal</td>
<td>UTI</td>
<td>Utilities</td>
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<tr>
<td>CDT</td>
<td>Commodities (Big Ticket)</td>
<td>GOV</td>
<td>Government Issues</td>
</tr>
<tr>
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<td>Railroads</td>
<td>VET</td>
<td>Veterans</td>
</tr>
<tr>
<td>COM</td>
<td>Communications/Broadcasting/Radio/TV</td>
<td>HCR</td>
<td>Health Issues</td>
</tr>
<tr>
<td>RES</td>
<td>Real Estate/Land Use/Conservation</td>
<td>WAS</td>
<td>Waste (hazardous/solid/interstate/nuclear)</td>
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<td>CPI</td>
<td>Computer Industry</td>
<td>WEL</td>
<td>Welfare</td>
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<tr>
<td>REL</td>
<td>Religion</td>
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BIBLIOGRAPHY


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