Industrial Specialization: Determinants, Processes and Consequences

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Where I love is home, home that my feet may leave, but not my heart.

- To my parents

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background - Growing Alike or Growing Apart?

Over the past few decades, the world economy has been undergoing an unprecedented wave of economic integration.[1] Economic integration is not a new phenomenon, but intensified especially since the 1990s. Integration has facilitated the interdependence of economic activities and has stimulated a rapid growth in cross-border trade and capital flows. The volume of trade has increased significantly relative to world output. Trade of goods and services as a share of world GDP has increased from around 15 percent in the early 1980s to around 25 percent before the start of the crisis in 2007 (Dées & Zorell, 2012). The trade to GDP ratio has increased in all major countries. As can be seen from Figure (1.1a), it has risen, on average, by around 15 percentage points in OECD countries during the period 1990-2007. Meanwhile, global capital flows have grown even faster than global trade. Gross cross-border capital flows have increased from about 5 percent of world GDP in the mid-1990s to about 20 percent in 2007 (OECD, 2011). The rise in international capital flows has

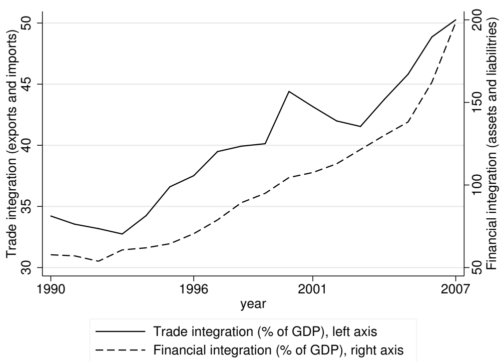
[1] In this thesis, as I measure integration by means of *de facto* openness, I use the terms "integration" and "openness" interchangeably. However, in practice openness is a necessary but not sufficient condition for integration. Integration requires openness as the first step, consequently ensures domestic markets effectively become part of the world market, synchronizing interest rate movements, saving and investment activities, etc. In this sense, openness is the mean, while integration is the goal.

led to a corresponding proliferation of foreign assets and liabilities holdings. Figure (1.1a) shows that foreign assets and liabilities as a percentage of GDP has increased by almost 150 percentage points in the same sample of OECD countries.

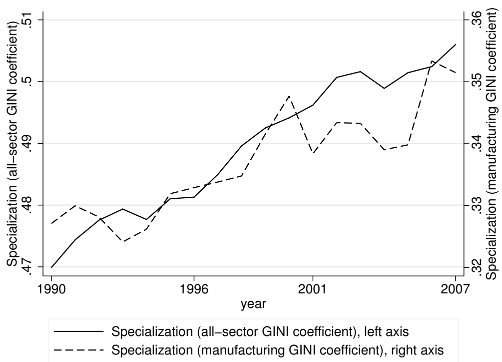
While economic integration is a catalyst for development, it is also a relentless process that entails changes and requires adjustments. The removal of trade and financial barriers has significantly reduced the costs of international transactions. The resulting enhanced mobility of capital, labor and technology, combined with the improvements in transportation and communication links has facilitated the relocation of production across sectors and geographical space and consequently has led to considerable changes in industrial composition of countries. Figure (1.1b) illustrates that industrial specialization, i.e., the concentration of industries has steadily increased over the same period. The increasing trend is pronounced both across all economic activity and within the manufacturing sector.

Figure 1.1: Developments in economic integration and specialization

(a) Development of economic integration



(b) Development of industrial specialization



Note: Both graphs are weighted by country size, based on authors' own calculations from a sample of 34 OECD countries.

Whether or not economic integration exacerbates (or decreases) structural differences among countries, industries and firms has far-reaching implications. On the one hand, the resulting specialization through an increased exploitation of efficiency and scale is crucial in determining long-run growth and competitiveness. On the other hand, countries with different specialized production structures are more vulnerable to asymmetric shocks (i.e. distances that affect countries differently). The resulting asymmetry in business cycles among countries affects the political sustainability of ongoing economic integration, particularly in the EU. The latest financial crisis has revived interest in the risks of structural differences within the Eurozone. With ongoing trade and financial integration, the role of industrial specialization may well become more prominent in determine future growth and asymmetry among countries. Better understanding of the dynamics of industrial specialization helps us recognize the heterogeneity of countries, allows for a more detailed assessment of the potential competitiveness, and facilitates the formulation, design and execution of (common) economic policies.

1.2 Questions and Hypotheses

Against this background, this thesis analyzes the determinants, processes and consequences of industrial specialization. More specifically, I address three sets of questions.

The first set of questions is how trade and financial integration affect industrial specialization. I investigate the hypothesis that trade and financial openness complement each other in shaping specialization patterns.

A second set of questions that deserves attention concerns the role of trade in particular and further explores how trade integration affects industrial composition. Put differently, I am interested in which industries are most likely to be affected by trade. I postulate that the potential for reallocation determines industries' sensitivity to trade openness and hypothesize that trade induces specialization towards industries with larger potential for reallocation.

A third set of questions relates to the macroeconomic consequences of specialization. My conjecture is that not only specialization per se matters for economic growth. Rather, what you specialize matters, and more importantly when you specialize them over subsequent development stages matters too. In other words, I hypothesize that specializing in new and innovative products has a growth enhancing effect for developed countries, whereas specializing in mature products boosts growth for emerging countries. Furthermore, I argue that the shifts in industrial structures in response to ongoing trade and financial integration also impact global linkages and are a driving force for reshaping the patterns of cross-border portfolio investments.

1.3 Places in the Literature and Contributions

This thesis aims to contribute to our understanding of the real effects of trade and financial integration. Economic research has focused intensively in recent years on the effects of either trade and financial integration on macroeconomic performance (e.g. growth, volatility, inflation, etc.). Scholars have provided robust empirical evidence that trade and financial openness are strongly associated with better economic performance, particularly for developed countries.

Having established this basic finding, the research effort has turned to the analysis of the mechanisms through which trade and financial integration affect real economic activity. This project goes straight to the heart of this line of research by investigating how trade and financial integration have shaped the specialization patterns and what the consequences of specialization are.

In a broader perspective, this thesis uncovers how rapid macroeconomic development (i.e., trade and financial integration) is characterized by continuous structural changes at the meso (i.e., industry) and micro (i.e., firm) level and how small micro-level dynamics (e.g., product) can exert large macroeconomic outcomes. I document how micro-meso-macro linkages work and what constitutes connections among them. The combination of macro and micro aspects provides a complete framework to understand the effects of trade and financial integration, beyond the lessons taught by the existing literature.

Several detailed innovative aspects of this thesis are of particular importance. First, economic literature has typically studied the roles of trade and financial integration in driving specialization in isolation. Most classical trade theories, with reference to the theory of comparative advantage, predict that trade integration leads to more industrial specialization (Dornbusch *et al.*, 1977; Ohlin, 1933; Ricardo, 1817). Financial integration may induce specialization through risk-sharing. Open and integrated financial markets offer a broader range of financial instruments and permit the diversification of ownership. With financial openness, countries are better-protected against idiosyncratic risks, and consequently can specialize more (Basile & Girardi, 2010; Kalemli-Ozcan *et al.*, 2003). The effects of trade integration in conjunction with financial integration as joint determinants of specialization are not explicitly examined in the literature. Chapter 2 aims to fill this gap. I take both trade and financial integration into account and show that the effect of trade (financial) integration on specialization depends on the level of financial (trade) integration.

Second, the economic literature has a long tradition of analyzing what drives the relationship between trade and specialization.[2] Much less is known about who drives this relationship. A growing body of recent theoretical and empirical literature has highlighted the importance of analyzing firm-level adjustment processes in response to the openness to foreign trade. These studies have documented the existence of a substantial degree of firm-level heterogeneity even within narrowly defined industries. A substantial part of the effect of international trade is channeled into the reallocation of resources within the industry, which in turn boosts the industry growth (Bernard *et al.*, 2006; Eslava *et al.*, 2009; Pavcnik, 2002; Trefler, 2004; Tybout & Westbrook, 1995). Drawing insights from this literature, my contribution in chapter 3 lies in introducing the true drivers of the trade-specialization nexus, namely productive firms. They benefit from the increase in trade-openness and can appropriate resources from less productive firms, thus causing the industry in which they

[2]Classical trade theories predict that trade integration will result in increasing specialization in sectors where a country has a comparative advantage due to cross-country differences in technology or factor endowment (Ohlin, 1933; Ricardo, 1817). New trade theories stress the importance of increasing returns to scale and product differentiation in facilitating intra-industry trade and predict that international trade will induce a shift of increasing-return industries towards countries with good market access, i.e., the core (Krugman, 1979, 1980). New economic geography theories emphasize agglomeration forces and suggest a non-monotonic relationship between trade liberalization and location of economic activities, depending on the level of trade costs (Krugman, 1991; Venables, 1996).

operate to expand, at the expense of other industries, in which there is no room to make such moves. In doing so, my findings can provide a micro basis for what is often studied as a purely macro phenomenon.

Third, a notable contribution in chapter 4 lies in the index that captures the average maturity of a country's export mix and brings back the perhaps somewhat forgotten product life cycle perspective to the empirical trade literature (Audretsch, 1987; Hirsch, 1967; Klepper, 1996). By means of this measure, I am then able to explore how export maturity matters for economic growth. Furthermore, I show that this effect critically depends on the stage of development and is thus significantly non-linear across countries. This finding extends and complements a strand of recent literature which typically postulates a linear monotonic relationship between these characteristics and growth in spite of notable differences in measures, specifications and econometric techniques used (An & Iyigun, 2004; Bensidoun *et al.*, 2002; Feenstra & Rose, 2000; Hausmann *et al.*, 2007; Lee, 2010).

Fourth, while a handful of studies emphasize that financial integration promotes industrial specialization through risk-sharing (Basile & Girardi, 2010; Kalemli-Ozcan *et al.*, 2003), far less attention has been paid to the reverse linkage. The feedback effect of changes in industrial changes on cross-border portfolio investments is less well-studied. Chapter 5 fills this gap in the literature by investigating the role of the shifts in industrial structures (in response to improved risk sharing arising from financial integration) in affecting the patterns of cross-border portfolio investments. This chapter belongs to the growing literature that has sought to identify the empirical determinants of bilateral asset holdings.[3] I add to this literature by examining an important missing element, namely the role of industrial structures in affecting bilateral portfolio investments while controlling for the determinants stressed in the earlier studies.

[3]These studies have emphasized the role of geography, culture and information frictions (Portes & Rey, 2005; Portes *et al.*, 2001), trade flows (Aviat & Coeurdacier, 2007; Lane & Milesi-Ferretti, 2008), external pull factors (e.g, low interest rates and economic downturns in developed countries, etc) and internal pull factors, such as institutional development (Alfaro *et al.*, 2008; Papaioannou, 2009), financial market development (di Giovanni, 2005; Lane & Milesi-Ferretti, 2008) and capital account liberalization as important determinants of the pattern of international financial transactions.

Lastly, in this thesis I have made significant progress in stepping away from a representative agent framework, where the response to a change (in for example trade openness) is the same for countries, industries and firms. The extent to which economic agents are sufficiently distinctive to be characterized by a heterogeneous process and what factors govern this heterogeneity have important implications. To tackle this issue, I advocate latent class modeling in chapters 3 and 4. This methodology posits that there are a finite number of classes, i.e. estimated relationships underlying the data. The sorting is not *ex ante* determined, rather is endogenously determined based on certain observable characteristics. With this methodology, I am able to examine the differential effects of trade openness across industries within which the potential for reallocation is different in chapter 3, and to study the heterogeneous relationship between export maturity and growth across three groups of countries that are at different stages of development in chapter 4.

1.4 Outline of the Thesis

This thesis consists of four chapters addressing the determinants (chapter 2), processes (chapter 3) and consequences of industrial specialization (chapters 4 and 5).

Chapter 2 investigates the relationship between openness and industrial specialization. My goal is to explicitly consider the roles of trade and financial openness, and discuss the complementarity of both channels in driving industrial specialization. I proceed in two steps. The first step is to examine the relationship between trade or financial openness with specialization separately. In addition, I look at whether trade-induced specialization is less prevalent if intra-industry trade dominates, as specialization in the latter case occurs mainly within the same industry (Krugman, 1980) and whether the relationship between financial openness and specialization is stronger in countries with more developed financial systems (Masten *et al.*, 2008). The second step is to examine to what extent trade and financial openness complement each other in shaping industrial specialization. In doing so, I examine the relationship between trade (financial) openness on specialization, *conditional* on the level of financial (trade) openness.

Having established the finding that openness has had a strong impact on specialization patterns across countries, chapter 3 further explores the role of trade openness in affecting industrial composition within the EU countries. Thereby, it aims to shed more light on the processes of industrial specialization. It is important to note that country-level analyses suffer from a drawback as they average out dynamics across industries and more importantly within industries. As a result, it is unclear which industries are driving the trade-specialization relationship and how firm-level dynamics might play an important role. I introduce firm-based measures to capture the potential for reallocation within industries, and subsequently investigate whether the potential for reallocation determines whether there is a trade-specialization nexus.

Apart from exploring the causes and processes of specialization, chapters 4 and 5 examine its macroeconomic consequences from different angles. Chapter 4 focuses on the export side and examines how export specialization affects economic growth. In particular, I propose a simple measure to characterize exports according to the maturity of each product in the global market. This measure is based on a well established empirical regularity in the product life cycle theory. With this measure, I explore whether the maturity of a country's export basket matters for its economic growth and how it matters over different development stages.

In chapter 5, I analyze the effects of ongoing changes in industrial structures on cross-border portfolio investments in a country-pair setting. I relate bilateral differences in economic structures to the size of portfolio investments and aim to uncover whether there is evidence in favor of a diversification motive, in other words, whether investors tilt their foreign equity portfolios towards countries with dissimilar structures. I look at structural dissimilarity not only within the manufacturing sector, but also across all sectors and consequently, demonstrate considerable differences in their effects on portfolio investments.

Finally, chapter 6 contains a recapitulation of the main findings and policy implications, followed by a discussion of the limitations of the analyses and some suggestions for future research.

Chapter 2

Specialization in the Presence of Trade and Financial Openness

2.1 Introduction

The past few decades have witnessed an accelerated pace of economic integration, reflected by a very rapid growth in cross-border commercial trade and capital flows.[1] Trade and capital flows have increased dramatically during the last decades, as shown in Figure (2.1a). Indeed, capital flows have shown a three-fold increase since the early 1990s.[2] At the same time, industrial specialization - the domination of economies by a limited number of industries - has steadily increased since 1985, as shown in Figure (2.1b).

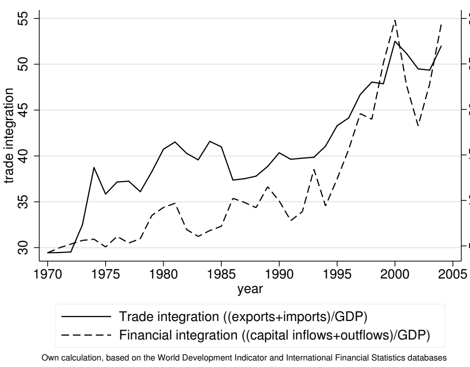
The reduction or, in some cases, complete elimination of trade and financial barriers has significantly reduced the costs of international transactions. The resulting enhanced mobility of production factors has facilitated the relocation of production across sectors and geographical spaces. The recent increases in specialization suggest that the effect of trade and financial openness has been a reorientation of most economies towards a more concentrated industry structure.

[1] In this paper, as we measure trade and financial integration by means of *de facto* openness, we use the terms "integration" and "openness" interchangeably.

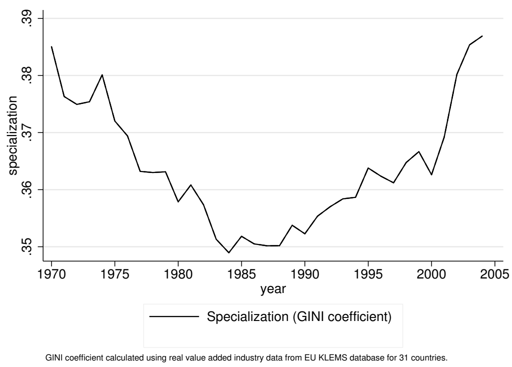
[2] Authors' calculations for the sample period, 1970-2005.

Figure 2.1: Developments in openness and specialization

(a) Development of trade and financial openness



(b) Development of industrial specialization



Note: Both graphs are weighted by the country size, based on authors' own calculations from a sample of 31 countries, see Table 2.A.1 in the Appendix.

An interesting question that arises, is what are the linkages between openness and industrial specialization? Increased specialization is desirable, as it enhances efficiency and competitiveness of a country and consequently has significant welfare implications (Eckel, 2008).[3] However, countries with specialized production structures are more vulnerable to asymmetric shocks - an issue of particular importance for monetary union country members. Trade and financial openness can both shape the dynamics of industrial specialization, creating potentially more (a)symmetric responses to the presence of a shock. Financial openness, for example, may contribute to industrial specialization, as firms can borrow from abroad to differentiate their production, but it also facilitates better risk sharing opportunities, as the borrowing risk is shared across different countries.[4] Therefore, understanding the nature of the relationship between economic integration and industrial specialization is

[3]According to Eckel (2008), if specialization falls and the losses from specialization are large, compared to gains from increases in firm size due to globalization, the per capita output can decrease and welfare can actually decline.

[4]A number of studies, for example, Greenwood & Jovanovic (1990), Saint-Paul (1992), and Acemoglu & Zilibotti (1997) have investigated the impact of insurance-induced specialization on economic growth and development.

important, both for economists and policy makers.

So far, the literature has typically studied the roles of trade and financial openness in isolation. A large strand of the literature has explored the relationship between trade openness and specialization. Early trade theories predict that the reduction of trade costs tends to increase inter-industry trade, i.e., trade of goods across industries. The main argument is that the former facilitates the way countries exploit comparative advantages due to cross-country differences in technology or factor endowment (Ohlin, 1933; Ricardo, 1817), which in turn results in divergence of production structures across countries. New trade theories (Krugman, 1979, 1980; Krugman & Venables, 1990), however, stress the importance of increasing returns to scale and product differentiation in facilitating intra-industry trade, i.e., trade of goods across countries that belong to the same industry. As a result, these theories predict that trade integration will induce a shift of increasing-return industries towards countries with good market access ("the core"), i.e., the home market effect. Theories of new economic geography (Krugman, 1991; Venables, 1996) emphasize spatial agglomeration forces in shaping specialization patterns and suggest a non-monotonic relationship between trade liberalization and location of economic activities, depending on the level of trade costs.[5]

A separate and smaller strand of literature investigates the relationship between financial openness and industrial specialization. This literature argues that with financial openness countries are better-protected against idiosyncratic risks, and consequently can specialize more.[6] The seminal study of

[5]In the presence of high trade costs, industry structures remain unaltered, whereas the reduction of trade costs results in the agglomeration of economic activities into fewer locations. When trade costs drop below a threshold, these agglomerations become smaller and more dispersed across space.

[6]A related literature investigates risk sharing patterns across countries. For example, Artis & Hoffmann (2007) and Sørensen *et al.* (2007) find improved risk sharing among industrialized countries as financial openness increases. Other studies find little evidence of improved risk sharing, despite massive financial openness (Bai & Zhang, 2006; Moser & Scharler, 2004). See Kose *et al.* (2009b) for an extensive literature survey. Obstfeld (1994) shows that financial market integration provides insurance through a globally diversified portfolio of investments, thereby encouraging countries to simultaneously shift from low-return, safe investments toward high-return, risky investments promoting higher growth.

Kalemli-Ozcan *et al.* (2003) investigates the relationship between risk sharing from financial openness and production specialization. The authors find a positive and robust link between risk sharing and specialization among regions in the US, as well as across some OECD countries. Basile & Girardi (2010) use more advanced estimation methods, allowing for non-linearity and spatial dependence, and confirm a similar positive relationship across European regions. Although Kalemli-Ozcan *et al.* (2003) acknowledge and control for the potential impact of trade openness on specialization, the effect of trade openness in conjunction with financial integration as joint determinants of specialization is not explicitly examined in both studies.[7]

The purpose of this paper is to investigate the relationship between openness and industrial specialization in a comprehensive manner for a large set of countries using a detailed sample of manufacturing industries. Our sample consists of 20 manufacturing industries in 31 countries over the period 1970-2004.

More particular, the paper aims to answer two important questions. The first, and most basic one, is how does openness relate to industrial specialization? To answer this question, we first consider two separate channels of openness, trade and financial openness, and examine their relationship with production specialization. Next, we find out whether trade-induced specialization is less prevalent if intra-industry trade dominates, as specialization in the latter case occurs mainly within the same industry (Krugman, 1980). Finally, we investigate whether the relationship between financial openness and specialization is stronger in countries with more developed financial systems (Masten *et al.*, 2008).

The second question we ask is to what extent trade and financial openness complement each other in shaping industrial specialization. To answer this question, we examine the relationship between trade (financial) openness on specialization, *conditional* on the level of financial (trade) openness. In doing so, we also explore whether the composition of financial flows matters, i.e. the relative shares of portfolio equity, foreign direct investment (FDI) and

[7] Kalemli-Ozcan *et al.* (2003) control for the gravity determinants of trade.

external debt. Portfolio equity and FDI flows are perceived to be more conductive to risk sharing (Kose *et al.*, 2009b), whereas debt flows are more prone to sudden stops, triggering economic crises. Thus, it would be desirable for (emerging) countries to reduce their reliance on debt finance and increase the importance of equity and FDI finances (Rogoff, 1999). We use various instruments for both openness measures and appropriate econometric techniques to enhance robustness of our results, explore threshold effects and to avoid endogeneity problems.

Our work relates to various strands of literature. We contribute to the literature that explores the patterns of industrial structures across countries and infers whether changes of patterns reflect ongoing economic integration (Brülhart, 2001b; Krugman, 1991; Longhi *et al.*, 2003; Riet *et al.*, 2004; Sapir, 1996). In this literature, trade and financial integration are mostly latent, at best, captured by a linear time trend (Longhi *et al.*, 2003). Our paper explicitly considers the roles of trade and financial openness, allowing for interaction between both channels.

We also contribute to a number of recent studies that investigate the dynamic impact of trade openness on specialization patterns. For instance, Beine & Coulombe (2007) study the impact of trade liberalization between Canada and the US, measured by the decrease of trade-weighted tariffs, on the degree of industrial specialization for Canadian regions. Their results favor a positive short-run relationship and a negative long-run relationship between trade integration and industrial specialization, i.e., short-run specialization and long-run diversification. Crabbé *et al.* (2007) perform a similar analysis for thirteen CEEC countries and show that trade integration leads to long-run specialization.[8] An important element missing in all aforementioned papers is financial openness, which is explicitly taken into account here.

[8]Crabbé *et al.* (2007) interpret the different results as evidence of a possible non-monotonic relationship between trade integration and industrial specialization along the development path. A closely related study in this respect is that of Imbs & Wacziarg (2003), who demonstrate a U-shaped pattern between the specialization of a country and the level of its per capita income. Countries initially diversify to reduce the risk of sector-specific shocks, while in the later stage of development, countries start to specialize when their per capita income has grown to a critical level.

We further relate to a handful of studies that have attempted to unify different strands of literature to analyze the effect of trade and financial openness on specialization. For example, the study of Imbs (2004) examines the complex relationships between trade, finance, specialization, and business cycle synchronization in the context of a system of simultaneous equations based on a cross-sectional country-pair setting in 24 countries.[9]

Our paper builds on these earlier contributions, mainly on Imbs (2004) and Kalemli-Ozcan *et al.* (2003, 2004). In contrast to those papers, this paper treats trade and financial openness as multilateral rather than bilateral phenomena (Imbs, 2006), thus chooses country-year instead of country-pair as the unit of our analysis, and discusses the complementarity of trade and financial openness as channels of specialization. The panel-based estimation techniques used here exploit both time-series as well as cross-section variations and are well-suited to solve endogeneity issues, thus yielding more efficient estimates. The empirical analysis is based on a sample that consists of manufacturing industries, twice as disaggregated as those used in past related studies (Kalemli-Ozcan *et al.*, 2003), and a time span that is more extensive than that of previous studies (Basile & Girardi, 2010; Imbs, 2004).

Our results reveal that both trade and financial openness have a positive relationship with specialization (Basile & Girardi, 2010; Imbs, 2004; Kalemli-Ozcan *et al.*, 2003). Whereas intra-industry trade lowers the impact of trade openness on specialization, financial development strengthens the effect of financial openness on specialization.

In addition, we find that both channels of openness enhance each other. The positive relationship between trade openness and specialization is present, independent of the levels of financial openness. However, the positive relationship between financial openness and specialization only exists when countries are sufficiently open to trade. These findings extend and complement those of Imbs (2004). Furthermore, portfolio equity, FDI and debt are all useful instruments for attaining the risk sharing benefits associated with financial openness, consequently inducing specialization. These results are robust to alter-

[9] Similar investigations are performed by Frankel & Rose (1998), Kalemli-Ozcan *et al.* (2004), Imbs (2006), Calderón *et al.* (2007), Inklaar *et al.* (2008).

native model specifications and the use of a range of different measures of openness and specialization.

Our findings highlight that policies for (further) trade and financial integration should be jointly designed for countries to fully seize the benefits of specialized production structures, economies of scale and increased efficiency. However, countries with specialized production structures are more vulnerable to asymmetric shocks. The latter is of particular interest for the Eurozone, where well-functioning risk-sharing mechanisms can secure the benefits of specialization.

The remainder of the paper proceeds as follows. Section 2.2 exposes the model(s) under estimation and the econometric strategy. Section 2.3 presents the data and the measures proposed. Section 2.4 discusses the results. Finally, Section 2.5 summarizes and concludes.

2.2 Methodology

This section presents the empirical specifications and discusses the estimation strategies followed.

2.2.1 Model Specification and Theoretical Considerations

To answer our first question, regarding the (independent) effects of trade and financial openness on specialization of production, we start with the following specification:[10]

$$S_{it} = \mu_i + \beta_1 T_{it} + \beta_2 F_{it} + \beta' Z_{it} + \varepsilon_{it}, \tag{2.1}$$

where i denotes the country and t time; S is a specialization index; μ_i is country-specific fixed effect; T and F capture the degree of trade and financial openness, respectively; β' is a $1 \times n$ parameter vector; Z is an $n \times 1$ vector of control variables; and, finally, ε_{it} is the error term. All variables are in logs.[11]

[10] See, for example, Kalemli-Ozcan *et al.* (2003), Basile & Girardi (2010).

[11] There is no theoretical guidance on whether to use levels or logs of variables in our specifications. Ultimately, we choose logs as they yield a better fit and make the results easier to

Most classical trade theories, with reference to the theory of comparative advantage, predict that trade openness leads to more industrial specialization and accordingly we expect a positive β_1. Falling trade costs result in a narrowing non-traded sector and therefore it is cheaper to import goods rather than produce them domestically (Dornbusch *et al.*, 1977). Thus, resources are freed up and used more intensely in fewer activities.

Financial openness may induce specialization through risk-sharing. Open and integrated financial markets offer a broader range of financial instruments and permit the diversification of ownership via two types of insurance. First, if residents in one country hold debt and equity claims on the output of the other country, then the dividend, interest, and rental income derived from these holdings contribute to smoothing the effects of output shocks across countries. It is thus a form of *ex ante* international insurance. Second, to achieve consumption smoothing, households in each country can *ex post* adjust their asset portfolios, following the occurrence of shocks in the region. Again, this will lead to income smoothing in all countries. Once insurance is available through trade in financial assets, each country will have a stronger incentive to specialize in fewer forms of production (or technology) in order to fully exploit economies of scale or technological competitive advantages. Therefore, β_2 is expected to carry a positive sign (Basile & Girardi, 2010; Kalemli-Ozcan *et al.*, 2003).

The vector Z contains a number of control variables that have been commonly used in the relevant literature. These variables capture the country size and the stage of its economic development. More specifically, country size is measured by population. A large country may foster a broader range of industrial productions and thus has a more balanced industrial structure, whereas the opposite could be the case for a small country. Consequently, the coefficient for country size is expected to bear a positive sign, as small countries are more likely to specialize. The stage of economic development is measured as GDP per capita, and the square of GDP per capita to allow for possible

interpret as elasticities. See, for example, Baltagi *et al.* (2009) for a similar treatment regarding the functional form.

nonlinear effects between economic development and specialization. For instance, Imbs & Wacziarg (2003) argue that specialization is likely to change along the development path of a country. They provide robust evidence that countries experience two stages of diversification. At low levels of per capita income, countries reduce their overall specialization to mitigate the adverse effect of sector-specific shocks, while when per capita income reaches a high level, countries specialize again to fully exploit the comparative advantage.[12]

Recent evidence (e.g. Kose *et al.*, 2006, 2009a) has demonstrated that trade and financial openness are closely related phenomena as they tend to move closely together and countries often cannot opt for trade (financial) integration independently of their degree of financial (trade) integration.

Therefore, to address our second question, which is to what extent financial (trade) openness acts as a moderator to the effect of trade (financial) openness on specialization, we introduce an interaction term ($T \times F$):

$$S_{it} = \mu_i + \beta_1 T_{it} + \beta_2 F_{it} + \beta_3 T_{it} \times F_{it} + \beta' Z_{it} + \varepsilon_{it}. \tag{2.2a}$$

In equation (2.2a) above, we allow the relationship of one type of openness with specialization to be moderated by the other type of openness. The marginal effect of trade (financial) openness on specialization is now conditional on financial (trade) openness, as shown in equations (2.2b) and (2.2c), respectively:

$$\frac{\partial S_{it}}{\partial T_{it}} = \beta_1 + \beta_3 F_{it}, \tag{2.2b}$$

$$\frac{\partial S_{it}}{\partial F_{it}} = \beta_2 + \beta_3 T_{it}. \tag{2.2c}$$

According to classical theories of trade, international trade works as a substitute for capital flows as trade reduces the incentives for capital to flow to capital-scarce countries. However, recent theoretical and empirical evidence offers and confirms a number of reasons that support the complementarity between trade and financial openness.

[12]From a theoretical point of view, Imbs & Wacziarg (2003) argue that this pattern is consistent with models featuring endogenous stages of specialization to both trade and economic growth.

On the one hand, trade openness may foster financial openness, either by creating demand for symmetric financial flows, or by promoting FDI in export-oriented sectors. The rapid growth of FDI and the establishment of multinational firms further drive the demand for financing, as those firms increasingly turn to banks and the stock exchange to raise funds, thus contributing to growing financial flows.[13]

On the other hand, financial openness may promote specialization via risk sharing or by facilitating the reallocation of capital to sectors that have a comparative advantage, therefore increasing the opportunities for trade (Feeney, 1994a,b). Antràs & Caballero (2009) model trade and capital flows as complements, especially in less financially developed economies, as trade integration increases the return to capital and capital inflows to these countries. This complementary relationship has also been confirmed empirically by a number of studies.[14] In line with this literature, we expect the impact of trade (financial) openness on specialization to increase with the degree of financial (trade) openness, resulting in a positive β_3 in equations (2.2b) and (2.2c).

2.2.2 Estimation Procedure

We use the two-step GMM estimator to extract consistent and efficient estimates of the various model specifications discussed above. With the two-step GMM estimation procedure, we can control for country-specific heterogeneity,

[13]For example, a number of studies show that multinational or foreign firms have easier access to international sources of external financing and face lower financing obstacles (Beck *et al.*, 2006; Harrison & McMillan, 2003; Schiantarelli & Sembenelli, 2000).

[14]For example, Aizenman & Noy (2009) find evidence of a two-way feedback between trade and financial integration, i.e., *de facto* trade (financial) openness is associated with larger future financial (trade) openness. Chambet & Gibson (2008) decompose trade openness into its natural and residual components and find that both measures contribute positively to stock market integration for a large panel of emerging economies. Chow *et al.* (2005) confirm the interdependence of trade and financial integration in East Asian countries. Kalemli-Ozcan & Nikolsko-Rzhevskyy (2010) confirm that trade *causes* capital flows, using historical evidence from trade and financial flows between three source countries (Germany, France, the UK) and one host country (the Ottoman Empire) over 1859-1913, whereas García-Herrero & Ruiz (2008) argue that trade linkages do not seem to be significantly affected by financial linkages in the country of their investigation, Spain.

non-stationarity of variables and possible endogeneity (reverse causality) of the regressors.[15] As a result, we are able to examine causal effects that most other related studies ignore. In particular, if there is reverse causality from specialization to trade and financial openness, this poses serious challenges to the validity and inferences of the estimates. For example, Imbs (2004) finds a negative relationship running from specialization to trade, as a result of intra-industry trade. Similarly, financial openness is likely to be an endogenous variable based on the argument that more specialized countries demand more international insurance, and are therefore more likely to engage in financial integration. We alleviate this endogeneity concern by using lagged levels to instrument the endogenous variable in the first-difference equation. As an additional check for the validity of using lagged levels of trade (financial) openness as instruments, for each country, we construct the average of its neighboring countries' trade (financial) openness (AT and AF) as alternative instruments. These two instruments allows us to exploit the (time-varying) exogeneity of this variable to identify the effects of trade and financial integration on specialization, following Baltagi *et al.* (2009). For comparison, we also report OLS estimates.

To check the consistency of our estimates, we employ various diagnostic tests. First, we perform a Durbin-Wu-Hausman (DHW) endogeneity test in order to examine whether trade and/or financial openness are indeed endogenous in our model(s). Then, we ensure the validity of the instruments used to overcome reverse causality issues. The key exogeneity assumption in our context is that a country's historical levels of trade are orthogonal to current shocks to specialization. Therefore, lagged variables must be uncorrelated with the error term in the level equations. To see whether this assumption

[15]More specifically, the two-step GMM estimator utilizes an optimal weighting matrix that minimizes the asymptotic variance of the estimator. It takes the first differences of the variables to remove unobserved country-specific effects and any endogeneity bias arising from the correlation of these fixed-effects with explanatory variables. First-differencing also ensures the stationarity of variables. Since the time dimension of our panel is relatively long, we need to adequately consider the non-stationary nature of regression variables in order to avoid running a spurious regression.

holds, we apply a Arellano-Bond serial correlation test.[16] The usage of multiple instruments allows us to perform a Hansen test of over-identifying restrictions. Then, the Kleibergen-Paap *rk* test is used to examine whether the endogenous regressor is well-identified by the instruments. Lastly, we employ the Anderson-Rubin weak-identification-robust test. The last two tests ensure the relevance and strength of our instruments.[17]

2.3 Data

In answering the questions posed in this paper, we face a number of data considerations. First, having a sufficiently disaggregated set of industries is important to avoid aggregation issues when measuring specialization. Put bluntly, at a higher level of aggregation, countries' industrial structures will appear alike by construction. A second consideration for the purpose of our analysis, is the fact that we require a relatively broad set of countries to ensure sufficient variation in specialization patterns. Third, trade and financial openness are complex processes that require time to develop.[18] Since reverse causality may be an issue, a long time span allows for a deeper lag structure and more appropriate instruments.

Our empirical analysis covers an unbalanced panel of 20 2-digit manufacturing industries in 31 countries during the period 1970-2004, the longest pe-

[16] If there is no serial correlation (in the level equation), one should reject the null hypothesis of absence of serial correlation in the first differences. In this case, any historical values of trade, beyond period $t-2$ are potentially valid instruments. In contrast, if serial correlation is present, one needs to take deeper lags from period $t-3$ as instruments. In principle, the number of lags available as instruments increases with the time dimension T. To alleviate the potential problems arising from a disproportional large number of instruments, we limit the number of lags to three. Our choice is also motivated by a practical reason that some countries are covered in our sample for a relatively short period of time. We limit the number of lags in order not to lose a significant amount of observations.

[17] For a comprehensive discussion of our methodology, see Baum *et al.* (2003).

[18] This holds even more for studies that use *de jure* (by law) measures of trade and finance, where one needs a considerable time span to see these policies to be realized.

Table 2.1: Descriptive Statistics

Variable	Description	Source	Mean	Min	Max	Std	Obs
S	Gini Coefficient of Specialization	KLEMS	0.424	0.280	0.699	0.079	770
HRI	Herfindahl-Hirschman index	KLEMS	0.090	0.063	0.241	0.032	770
VSI	Coefficient of variation	KLEMS	0.854	0.517	1.991	0.243	770
T	Trade openness, % of GDP	WDI	71.893	11.254	278.991	45.023	770
AT	Average trade openness, % of GDP	WDI	65.360	12.760	134.059	24.084	760
IIT	Intra-industry trade intensity (0 to 1)	STAN	67.592	26.460	99.330	14.826	680
IMP	Imports, % of GDP	WDI	36.011	5.444	129.010	21.487	770
EXP	Exports, % of GDP	WDI	35.883	5.658	150.000	23.883	770
MANT	Manufacturing trade, % of GDP	WDI	38.548	5.324	133.740	24.816	738
F	Financial openness,% of GDP	LMF07	274.455	18.553	19258.465	1400.936	738
AF	Average financial openness, % of GDP	LMF07	162.643	18.697	1880.037	170.702	770
Equity	Portfolio equity,% of GDP	LMF07	57.746	0.006	6546.909	483.167	711
FDI	FDI,% of GDP	LMF07	59.018	0.472	5758.237	385.023	739
Debt	Debt,% of GDP	LMF07	160.083	7.737	8256.125	626.731	738
FD	Liquid liability, % of GDP	Beck *et al.* (1999)	0.734	0.301	3.216	0.477	731
Size	Population(1000 persons),	WDI	36656	340	292892	54792	770
GDPpc	Per capita real GDP (2000 $K)	WDI	16.695	1.994	50.573	8.695	770
AGRI	Agriculture, % of GDP	WDI	5.356	0.92	29.824	4.752	698
RES	Natural resource rents, % of GDP	WDI	1.369	0.000	19.378	2.386	735
HC	Years of schooling	BL2012	8.891	3.386	13.153	2.065	735

Luxembourg is excluded. KLEMS refers to the EU KLEMS database. UNCTAD refers to the United Nations Conference on Trade and Development *Handbook of Statistics*, 2008. WDI refers to the World Development Indicator database. LMF07 and BL2010 refers to Lane & Milesi-Ferretti (2007) and Barro & Lee (2012), respectively.

riod for which data are available for the largest amount of countries.[19] We focus on manufacturing industries on the premise that these industries, in contrast to services, are involved in trade, and are therefore more responsive to trade integration.

We ensure that the number of sectors available through time is constant across countries, while coverage across time varies per country. This way, both within-country and cross-country changes in specialization can be compared and interpreted in a consistent manner. Table 2.A.1 in the Appendix lists the 31 countries and the corresponding time span. Table 2.A.2 in the Appendix reports the 20 industries and their NACE codes considered in our analysis. Annual raw data are retrieved from various sources.

Below, we present the construction of our variables and their sources.

Industrial Specialization

Our primary index of specialization (S) is the Gini coefficient, which measures the degree of concentration or inequality of the distribution of sector shares in an economy (Gini, 1921) and is defined as follows:[20]

$$S = \frac{2}{n^2 \cdot \bar{s}} \sum_{j=1}^{n} j(s_j - \bar{s}), \tag{2.3}$$

where j denotes the sector, n denotes the number of sectors, s represents the share of each sector, and $\bar{s}$ refers to the average sector share. The index ranges from zero, where all sectors have an equal share of total manufacturing value added implying a perfectly diversified economy, to one, where only one sector produces all manufacturing value added, reflecting a strongly specialized economy. To check the robustness of our results, we also use two other indices of industrial specialization often used in the conventional literature. These indices are the Herfindahl-Hirschman index (HRI), which sums up the square

[19] A November 2009 update to the EU-KLEMS database, running to 2007, includes only a limited number of variables and industries. For reasons explained above, our analysis ends in 2004, and we rely on the two-digit disaggregation throughout.

[20] The Gini coefficient is commonly used in the empirical literature to measure industrial specialization (Amiti, 1999; Imbs, 2004; Krugman, 1991).

of each sector's share in the total manufacturing value added of a country, and the coefficient of variation of sector shares (VSI), which is defined as the ratio of the standard deviation to the mean of sector shares in one country.

An important consideration in comparing specialization across countries, is the level of aggregation at which the specialization measures are calculated. On the one hand, the lower the aggregation level, the more we risk contaminating our analysis of the openness-specialization nexus by differences in comparative advantage between small and large sectors in each country. To see why, consider a country in which the small sectors have a comparative advantage, compared to the large sectors. An increase in trade openness will then result in less specialization. On the other hand, the higher the aggregation level, the more we risk distorting our analysis of the openness-specialization nexus by picking up the general trend towards a more services oriented economic structure that is common among (most) countries in our sample. Trade openness will then correlate positively with specialization, but without any causality implied.

In this paper, we are interested in examining the industrial specialization patterns that result from changes in trade and financial openness. As a result, we focus on the manufacturing sector (where most international trade takes place), and we use industry-specific data from the EU KLEMS database. We extract annual raw data on nominal value added for 20 NACE industries to compute the specialization indices. Table 2.A.2 in the Appendix lists all industries included in our index.

Our aim is to ensure that our index of choice, based on 20 NACE industries, minimizes the likelihood of both biases occurring. In order to verify this, we re-calculate the specialization indices using nominal value added and employment, aggregated to 11 NACE industries. In addition, we also take data at the ISIC 3-digit disaggregation (maximum 28 industries), for a subset of countries from the Nicita & Olarreaga (2007) database. The coverage of this database is fairly limited and the quality of data varies hugely across countries. Therefore, we only use this data source for comparison purposes. Finally, we also calculate a specialization index at the highest aggregation level, with agriculture, services and manufacturing as the three sectors of the economy. Table

2.A.1 in the Appendix shows the Gini coefficient and its changes over time for each country in our sample. We find that Latvia, Cyprus and Ireland are the most specialized countries in our sample, whereas United States, Austria and Poland are the least specialized ones. Norway, Ireland and Germany experience the most significant increases in specialization, where their Gini coefficients rise by 23.8, 17.8 and 13.5 percent. The Gini coefficients in Luxembourg, Hungary and Spain decrease sharply by 37.7, 19.6 and 16.7 percent. However, most countries in our sample become increasingly specialized since 1985.

Ideally, we aim to find that our preferred index is positively, significantly correlated with the lower aggregation indices, and not correlated with the highest aggregation index. Figure 2.A.1 in the Appendix shows scatterplots for the ISIC 3-digit Gini coefficient and the 3-sector Gini, both compared to the 20 NACE Gini coefficient. The latter is indeed positively (0.477) and significantly (at the one percent level) correlated with the ISIC 3-digit Gini coefficient, whereas correlation with the 3-sector Gini coefficient is -0.077, and not significantly different from zero.[21]

Therefore, we continue using the 20 NACE Gini coefficient as our main measure of specialization. For robustness purposes, we take into account the higher level sectoral composition changes by examining the openness-specialization nexus in two sub-samples. One includes countries that experience less changes in the manufacturing shares of GDP, whereas the other consists of countries that experience more changes. Finally, as our estimation strategy exploits the changes in specialization (i.e., we estimate in first differences), we do not expect that our results are driven by industry aggregations.

Trade Openness

Our primary measure for trade openness is the ratio of imports plus exports divided by GDP (T). This continuous measure is widely used in the empirical literature. For robustness purposes, we also use the share of imports to GDP (IMP) and the share of exports to GDP (EXP), as well as manufacturing trade

[21] Correlation with the 11 NACE Gini coefficient is 0.7872, and also significant at the one percent level.

as a percentage of GDP ($MANT$), a narrower measure of trade openness. To construct an instrument for trade openness in each country, we take the average of its neighboring countries' trade openness (Baltagi *et al.*, 2009).

Country-level data of trade volume, imports, exports, manufacturing trade, GDP have been taken from the World Bank (2008) *World Development Indicators* (WDI). Lastly, we also consider the role of intra-industry trade intensity (IIT).[22] This measure allows for a more explicit test on the impact of trade integration, controlling for the nature of trade. We derive aggregate country-level IIT indicators from the OECD (2006) *Structural Analysis database* (STAN), which is computed using detailed trade data of two- and three-digit manufacturing industries.

Financial Openness

We follow a similar approach with financial openness, where our primary measure F is the ratio of total foreign assets and total foreign liabilities as a percentage of GDP. This stock-based measure is constructed following Lane & Milesi-Ferretti (2007).[23] As in the case of trade openness, an external instrument for financial openness is also constructed for each country by taking the average of neighboring countries' financial openness.[24]

[22] The Grubel-Lloyd index (Grubel & Lloyd, 1975) of intra-industry trade is defined as: $IIT_{it} = 1 - \frac{\sum_j |EXPO_{jit} - IMPO_{jit}|}{\sum_j (EXPO_{jit} + IMPO_{jit})}$, where i denotes country, j sector and t year. It ranges from 0, indicating pure inter-industry trade, to 1, indicating pure intra-industry trade.

[23] Unlike a flow-based measure, like gross capital inflow plus outflows divided by GDP, this stock-based measure takes into account the history of a country's financial integration and its changes over time. It is typically less prone to short-run changes in the political and economic climate, and is thus a preferred measure for our purpose. See Edison *et al.* (2002) for the discussion of flow-based vs. stock-based measures.

[24] We also compute the weighted average of its neighboring countries' trade and financial openness, weighted by the country size (i.e. the number of the population). We find the correlations between the unweighted and weighted measure are 0.845 and 0.976 for trade openness and for financial openness, respectively. The correlations remain unchanged, i.e. 0.847 and 0.978 if we use GDP as the weights. Therefore, following Baltagi *et al.* (2009), we use the unweighted average.

To address the issue of whether specific types of capital flows (and corresponding stocks) are more conducive to attaining the risk sharing benefits of financial integration, we construct three disaggregated measures of gross external assets and liabilities relative to GDP: equity ($Equity$), FDI (FDI) and debt ($Debt$). Data are retrieved from the Lane & Milesi-Ferretti (2007) database.

Other Variables

To examine how financial development mediates the role of financial openness on specialization, we take liquid liabilities (currency plus demand and interest-bearing liabilities), relative to GDP as a proxy for financial development (FD). This measure is the broadest available indicator of financial development, commonly described as "financial depth"(Levine, 1997). We obtain it from the Beck *et al.* (1999) database.

The vector Z includes country size ($Size$), measured by the population, as well as GDP per capita ($GDPpc$) and its squared term ($GDPpc2$) to characterize the stage of economic development. Total population and GDP per capita (constant 2000 US dollars) are taken from the World Bank (2008) *World Development Indicators* (WDI). For the robustness analysis, we also include three additional control variables to capture country factor endowments, namely the size of agricultural production as a share of GDP ($AGRI$), total natural resource rents (sum of oil, natural gas, coal, minerals and forest rents) as a percentage of GDP (RES) and education attainment (HC) measured by the average years of schooling for the population aged 25 or over. Agricultural production and total natural resource rents are retrieved from the WDI and years of schooling is retrieved from Barro & Lee (2012) database. We interpolate these authors' data to obtain annual observations. Table 2.1 summarizes the definitions, sources and descriptive statistics of main variables as well as those used in robustness analysis, respectively.

The presentation and discussion of the empirical findings is the task of the next section.

2.4 Empirical Results

This section presents the empirical results. We examine, first, how trade and financial openness relate to industrial specialization individually and, second, how they jointly relate to industrial specialization.

2.4.1 Does openness matter for industrial specialization?

We start by investigating the independent impact of trade and/or financial openness on industrial specialization. The results are reported in Table 2.2. Columns (I), (II) and (III) only consider the role of trade openness. Similarly, columns (IV), (V) and (VI) only include financial openness. In columns (VII), (VIII) and (IX), trade and financial openness are both included, but (not yet) interacted.

For every specification, we first report the OLS estimates, in columns (I), (IV) and (VII). However, the OLS estimator yields biased and inconsistent estimates of the causal effect of openness on specialization in the presence of endogenous regressors. Trade and financial openness are endogenous from a theoretical viewpoint due to reverse causality with specialization. Additionally, the DHW statistics reject the null hypothesis that introducing instruments has no effect on the estimated coefficients and confirm that both trade and/or financial openness are indeed endogenous across all three specifications. We then proceed with the two-step GMM results using the lagged levels of trade and financial openness at $t-2$, $t-3$ and $t-4$ as instruments, in columns (II), (V) and (VIII). The validity of using lags from $t-2$ as instruments is guaranteed by not rejecting the absence of second-order serial correlation. Next, the Hansen J test does not reject the over-identifying restrictions, confirming the validity of our instruments. Moreover, the Kleibergen-Paap *rk* test and the Anderson-Rubin test confirm that these specifications are properly identified and do not suffer from under- and weak-identification problems. Lastly, columns (III), (VI) and (IX) replicate (II), (V) and (VIII) with trade and/or financial openness instrumented by the average of neighboring countries' trade

Table 2.2: Does openness matter for industrial specialization?

	(I) OLS	(II) GMM	(III) Instrument	(IV) OLS	(V) GMM	(VI) Instrument	(VII) OLS	(VIII) GMM	(IX) Instrument	(X) IIT	(XI) FD
T	0.011	0.240***	0.304*				0.006	0.247***	0.277**	2.366***	0.210***
	(0.016)	(0.092)	(0.168)				(0.017)	(0.075)	(0.113)	(0.669)	(0.0774)
F				0.016*	0.077***	0.084***	0.015	0.028	0.067***	0.0810**	-0.226*
				(0.009)	(0.025)	(0.023)	(0.009)	(0.024)	(0.023)	(0.0343)	(0.120)
T*IIT										-0.525***	
										(0.156)	
F*FD											0.0629**
											(0.0287)
IIT										2.025***	
										(0.581)	
FD											-0.283*
											(0.155)
Size	-0.004	0.077	0.098	-0.011	-0.126	-0.165	-0.011	0.074	0.033	-0.0774	0.293**
	(0.156)	(0.137)	(0.138)	(0.161)	(0.136)	(0.110)	(0.163)	(0.135)	(0.123)	(0.0975)	(0.119)
GDPpc	-0.373***	-0.390***	-0.456***	-0.377***	-0.301***	-0.354***	-0.379***	-0.312***	-0.371***	-0.247	-0.0606
	(0.100)	(0.079)	(0.100)	(0.101)	(0.061)	(0.064)	(0.102)	(0.069)	(0.099)	(0.162)	(0.173)
GDPpc2	0.063***	0.050***	0.056***	0.061***	0.034**	0.045**	0.061***	0.0252	0.015	0.0132	-0.0268
	(0.022)	(0.019)	(0.021)	(0.022)	(0.016)	(0.018)	(0.022)	(0.0172)	(0.021)	(0.0338)	(0.0321)
Endogeneity		0.090	0.045		0.023	0.014		0.015	0.088	0.108	0.165
AR(2)		0.079	0.170		0.253	0.258		0.100	0.274	0.164	0.122
Over-identification		0.150	0.352		0.832	0.026		0.288	0.037	0.493	0.619
Under-identification		0.007	0.004		0.001	0.000		0.011	0.015	0.017	0.016
Weak-identification		0.010	0.018		0.009	0.000		0.000	0.000	0.000	0.000
Observations	740	689	679	743	690	694	738	685	679	639	622

All models are estimated in first differences. Variables are expressed in logs. The dependent variable is S, the Gini specialization index in all specifications; T is trade openness, defined as total imports plus exports/GDP; F is Financial openness, defined as total financial assets plus liabilities/GDP; IIT is intra-industry trade intensity, defined as Grubel-Lloyd index; FD is liquid liabilities divided by GDP; $Size$ is the country size, measured as the number of population; $GDPpc$ is per capita real GDP (Constant 2000 U.S. dollars); $GDPpc2$ is per capita GDP squared; Endogeneity is the Durbin-Wu-Hausman test; AR(2) is the Arellano-Bond serial correlation tests; Over-identification is the Hansen J statistic; Under-identification is the Kleibergen-Paap rk test; Weak-identification is the Anderson-Rubin test. Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

and/or financial openness. The results are very similar, further confirming the validity of lagged trade and financial openness as instruments.

As column (II) shows, we find a statistically significant (at one percent) positive relationship between trade openness and specialization, indicating that further openness to foreign trade coincides with a more specialized industrial structure - a finding in line with the prediction of classical trade theories based on comparative advantage. This result corroborates Crabbé *et al.* (2007), who find a long-run positive impact of trade integration on specialization of thirteen CEEC countries, but is in contrast with Beine & Coulombe (2007), who employ the same estimation strategy and show the opposite for Canadian regions. Martincus & Gallo (2009) find a similar relationship between trade integration and specialization in ten Latin American countries. In terms of magnitude, ceteris paribus, a one standard-deviation increase in the (log of) trade openness is associated with an increase in the (log of) Gini coefficient equivalent of 0.825 standard deviations. Moreover, the sign, magnitude and significance remain the same after introducing financial openness into the equation in column (VIII), suggesting that international trade has been an important force in driving increased specialization over time.

Turning to the role of financial openness in column (V), we observe a statistically significant (at one percent) positive effect of financial openness on specialization, in line with the risk-sharing rationale put forward by Kalemli-Ozcan *et al.* (2003). By allowing access to foreign markets, financial integration can bring a wider range of financing sources and investment opportunities, permitting the decoupling of production and consumption via cross-country risk sharing mechanisms and making it less costly for countries to achieve greater specialization. Ceteris paribus, a one standard-deviation increase in the (log of) financial integration is associated with an increase in the (log of) Gini coefficient of 0.354 standard deviations. However, the magnitude and significance somewhat decline when trade openness is also included in column (VIII).

In line with past evidence (Imbs & Wacziarg, 2003), we do not find a positive coefficient for country size. We report some evidence of a U-shaped relationship between GDP per capita and specialization. In the early stages of development, countries diversify and hold a more balanced structure of economic activities in order to reduce the negative impact of sector-specific shocks. At the later stages of development, countries begin to specialize to fully exploit comparative advantages. However, the threshold level of GDP per capita (based on columns (II) and (V)) where countries re-specialize is close to the maximum level in our sample, suggesting that the diversification effect may seem to be more relevant. The effect becomes insignificant in column (VIII).

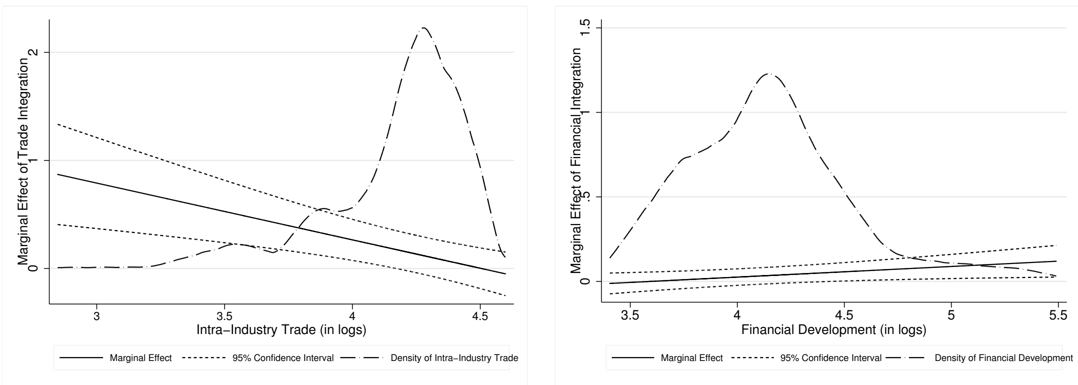
Having established that trade and financial openness have a significant relationship with specialization, we are interested in examining whether the strength of this relationship is determined by intra-industry trade (IIT) and financial development (FD), respectively.

Classical trade theories postulate that further trade openness is likely to result in more specialization if trade is predominantly of the inter-industry type. On the contrary, if trade is of the intra-industry type, trade-induced specialization may be weaker, as trade leads countries to concentrate on the production of a limited number of products within the industry.

Figure 2.2: The role of intra-industry trade intensity and financial development as mediators

(a) Intra-industry trade intensity as a mediator

(b) Financial development as a mediator



In column (X) in Table 2.2, an intra-industry trade intensity index IIT therefore interacts with trade openness.[25] The index ranges from zero, indicating pure inter-industry trade, to one, indicating pure intra-industry trade. Both terms are individually and jointly significant at one percent. The DHW statistic confirms that trade openness and its interaction term with IIT are endogenous, so we instrument lagged values at $t-2$, $t-3$ and $t-4$. The absence of second-order serial correlation and the inability to reject the over-identifying restrictions confirm the validity of our instruments. The Kleibergen-Paap *rk* test and the Anderson-Rubin test suggest that this regression is well-specified.

Figure (2.2a) shows the marginal effect of trade openness on specialization, conditional on the intra-industry trade intensity. Consistent with column (VIII), trade openness has a positive relationship with specialization, independent of the level of intra-industry trade. In addition, we find that countries with high levels of intra-industry trade experience less specialization in response to further trade openness than countries with low levels of intra-industry trade. In line with our expectation, intra-industry trade seems to dilute the specialization effect of trade. Financial openness enters with a positive and statistically significant coefficient at the five percent level. The magnitude is comparable to that found in column (V), but considerably larger than that found in column (VIII) in Table 2.2, confirming the important role of financial openness in driving specialization.

Next, we explore the role of financial development as a facilitator to the relationship between financial openness and specialization. A vast body of existing literature has strongly emphasized that benefits associated with fi-

[25]Including both intra-industry trade and our traditional trade integration measure, as well as an interaction term, may raise concerns regarding multicollinearity. However, in light of our analysis of the conditional marginal effects in Figures (2.2a) and (2.2b), two aspects of columns (X) and (XI) are worth mentioning (Brambor *et al.*, 2006). First, given the inclusion of interaction terms, we never intend to measure the average effect of a variable in the same way as we would in an additive model, as in column (IX). As a result, a change in coefficients as a result of including the interaction terms, should not be interpreted as a sign of multicollinearity. Second, the main 'problem' with multicollinearity would be large standard errors, something that would be accurately captured by Figures (2.2a) and (2.2b) and would thereby not lead us to overstate the significance of our results.

nancial openness only become significant at higher levels of financial development.[26] Financial development facilitates financial openness as domestic financial intermediaries, who distribute international assets, offer a local channel by which investors can gain foreign exposure. The latter may also increase the desire for international diversification. Furthermore, a well-developed financial system is attractive to foreign investors. Thus, financial openness and financial development may be complements in shaping specialization.

In column (XI), a financial development measure (FD) therefore interacts with financial openness. We instrument financial openness using values at $t-2$, $t-3$ and $t-4$. The validity of the instruments is guaranteed by the absence of serial correlation and the inability to reject the over-identifying restrictions. The Kleibergen-Paap *rk* test and the Anderson-Rubin test confirm the appropriateness of this specification.

We first note that trade openness still exhibits a significant, positive relationship with specialization. Figure (2.2b) shows that the marginal effect of financial openness on specialization is positively associated with the degree of financial development, implying that the effect of financial openness in promoting specialization is larger in countries with more developed financial systems and smaller in those with less developed financial system.

To summarize, three key findings emerge from our analysis so far. First, trade and to a somewhat less extent financial openness are important in explaining variations in industrial specialization across countries. Second, trade-induced specialization is stronger if trade is predominantly of the inter-industry type. Third, the effect of financial openness on specialization is particularly present when the level of financial development is high.

2.4.2 Are openness to trade and financial openness complements?

So far, we have neglected the possible connection between trade and financial openness in affecting specialization. We now proceed by examining the joint effect of trade and financial openness, as described in equation (2.2a).

[26] See, for example, the studies of Masten *et al.* (2008) and Klein & Olivei (2008).

The results are shown in columns (I) to (III) of Table 2.3. Column (I) reports the OLS estimates, which are likely to be biased and inconsistent since they neglect the endogeneity of trade openness, financial openness and their interaction term, as evidenced by the DHW statistic shown in column (II). Therefore, we primarily rely on two-step GMM estimates in column (II), where we instrument trade and financial openness as well as their interaction term using lagged values at $t-2$, $t-3$, $t-4$. Again, the Arellano-Bond test and Hansen J test guarantee the validity of our instruments. Finally, the Kleibergen-Paap *rk* test and the Anderson-Rubin test show that equation (2.2a) is properly identified. Lastly, column (III) applies the average of neighboring countries' trade and financial openness as alternative instruments. The results are similar in magnitude, albeit less significant.

To see the role of each type of openness, we have to also consider the interaction effect, which enters with a positive sign, significant at the one percent level, suggesting a complementary relationship between trade and financial openness. In other words, the effect of trade openness is further enhanced by the degree of financial openness, and vice versa.

In order to further assess the strength of each type of openness, we calculate the marginal effect of one type of openness *conditional* on the other type, based on equations (2.2b) and (2.2c). Figures (2.3a) and (2.3b) illustrate these conditional marginal effects and the corresponding 95 percent confidence intervals (Brambor *et al.*, 2006).[27]

[27] The magnitude and significance of β_1 and β_2 in equation (2.2a) do not bear direct interpretation regarding the impact of trade and financial integration on specialization as the interaction term, i.e., β_3, needs to be taken into account. Since we are mainly interested in how trade and financial integration act as moderators of each other's relationship with specialization, we therefore compute the conditional marginal effect, following Brambor *et al.* (2006). This approach sheds more light on the threshold effects demonstrated in the following paragraphs. Ozer-Balli & Sorensen (2010) propose a different treatment and interpretation of linear regression models with interaction terms. They suggest that a model with a demeaned instead of a conventional interaction term is preferable as the former maintains the interpretation of the coefficients to main terms similar to a model without the interaction term, while keeping the coefficient on the interaction term (largely) unchanged. Following their approach, we re-estimate equation (2.2a), where in place of $T_{it}xF_{it}$, we use a demeaned interaction term

Table 2.3: Are openness to trade and financial openness complements?

Column	(I)	(II)	(III)	(IV)	(V)	(VI)
Specification	OLS	GMM	Instrument	Equity	FDI	Debt
T	-0.014	-0.212**	-0.387	0.158*	0.052	-0.150*
	(0.057)	(0.083)	(0.436)	(0.088)	(0.067)	(0.089)
F	-0.003	-0.351***	-0.500			
	(0.053)	(0.101)	(0.365)			
Equity				-0.263***		
				(0.102)		
FDI					-0.477***	
					(0.136)	
Debt						-0.259**
						(0.102)
T*F	0.004	0.093***	0.137			
	(0.012)	(0.022)	(0.089)			
T*Equity				0.065***		
				(0.023)		
T*FDI					0.112***	
					(0.030)	
T*Debt						0.069***
						(0.023)
Size	-0.001	0.209	0.274	0.310***	0.304**	0.271
	(0.165)	(0.146)	(0.223)	(0.115)	(0.139)	(0.172)
GDPpc	-0.378***	-0.329***	-0.400***	-0.326***	-0.474***	-0.285***
	(0.102)	(0.069)	(0.124)	(0.076)	(0.079)	(0.046)
GDPpc2	0.060***	0.018	0.009	0.013	0.045***	0.020
	(0.022)	(0.015)	(0.026)	(0.018)	(0.017)	(0.014)
Endogeneity		0.056	0.147	0.119	0.019	0.035
AR(2)		0.125	0.186	0.062	0.244	0.101
Over-identification		0.124	0.166	0.104	0.662	0.502
Under-identification		0.009	0.110	0.045	0.009	0.004
Weak-identification		0.000	0.000	0.000	0.000	0.000
Observations	738	685	679	645	685	685

All models are estimated in first difference. Variables are expressed in logs. The dependent variable is S, the Gini specialization index in all specifications; T is trade openness, defined as total imports plus exports/GDP; F is Financial openness, defined as total financial assets plus liabilities/GDP; *Equity* is the assets and liabilities of portfolio equity/GDP; FDI is the assets and liabilities of FDI/GDP; *Debt* is the assets and liabilities of debts/GDP; *Size* is the country size, measured as the number of population; $GDPpc$ is per capita real GDP (Constant 2000 U.S. dollars); $GDPpc2$ is per capita GDP squared; Endogeneity is the Durbin-Wu-Hausman test; AR(2) are Arellano-Bond serial correlation tests; Over-identification is the Hansen J statistic; Under-identification is the Kleibergen-Paap *rk* test; Weak-identification is the Anderson-Rubin test. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Figure (2.3a) demonstrates that trade openness always has a positive relationship with specialization, independent of the level of financial openness. To shed more light on the economic nature of the relationship between trade openness and specialization, we can now evaluate equation (2.2b) at the mean, minimum and maximum value of financial openness. The marginal effect of trade openness on specialization at the mean level of financial openness is 0.232. When financial openness is at its lowest and we reach the bottom left corner of Figure (2.3a), the marginal effect of trade openness is zero. Finally, when financial integration peaks and we reach the top right corner of Figure (2.3a), the effect of trade integration is 0.947.[28] Summing up, trade openness results in more specialization as countries become more financially integrated. Once risk sharing opportunities - caused by the higher level of financial integration - are sufficient, trade openness appears to induce specialization. This result is also in line with the argument that financial openness facilitates the reallocation of capital to sectors that have a comparative advantage, thus increasing the opportunities for trade (Feeney, 1994a,b).

Figure (2.3b) demonstrates that the relationship between financial openness and specialization strongly depends on the level of trade openness. We find evidence of a threshold effect, since the positive effect of financial openness on specialization only occurs when countries are sufficiently open to international trade. The marginal effect of financial integration becomes positive when the log of trade openness equals to 3.77, corresponding to a trade openness ratio of approximately 45 percent of GDP. At the mean level of trade openness, the impact of financial integration on specialization is 0.1. When evaluated at the minimum level, the impact takes the value of -0.278, while it becomes

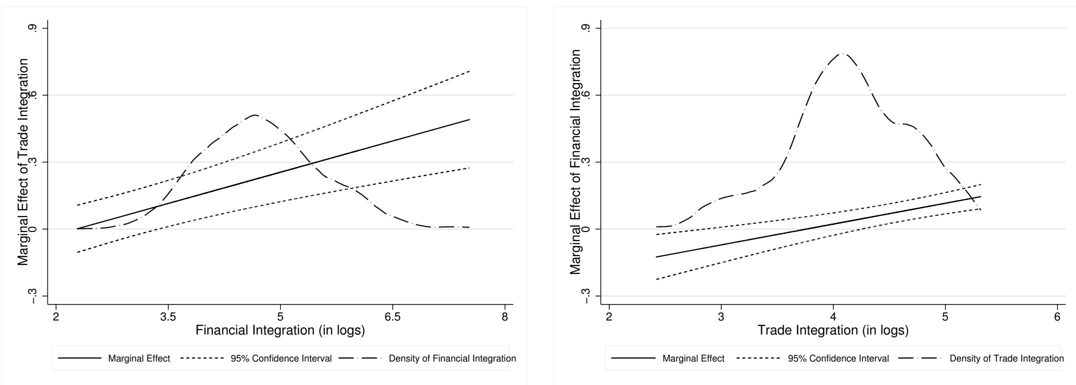
$(T_{it} - \bar{T_{it}})x(F_{it} - \bar{F_{it}})$. We find that the coefficients of T_{it} and F_{it} bear positive signs, significant at 1 percent and 5 percent, respectively, and the magnitudes are very close to those reported in column (VIII) in Table 2.2. Moreover, the coefficient on the demeaned interaction team is slightly higher than that of the conventional interaction term T_{it} and F_{it} reported in column (II) in Table 2.3.

[28]The calculation is as follows: $-0.212 + 0.093 \times 4.757 = 0.232$, $-0.212 + 0.093 \times 2.284 = 0$, $-0.212 + 0.154 \times 7.525 = 0.947$, all numbers are expressed as elasticities.

0.528 when the level of trade openness reaches its maximum.[29] This finding provides evidence that growing trade flows create extra demands for international insurances and enlarge the scope for financial openness to have a bigger impact on specialization.

Figure 2.3: The role of trade integration and financial integration as complements

(a) Financial integration as a moderator **(b)** Trade integration as a moderator



Our results also relate to a strand of recent research documenting that the level of trade openness matters for the effects of financial openness. For example, more open economies are found to be less vulnerable to financial crises (Calvo *et al.*, 2004; Cavallo & Frankel, 2008; Edwards, 2004b). Countries that are more open to trade suffer smaller growth declines than those with a lower degree of trade openness (Edwards, 2004a; Guidotti *et al.*, 2004). Such findings are consistent with the notion that trade integration precedes financial integration. In other words, (developing) countries should liberalize trade before they liberalize capital flows. Our results also lend support to this notion as finance-induced specialization can only be realized when a threshold level of trade openness is achieved. The fact that the effect of country size is still

[29]The calculation is as follows: $-0.351 + 0.093 \times 4.14 = 0.034$, $-0.351 + 0.093 \times 2.42 = -0.126$, $-0.351 + 0.093 \times 5.316 = 0.143$.

insignificant and the U-shaped pattern between GDP per capita and specialization is not present in column (II) lends further support to the relevance of the diversification effect of economic development.

A widespread view from the literature is that the extent of risk sharing achieved via financial integration is not only dependent on the overall size of capital flows, but also on their composition, i.e., the relative shares of portfolio equity, FDI and external debt. Portfolio equity and FDI flows are perceived to be more conductive to risk sharing (Kose *et al.*, 2009b), whereas debt flows are more prone to sudden stops, triggering economic crises. Thus, it would be desirable for (emerging) countries to reduce their reliance on debt finance and increase the importance of equity investments and FDI (Rogoff, 1999).

To investigate whether the specific types of capital flows (or the corresponding stocks) have different effects on specialization, we focus on three narrower measures of financial openness, corresponding to the stocks of total portfolio equity ($Equity$), FDI (FDI) and debt ($Debt$) relative to GDP, respectively. We re-estimate equation (2.2a) but replace F with $Equity$, FDI, and $Debt$. We want to uncover whether portfolio equity and/or FDI flows are more conducive to risk sharing, therefore exerting a greater positive impact on specialization.

Columns (IV), (V) and (VI) in Table 2.3 report the two-step GMM estimates. The DHW statistics confirm that trade and financial openness (different types of stocks), together with their interaction term are indeed endogenous variables, except in Column (V). To ensure the consistency of our estimations, we use lagged levels at $t-2$, $t-3$, $t-4$ as instruments. The diagnostic tests again confirm the validity of our instruments and the proper identification of the results.

With the results in columns (IV) to (VI), we also compute the marginal effects of trade openness on specialization at the mean level of portfolio equity, FDI and debt, respectively. In line with Kose *et al.* (2009b) and Rogoff (1999), we find that the marginal effect is largest for FDI (0.354), followed by portfolio equity (0.268). The effect is considerably small for debt (0.147).

Summing up, we find that trade and financial openness are complementary in their effects on specialization. We find a threshold effect for trade openness as a moderator for the effect of financial openness on specialization. Further analysis shows that trade openness has a stronger effect when financial openness facilitates risk-sharing, i.e., involves equity investments and/or FDI.

Robustness analyses

We conduct a series of robustness checks based on equation (2.2a) and demonstrate that our results are insensitive to alternative measures and specifications in Table 2.4.

We first consider alternative measures of trade openness. Columns (I), (II) and (III) in Table 2.4 employ the imports share to GDP (IMP), exports share to GDP (EXP) and manufacturing trade openness ($MANT$), respectively. Results are very similar to those reported in column (II) in Table 2.3. Overall, our results do not seem to be driven by the choice of a particular trade openness measure.

Next, we check whether the estimation results are driven by outliers. One or more very open countries could potentially drive the results. We drop Ireland, where the financial openness is the highest in our sample, re-run the estimation and find quantitatively similar results in column (IV) in Table 2.4.

Furthermore, we adopt two other measures of industrial specialization, namely the Herfindahl-Hirschman index (HRI) and the coefficient of variation (VSI), calculated using value added data on 20 NACE industries. Results are reported in columns (V) and (VI) in Table 2.4. We find no changes to our main findings.

One possible source of bias in our estimates is that changes in industrial specialization may capture the declining share of manufacturing in general. Based on the distribution of in-sample changes in manufacturing shares of total GDP, we therefore construct two sub samples, one excluding countries in the highest quantile, and the other one excluding the lowest quantile. We find that the results, reported in columns (VII) and (VIII) are qualitatively similar across the two sub samples, meaning that the changes in specialization can not be attributed to the contraction of manufacturing activity as a whole.

Table 2.4: Robustness analyses

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)	(XIII)	(XIV)	(XV)
	Trade Openness			Outlier	Specialization Indices		Decline in Manufacturing		Small	Large	Sample period		Time Effect		Controlling for
					HRI	VSI	Less Decline	More Decline	Countries	Countries	1970-1985	1986-2004	Trend	Dummies	Endowments
T				-0.183*	-0.236**	-0.244**	-0.375***	-0.170*	-0.145	-0.523***	-0.360***	-0.149	-0.206*	-0.092	-0.-084
				(0.099)	(0.096)	(0.116)	(0.092)	(0.094)	(0.109)	(0.135)	(0.131)	(0.134)	(0.109)	(0.096)	(0.092)
IMP	-0.237***														
	(0.087)														
EXP		-0.176**													
		(0.077)													
MANT			-0.202**												
			(0.103)												
F	-0.303***	-0.207*	-0.436***	-0.345***	-0.318**	-0.333**	-0.462***	-0.320***	-0.309**	-0.550***	-0.403***	-0.287*	-0.385***	-0.295**	-0.278**
	(0.079)	(0.106)	(0.139)	(0.118)	(0.125)	(0.156)	(0.118)	(0.108)	(0.121)	(0.143)	(0.138)	(0.172)	(0.142)	(0.130)	(0.129)
Fjure															
T*F				0.089***	0.083***	0.096***	0.121***	0.084***	0.077***	0.139***	0.095***	0.079**	0.093***	0.078***	0.082***
				(0.026)	(0.026)	(0.031)	(0.0239)	(0.026)	(0.028)	(0.030)	(0.032)	(0.036)	(0.027)	(0.029)	(0.029)
IMP*F	0.110***														
	(0.022)														
EXP*F		0.067***													
		(0.023)													
MANT*F			0.124***												
			(0.037)												
ARGI															-0.019
															(0.018)
RES															-0.017***
															(0.006)
HC															-0.221
															(0.175)
Size	0.321**	0.064	0.497**	0.204	0.432**	0.415*	0.266	0.412***	0.324*	0.145	-0.402**	0.988***	0.024	0.262	0.237
	(0.140)	(0.156)	(0.230)	(0.162)	(0.188)	(0.241)	(0.163)	(0.142)	(0.192)	(0.166)	(0.163)	(0.302)	(0.189)	(0.185)	(0.182)
GDPpc	-0.347***	-0.306***	-0.492***	-0.326***	-0.698***	-0.661***	-0.328***	-0.104	-0.429***	-0.336***	-0.533***	0.019	-0.392***	-0.329***	-0.378***
	(0.083)	(0.060)	(0.096)	(0.078)	(0.113)	(0.113)	(0.051)	(0.125)	(0.123)	(0.078)	(0.141)	(0.132)	(0.100)	(0.081)	(0.102)
GDPpc2	-0.004	0.032**	0.026	0.021	0.089***	0.064***	0.014	-0.031*	0.038	0.014	0.105***	-0.059**	0.034*	0.020	0.019
	(0.017)	(0.015)	(0.025)	(0.018)	(0.021)	(0.0240)	(0.013)	(0.019)	(0.025)	(0.017)	(0.030)	(0.025)	(0.018)	(0.0187)	(0.016)
Observations	685	685	672	654	685	685	499	555	608	450	243	459	685	685	645
Endogeneity	0.048	0.076	0.130	0.112	0.101	0.056	0.066	0.278	0.234	0.107	0.452	0.029	0.084	0.015	0.000
AR(2)	0.116	0.750	0.440	0.230	0.351	0.069	0.481	0.137	0.164	0.358	0.034	0.516	0.093	0.081	0.448
Over-identification	0.140	0.127	0.395	0.137	0.241	0.189	0.204	0.138	0.208	0.266	0.417	0.185	0.124	0.310	0.505
Under-identification	0.018	0.074	0.615	0.009	0.009	0.009	0.061	0.043	0.022	0.053	0.018	0.056	0.133	0.018	0.034
Weak-identification	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

All models are estimated in first difference using the two-step GMM estimator. Variables are expressed in log. The dependent variable is S, the Gini specialization index in all specifications, except in (V) to (VI) where the dependent variables are HRI and VSI, respectively. HRI and VSI are Herfindahl-Hirschman index and coefficient of variation, calculated using value added data; T is trade openness, defined as total imports plus exports/GDP; F is Financial openness, defined as total financial assets plus liabilities/GDP; IMP is the share of imports/GDP; EXP is the share of exports/GDP; $MANT$ is manufacturing trade/GDP; F is Financial openness, defined as total financial assets plus liabilities/GDP; $Size$ is the country size, measured as the number of population; $GDPpc$ is per capita real GDP (Constant 2000 U.S. dollars); $GDPpc2$ is per capita GDP squared; $ARGI$ is the agricultural production as a share of GDP; RES is the total natural resource rents as a percentage of GDP; HC is education attainment measured by the average year of schooling for the population aged 25 or over; Endogeneity is the Durbin-Wu-Hausman test; AR(2) is the Arellano-Bond serial correlation tests; Over-identification is the Hansen J statistic; Under-identification is the Kleibergen-Paap rk test; Weak-identification is the Anderson-Rubin test. Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Another potential bias may arise from the equal treatment of large and small countries. The dynamic relationship between openness and specialization may differ across these two groups of countries. To further investigate the effect of country size, we employ the same methodology as previously, following Imbs & Wacziarg (2003), where we construct two sub samples, one excluding countries in the highest quantile of the distribution of country size, measured as total population, the other one excluding countries in the lowest quantile. The results are shown in columns (IX) and (X) in Table 2.4. We find that the estimated openness-specialization nexus is very similar using the first sub sample of small countries. A notable difference using the second sub sample of large countries is that the threshold effect of trade openness is in place, indicating that trade openness results in more specialization only when financial openness reaches a certain threshold level, corresponding to a financial openness ratio above 45 percent of GDP, which is above 10th percentile of the distribution of financial openness.

In addition, we examine whether the openness-specialization relationship has changed over time. To do so, we split the sample at 1985, run the same specification for both sub samples and report results in columns (XI) and (XII) in Table 2.4. We find no evidence that the estimated relationships are substantially different over time.

Furthermore, we check whether our results are driven by the time effects in two ways. We include a linear time trend in column (XIII) and a series of time dummies (per every 5-year period) in column (XIV), respectively. The results are very similar, albeit some decrease in the significance of trade openness. Therefore, we find no support of possible time effects that could potentially drive our results.

Lastly, we control for the effects of country factor endowments on specialization by including the agricultural production, natural resource rents and education attainment in column (XV). Besides a significant negative relationship between natural resource rents and specialization, we do not find that agricultural production and education attainment are significantly correlated with specialization. The main results are again very similar, and thus not affected by country factor endowments.

In summary, we conclude that our findings are robust to a wide range of alternative measurement strategies.

2.5 Conclusion

This paper investigates the economic integration - industrial specialization nexus and empirically establishes the direct linkages between trade, financial openness and industrial specialization for a panel of 31 countries over the period 1970-2005.

We contribute to the existing literature by answering two important questions. First, we document the relationship between economic integration and specialization via two separate channels, trade and financial openness. We find a statistically significant and positive relationship between trade openness and specialization, suggesting that further openness to foreign trade induces a more specialized industrial structure, and a statistically significant positive effect of financial openness on specialization, in line with the risk-sharing rationale put forward by Kalemli-Ozcan *et al.* (2003), and subsequently confirmed by Basile & Girardi (2010) and Imbs (2004). In terms of magnitude, the impact of trade openness appears to be larger than that of financial openness. In addition, our results reveal that trade openness has a stronger relationship with specialization in countries with low levels of intra-industry trade. Financial openness has a stronger relationship with specialization in countries with more developed financial systems, although this complementary effect does not appear to be very strong.

Second, we show that the role of trade (financial) openness is further enhanced by the degree of financial (trade) openness. Our finding indicates that trade and financial openness complement each other in shaping industrial specialization across countries. Furthermore, trade openness coincides with increased specialization for all levels of financial openness, whereas financial openness co-exists with high degrees of specialization only if countries are sufficiently open to trade. These findings extend Imbs (2004) by offering additional insights in understanding trade and financial openness as joint determinants of specialization across countries. Moreover, we find some evidence that portfolio equity and FDI are somewhat more effective in complementing trade openness than debt. Overall, our results are robust to a wide range of alternative measures and estimation strategies.

A main implication of our results is the importance of simultaneously deepening trade and financial integration. Countries that exploit integration along both lines can expect to benefit the most from integration, while insuring themselves against idiosyncratic shocks. However, both effects depend crucially on the degree to which trade is intra-industry and the level of development of the domestic financial system. On the one hand, countries with more intra-industry trade and a low level of financial development may not reap great benefits from specialization. On the other hand, countries with large inter-industry trade and a relatively high level of financial development stand to gain the most from increased trade and financial integration, as the former will allow them to reap the fruits of comparative advantage, whereas the latter may improve risk-sharing. Finally, our analysis underlines the fact that in the presence of asymmetric shocks, there is still a need for better risk-sharing mechanisms, in particular in the presence of common policy objectives, such as is the case, for example, in the Eurozone.

Appendix

Table 2.A.1: Specialization Patterns across Countries

Country	Specialization 2004	△ Specialization	△ Specialization 1986-2004	△ Manufacturing
Australia (1970-2004)	0.455	11.371	9.112	-12.817
Austria (1970-2004)	0.337	-16.193	2.763	-8.575
Belgium (1970-2004)	0.444	-2.176	-1.616	-12.000
Canada (1979-2003)	0.381	6.932	6.306	-3.121
Cyprus (1995-2004)	0.561	-1.947	-1.947	-5.062
Czech Republic (1995-2004)	0.404	-2.604	-2.604	2.538
Denmark (1970-2004)	0.517	6.866	13.915	-5.998
Estonia (1995-2004)	0.478	-4.648	-4.648	-3.888
Finland (1970-2004)	0.463	10.199	15.899	-2.725
France (1970-2004)	0.379	-7.696	6.125	-10.817
Germany (1970-2004)	0.448	13.527	15.151	-12.353
Greece (1970-2004)	0.491	-3.500	-3.418	-12.368
Hungary (1995-2004)	0.386	-19.653	-19.653	1.378
Ireland (1970-2004)	0.658	17.789	18.005	4.408
Italy (1970-2004)	0.383	-0.506	5.965	-8.729
Japan (1973-2004)	0.415	5.291	16.854	-11.853
Korea (1970-2004)	0.456	-13.253	22.583	10.806
Latvia (1995-2004)	0.574	-8.822	-8.822	-7.525
Lithuania (1995-2004)	0.489	-13.952	-13.952	0.999
Malta (1995-2004)	0.561	9.119	9.119	-4.364
Luxembourg (1970-2004)	0.437	-37.697	-37.699	-31.850
Netherlands (1970-2004)	0.486	8.938	-0.386	-10.935
Norway (1979-2002)	0.473	23.825	11.035	-8.142
Poland (1995-2004)	0.353	-6.129	-6.129	-2.044
Portugal (1970-2004)	0.418	-9.074	-6.351	-1.575
Slovakia (1995-2004)	0.364	-4.954	-4.954	-2.826
Slovenia (1995-2004)	0.399	7.756	7.756	-1.128
Spain (1970-2004)	0.398	-16.715	2.576	-14.457
Sweden (1970-2004)	0.417	9.246	5.906	-3.329
United Kingdom (1970-2004)	0.404	10.076	17.047	-20.461
United States (1970-2004)	0.319	2.966	13.522	-7.227

The time span for each country is in parentheses. Specialization is the Gini coefficient (value added) in 2005.△ Manufacturing indicates the total changes in the manufacturing share of GDP over time.

Figure 2.A.1: Specialization at different aggregation levels

(a) Comparison with lower aggregation **(b)** Comparison with higher aggregation

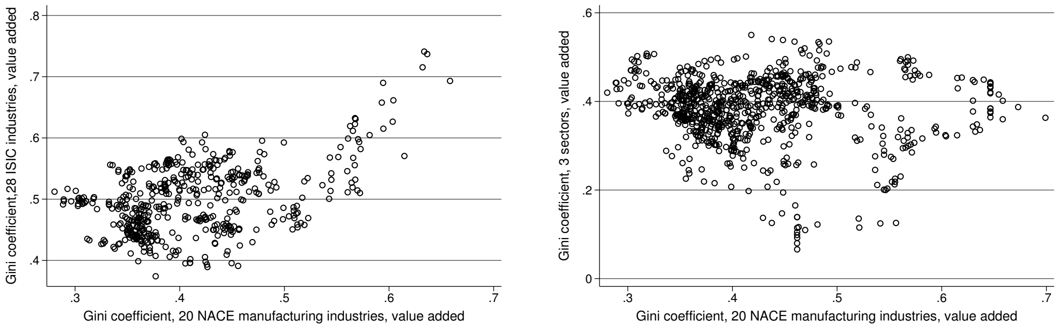


Table 2.A.2: Industries and NACE Codes

Industry	NACE Code
Food, beverages and tobacco products	15-16
Textiles, wearing apparel	17-18
Leather products and footwear	19
Wood products and cork	20
Pulp, paper products	21
Publishing and printing	22
Coke, refined petroleum and nuclear fuel	23
Pharmaceuticals	24
Rubber and plastics products	25
Other non-metallic mineral products	26
Basic metals	27
Fabricated metal products	28
Machinery, NEC	29
Office machinery	30
Other electrical machinery	31
Electronic valves and tubes	32
Scientific instruments	33
Motor vehicles, trailers and semi-trailers	34
Building repairing aircraft and spacecraft	35
Manufacturing nec, recycling	36-37

Chapter 3

Room to Move: Why Some Industries Drive the Trade-Specialization Nexus and Others Do Not

3.1 Introduction

Over the past two decades, economic integration, mirrored by a rapid growth in international trade, has had a strong impact on specialization in the European Union (EU). During the 1997 to 2006 period, all EU14 countries except Portugal have experienced a significant increase in industrial specialization. Particularly large increases are observed in United Kingdom, Austria and France, where Gini coefficients have risen by 14.5, 10.1 and 9.8 percent, respectively. The Gini coefficient in Portugal has decreased by 5.6 percent.

The economic literature has a long tradition of analyzing *what* drives the relationship between trade and specialization. Classical trade theories predict that trade integration will result in increasing specialization in sectors where a country has a comparative advantage due to cross-country differences in technology or factor endowment (Ohlin, 1933; Ricardo, 1817). New trade theories stress the importance of increasing returns to scale and product differentiation in facilitating intra-industry trade and predict that international trade will induce a shift of increasing-return industries towards countries with good market access, i.e., the core (Krugman, 1979, 1980). New economic geography theories emphasize agglomeration forces and suggest a non-monotonic relationship between trade liberalization and location of economic activities, depending on the level of trade costs (Krugman, 1991; Venables, 1996).[1]

Much less is know about *who* drives the relationship between trade and specialization. Melitz (2003) argues that within-industry reallocation of resources contributes to a major part of industry productivity growth following increases in trade openness.[2] Bernard *et al.* (2007) extend Melitz (2003) by combining his setup with a standard Heckscher-Ohlin model, showing that within-industry reallocation, induced by the decline of trade costs as described in Melitz (2003) is stronger in comparative advantage industries than in comparative disadvantage industries. Since the imposition of constant mark-ups seems at odds with the pro-competition effect of trade, Melitz & Ottaviano (2008) introduce quasi-linear firm preferences to generate endogenous mark-ups that vary with firm productivity, market size and international trade. In their model, intra-industry reallocation is magnified by the fact that by lowering the level of protection, trade intensifies product market competition, reduces prices and mark-ups, and forces high-cost firms to exit. In addition to exporting, importing (Kasahara & Lapham, 2008) and engaging in foreign direct investment (FDI) (Helpman *et al.*, 2004) have also been considered as channels to induce within-industry reallocation.

In this paper, we investigate which industries are driving the trade-specialization nexus. We follow Melitz (2003), and argue that industries need 'room to move' in order for increasing trade openness to translate into increased specialization. We are further motivated by a growing body of recent theoretical and empirical literature that has highlighted the importance of analyzing firm-level

[1]Lower trade costs result in the agglomeration of economic activities into fewer locations. However, a further reduction in trade costs leads to a geographical dispersion of activities when labor mobility across sectors exhibits finite costs.

[2]He demonstrates this by building a dynamic industry model incorporating firm heterogeneity into Krugman's (Krugman, 1979) monopolistic competition framework.

adjustment processes in response to the openness to foreign trade (Bernard *et al.*, 2006; Eslava *et al.*, 2009; Pavcnik, 2002; Trefler, 2004; Tybout & Westbrook, 1995). These studies have documented the existence of a substantial degree of firm-level heterogeneity even within narrowly defined industries.[3] A substantial part of the effect of international trade is channeled into the reallocation of resources within the industry, which in turn shapes the industry aggregates. In our paper, the true drivers of the trade-specialization nexus are productive firms, who benefit from the increase in trade-openness and can appropriate resources from less productive firms, thus causing the industry in which they operate to expand, at the expense of other industries, in which there is no room to make such moves. We argue and find that the potential for reallocation in industries determines whether there is a trade-specialization nexus; in industries with little potential for reallocation, increased trade openness has no effect, or a negative effect, on that industry's share of total value added. As a result, the trade-specialiation nexus is driven by a small number of industries, which nevertheless have a significant impact on concentration patterns.

To analyze who drives the trade-specialization nexus, we use a panel data set consisting of 330,852 manufacturing firms spanning 18 industries in 14 EU countries over the period 1997-2006. After we estimate firm-level economies of scale and technical efficiency levels for each industry, we use the initial level and dispersion in both productivity measures to endogenously sort each industry into one of two classes. We observe a positive, inverted-U shape trade-specialization relationship for the high-potential class; the same relationship is insignificant or slightly negative for the low-potential class. Our analysis is further supported by a detailed instrumentation strategy, and an elaborate robustness analysis. In addition, we verify the relevance of our approach by demonstrating how closely our predicted specialization patterns match the actual specialization that took place in the EU over our sample period.

[3]Bartelsman *et al.* (2004) have made important advancements in compiling firm-level panel data across a considerable number of countries and conducting international comparison of productivity and firm-level dynamics, although the role of trade-induced reallocation has not been explicitly examined.

Our study is related to two strands of literature. The first strand has examined the dynamic relationship between trade liberalization and specialization patterns. For instance, Beine & Coulombe (2007) study the impact of trade liberalization between Canada and the US and find a positive short-run relationship and a negative long-run relationship, i.e., short-run specialization and long-run diversification. Crabbé *et al.* (2007) conduct a similar analysis for 13 CEEC countries and find that trade liberalization leads to long-run specialization. Compared with both studies, our analysis benefits from having far less potential for aggregation bias.

The second strand of the literature relevant to our work concerns the intra-industry reallocation process in response to trade liberalization. Pavcnik (2002) finds that trade liberalization in Chile during the 1979-1986 period has had substantial reallocation and productivity effects. Trefler (2004) examines the reallocation and productivity effect of the Canada-U.S. Free Trade Agreement (FTA) on Canadian industries, and finds that industries with the deepest Canadian tariff reduction experienced a reduction in employment by 12 percent plus a 15 percent increase in industry labor productivity due to the contraction of low-productivity plants. For the US, Bernard *et al.* (2006) demonstrate that productivity gains are most pronounced in industries where trade barriers have declined the most.[4] To the best of our knowledge, our study is the first contribution to the literature on how firm-level dynamics affect the integration-specialization nexus, based on a unique sample of EU manufacturing firms.

The remainder of the paper proceeds as follows. Section 3.2 presents the models used and the econometric strategy. Section 3.3 presents the data and the measures proposed. Section 3.4 discusses the results. Finally, section 3.5 summarizes and concludes.

[4] For a comprehensive survey, see Tybout (2000).

3.2 Methodology

In this section we first present our empirical model. A conditional latent class framework is employed to examine the heterogeneous effect of trade integration on specialization, conditional on the within-industry potential for reallocation. Next, we discuss methodological concerns and our identification strategy.

3.2.1 Empirical Framework

Substantial theoretical and empirical research has shown a positive relationship between trade openness and specialization (i.e., concentration of industries) at the country-level,[5] implying that the effect of trade has been different across industries. More specifically, it must be positive for those industries have increased their share of the total value added, and negative or not significantly different from zero for all other industries, consequently results in a changing in the distribution of industry shares. The aim of this paper is therefore to examine this differential effect of trade openness across industries and thereby uncover which industries drive the trade-specialization nexus. To do so, we start our analysis by using the following equation at the industry-level:

$$S_{iot} = f\left(T_{iot}\right) \tag{3.1}$$

where S_{iot} is a measure describing the extent to which a country o at time t specializes in industry i, and T is that industry's trade openness at the same time. Using the simplest possible parametrization, while allowing for a non-linear effect in the spirit of new economic geography theories (Krugman, 1991;

[5]Most neoclassical trade theories, with reference to the theory of comparative advantage, predict a positive relationship between trade liberalization and industrial specialization. For example, Dornbusch *et al.* (1977) demonstate that falling trade costs result in a narrowing non-traded sector; it is therefore cheaper to import goods than to produce them domestically. Thus resources are freed up and used more intensely in fewer activities. The empirical studies are numerous. See for example,Sapir (1996), Brülhart (2001a), Longhi *et al.* (2003) and Riet *et al.* (2004).

Venables, 1996), we can write:

$$S_{iot} = \beta_0 + \beta_1 T_{iot} + \beta_2 T_{iot}^2 + \beta' Z_{iot} + \varepsilon_{iot} \tag{3.2}$$

where β' is an $1 \times n$ parameter vector; Z is a $n \times 1$ vector of control variables, where we include the size of the manufacturing sector and industry-level labor productivity.

But what drives the trade-specialization nexus? Or, rather, *who* drives it? Since Melitz (2003), we know that intra-industry reallocation of resources contributes to a major portion of industry productivity growth following increases in trade openness. Melitz (2003) also teaches us that *actual* reallocation is expected to be endogenous to trade openness. Important for the purposes of our analysis is the *potential* for reallocation, as trade openness can act as the catalyst that facilitates the realization of this potential, as *reflected* in changes in specialization. Put differently, we expect the trade-specialization nexus to be driven by those industries that have a large enough potential to reallocate resources, thus benefiting from the increased trade openness. Let us call these industries high-potential (HP) industries, as opposed to low-potential (LP) industries.

In practice, of course, HP is a latent variable. However, we can estimate that variable using a sorting equation, which assigns each industry i in country o at time t to either the HP industries or the LP industries class. If we let θ_{iot} measure the odds of being an HP industry, conditional on the set of variables in the vector V_{iot}, then

$$\theta_{iot} = \frac{\exp\left(V_{iot}\theta^{HP}\right)}{\exp\left(V_{iot}\theta^{HP}\right) + \exp\left(V_{iot}\theta^{LP}\right)}. \tag{3.3}$$

Of importance in the light of our analysis is the vector V_{iot}: it should contain covariates that predict whether an industry will be able to reallocate from its least productive to its most productive firms, thus benefiting from the opportunities that have arisen as a result of increased trade openness and resulting in an increased share of this industry in total production or value added. In Section 3.3, we explain the variables contained in V_{iot} in detail. For now, we note that these variables capture productivity differences at the firm level *within* each industry i in country o at time t, at the *start* of our sample period. As a result, V_{iot} captures the potential for reallocation, and is then used to estimate θ_{iot}.

Once we know the prior probability, for each industry i in country o at time t, of being part of the HP class, we can estimate θ_{iot} with a logit model. We can then also allow for endogenous sorting of each industry i in country o at time t into each of the classes, and can rewrite equation (3.2) as follows:

$$S_{iot} = \beta_{0|HP,LP} + \beta_{1|HP,LP}T_{iot} + \beta_{2|HP,LP}T_{iot}^2 + \beta'_{HP,LP}Z_{iot} + \varepsilon_{iot|HP,LP} \quad (3.4)$$

where each class, HP and LP, has its own parameter vector β. In other words, β_0, β_1, β_2 and β' are allowed to differ across classes.

To obtain those parameter estimates, equation (3.4) is jointly estimated with equation (3.3) using a maximum likelihood procedure, following Greene (2007). In this procedure, the unconditional likelihood for each industry i in country o at time t is obtained as a weighted average of its class-specific likelihood using the prior probabilities of being in classes HP and LP as the weights. Each industry i in country o at time t is thereby placed in the class where it contributes the most to the total likelihood of the estimated system, which is being maximized.[6]

Although it is natural in light of our investigation to estimate equations (3.3) and (3.4) for two classes, we need to identify the optimal number of classes. Orea & Kumbhakar (2004) suggest using the Akaike Information Criterion (AIC) and Schwartz Bayesian Information Criterion (SBIC), where the preferred specification has the lowest AIC and/or SBIC. [7]

[6]The sum of all unconditional likelihoods over all industries i in countries o at time t is maximized with respect to the parameter vectors for each class in equation (3.4) and the parameters in the sorting equation (3.3). With these parameter estimates, a posterior estimate of the class membership probability for each industry i in country o at time t can be computed using Bayes' theorem. Each observation is assigned to a particular class with the largest posterior probability. The posterior estimate of the parameter vector β can also be obtained by multiplying the posterior membership probability.

[7]Theoretically, the maximum number of classes is only restricted by the number of cross-sections, i.e., the number of observations in the data. However, empirically an over-specification problem limits the existence of a large number of classes.

In practice, the class allocation may exhibit a certain degree of persistence and is likely to be stable. However, following Bos *et al.* (2010), industries can switch classes over time, since an industry's allocation in a given period is *ex ante* independent of its allocation in other periods. We can thus study how the changes in the potential for reallocation affect the dynamics of the trade-specialization relationship. In addition, adding this flexibility to the model may allow us to identify causality, as explained below.

To summarize, we employ a conditional latent class model to examine the heterogeneous relationship between trade integration and specialization in K endogenously determined groups of industries. The group membership probabilities are conditional on the potential for reallocation by exploring firm-level efficiency and scale characteristics within industries.

3.2.2 Identification of causality

In order to analyze whether there is a *causal* effect of trade openness on specialization, we need an identification strategy. Obviously, the simple correlation between trade openness and specialization can not be interpreted as evidence of causality because specialization itself also affects trade. For example, Imbs (2004) demonstrates a negative relationship running from specialization to trade, as a result of intra-industry trade. Furthermore, unobserved industry/country characteristics can influence both trade and specialization/production - such as industrial policies or demand shifts that are difficult to measure and control for.[8] Given these concerns, identification based on the direct impact of trade openness on specialization will yield inconsistent estimates.

As a first step to proper inference, we observe that the three-dimensional panel that we have (industry, country, time) makes it possible to include a wide array of fixed effects in order to control for the unobserved heterogeneity.

[8] Another reason is that specialization is theoretically linked to the factor content of trade, as an industry that has a large share in GDP is likely to be an exporting sector. So the relationship between production patterns and endowments is not independent of the relationship between trade and endowments.

In particular, the possibility to introduce interacted fixed effects enables us to sweep out a much wider range of omitted variables. For example, industry $\times$ time (*it*) effects would not only absorb industry fixed effects, but also the average effects of time-varying industry characteristics, such as economies of scale, research-orientation, technology level and labor intensiveness (Longhi *et al.*, 2003; Midelfart-Knarvik *et al.*, 2000). Similarly, country $\times$ time (*ot*) effects eliminate all time-varying country characteristics that affect specialization, such as market potential, R&D spending or labor abundance (Longhi *et al.*, 2003; Midelfart-Knarvik *et al.*, 2000). Furthermore, the industry $\times$ country effects capture any peculiar characteristics that vary for each industry-country combination and stay constant during our sample period 1997-2006. Therefore, in our specification, we control for all these three types of interactive fixed effects, namely industry $\times$ time, country $\times$ time and industry $\times$ country by demeaning both sides of equation (3.4) along these three dimensions. However, all these fixed effects may still not eliminate factors at the industry $\times$ country $\times$ time dimension. To deal with this concern, we incorporate output per worker as a control variable to correct for any technological shifts at the industry $\times$ country $\times$ time level that could affect specialization (López & Sánchez, 2005). Essentially, our identification strategy thereby exploits the time variation within each industry in each country, in line with our aim of exploring the role of (time-varying) firm dynamics in the trade-specialization relationship.

Furthermore, we endeavor to establish a causal link between trade openness and specialization by addressing reverse causality in two ways through the use of instrumental variables.

First, we construct an instrumental variable for trade openness at the industry level, using gravity estimates. This methodology is developed by Frankel & Romer (1999) in the context of studying the relationship between trade openness and growth at the country level, and has been extended by Di Giovanni & Levchenko (2009) to the industry level. For each industry, Di Giovanni & Levchenko (2009) estimate a (cross-section) gravity equation to predict bilateral trade openness by means of distance, population, language, land-border, land area and land-locked status. The summation of the predicted trade openness across trading partners yields an industry-level natural openness measure, i.e., predicted trade volume as a percentage of output not only in each country, but also in each industry within each country. Gravity estimates provide a good instrumental variable as the geographical variables used are plausibly exogenous and highly correlated with the actual trade openness. Our point of departure is to extend Di Giovanni & Levchenko (2009) within a panel framework. Our approach corrects for important mis-specifications of gravity models commonly used in the literature, and yields a time-varying industry-level natural openness. The latter is particularly appealing in our context as we are interested in the evolution of the effects of trade openness on specialization over time, given the fact that trade barriers and costs have decreased significantly in the EU during the past few decades (Chen & Novy, 2011).

Second, we construct an industry-specific time-varying trade integration measure proposed by Chen & Novy (2011). They derive a micro-founded measure of bilateral sector-specific trade frictions, i.e., the inverse of bilateral trade integration. They model disaggregated trade flows at the industry level in a gravity framework, allowing trade costs to be heterogeneous across industries. This measure is proven to be theoretically consistent with a wide range of trade models and correlated with a large set of observable trade cost proxies.[9] Appendix A lays out the details of our approach.

3.3 Data

We use an extensive data set that contains firm-level, industry-level and country-level data for 18 manufacturing industries in 14 EU countries over the period 1997-2006. For the firm-level data, we have compiled a comprehensive data set based on annual editions of the AMADEUS (Analyze Major Databases from

[9] It is worth noting that measurement error in independent variables can lead to misleading inferences in regression-type applications. Although employing the instrumental variable of trade openness we have constructed might introduce measurement errors in our estimations, using Chen & Novy (2011)'s measure does not have this problem. Therefore, we present results using both approaches and are confident that measurement errors do not pose a serious challenge to the validity of our results.

European Sources) database.[10] We supplement this data set with industry- and country-level data from various sources. Industry-level data - disaggregated at NACE 2-digit - on value added, output, imports, exports and employment are taken from the OECD (2008) Structural Analysis Database (STAN). Country-level data on manufacturing GDP and GDP are retrieved from the World Bank (2008) *World Development Indicators* (WDI). Except for employment, all data are reported in current U.S. dollars. The industries and countries included in our sample are listed in Table 3.A.1 and Table 3.A.2 in Appendix A, respectively. Below, we explain how each of the variables we use is constructed.

Our aim is to construct an industry-specific specialization index, since we are primarily interested in examining the heterogeneity of the trade-specialization relationship across industries. Our starting point is Redding (2002), who uses neoclassical trade theory to derive a specialization measure (spe), defined as nominal industry value added as a percentage of a country's total GDP.[11] In equation (3.5), we express Redding (2002)'s measure as the product of an industry's share of a country's manufacturing value added (S) and manufacturing's share of a country's GDP (MS).

$$spe_{iot} = \frac{VA_{iot}}{GDP_{ot}} = \frac{VA_{iot}}{VA_{ot}^{\text{manufacturing}}} \times \frac{VA_{ot}^{\text{manufacturing}}}{GDP_{ot}} = S_{iot} \times MS_{ot} \qquad (3.5)$$

In our estimations, we log transform each of these components, which then allows us to include the log of MS as a control variable and the log of S as our dependent variable. In this manner, we isolate the impact of increased trade openness within manufacturing industries from the overall decline in

[10] One of the characteristics of the AMADEUS database is that each edition only includes surviving firms. In addition, as time has gone by, the coverage of AMADEUS has increased. By using all annual editions of AMADEUS, and compiling the dataset both backward looking (to reduce survivorship bias) and forward looking (to increase the coverage), we are able to construct the most comprehensive firm-level data set of European manufacturing firms.

[11] This measure has the advantage of being theory-consistent, in contrast with ad-hoc definitions of specialization that have been used by other authors, such as the indexes of revealed comparative advantage, pioneered by Balassa (1965).

manufacturing activity.[12]

As a robustness test, we also construct an additional measure of specialization, S'. This measure is the log of the normalized value added, where for each country, normalization is based on the value added of the food industry (NACE 15-16), which is set at 100 at the beginning of our sample, in 1997. Essentially, this normalized variable captures the changes of industry composition within a country over time. We describe the results using this variable as a robustness check in Appendix D. From Table 3.1, we observe that there is a wide variation in shares across manufacturing industries, as expected. The variation of the share of the manufacturing sector as a whole, however, varies much less. In addition, we control for industry-specific, time-varying productivity by including output per worker (Y/L), which varies significantly across our sample.

In a similar vein, we measure trade integration at the industry level. The existing literature distinguishes between *de jure* and *de facto* measures of trade integration (Sachs & Warner, 1995; Wacziarg & Welch, 2008). *De jure* measures capture the extent of government restrictions on trade flows, whereas *de facto* measures quantify the degree of openness through realized trade flows. Since *de jure* measures are typically not available at the industry level, we mainly rely on the measure of *de facto* openness (T), defined as the ratio of industry imports and exports to output (Di Giovanni & Levchenko, 2009). Table 3.1

[12] One point worth noting is that the sum of S equals to one each country each year, implying that trade openness can not result in specialization, i.e. increasing shares of all industries simultaneously. Put differently, when can we expect to get a positive marginal effect, $\frac{\partial S_{iot}}{\partial T_{iot}} = \beta_1 + 2 * \beta_2 T_{iot} > 0$ from estimating equation (3.2)? Clearly, this is the case if $\frac{\partial S_{iot}}{\partial T_{jot}}$ is positive for all industries in all countries *and* T_{iot} is increasing in roughly half of the sample, whereas it is decreasing in the other half of the sample. In practice, trade openness has increased over time in most industries in our sample, rendering it impossible to find a positive relationship trade openness and specialization under the assumptions just mentioned. However, there is another possibility: even if T_{iot} is non-decreasing in all (or most) of the sample, we can still find a positive β_1 if the sign and/or magnitude of the underlying relationship between trade openness and specialization is *not* the same for all industries in a country. More specifically, in that case the relationship must be positive for those industries that have increased their share of the total value added, and negative or not significantly different from zero for all other industries. Our latent class framework therefore exploits this possibility.

contains descriptives of both T and its instruments T' and T'', described in the previous section. The main observation from comparing the three trade openness measures, is that the measure based on Chen & Novy (2011) has far less variance than the other two measures. The correlation between openness and natural openness is 0.9, whereas the correlation between openness and trade integration is 0.2. Both correlations are significant at the 1 percent level.

Table 3.1: Descriptive statistics[a]

	Variable	Description	Source	Mean	Min	Max	Std
S	S	Specialization	OECD STAN	5.877	0.016	23.585	4.267
	S'	Normalized specialiation	OECD STAN	1.458	-4.110	3.161	0.905
T	T	Openness	(imports+exports)/value added	153.290	16.677	5735.303	405.529
	T'	Natural openness (instrument)	Di Giovanni & Levchenko (2009)	165.858	11.655	9344.317	562.117
	T''	Trade integration (instrument)	Chen & Novy (2011)	2.273	0.710	6.206	1.017
Z	Y/L	Labor productivity, \$1000	OECD STAN	281.449	17.895	8036.795	522.882
	MS	Manufacturing share	OECD STAN	18.311	8.715	26.452	4.071
V	$DS_{25/75}$	Scale dispersion, 25/75 ratio	AMADEUS, own calculations	1.035	1.002	1.109	0.014
	$DS_{10/90}$	Scale dispersion, 10/90 ratio	AMADEUS, own calculations	1.070	1.003	1.174	0.026
	DS_{σ}	Scale dispersion, standard deviation	AMADEUS, own calculations	0.028	0.002	0.073	0.009
	$DE_{25/75}$	Efficiency dispersion, 25/75 ratio	AMADEUS, own calculations	1.151	1.001	13.085	0.279
	$DE_{10/90}$	Efficiency dispersion, 10/90 ratio	AMADEUS, own calculations	1.435	1.001	13.516	0.576
	DE_{σ}	Efficiency dispersion, standard deviation	AMADEUS , own estimations	0.112	0.001	0.365	0.038
	$Sca_{t=0}$	Initial scale level (weighted)	AMADEUS, own calculations	1.091	0.886	1.623	0.149
	$Eff_{t=0}$	Initial efficiency level (weighted)	AMADEUS, own calculations	0.773	0.176	0.910	0.082

[a] Number of observations is 2,138; based on specifications given in Table 3.3; Std=standard deviation.

To capture the intra-industry potential for reallocation, we need a set of conditioning variables V_{iot}. Since this type of reallocation takes place *between* firms in the same industry, we require firm-level observations to construct industry-level measures. Our objective is to show the extent to which the most productive firms in an industry can grow by appropriating the assets of the least productive firms. Therefore, we need to measure the dispersion in productivity within each industry in each country. We measure the productivity of each firm in two ways. First, and most closely related to Melitz (2003), we estimate each firm's economies of scale. Second, and based on the same estimations, we estimate each firm's efficiency. Our primary measure of dispersion is the ratio of the productivity of firms in the top quantile (i.e., with the highest economies of scale, or the most efficient) to the productivity of firms in the bottom quartile (i.e., with the lowest economies of scale, or the least efficient), the 25/75 ratio. To check the robustness of our results, we also use two other measures of dispersion, the 10/90 ratio and the standard deviation of scale and efficiency, described in the robustness analysis in Appendix D. To control for the initial level of industry efficiency/scale, for each industry we take the weighted-average of efficiency/scale by the firm's total assets.

We estimate each firm's economies of scale and efficiency as follows. First, we estimate a stochastic production frontier for each industry, described in detail in Appendix B. Our approach has three distinct features. First, by estimating a translog production function, we allow for increasing, decreasing and constant economies of scale within an industry at any time. Second, by estimating this production function using stochastic frontier analysis (SFA), we can also measure efficiency, i.e., the extent to which firms with the *same* economies of scale and input levels produce different levels of output. In our approach, the error term of that stochastic production frontier is composed of two parts (Aigner *et al.*, 1977; Battese & Corra, 1977; Meeusen & Broeck, 1977): a one-sided component with a truncated distribution that captures inefficiency, as well as a systematic component that allows for measurement errors or other random shocks around the production frontier. Third, we account for systematic differences in production technologies, which may otherwise be wrongly labeled as inefficiency (Orea & Kumbhakar, 2004), by estimating true fixed effects frontiers (Greene, 2005), with firm- and country-fixed effects for each industry-specific frontier. In so doing, we still assume that firms that produce similar products and thereby operate in the same industry can be benchmarked against each other, even if they operate in different countries. Put differently, even though we allow for structural differences in output (and productivity) between firms that operate in the same industry, but in different countries, we assume that these firms have access to the same production technology.[13]

[13]Bos *et al.* (2010) endogenize the allocation of European manufacturing industries in a low- and high-technology class. Although, in their paper, the same industry can belong to one class in one country and another class in another country, in their Table A4 they show that most industries cluster in the same class, confirming that technology difference, in EU manufacturing,

For our firm-level productivity estimations, we use the all-companies module of AMADEUS, a database provided by Bureau Van Dijk Electronic Publishing. This pan-European database contains detailed financial and business data on more than 10 million public and private firms in 44 European countries. The homogeneity of the data collecting process across countries and its fairly complete coverage, especially of privately held firms makes it well suited for our analysis. Our sample consists of 330,852 manufacturing firms across 14 EU countries over the 1997-2006 period. We choose manufacturing industries because in contrast to services, they are more involved in trade and more responsive to trade integration.[14] We group all firms into 18 industries to ensure a sufficient number of firms in each industry-country combination, and compatibility with other industry-level data. The choice of countries is based on the quality of firm-level coverage.[15] To estimate the stochastic production frontier, we use raw data on gross value added, tangible fixed assets and number of employees to construct firm-level output (Y), capital (K) and labor (L), respectively. Appendix C describes the AMADEUS database, the sample selection procedure and the construction of our variables in details. Table 3.1 summarizes the definitions, sources and descriptive statistics of the main variables used in our analysis, respectively.

In Table 3.1, we observe that the most efficient quartile of firms is on average 15% more efficient than the least efficient quartile. However, if we move one standard deviation (0.279) above this average, the difference has increased to more than 40%. Results are similar for the other two efficiency dispersion measures. Average efficiency at the beginning of the sample period is 77.3%, indicating that the average firm should be able to increase its output by 22.7% without increasing its use of inputs. The average economies of scale at the beginning of the sample period are 1.091, indicating that the average firm experiences increasing returns to scale, and can increase its output by 1.091% by

are industry- rather than country-specific.

[14]On average, manufacturing trade accounts for 80 percent of total merchandize trade in the EU.

[15]We compare the total number of manufacturing firms and the number reported in OECD 2006 Structural and Demographic Business Statistics (SDBS) and select countries with more than 30 percent of firms covered.

increasing its inputs by 1%. The top quartile firms operates with economies of scale that are on average 3.5% larger than the bottom quartile, although this difference can increase to more than 10% for some industries.

As explained in the previous section, for the purpose of our analysis, we aim to measure the potential for reallocation in each of the industries in each of the countries. But how valid are our measures introduced above? In order to validate them, we also calculate the actual degree of reallocation that takes place in each industry in each country over the sample period, using a decomposition method suggested by Olley & Pakes (1996). Consider the following decomposition of efficiency and scale for an industry i in country o at the period t:

$$Sca_{iot} = \sum_j w_{jiot} Sca_{jiot} = \overline{Sca_{iot}} + \sum_j (w_{jiot} - \overline{w_{iot}})(Sca_{jiot} - \overline{Sca_{iot}}) \tag{3.6}$$

$$Eff_{iot} = \sum_j w_{jiot} Eff_{jiot} = \overline{Eff_{iot}} + \sum_j (w_{jiot} - \overline{w_{iot}})(Eff_{jiot} - \overline{Eff_{iot}}) \tag{3.7}$$

where j indexes firms, and Sca and Eff refer to efficiency and economies of scale, respectively. In equation (3.6), Sca_{iot} represents the value-added weighted average economies of scale in industry i in country o at time t and $\overline{Sca_{iot}}$ the unweighted average economies of scale. Equation (3.6) decomposes the value added weighted average scale into a first component that is size invariant, and a second component that is not. It is this second component in which we are interested, as it measures the sample covariance between economies of scale and value added. The larger this covariance, the higher the share of the value added that is produced by firms with higher economies of scale, and consequently the higher the industry-level economies of scale. The same applies to efficiency, in equation (3.7). Validating our measures of the potential for reallocation therefore involves assessing whether they are positively correlated with these two covariance terms.

3.4 Results

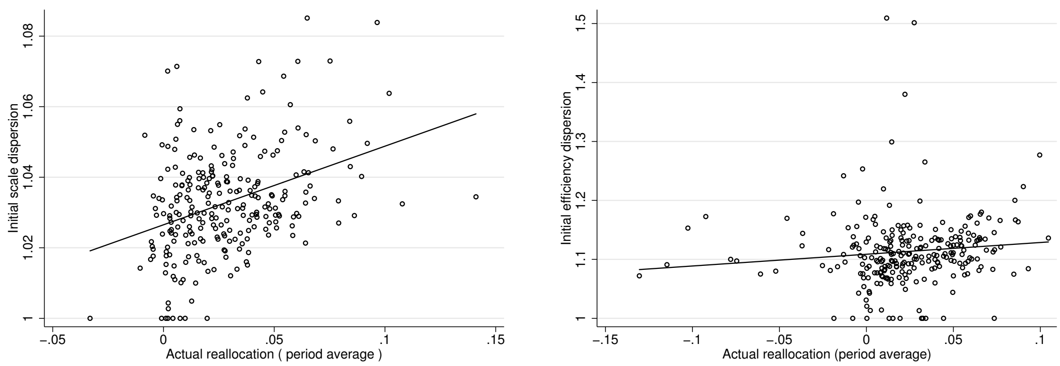
In this section we present our results. First, we validate our measures of the potential for reallocation. Secondly, we examine whether the potential for reallocation has indeed driven the trade-specialization nexus. Thirdly, we explore the treatment effect from changes in trade openness, and fourthly we verify our results by comparing the actual shares of industries with the ones predicted by our model.

3.4.1 Validation: actual and potential reallocation

Do we find that industries with the most 'room to move' are also the ones where subsequently reallocation is most likely to take place? To validate our measures of the potential for reallocation, in Figures (3.1a) and (3.1b) we compare them to the actual reallocation that took place during our sample period.

Figure 3.1: Potential vs. Actual Reallocation

(a) Scale **(b)** Efficiency



Two concurrent developments can be noted from these figures. First, we observe that higher levels of dispersion, signifying the greater potential for reallocation, are positively correlated with actual reallocation, especially for economies of scale. Second, as most covariance terms are positive, the reallocation is indeed in line with Melitz (2003), and can lead to the expansion of the industry in which firms are located.

3.4.2 How has the potential for reallocation driven the trade-specialization nexus?

Our aim is to explain why some industries drive the trade-specialization nexus and others do not. Therefore, we start by determining the number of groups or classes of industries identified by our latent class model. Following Orea & Kumbhakar (2004), we estimate for two, three and four classes, respectively, and formally test using the Akaike and Schwartz Bayesian information criteria (AIC and SBIC, respectively). We do so using the natural openness measure following (Di Giovanni & Levchenko, 2009) and the trade integration measure from Chen & Novy (2011). As shown in Table 3.2, a specification with two classes is preferred for both measures, since this results in the lowest AIC and SBIC.[16]

Table 3.2: Specification Tests of the Number of Groups[a]

	Natural Openness[b]				Trade Integration[c]			
Specification	Likelihood	Parameters	AIC	SBIC	Likelihood	Parameters	AIC	SBIC
Two-group	2313,357	15	14,507	100,734	2195,605	15	14,612	100,83
Three-group	2360,783	25	34,467	178,178	2256,219	25	34,557	178,269
Four-group	2415,082	35	54,421	255,617	no convergence			

[a] Akaike Information Criterion (AIC)= $2m - 2nLF(k)$, Schwartz Bayesian Information Criterion (SBIC)= $-2lnLF(k) + mln(n)$; m is the number of parameters, n is the number of observations, LF(k) is the log likelihood for groups. The preferred specification has the lowest AIC or the lowest SBIC. See Orea & Kumbhakar (2004). Obs=2,318;
[b] Di Giovanni & Levchenko (2009); [c] Chen & Novy (2011).

Table 3.3 contains our estimation results. Panel B contains parameter equality tests and confirms what we have found so far: there are two distinct groups of industries, with significantly different parameters, both for trade openness and output per worker. Also, the parameters for variables used in the sorting equation are jointly significantly different from zero.

[16]For a possible third group, we find that parameters are jointly not significant from zero, and the number of observations allocated in this additional group is rather small.

Turning to Panel C, we see that the industries in the first class are characterized by a higher efficiency dispersion, a lower initial efficiency level, and a higher initial economies of scale level. Scale dispersion, however, is not higher in this first class. Most notable is the difference in the change in S, the manufacturing share of industries. In the first class, the change is between 2.5 and 3.2%, whereas it is approximately -1.5% on average in the second class. Summing up, we henceforth refer to the first class as the high-potential or HP class, whereas the second class is referred to as the low-potential or LP class. The prior class probabilities (at data means) show that approximately between 7% and 9.2% of our sample belongs to the HP class, while the rest is assigned to the LP class.

Table 3.3: The Trade-Specialization Nexus at the Industry Level

Panel		Parameter Estimates	Natural Openness[b]		Trade Integration[c]	
			High-potential	**Low-potential**	**High-potential**	**Low-potential**
Panel A[a]	Kernel	T	0.708 (0.218)***	-0.171 (0.067)**	0.396 (0.320)	-0.261 (0.062)***
		T^2	-0.087 (0.017)***	-0.016 (0.007)**	-0.421 (0.581)	0.077 (0.048)
		Output per worker	0.251 (0.066)***	0.215 (0.021)***	0.408 (0.071)***	0.285 (0.021)***
		Constant	0.001 (0.016)	0.000 (0.001)	0.007 (0.017)	0.000 (0.002)
	Sorting	Scale dispersion	17.719 (8.137)**	Reference	14.066 (9.459)	Reference
		Efficiency dispersion	5.940 (1.438)***	Reference	5.720 (1.411) ***	Reference
		Initial scale level	14.282 (1.426)***	Reference	14.998 (1.475)***	Reference
		Initial efficiency level	-4.144 (1.860)**	Reference	-2.499 (2.576)	Reference
		Constant	-39.846 (8.665)***	Reference	-38.130 (9.856)***	Reference
		Prior class probability	0.092	0.908	0.072	0.928

Panel	Equality Tests	Natural Openness[b]			Trade Integration[c]		
		Wald	**P-value**	**Conclusion**	**Wald**	**P-value**	**Conclusion**
Panel B	All parameters	14.519	0.000	Rejected	32.980	0.000	Rejected
	T and T^2	15.306	0.000	Rejected	19.362	0.000	Rejected
	Sorting variables	62.224	0.000	Rejected	50.380	0.000	Rejected

Panel	Class Characteristics	Natural Openness[b]			Trade Integration[c]		
		HP	**LP**	**P-value[e]**	**HP**	**LP**	**P-value[e]**
Panel C	Scale dispersion	1.033	1.036	0.000	1.032	1.036	0.000
	Efficiency dispersion	1.243	1.135	0.000	1.252	1.135	0.000
	Initial scale level	1.333	1.048	0.000	1.349	1.050	0.000
	Initial efficiency level	0.708	0.784	0.000	0.704	0.784	0.000
	ΔS (%)	2.504	-1.511	0.001	3.203	-1.548	0.000

[a] Standard errors in parentheses; significance at the 10/5/1 percent level (*/**/***);
[b] Di Giovanni & Levchenko (2009); [c] Chen & Novy (2011); [d] Measured at data means;
[e] Significance of difference in means.

Of course, what remains to be seen is whether the trade-specialization nexus is indeed driven by the *HP* class, as we conjecture. We therefore turn to Panel A, which contains the parameter estimates. We start with the parameters in the sorting equation. Scale and efficiency dispersion increase the likelihood of being in the *HP* class, as expected. High initial scale levels make it more likely that an industry will be driving the trade-specialization nexus, whereas high efficiency levels make it less likely that an industry is in the *HP* class. Overall, results are more significant for the natural openness measure (Di Giovanni & Levchenko, 2009) than for the trade integration measure (Chen & Novy, 2011), which may be explained by the latter's low variance.

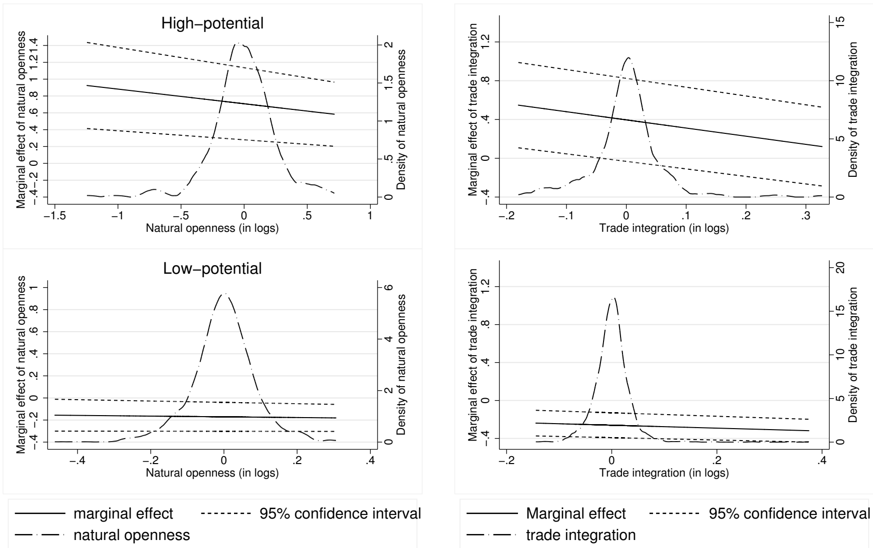
In the top part of panel A, we find the parameter estimates for trade openness and labor productivity. As expected, labor productivity always has a positive relationship to an industry's manufacturing share (López & Sánchez, 2005). More interesting are the results for trade openness: in line with our expectations, an increase in natural openness (Di Giovanni & Levchenko, 2009) increases an industry's share in manufacturing in the *HP* class, whereas it has a negative, but much smaller effect in the *LP* class. Both effects are similar, but less significant for an increase in trade integration (Chen & Novy, 2011). For the *HP* class, results are in line with the trade-specialization nexus. For the *LP* class, increases in trade openness have a negative effect on an industry's share in manufacturing. This is in line with López & Sánchez (2005), who find a negative relationship between openness and specialization for ten European countries. They assert that the convergence of industrial structures following the openness to foreign trade is consistent with the prediction of the Hechscher-Ohlin-Vanek theory: when factor prices are equalizing, the sources of comparative advantage arising from relative differences in factor prices disappear.[17]

An interesting question to ask at this point is whether there is a saturation point beyond which further opening-up to international trade may not lead to

[17]Trade integration implies the creation of new exporting industries, which in turn leads to the expansion of aggregate production in those industries. This process could be driven by agglomeration forces and forward (large market)-backward (large input variety) linkages identified by new economic geography theories (Fujita *et al.*, 2001).

Figure 3.2: Conditional Marginal Effect

(a) Natural openness **(b)** Trade integration



increased specialization. Thus, the relationship between trade openness and specialization may no longer be positive for industries with very high levels of openness - a phenomenon that is identified in new economic geography theories (Krugman, 1991; Venables, 1996). These theories postulate a non-linear relationship between trade costs and location of economic activity. The decrease in trade costs induces firms to agglomerate into fewer locations, and a further decline in trade costs can result in geographical dispersion of activities when mobility across sectors exhibits a finite cost. Beine & Coulombe (2007) document a similar positive short-run relationship and a negative long-run relationship between trade integration and specialization, i.e., short-run specialization and long-run diversification based on export data of Canadian regions.

Therefore, in order to further assess the economic nature of the relationship between trade openness and specialization, we calculate the marginal effect of trade on specialization, i.e., the partial derivative of S with respect to T in equation (3.4), conditional on the level of trade openness T for both the HP

and the *LP* class. Figure (3.2a) and Figure (3.2b) illustrate these conditional marginal effects and the corresponding 95 percent confidence intervals (Brambor *et al.*, 2006). We infer for the *HP* class that although the effect of openness on specialization decreases as industries' natural openness (in the top part of Figure (3.2a) and as trade integration increases (in the bottom part of Figure (3.2b). The marginal effects remain positive and significantly different from zero in both cases. Thus, although there is some saturation with respect to trade openness, we do not find evidence of a threshold effect for the *HP* class.

Things are even clearer for the *LP* class, where the marginal effect of natural openness (in the bottom part of Figure (3.2a)) and trade integration (in the bottom part of (3.2b)) is scarcely affected by changes in openness or integration and is consistently below zero.

To check the robustness of our results, we first consider an alternative measure of specialization, i.e., (the log of) normalized industry value added. The results are reported in Panel A of Table 3.D.1 in Appendix D. We find that they are qualitatively and quantitatively very similar to those in Table 3.3, despite of the lack of significance for two of the conditioning variables, namely scale dispersion and initial efficiency level. In addition, the division of the sample into a small *HP* and a large *LP* group resembles that of our main specification in Table 3.3.

We then consider two other measures of dispersion, namely the 10/90 ratio and the standard deviation. Panels B and C of Table 3.D.1 in Appendix D display the results. We find no significant changes from our main results, except that the scale dispersion and/or initial efficiency level loses its significance when the dispersion is measured as 10/90 ratio in Panel B of Table 3.D.1. Similar results are found when using the standard deviation as the dispersion measure in Panel C of Table 3.D.1. We find no evidence of changes in the main parameter estimates. But the power of our conditioning variables becomes somewhat weaker - except for the initial economies of scale level - as the individual significance of three variables drops and the efficiency dispersion appears to have the "wrong" sign. These results may highlight the problems of using the standard deviation as the dispersion measure, because firm efficiency and economies of scale are not normally distributed within each industry. Overall, our results do not seem to be driven by the use of an alternative specialization measure, nor by the choice of a particular dispersion measure.

To summarize, we find that the effects of trade openness on specialization appear to be very different in the *HP* and *LP* class. Using the potential for reallocation, i.e. the four conditioning variables jointly determines the allocation of an industry into either the *HP* or *LP* class.

3.4.3 How have the changes in the potential for reallocation affected the dynamics of trade-specialization nexus?

An interesting question that arises is how the changes in the potential for reallocation affect the dynamics of the trade-specialization nexus. The distinctive features of our latent class model allow us to explore this question. In our modeling framework, the probability of belonging to a certain group depends on the average of all four conditioning variables. As a result, the changes in these variables can alter this probability. Therefore, we prefer here to permit industries to switch groups over time, rather than imposing the assumption that they are restricted to one group. Panel A in Table 3.4 shows the migration matrices, including the absolute number and percentage of group allocation changes over time. We can see both in panel A and B that the diagonal elements carry the largest percentage as would be expected, which indicates that the potential for reallocation displays considerable persistence. Transitions from the *LP* to *HP* group are rare. At the same time, transitions from the *HP* to *LP* group are more frequent, suggesting that if industries react to the trade openness by realizing the potential for reallocation, the remaining potential is reduced. Thus, these industries are more likely migrate to the *LP* group. [18]

Most of the industry transitions, i.e., 31.03 percent of all cases, take place in the petroleum industry (18 out of 58), followed by 13.8 and 12.07 percent

[18] We checked whether the occurrence of transition is due to the fact that the conditional probability of an industry being in one group our model assigned is close to 50 percent, which is the conventional cut-off point in the multinomial logit model of equation (3.3). However, the conditional probability of group membership is very high in almost all cases, i.e., above 90 percent. Therefore, the transition is not related to the flexibility of our model.

respectively in basic metals and electronic equipment industries. In terms of country divisions, 22.41 percent of industries transit from the *HP* to *LP* group in Hungary (13 out of 58), which seems not surprising given that CEEC countries are expected to be mostly affected by trade integration. They are closely followed by Portugal and Sweden with 12.07 and 10.34 percent (7 out 58 and 6 out of 58), respectively. However, we find no trends with regard to when these transitions occur.

Panel B in Table 3.4 provides some further insights into why and how some industries migrate from the *HP* to the *LP* group. We examine whether the potential for reallocation is significantly lower for these switchers. More specifically, we employ t-test and Kruskal-Walllis test to test whether the four conditioning variables used to predict group membership differ significantly on average between industries that switch and those that stay in the *HP* group. A positive (negative) sign indicates the variable is higher (lower) than for the industries that stay in the *HP* group. For example, the first column in panel A indicates that efficiency dispersion is significantly lower (at 5 percent and 1 percent) than that of the average of the *HP* group. Overall, we find that the potential for reallocation of these switchers is significantly lower, evidenced by a lower efficiency dispersion, a higher efficiency level and a lower scale level. The scale dispersion appears to have the "wrong" sign, however. These results provide additional support for the saturation effect of trade openness: that the process of openness-driven-specialization is not monotonic, but rather, it is slowing down.

3.4.4 Verification: actual and predicted industry shares

Last but not least, we examine the predictive power of our model by looking at how well it predicts our specialization measure *S*, i.e., the industry shares. To do so, the top parts of Figure (3.3a) and Figure (3.3b) plot the predicted *S* against the actual *S* on the basis of equation (3.4) using natural openness and trade integration, respectively. It shows that the predicted *S* captures a considerable amount of variation embedded in the actual *S* (the correlation

Table 3.4: Transitioning from High-potential to Low-potential

Panel A: Transition matrices

		Natural Openness[b]				Trade Integration[c]		
		To				*To*		
		HP	*LP*	Total		*HP*	*LP*	Total
From	*HP*	215	58	273	*HP*	193	55	248
		(78.75)	(21.25)	(100)		(77.82)	(22.18)	(100)
	LP	56	1574	1630	*LP*	54	1601	1655
		(3.44)	(96.56)	(100)		(3.26)	(96.74)	(100)
	Total	271	1632	1903	Total	247	1656	1903
		14.24	85.76	(100)		(12.98)	(87.02)	(100)

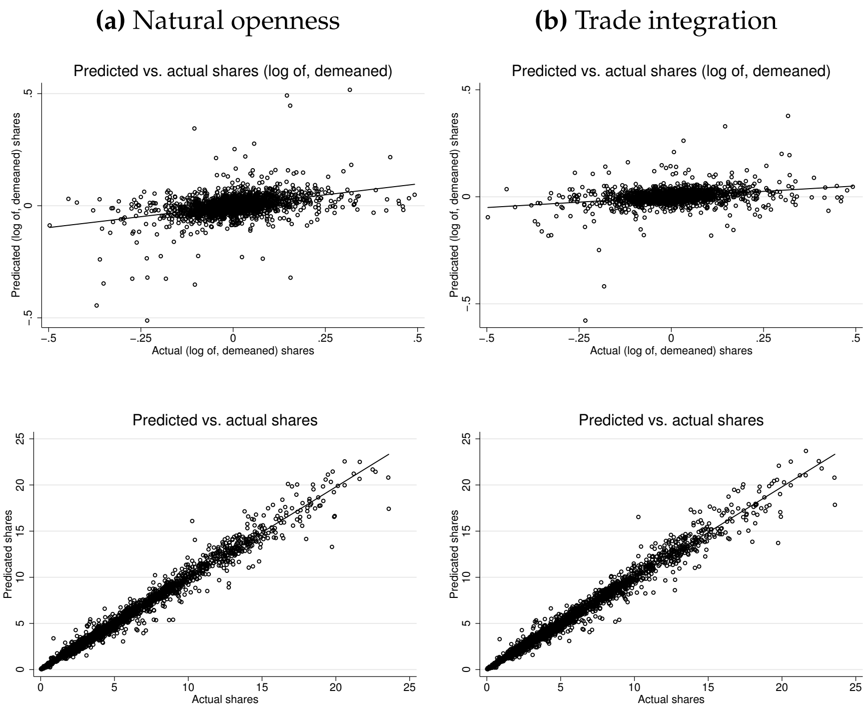
Panel B: Covariates

Variable	Mean	Sign	t-test	KW	Mean	Sign	t-test	KW
Scale dispersion	1.038	+	**	***	1.038	+	***	***
Efficiency dispersion	1.156	-	**	***	1.146	-	**	***
Initial scale level	1.155	-	***	***	1.170	-	***	***
Initial efficiency level	0.766	+	***	***	0.776	+	***	***

[a] Percentages in parentheses; significance at the 10/5/1 percent level (*/**/***); [b] Di Giovanni & Levchenko (2009); [c] Chen & Novy (2011); [d] Measured at data means; [e] Significance of difference in means.

coefficient of 0.4 and 0.35, respectively). One point which deserves noting here is that since the specialization measure used in the estimation is in logs and demeaned, our model essentially predicts the deviation from the means. To retrieve the predicted shares, we add back the actual means (i.e., country-time, industry-time, and industry-country averages discussed in the methodology section).

Figure 3.3: Predictability of the Latent Class Model



The bottom parts of Figure (3.3a) and Figure (3.3b) plot the predicted industry shares (in levels) against the actual shares. It is clear from the figures that they are highly correlated (the correlation coefficient is 0.99 and 0.98, respectively), confirming the predictive power of our model. The caveat to bear in mind is that the "means" we take out may contain important information in explaining specialization, that is beyond the scope of our model.

To summarize, three main findings emerge from our analysis so far. First, the trade-specialization nexus is not homogeneous across all industries, nor is the relationship entirely unique for each industry. Instead, we find two distinctive groups of industries, and the potential for reallocation, i.e. the four conditioning variables, determines the assignment of each industry into a specific group. Second, the trade-specialization relationship is in stark contrast between the *HP* and *LP* group. We find that trade openness induces more specialization towards industries with high potential for reallocation. And the effect of trade decreases when trade openness is beyond a certain threshold. On the contrary, trade openness leads to less specialization in industries when their potential for reallocation is low. Lastly, some industries switch from the *HP* and *LP* group further when the remaining potentials are lower, furthering confirming that the trade-induced specialization process slows down over time.

3.5 Conclusion

This paper has examined the role of reallocation as a driver of the trade-specialization nexus, and shown how firm dynamics constitute a channel through which trade liberalization affects the industrial composition within EU economies.

We have proposed a conditional latent class model to examine the dynamic effect of trade liberalization on specialization across industries. The proposed model allows for a heterogeneous trade-specialization relationship across different endogenously determined groups of industries. The group membership probability is modeled as a function of four firm-based measures that encapsulate the intra-industry potential for reallocation, namely the dispersion of firm efficiency and scale and the initial level of industry average efficiency and scale. To obtain firm-specific efficiency and scale, we set up a model of production that permits the inefficient use of resources and estimate a stochastic production function. In order to overcome endogeneity problems, we employ two novel instrumentation strategies based on the exogenous geographic determinants of trade flows and a micro-founded measure of industry-specific trade frictions.

Using a unique panel of manufacturing firms in 14 EU countries during 1997-2006, we have found evidence that the trade-specialization relationship differs markedly between two distinctive groups of industries and that the relationship depends on the potential for reallocation. We have shown that the potential for reallocation appears to be positively associated with the future actual reallocation observed in reality. On the one hand, an inverted U-shaped trade-specialization pattern has been found in one group of industries which are characterized by greater potential for reallocation, indicating that trade openness induces specialization at a decreasing rate. On the other hand, trade openness results in less specialization in the other group when the potential for reallocation is small. Our results are consistent with the theoretical and empirical evidence that international trade acts as a catalyst in facilitating the intra-industry reallocation of economic activity.

Our findings have important policy implications. As reallocation is a key channel through which industries can benefit from trade liberalization, policies aimed at removing barriers in the factor and product markets are likely to enhance the reallocation of economic activity. The resulting gains in efficiency and economies of scale appear to be an important source of long-run competitiveness and economic growth in the EU.

Appendix A: Instrumentation Strategies

This appendix gives a detailed description of two time-varying industry-level instruments for trade openness used in the estimations of equations (3.3) and (3.4).

Industry-level natural openness

Our first instrument consists of a time-varying measure of industry-level natural openness. Our starting point is the use of the gravity model of trade that has enjoyed remarkable empirical success in predicting a large proportion of variations in observed trade volumes. Furthermore, the gravity model has a solid theoretical foundation and can be derived from almost any standard trade model, including the monopolistic competition model, the Heckscher-Ohlin model, and the latest trade models featuring firm heterogeneity. Frankel & Romer (1999) introduce a natural openness measure that can be used as an instrument. They propose a (cross-section) gravity equation to predict bilateral trade openness between each pair of countries based on a large set of geographical variables, such as distance, population, language, land-border, land area and land-locked status.[19] The summation of predicted trade openness across all trading partners yields a natural openness measure, i.e., the ratio of predicted trade volume to GDP for each country. This measure carries exogenous elements and permits the examination of the causal effect of trade on growth, and is later applied to a wide range of settings in which trade openness and other variables are potentially jointly determined.[20]

Recent literature has extended the gravity estimation using disaggregated data. Although the dependent variable in a gravity equation is generally observed at the country level and does not vary across industries, trade volumes react differently to geographical characteristics in different industries. In other

[19] Instead of predicting trade volumes, Frankel & Romer (1999) predict trade openness, i.e. the trade volumes as a percentage of a country's GDP.

[20] See, for example, Rose *et al.* (2000), Glick & Rose (2002), Subramanian & Wei (2007).

words, the gravity coefficients are found to vary considerably across industries. Consider for example the coefficient for distance: assuming some industries are more sensitive to distance than others, countries that are located further away from their trading partners will have less predicted trade in sectors that are distance-sensitive. Theoretically, Anderson & van Wincoop (2004) demonstrate that the estimated coefficient for distance in the gravity model is a function of trade costs and the elasticity of substitution between product varieties within the sector. Since both trade costs - direct and informational - and the elasticity of substitution differ significantly across industries, it is not surprising that the distance coefficient exhibits significant variations. Di Giovanni & Levchenko (2009) report an industry-specific distance coefficient ranging from -0.8 to -1.6, close to the range of -0.5 to -1.5 reported in Chaney (2008). Therefore, the variation in (all) gravity coefficients is the key for this procedure to work.

Di Giovanni & Levchenko (2009) apply the methodology of Frankel & Romer (1999) at the industry level and subsequently construct an industry-level natural openness measure. Following Di Giovanni & Levchenko (2009), we estimate the following gravity specification for each industry i:

$$\begin{aligned} ln(T_{iodt}) = {} & \alpha_i^0 + \eta_i^1 ldist_{od} + \eta_i^2 lpop_{ot} + \eta_i^3 larea_o + \eta_i^4 lpop_{dt} + \eta_i^5 larea_d \\ & + \eta_i^6 landlock_{od} + \eta_i^7 border_{od} + \eta_i^8 border_{od} \times ldist_{od} + \eta_i^9 border_{od} \times lpop_{ot} \\ & + \eta_i^{10} border_{od} \times larea_c + \eta_i^{11} border_{od} \times lpop_{dt} + \eta_i^{12} border_{od} \times larea_d \\ & + \eta_i^{13} border_{od} \times landlock_{od} + D_{ot} + D_{dt} + \epsilon_{iodt}, \end{aligned} \tag{3.A.1}$$

where c denotes sector, o denotes origin country, d denotes destination country and t denotes time. $ln(T_{iodt})$ is the natural log of bilateral trade (imports plus exports) as a share of output in industry i, from country o to country d at time t. We follow Di Giovanni & Levchenko (2009), and include a gravity variables: $ldist_{od}$ is the natural log of the distance between two countries, defined as the distance between the capitals in the two countries; $lpop_{ot}$ is the natural log of the population of country o at t; $larea_c$ is the natural log of land area of country c; $lpop_{dt}$ is the natural log of the population of country d at t; $larea_d$ is the natural log of land area of country d; $landlock_{od}$ takes the value of 0, 1 or 2 depending on whether none, one or both of the countries are landlocked; $border_{od}$ is a contiguity dummy that takes the value of 1 if countries o and d share a land border; D_{ot} and D_{dt} are a list of time-varying origin and destination country dummies, serving as proxy for multilateral resistance in Anderson & van Wincoop (2003); ϵ_{iodt} is a normally distributed random error term that has a zero mean and a constant variance.

Having estimated equation (3.A.1) for each industry i, we then obtain the predicted log of bilateral trade as a share of output from country o to each of its trading partners d at time t, i.e., $\widehat{ln(T_{iodt})}$. To construct the predicted overall trade in industry i from country o at t, we take the exponential of $\widehat{ln(T_{iodt})}$, and sum across all trading partner countries d as shown in equation (3.A.2):

$$T_{iot} = \sum_{d} \exp\,(\widehat{ln(T_{iodt})}). \tag{3.A.2}$$

Hence, we have created a time-varying measure of industry-level natural openness, i.e., the predicted trade volume as a share of output for each industry i in each country o at time t. Importantly, our instrument is entirely independent of trade liberalization, as all variables used to generate the instrument are deep parameters that are not themselves endogenous to the trade liberalization process.

It is worth noting that in contrast to past gravity literature based on cross sectional data, we use panel data. Therefore, our approach has three distinctive advantages, compared to Di Giovanni & Levchenko (2009). First, following Anderson & van Wincoop (2003), we recognize that the standard gravity specification may have been misspecified in ignoring a multilateral resistance term, since a country pair's relative distance to all other markets may have a punitively large effect on its bilateral trade. Failing to properly incorporate this term can a serious estimation bias, yielding the so-called the 'gold medal error' of gravity model estimations (Baldwin & Taglioni, 2006). An early study by Rose *et al.* (2000) includes a 'remoteness' term. Anderson & van Wincoop (2004) suggest that the inclusion of time-invariant importer and exporter dummies captures multilateral resistance reasonably well in a cross-section setting; however, it does not address the time-varying nature of trade costs in panel data. Hence, we correct by including a series of time-varying importer and exporter dummies to avoid the gold medal error. Second, and equally important, by including these time-varying dummies we can avoid the 'bronze medal error', i.e., the inappropriate deflation of nominal trade values by the US aggregate price index. Thus, our ability to incorporate these time-varying dummies in a panel context allows us to properly address these two misspecification issues. Third, the panel setup permits the construction of an industry-level natural openness that is time-varying. This is much more appealing in our context as we are interested in the evolution of trade openness and specialization over time, given the fact that trade barriers and costs have decreased significantly in the EU over the past few decades.[21]

To estimate equation (3.A.1), we use the OECD STAN Bilateral Trade Database to obtain information on bilateral trade flows (imports and exports) for 18 manufacturing industries in 14 EU countries across 53 trading partner countries over the 1997-2006 period. The industry output data is obtained from the same source. Table 3.A.1 lists the 18 industries and their corresponding NACE codes. The countries included in our sample are listed in Table 3.A.2. All gravity variables are taken from the database, which was compiled by Centre d'Études Prospectives et d'Informations Internationales (CEPII).

Industry-level trade integration

Our second approach to addressing the endogeneity of trade openness is to compute a time-varying measure of industry-specific trade integration pro-

[21] As robustness checks, we estimate two extended specifications. The first one adds additional covariates, such as language, trade agreement, colonial history, monetary union as commonly used in the gravity literature (Rose *et al.*, 2000). The second one introduces a set of country-pair dummies to capture any unobserved factors that are influencing bilateral trade. As a result, some country-pair specific covariates may be absorbed into the pair fixed effects. We find that the industry-level natural openness derived from these two specifications is highly correlated with our preferred specification.

Table 3.A.1: Industries and NACE Codes

Industry	NACE Code
Food products, beverages and tobacco products	15-16
Textiles, wearing apparel, footwear	17-19
Wood and products of wood and cork	20
Pulp, paper products and printing	21-22
Coke, refined petroleum and nuclear fuel	23
Pharmaceuticals	24
Rubber and plastics products	25
Other non-metallic mineral products	26
Basic metals	27
Fabricated metal products	28
Machinery, NEC	29
Office, accounting and computing machinery	30
Insulated wire, other electrical machinery	31
Electronic valves and tubes, telecommunication equipment	32
Scientific instruments	33
Motor vehicles, trailers and semi-trailers	34
Building and repairing of ships and boats, aircraft and spacecraft	35
Manufacturing nec, recycling	36-37

posed by Chen & Novy (2011). They derive a micro-founded measure of bilateral sector-specific trade frictions. Measured as the inverse of bilateral trade integration, the measure is derived from a model of disaggregated trade flows at the sector level in a gravity framework, allowing trade costs to be heterogeneous across sectors. This measure is shown to be consistent with a wide range of theoretical trade models. Empirically, Chen & Novy (2011) regress it on a large set of observable trade cost proxies and find that technical barriers to trade as well as high transportation costs associated with heavy-weight goods are the most important factors in explaining the variation in their bilateral trade integration measure.

Following Chen & Novy (2011), we compute the following for each industry i:

$$\theta_{iodt} = \left(\frac{x_{ioot} \cdot x_{iddt}}{x_{iodt} \cdot x_{idot}}\right)^{\frac{1}{2(\sigma_i - 1)}}, \tag{3.A.3}$$

where i denotes industry, o denotes origin country, d denotes destination country, t denotes time and x represents export flows. The more two countries trade with each other, i.e., the higher $x_{iodt} \cdot x_{idot}$ is, the lower the trade frictions, ceteris paribus. Conversely, the more two countries trade domestically, i.e. the higher $x_{ioot} \cdot x_{iddt}$, the higher the trade frictions, ceteris paribus. Domestic trade in industry i is defined as gross industry output minus total industry exports to the rest of the world. A higher elasticity of substitution σ_i means that consumers are price sensitive; a small price difference induced by bilateral trade costs can lead to a high ratio of domestic to bilateral trade, resulting in a lower θ_{iodt}. The elasticity of substitution σ_i is taken from Imbs & Mejean (2009). Therefore, θ_{iodt} not only captures bilateral trade barriers but also a low degree of product differentiation. We take the weighted average of θ_{iodt} across all trading partners d using the bilateral trade volumes as the weights and then invert it, yielding a time-varying industry-level trade integration measure.

Table 3.A.2: Country of Origin and Destination

Country of Origin (14)
Austria, Belgium, Denmark, Estonia, Finland, France, Hungary, Italy, Netherlands, Norway, Portugal, Spain, Sweden, United Kingdoms
Country of Destination (52)
Argentina, Australia, Austria, Belgium, Bangladesh, Brazil, Canada, Switzerland, Chile, China, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, United Kingdoms, Greece Hong Kong, Hungary, Indonesia, India, Ireland, Iceland, Israel, Italy, Japan, Korea, Lithuania, Latvia Mexico, Malta, Malaysia, Netherlands, Norway, New Zealand, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, Sweden, Thailand, Turkey, Taiwan, United States, Vietnam, South Africa

Appendix B: A Stochastic Frontier Production Model

We model the firm performance by means of a stochastic frontier production function (Aigner *et al.*, 1977). A frontier production function defines the maximum output achievable, given the current production technology and available inputs. If all firms in produce on the boundary of a common production set that consists of an input vector with two arguments, physical capital (K)

and labor (L), output of each firm can be described as:

$$Y^*_{jiot} = f(K_{jiot}, L_{jiot}, t; \beta) \exp\{v_{jiot}\}, \tag{3.B.1}$$

where Y^*_{jiot} is the firm's frontier (optimum) level of output; f and parameter vector β characterizes the production technology; t is a time trend variable that captures neutral technical change (Solow, 1957); and v_{jiot} is an i.i.d. error term distributed as $N(0, \sigma_v^2)$, which reflects the stochastic nature of the frontier.

Some firms, however, may lack the ability to employ existing technologies efficiently and therefore produce less than the frontier output. If the difference between the optimum and actual (observable) output is represented by an exponential factor, $\exp\{-u_{jiot}\}$, then the actual output, Y_{jiot} can be written as $Y_{jiot} = Y^*_{jiot} \exp\{-u_{jiot}\}$, or equivalently:

$$Y_{jiot} = f(K_{jiot}, L_{jiot}, t; \beta) \exp\{-u_{jiot}\} \exp\{v_{jiot}\}, \tag{3.B.2}$$

where $u_{jiot} \geq 0$ is assumed to be i.i.d., with a normal distribution truncated at zero $\mid N(0, \sigma_u^2) \mid$ and independent from the noise term, v_{jiot}.[22]

To operationalize equation (3.B.2), we test different functional forms, and find that a translog production function is preferred. Thus, the stochastic frontier production specification function becomes:

$$\begin{aligned} \ln Y_{jiot} = {} & \beta_i + \beta_1 \ln K_{jiot} + \beta_2 \ln L_{jiot} + \tfrac{1}{2}\beta_{11} \ln K^2_{jiot} \\ & + \tfrac{1}{2}\beta_{22} \ln L^2_{jiot} + \beta_{12} \ln K_{jiot} \ln L_{jiot} + \gamma_t D_t \\ & + \delta_1 \ln K_{jiot} D_t + \delta_2 \ln L_{jiot} D_t + \alpha X + v_{jiot} - u_{jiot} \end{aligned} \tag{3.B.3}$$

where β_i are firm-specific fixed effects, and X is a vector of country dummies. We include a set of time dummies D - which also interact with the vectors K and L - to encapsulate a general index of technical changes(Baltagi & Griffin, 1988). We estimate equation (3.B.3) using a true fixed effects model, following Greene (2007). In this model, the fixed effects β_i are allowed to be correlated with other parameters, but are truly independent of the inefficiency and the error term.

[22] When estimating equation (3.B.2), we obtain the composite residual $\exp\{v_{jiot}\} = \exp\{-u_{jiot}\} \exp\{v_{jiot}\}$. Its components, $\exp\{-u_{jiot}\}$ and $\exp\{v_{jiot}\}$, are identified by the λ (=σ_u / σ_v) for which the likelihood is maximized (for an overview, see Coelli & Battese, 2005).

Recent studies have shown that industries employ different technologies, and are therefore likely to be characterized by different production frontiers(Bos *et al.*, 2010). Imposing a common frontier across industries can create biased estimates of the true underlying technology. Moreover, omitted technological differences may be wrongly labeled as inefficiency (Orea & Kumbhakar, 2004). We account for the heterogeneity in production technology by estimating a separate frontier for each of the 18 industries, and including country dummies. In other words, we assume technology is industry-specific, with (limited) country-level variation. As a result, we obtain efficiency and economies of scale for each firm that reflects the distance to an industry-specific technology.

Two final aspects are worth noting regarding our approach. First, the production frontier represents a set of maximum outputs for a range of input vectors. It is defined by the observations from a number of firms in a specific industry at each time period, in contrast to the conventional approach of assuming that the leading firm constitutes the frontier (Cameron *et al.*, 2005). Second, our approach treats the frontier as stochastic through the inclusion of the error term u_{jiot}, which accommodates noise in the data and therefore allows for statistical inference. In this respect, it differs fundamentally from other non-parametric frontier analysis.[23]

After obtaining the estimated parameters of frontier, the efficiency score for each *jiot* is computed as the ratio of actual over maximum output, $\exp\{-u_{jiot}\} = \frac{Y_{jiot}}{Y^*_{jiot}}$, where $(0 \leqslant \exp\{-u_{jiot}\} \leqslant 1$ and $\exp\{-u_{jiot}\} = 1$ implies full efficiency.

The economies of scale of each firm *j* in industry *i* in country *o* at time *t* are computed by taking the derivative of the production function with respect to *K* and *L* in equation (3.B.3) as follows:

$$scale_{jiot} = \underbrace{\beta_1 + \beta_{11} \ln K_{jiot} + \beta_{12} \ln L_{jiot} + \delta_1 D_t}_{\frac{\partial lnY_{jiot}}{\partial lnK_{jiot}}} + \underbrace{\beta_2 + \beta_{22} \ln L_{jiot} + \beta_{12} \ln K_{jiot} + \delta_2 D_t}_{\frac{\partial lnY_{jiot}}{\partial lnL_{jiot}}} \tag{3.B.4}$$

[23] Comprehensive reviews of frontier approaches can be found in Kumbhakar & Lovell (2003), and Coelli & Battese (2005).

If $scale_{jiot}$ is equal to one, the production of the firm is subject to constant returns to scale, referring to a situation where the output change is proportional to the change in all inputs. If the value is larger (smaller) than one, this indicates increasing (decreasing) return to scale, where output increases by more (less) than that proportional change in inputs.

Appendix C: Data and Variables

The AMADEUS Database

We take the core data used in our analysis from the AMADEUS database. This is a firm-level panel created by the Bureau Van Dijk Electronic Publishing (BvD), which collects standardized commercial data from 50 regional information providers (IPs) across Europe. The AMADEUS 2007 edition, for example, covers more than 10 million private and public firms in 44 European countries.[24] It not only contains detailed information about the profile of companies, such as legal status, year of incorporation, activity code, etc., but also includes financial information on standard balance sheet and income statement items. The AMADEUS database comprises all sectors with the exception of the financial sector and consists of observations for up to 10 years per firm, although the coverage varies by industry and country.[25] The coverage improves significantly over time.

The AMADEUS database has several important advantages, which make it especially well suited to our analysis (Gomez-Salvador *et al.*, 2004). First, the data collection process is fairly homogeneous, ensuring the comparability of results across industries and countries. This overcomes the drawbacks of other cross-country firm panels which are typically constructed using different sources of data (administrative vs. survey), various units of measurement

[24]The AMADEUS database is supplied at three levels of coverage, depending on the number of firms included, namely the Top 250000 module, the Top 1.5 million module, and the All companies module. We use the All companies module, which is the most complete version.

[25]Information on banks and insurance companies are not included in the AMADEUS database. They are presented in two separated databases, i.e. BankScope and ISIS, provided also by BvD.

(firm vs. establishment), inconsistent inclusion criteria (large firms vs. small firms), and uneven sector coverage (manufacturing vs. service) and periods of observation (cross-section vs. panel). Secondly, AMADEUS covers a large proportion of privately-held firms, which account for more than 99.5 % of the total number of firms in the 2007 edition. Previous firm samples which only cover public/large firms are far from representative and may have yielded misleading conclusions regarding the overall behavior of firms. Therefore, the availability of data on private firms in AMADEUS provides a better representation of the entire population of firms, which is the key to measuring the intra-industry dispersion in a more accurate manner. Lastly, one unique advantage of our sample is that the "attrition bias" has been corrected by using different editions of the AMADEUS database. We are able to retrieve data on firms that are no longer exist in the current version, but did exist in the previous editions.

Sample Selection

In constructing the sample for our analysis, we face a number of considerations. First, having a sufficiently complete set of firms within each industry-country combination is crucial in order to derive an accurate measure of dispersion. Additionally, the choice of industry aggregation needs to be compatible with other industry data, in particular industry-level trade and production data. A third consideration lies in the fact that we require a relatively broad set of countries to ensure sufficient variations in industry structural patterns. Last but not least, a longer time span is preferred to show the effects of trade integration as this is a complex process that requires time to develop.

Our main source is the 2007 edition of AMADEUS, which is the latest edition at our disposal. We limit our sample to manufacturing firms, based on the premise that manufacturing industries are more involved in trade and more responsive to trade liberalization. We aggregate these firms into 18 industries. We follow additional steps to complete our sample. We correct for attrition bias by obtaining data from previous editions of AMADEUS on exiting firms that are no longer exist in the current edition. For example, we compare the 2007 edition with the 2006 edition of AMADEUS and detect the firms which are included in the 2006 edition, but no longer in the 2007 edition. We then retrieve data on those firms from the 2006 edition. Similarly, data on those firms that exited in 2006, but remained active in 2005 are extracted from the 2005 edition. The same procedure is repeated between three other pairs, i.e. the 2005 and 2004 editions, the 2004 and 2003 editions and the 2003 and 2002 editions.[26] Following this step, we have assembled the data on a series of exiting firms that are not overlapping with those in 2007 edition. The combination of the main source, together with these non-overlapping firms ensures the unique coverage of our sample.[27] We find that on average, the exit rate is between 5% to 10% on an annual basis.[28]

We apply several exclusion restrictions to our sample. First, our frontier estimation requires firms to have some basic information in their annual accounts. Specifically, we drop all firm-year observations where input (capital, labor) and/or output (value added) information is missing. The reasons for dropping these non-reporting firms are twofold (Klapper *et al.*, 2006). One, there could be country differences in the criteria for including firms with no account information. The other reason is that this restriction eliminates any "phantom" firms established for tax or other purposes. Secondly, to minimize measurement error in the data, we also drop firms where the absolute value

[26] The 2002 edition is the earliest edition in which AMADEUS substantially improves its coverage by including private firms; editions prior to 2002 only covered listed firms. As the coverage of firms increases from 200,000 in the 2001 edition to 3,500,000 in the 2002 edition, this makes prior data less comparable in this respect.

[27] In order to maximize the time-series dimension, we also retrieve some observations in 1994, 1995 and 1996 from the 2004, 2005 and 2006 editions respectively. Since company accounts are typically published annually at the end of March, the AMADUES 2007 edition records data for the 10 years from 1997 to 2006. Thus, we extract additional data going back to 1996 from the 2006 edition, and similarly, to 1995 from the 2005 edition and 1994 from the 2004 edition. However, the quality of the early data is rather poor and we decide to begin our sample in 1997.

[28] Arguably, the AMADEUS database may be subject to selection bias as well. Since it is not census data, there is no legal commitment for firms to provide information. Firms can self-select into the sample or stay out, as, for example, in the case of small and medium sized German firms which are not legally required to disclose (Gomez-Salvador *et al.*, 2004). However this bias appears to be less severe, as coverage of most firms in Europe is provided - i.e., 95 % guaranteed by the IPs.

of either the output or the input growth rate is above 500 percent over the entire sample period. Next, we exclude consolidated accounts if firms also have unconsolidated accounts, to avoid double counting.[29] After data cleaning, our final sample consists of 330,852 firms in 14 countries over the 1997-2006 period.

Variable Definitions

To estimate the stochastic frontier, we require data on firm output (Y), capital (K) and labor (L) from the AMADEUS database. We take gross value-added as the preferred measure of firm output.[30] Since value added is measured in local currency units at current prices, we apply an industry-level value added deflator extracted from the EU KLEMS database and convert each series to constant prices based on the year 1995. For cross-country comparisons, we then use purchasing-power parity (PPP) exchange rates, taken from the Penn World Table, Version 6.3 (PWT 6.3) to convert the local currency measures into 1996 international PPP dollars.

We construct capital stocks using data on tangible fixed assets in local currency at current prices. Next, we use a gross fixed capital formation (GFCF) deflator, extracted from the EU KLEMS and AMECO database, and a PPP ex-

[29] The accounting practice in AMADEUS is classified into six types. 1) Consolidated accounts C1 - accounts of the company headquarters of a group, aggregating all companies belonging to the group (affiliates, subsidiaries, etc.), where the company-headquarter has no unconsolidated account. 2) Consolidated accounts C2 - accounts of the company headquarters of a group, aggregating all companies belonging to the group (affiliates, subsidiaries, etc.), where the company headquarters does have an unconsolidated account. 3) Unconsolidated accounts U1 - accounts of a company with no consolidated accounts. 4) Unconsolidated accounts U2 - accounts of a company which does have a consolidated account. 5) Limited number of financial items LF - accounts of a company with only a limited number of information/variables included. 6) No financial items at all NF - accounts of a company with no financial items/variables included. Therefore, we drop firms with the type C2.

[30] Value-added is defined as total staff costs plus depreciation plus profit before tax. We impute some missing value-added data using this formula. We have also calculated an alternative measure of value-added without depreciation. However, the two measures are highly correlated (correlation coefficient 0.88) and results using both measures are quantitatively similar.

change rate, taken from PWT 6.3, to convert each series.[31] We take the number of employees as the labor input.

Appendix D: Robustness Checks

[31]We use the industry-level GFCF deflator from the EU KLEMS database whenever it is available. Otherwise, we employ the country-level GFCF deflator from the AMECO database instead.

Table 3.D.1: Robustness tests

Panel A: Normalized Industry Value Added as the Dependent Variable[a]

		Natural Openness[b]		Trade Integration[c]	
		High-potential	**Low-potential**	**High-potential**	**Low-potential**
Kernel	T	0.871 (0.240)***	-0.089 (0.074)	0.513 (0.285)*	-0.252 (0.065)***
	T^2	-0.098 (0.019)***	-0.023 (0.008)**	-0.159 (0.443)	0.116 (0.052)**
	Output per worker	0.237 (0.069)***	0.226 (0.022)***	0.395 (0.069)***	0.283 (0.023)***
	Constant	-0.005 (0.015)	0.000 (0.016)	0.004 (0.015)	0.000 (0.002)
Sorting	Scale dispersion	8.995 (7.629)	Reference	2.718 (8.316)	Reference
	Efficiency dispersion	5.260 (1.228)***	Reference	5.334 (1.210) ***	Reference
	Initial scale level	10.256 (0.999)***	Reference	10.111 (0.987)***	Reference
	Initial efficiency level	-1.062 (1.869)	Reference	-0.544 (1.852)	Reference
	Constant	-27.643 (7.816)***	Reference	-21.529 (8.379)**	Reference
	Prior class probability	0.129	0.871	0.123	0.877

Panel B: 10/90 Ratio as the Dispersion Measure[a]

		Natural Openness[b]		Trade Integration[c]	
		High-potential	**Low-potential**	**High-potential**	**Low-potential**
Kernel	T	0.716 (0.222)***	-0.158 (0.066)**	0.389 (0.320)	-0.260 (0.061)***
	T^2	-0.087 (0.018)***	-0.017 (0.007)**	-0.438 (0.576)	0.077 (0.048)
	Output per worker	0.247 (0.067)***	0.216 (0.021)***	0.405 (0.071)***	0.288 (0.014)***
	Constant	0.001 (0.016)	0.000 (0.016)	0.008 (0.017)	-0.000 (0.002)
Sorting	Scale dispersion	1.924 (4.721)	Reference	0.321 (5.347)	Reference
	Efficiency dispersion	0.881 (0.381)**	Reference	0.844 (0.444) **	Reference
	Initial scale level	13.675 (1.351)***	Reference	14.678 (1.454)***	Reference
	Initial efficiency level	-3.189 (1.871)**	Reference	-2.558 (2.536)	Reference
	Constant	-18.078 (5.341)***	Reference	-18.140 (5.974)***	Reference
	Prior class probability	0.091	0.909	0.072	0.928

Panel C: Standard Deviation as the Dispersion Measure[a]

		Natural Openness[b]		Trade Integration[c]	
		High-potential	**Low-potential**	**High-potential**	**Low-potential**
Kernel	T	0.749 (0.235)***	-0.148 (0.066)**	0.411 (0.335)	-0.281 (0.062)***
	T^2	-0.089 (0.019)***	-0.018 (0.007)**	-0.489 (0.613)	0.065 (0.048)
	Output per worker	0.250 (0.069)***	0.213 (0.020)***	0.409 (0.073)***	0.284 (0.021)***
	Constant	0.000 (0.001)	0.000 (0.001)	0.006 (0.017)	0.000 (0.000)
Sorting	Scale dispersion	19.047 (12.971)	Reference	18.461 (15.325)	Reference
	Efficiency dispersion	-3.408 (2.799)	Reference	-4.126 (3.073) ***	Reference
	Initial scale level	13.164 (1.328)***	Reference	14.820 (1.515)***	Reference
	Initial efficiency level	-3.148 (1.910)*	Reference	-2.084 (2.604)	Reference
	Constant	-14.528 (1.987)***	Reference	17.346 (2.675)***	Reference
	Prior class probability	0.080	0.920	0.061	0.939

[a] Standard errors in parentheses; significance at the 10/5/1 percent level (*/**/***);
[b] Di Giovanni & Levchenko (2009); [c] Chen & Novy (2011);
[d] Measured at data means; [e] Significance of difference in means.

Chapter 4

How Exports Matter: Trade Patterns over Development Stages

4.1 Introduction

Competitiveness in global markets seems to be the key to development and higher standards of living. Specializing in the "right" products and markets helps countries move ahead, whereas a focus on the "wrong" export bundle can keep a nation in a poverty trap (Bensidoun *et al.*, 2002; Hausmann *et al.*, 2007; Redding, 2002). Despite the fact that much of the academic literature on this topic stresses the dynamic nature of comparative advantage, we argue it fails to consider that "right" and "wrong" are not absolutes. The "right" products in early stages of development may well be different from the "right" products in advanced economies and the bundle of right and wrong products will change over time as products mature over their life cycle. In this paper we propose an index to proxy for product maturity and show that the growth performance of a country indeed depends on the maturity of its exports in a non-linear way over three distinct growth regimes.

The first contribution lies in our index that captures the average maturity of a country's export mix and brings back the perhaps somewhat forgotten product life cycle perspective to the empirical trade literature.[1]. To this end, we

[1] see Mullor-Sebastian (1983) for an overview of the early empirical literature on the product

introduce a product-specific maturity measure using a well established empirical regularity over the product life cycle (e.g. Hirsch, 1967; Klepper, 1996) Over the typical life cycle total sales in the relevant market first increase at an increasing rate, then at a decreasing rate and finally decline. Following Hirsch (1967), Audretsch (1987) and Bos *et al.* (2013), we therefore proxy for the life cycle stage of a product by the first (growth) and second (growth in growth) moment in its global total export volume. We then calculate an aggregate maturity measure for a country's export bundle by weighing the product maturity by the shares of these products in a country's export mix. With this proxy, we are thus able to explore whether the maturity of a country's export basket matters for its economic performance.

The second contribution of this paper is to employ a conditional latent class model to estimate our growth regression. To the best of our knowledge, this approach is quite new to this literature and brings several advantages over more standard econometric techniques. First, instead of ex ante assuming what countries are in how many different growth regimes and then use the data to verify these assumptions, we turn the procedure around and let the data tell us how many different regimes best fit our data, given that growth is modeled to depend on export maturity and other, more conventional growth determinants. We then show that the level of GDP per capita has explanatory power in predicting in which of the endogenously determined three growth regimes our countries fall. Second, a latent class model allows for parameter heterogeneity. Addressing heterogeneity has become one of the most debated issues in the growth literature (Durlauf *et al.*, 2005; Temple, 1999) and in light of this issue, conventional empirical approaches have often been deemed unsatisfactory.[2] In short, our modeling approach enables us to avoid the pitfalls of imposing a common relationship between export maturity and growth for

life cycle in the 60s

[2]The most common practice is to include regional dummies or country fixed effects in a panel framework and the major drawback of these approaches is that they do not allow for differences in the marginal effect of regressors across regimes. Our conditional latent class model estimates regime-specific parameters. In other words, countries in the same regime share a common parameter vector, but this vector will differ across regimes.

all countries but yields results that are comparable across countries and time.[3]

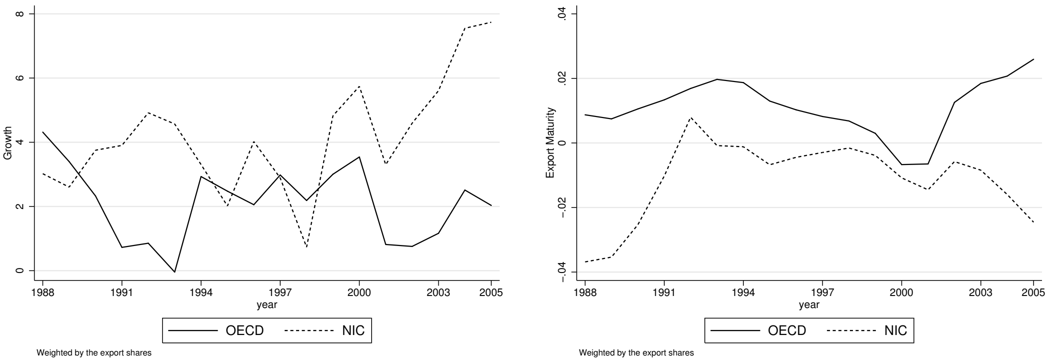
Linking the product life cycle stage of exports to a country's growth performance helps us explain a few of the most salient features of global trade and development in recent decades. Figure (4.1a) shows growth in the OECD was depressed in the early 90s and 00s and has not reached more than 4 percent since 1988. The Newly Industrializing Countries (NIC) by contrast show a period of volatile and relatively depressed growth in the mid 90s and a strong recovery after 2000 with (average) growth rates reaching 7 percent. Over this period we also know the NICs and most notably China have integrated in global markets and increased their volume and share in global trade (OECD, 2005). We hypothesize that these developments can be linked to the dynamics in the global pattern of specialization in general and the composition of exports over product life cycle stages in particular (Audretsch, 2007). Figure (4.1b) shows how OECD countries have maintained a comparative advantage in young, less mature products, whereas emerging economies rapidly closed the gap over the early 90s but NICs remain specialized in more mature markets, increasingly so since 2000. But the figures do not tell an unambiguous story and the challenge is to find an adequate measure of life cycle maturity at the product level. The purpose of this paper is to address that issue by

[3]Our approach is closely related to recent studies that apply conditional latent class (or finite mixture) models to examine the the heterogeneity of growth and convergence patterns across countries. Paap *et al.* (2005) apply a latent class analysis to sort a number of developing countries according to their average growth rates over the period 1961-2000. Alfo *et al.* (2008) develop a mixture of cross-sectional growth regressions to uncover multiple regimes of per capita income convergence across EU regions for the period 1980-2002. Owen *et al.* (2009) apply a conditional finite mixture model based on the similarity of the conditional distribution of growth rates for a broad set of countries for the period 1970-2000, and find evidence of two distinct clubs, each with its own distinctive growth dynamics. They also find that institutional quality is a good predictor of the club membership. Bos *et al.* (2010) estimate a latent class production frontier and uncovers three different growth regimes using human capital, openness to trade, financial development, and the primary sector share as regime predictors for a sample of 77 countries during the period 1970-2000. Vaio & Enflo (2010) support that growth patterns were segmented in two worldwide regimes, the one characterized by convergence in per capita income, and the other by divergence based on a sample of 64 countries over a very long horizon 1870-2003. Owen & Videras (2012) use latent class analysis to characterize development experiences of countries by taking into account the quality of growth.

zooming in on empirically measuring product maturity and investigating the differential impact of countries' export maturity on economic growth across a wide range of developing and developed countries.

Figure 4.1: Economic Growth and Export Maturity

(a) Economic Growth **(b)** Export Maturity



Note: Both graphs are weighted by the country share in world exports, based on authors' own calculations. Growth is expressed in percentage points in Figure (4.1a). Export maturity is an index number. The higher this number is, the younger the export bundle (i.e. the lower the export maturity) is in Figure (4.1b).

Our paper builds on recent advances in two long traditions in the literature. The first strand, pioneered by Vernon (1966), applies stylized life cycle models to explain the shift of dynamic comparative advantages and the evolvement of trade patterns over time (Dollar, 1986; Flam & Helpman, 1987; Grossman & Helpman, 1991; Hirsch, 1967; Jensen & Thursby, 1986; Krugman, 1979; Lai, 1995). An important prediction in this line of literature is that developing countries will increasingly compete in those products that reach the later stages of the product life cycle, implying that the advanced economies must "run to stand still" (Krugman, 1979). A steady flow of new product innovations is necessary to maintain international income differentials. In these models the assumed relative abundance of cheap, unskilled labour in the less developed South is the source of a dynamic comparative advantage in copying mature products and technologies from the more advanced North. If, in such a context, globalization and trade integration imply that populous developing economies enter global market competition, then advanced economies experience a shift of their comparative advantage towards products that are in the earliest stages of the product life cycle (see e.g. Audretsch, 2007; Lai, 1995).

We rely on this theoretical literature to develop our hypotheses that exporting more mature products has a growth enhancing effect for emerging economies below the global technology frontier. Of course, in these models exporting more mature products would have exactly the opposite effect on the growth of advanced economies.

The second strand of literature relevant to our work extensively documents the effect of trade and more specifically exports on economic growth. The vast bulk of the early empirical literature asks: "Do Exports Matter?".[4] Most of these studies include either a measure of export (growth) or trade openness in a standard regression framework covering a wide range of countries, time periods and using a variety of estimation techniques. Consistent with the difficulties in establishing robust empirical evidence linking growth to fundamentals in general (Durlauf *et al.*, 2005; Temple, 1999), the evidence is rather mixed. Some find a significant positive relationship between export (growth) and per capita GDP growth, while others caution us not to assign the direction of causality (Rodriguez & Rodrik, 2001). A salient feature of this literature is that the measure of export/trade openness is typically broadly defined. As a result, the channels through which international trade influences economic growth remain unclear.

A number of studies does examine the relationship between the structure of exports and long-term economic performance in more detail and asks: "How do Exports Matter?".[5] In particular, this literature has focused on the rela-

[4]This literature is massive. Giles & Williams (2000) provides a comprehensive survey of more than 150 papers that test the export-led growth hypothesis alone. Singh (2010) provides a recent survey of a growing body of studies that explore linkages between trade openness and growth.

[5]The structure of imports may have direct impact on economic performance as well. Earlier studies show that imports of quality foreign capital goods serves as a means to acquire foreign technology through reverse engineering (Connolly, 1999). Lee (1995) and Lewer & den Berg (2003) find that capital-importing countries benefit from trade because trade causes the cost of

tionship between export diversification and growth. Export diversification is widely seen as a desirable trade objective in promoting economic growth (Herzer & Nowak-Lehnmann, 2006). Diversification makes countries less vulnerable to adverse terms of trade shocks. By stabilizing export revenues it is then easier to channel positive terms of trade shocks into growth, knowledge spillovers and increasing returns to scale, creating learning opportunities that lead to new forms of comparative advantage.[6] In a dynamic growth framework, some recent studies have uncovered a non-linear link between export diversification and economic growth (Aditya & Roy, 2007; Cadot *et al.*, 2007; Hesse, 2008). The main insight is that developing countries benefit from diversifying their exports, whereas developed countries perform better with export specialization.[7] What remains unclear from this literature, however, is whether the mix of particular products, diversified or specialized, has any implications for growth.

That raises the question: "Does What We Export Matter?" and our paper is close to a handful of studies that have started to address that question by zooming in on the specific characteristics of exports in relation to economic performance. The earliest studies distinguish between primary sector and manufacturing exports. Exporting primary products, which suffer from unfavorable price trends and from great price variability, are suspected to lead to poor growth performance (Rodriguez & Rodrik, 2001), whereas the expansion of manufactured exports has been a vital source of growth for many countries (Cline, 1982, 2010; Martin, 1993; Ranis, 1985). Thanks to the increasing availability of highly disaggregated trade data, first in the OECD and then for other parts of the globe, the research focus has recently shifted to the product

capital to fall. However, others do not reveal any significant role for the composition of imports in economic growth (An & Iyigun, 2004; Wörz, 2005). In line with recent papers that analyze the importance of export structure for better economic performance, this paper focuses on the export side and leave the import side for future research.

[6]In a similar vein, export concentration is found to be associated with slow growth, in particular when export concentration reflects the predominance of primary products (Gylfason, 2004; Klinger & Lederman, 2006; Sachs & Warner, 1995).

[7]This finding is consistent with Imbs & Wacziarg (2003) who find a similar pattern using production and employment data.

characteristics of exports. Dalum *et al.* (1999) demonstrate that exports with higher levels of technological opportunity and higher income elasticities tend to have greater impact on growth among OECD countries. Feenstra & Rose (2000) develop a procedure to order countries according to how soon they export advanced commodities to the US market and find that countries exporting sooner to the United States tend to grow faster. Bensidoun *et al.* (2002) show that countries specializing in products for which the share in international trade has increased, grow faster than those that maintained a comparative advantage in stable or declining products. An & Iyigun (2004) compute the skill content of exports based on the US industry-wide R&D expenditures as a share of gross sales revenue as the benchmark. They show that a higher skill content of exports generates a higher growth rate. Lee (2010) adds to the evidence that countries have tended to grow more rapidly when they have increasingly specialized in exporting high-technology as opposed to traditional or low-technology goods. Last but not least, a small number of recent papers examines how the network structure of economic output influences a country's overall wealth and development (Hausmann & Hidalgo, 2011; Hidalgo & R.Hausmann, 2009; Hidalgo *et al.*, 2007). For example, Hidalgo *et al.* (2007) present the network of relatedness between products, i.e. the "product space" and reveal that the types of products a country currently produces determine the probability of that country developing more competitive products in the future. This may help explain the lack of economic convergence of poor countries as they failed to produce more advanced goods.

A seminal study by Hausmann *et al.* (2007) develops a theoretical model where local cost discovery generates knowledge spillovers to show that a country's specialization pattern becomes partly indeterminate in the presence of such externalities. They conclude from this that the mix of goods that a country produces may therefore have important implications for economic growth and they construct a product-specific sophistication measure based on the income of the *average* exporter. They then test their hypothesis and find that exporting more sophisticated products is positively associated with subsequent growth. This result suggests a development strategy for developing countries that should shoot for the stars and export what the developed countries are exporting. But this is far from trivial. Developing countries may lack the capability to produce complex products. The supply side constraints faced by these countries, such as the lack of physical infrastructure and skilled labour force, and poor institutional qualities render them unable to put the upgrading in place. Sutton & Trefler (2010) therefore caution us not to take the evidence of Hausmann *et al.* (2007) at face value. They instead develop a model postulating that a country's wealth and its export mix are simultaneously determined by its capabilities, i.e. the country's productivity and quality level in each product. Thus, economic growth can be achieved either through the shift to a different mix of products or through the improvement in quality/productivity in the existing portfolio of products. Empirically, they demonstrate that the income differences between the richest and poorest exporters of the same product, i.e. the product-income range, is huge, raising concerns about the informativeness of Hausmann *et al.* (2007)'s measure. As a consequence, they illustrate that changes in the export mix will substantially over-predict economic growth for developing countries. Exporting more sophisticated products may not turn out to be the most effective development strategy.

Building on these recent studies we propose not to focus on a static product sophistication measure but rather on a product's life cycle stage in the global market. In our study we analyze Statistics Canada's version of the UN-COMTRADE database that contains the export data on 430 Standard International Trade Classification (SITC) four-digit products for 93 countries over the period 1988-2005. This comprehensive database gives us the unique opportunity to zoom in on more precisely defined products and generalize trade patterns across more countries than most studies to date. We propose a simple measure of product maturity in the global market and link the overall average maturity of a country's export portfolio to their economic growth performance.

Our results are easy to summarize. We find evidence that i) developed countries (with high GDP per capita) are exporting products in the early stages of their (global) life cycle, whereas the opposite is true for developing countries. And ii) our results suggest the existence of three quite distinct growth regimes and we demonstrate that for the most advanced countries' regime, countries tend to grow more rapidly when they export new (less mature) products, whereas this effect is insignificant for the developing countries' regime. In stark contrast, we can identify an emerging countries' regime where countries grow faster when exporting more mature products. These findings have important implications for trade and economic development theory and policies.

The remainder of the paper proceeds as follows. In Section 2, we develop our maturity proxy and discuss our data and estimation strategies. The empirical results are then presented in Section 3. Section 4 discusses the implications and limitations of our paper and concludes.

4.2 Methodology and Data

In this section we first develop a measure of product maturity drawing on the insights from product life cycle theory and then compute the average maturity of our countries' export portfolios. We then turn to the empirical evidence, describing the estimation strategy, as well as the data before turning to our results in Section 3.

4.2.1 Measuring Product Maturity

Our measure is based on one of the well established empirical regularities found in the product life cycle literature. Total sales of a product in the market first increase at an increasing rate, then at a decreasing rate and finally decline, tracing out an S-shaped diffusion curve (Klepper, 1996). We therefore develop our measure of maturity at the product level by looking at the dynamics in market volume at the global level. Following Audretsch (1987) and Bos *et al.* (2013), we characterize the life cycle stage of a product using the first and second moment in its global export volume. To control for the global business cycle we estimate the following equation:

$$ln(exp_{it}) = \gamma_0 + \gamma_{1i}t + \gamma_{2i}t^2 + \gamma_3 ln(exp_t) + \varepsilon_{it} \tag{4.1}$$

where $ln(exp_{it})$ is the log of global exports of product i at time t in constant dollars; t and t^2 are time (1 in 1988) and time squared, respectively; $ln(exp_t)$ is the log of global total exports of all products; ε is the disturbance term.

We can then set our measure of maturity, M_{it}, equal to the effect of an increase in time t on the log of global exports $ln(exp_{it})$. M_{it} is then defined as:

$$M_{it} = \frac{\partial ln(exp_{it})}{\partial t} = \gamma_{1i} + 2 \times \gamma_{2i} \times t, t = 1, 2...18 \tag{4.2}$$

Assuming the typical S-shaped pattern of sales over the life cycle we can show that the lower (more negative) M_{it} is, the more mature a product is. For early stage products both coefficients are typically positive, whereas for more mature products first γ_{2i} and then γ_{1i} will first show up insignificant and than negative in the regression.

We calculated M_{it} for each of the 430 SITC four-digit products over the period 1988-2005 using global-level export data retrieved from the COMTRADE database.[8] More specifically, we estimate equation (4.1) taking a rolling window of 9 years, namely 1988-1996, 1989-1997, 1990-1998, 1991-1999, 1992-2000, 1993-2001, 1994-2002, 1995-2003, 1996-2004, 1997-2005 to calculate M_{it} as in equation (4.2) and taking the average of all M_{it} estimated using the different sub-samples. In this way, we allow for maturity to change over time in a non-linear fashion.[9]

[8] For the estimation purpose, we keep products that have at least have 5 observations during 18 years. The average number of observations per product is 16. We drop 180 products that are in the residual categories "X" since the export data on those products are subject to serious measurement problems. These products only account for on average less than 1 percent of the global export over our sample period.

[9] The second order polynomial specified in equation (4.1) combined with the rolling window analysis provide a good approximation of a theoretical S-shaped life cycle curve. As a robustness check, we also estimated equation (4.1) using all information 1988-2005, evaluating M_{it} at each point in time t. That is an approximation of our preferred approach, as it makes maturity linearly dependent on time by construction. The pairwise correlation of maturity measures computed in these ways is 0.23 (significant at 1 percent), and the Spearman rank-order correlation is 0.38 (where the null hypothesis that both measures are independent is rejected), suggesting some similarity in their ability to rank products by maturity. However, as the rolling window approach permits the maturity to change over time in a more flexible manner we chose the rolling window approach as our preferred measure.

Four important aspects of our measure M_{it} are worth pointing out at this stage. First, in contrast to a binary measure to classify industries into either "growing" or "declining" as in Audretsch (1987), our measure is continuous.[10] This property permits a sensible ranking of products based on maturity level in the global export market. Second, our measure is time-varying. In other words, we allow products to move from one stage of the life cycle to the next and back. This latter property may seem undesirable, but in fact there are good reasons not to exclude such dynamics by construction. For example, mature products can rejuvenate themselves through the upgrading of existing products and/or the introduction of new product varieties in the same product category. Such rejuvenation would set off a new S-shaped pattern in global sales. In this respect, our measure differs from Bos *et al.* (2013) who evaluates equation (4.2) at the mean of t for all industries and does not allow for the changes of product maturity over time. Third, we based our measure on the global exports of a product. Under the assumption that total global exports correlate with total global production and sales, this will reflect the product life cycle. Our proxy, however, will also carry some exogenous elements that reflect the growth potential of products in the global market place. Finally, we prefer a product specific measure based on global export volumes over the alternative of country level maturity measures as this measure is less prone endogeneity problems in the country level growth regressions that follow.[11]

Table 4.1 provides descriptive statistics on these products, aggregated to the one-digit level.[12] According to Table 4.1, we find that manufacturing products account for more than 70 percent of world total exports. The product matu-

[10] Audretsch (1987) suggests to consider the sign and significance of γ_{1i} and γ_{2i} to classify industries. An industry is classified as growing when either γ_{2i} was positive and statistically significant at the 90 percent level or γ_{2i} was statistically insignificant, but γ_{1i} was positive and statistically significant.

[11] In a similar vein, Bekaert *et al.* (2007) proposes an exogenous measure of industry-specific growth opportunities by using global average price to earnings ("PE") ratios in stock markets. They argue that global PE ratios contain information about (global) growth opportunities. Thus, for each country, it permits the construction of an exogenous growth opportunities measure that does not use local price information and is less prone to endogeneity issues.

[12] A list of all products included in our analysis is available upon request.

rity exhibits significant cross-section and time-series variation, suggesting that products within 1 digit categories differ in terms of both their maturity in the global market and the maturity changes over time.

A first "test" of our maturity measure is to simply look at which products actually get classified as mature and young. Ranking products based on their maturity in the global market yields Tables 4.A.1 and 4.A.2 in the Appendix, which show the maturity and ranking of the 50 products with the lowest and highest maturity values at the end of our sample period (i.e., 2005), respectively. The corresponding rank number at the start of the period (i.e., 1988) is also given. The pairwise correlation between maturity 2005 and maturity 1988 is -0.021, which is not significant at any conventional level. The negative correlation may imply that products classified as mature in 1988 are classified as newer in 2005 and the other way around. The reason is that most products apparently have a (very) negative γ_2, such that they start with a very high M_{it} (low maturity) and end with a very low value (high maturity), whereas the products with a positive γ_2 tend to start from a very low γ_1. This is consistent with a more or less random distribution over the life cycle stages as early stage products would be expected to have low average growth (captured by a low γ_1) but high growth in growth (captured in a positive γ_2), whereas mature products have low average growth and negative growth in growth. The Spearman ranking correlation (0.053) shows that the ranking at 1988 and 2005 is independent (p value is 0.254).

The products at the extremes of the ranking, are not perhaps making a very convincing case at first glance. Especially the list of least mature products includes several raw materials, ores, basic metals and food products that cannot be considered early stage products. Our measure is clearly sensitive to the 90s resource boom. Rising demand for many internationally traded raw materials, ores and energy resources have caused the trade volumes for those commodities to increase faster than the global trade volume for which we correct. Consequently, the boom in commodities trade is interpreted by our measure as a rejuvenation of traded commodities, when of course nothing has happened to the product itself. We will leave these products in for now, exactly because

Table 4.1: Descriptive Statistics

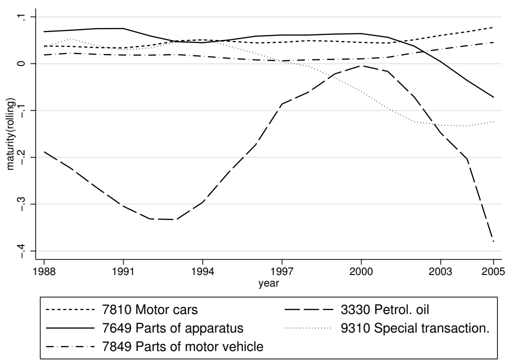
Code	Name	Number	Share	Maturity Mean	Maturity Stand. Devi.	Maturity 25 percentile	Maturity 50 percentile	Maturity 75 percentile
0	Food	78	0.087	0.017	0.103	-0.031	0.011	0.065
1	Beverages and tobacco	9	0.014	0.043	0.076	-0.009	0.038	0.084
2	Crude materials	73	0.045	-0.060	0.164	-0.132	-0.041	0.023
3	Mineral fuels, lubricants	13	0.086	-0.117	0.513	-0.097	-0.015	0.050
4	Animal and vegetable oils	9	0.005	-0.006	0.171	-0.090	-0.016	0.060
5	Chemicals	32	0.070	0.026	0.086	-0.015	0.026	0.073
6	Manufacture	99	0.156	-0.011	0.107	-0.043	-0.002	0.034
7	Machinery and transport	55	0.321	0.002	0.090	-0.036	0.008	0.051
8	Miscellaneous manufactures	57	0.152	0.039	0.105	-0.006	0.034	0.076
9	Unclassified manufactures	2	0.032	0.007	0.065	-0.006	0.014	0.038

Number denotes the number of four-digit products included in our analysis. Share denotes the percentage of export in the global total export at year 2005.

this will bias the estimations against finding the results we are most interested in. [13] The reader should keep in mind, however, that what we measure as maturity is a rough proxy and measurement error is an issue.

The second "test" of our maturity measure is to explore the trend of major products in the global market. Figure (4.2) shows the maturity of the most important five products (in terms of their size in the global trade) over time. As can be seen from the figure, most manufacturing products are relatively stable and mature. Only petrol oil is moving up and down a lot. Obviously this reflects the peculiarities of global oil markets.

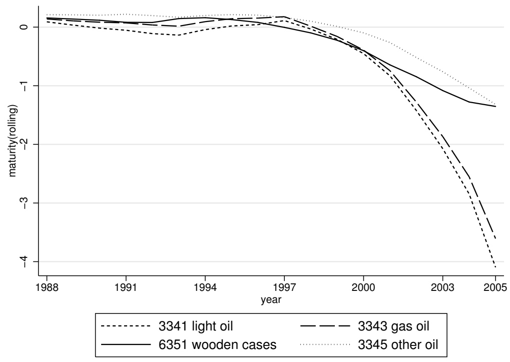
Figure 4.2: Product Maturity - Most Important Products



The third "test" of our maturity measure is to explore the volatility of product maturity over time. We want to eliminate those products that exhibit too much volatility over time, e.g. oil. We therefore computed the standard deviation of maturity for each product over the entire sample period. Figure (4.3) shows the maturity of four products, for which the standard deviation of maturity was above the 99 percentile of the sample. It too suggests that oil products should be treated with caution in our analysis. We keep these "products" in our sample for now, however, to avoid selection bias in our empirical analysis below.

[13] A high degree of specialization in resources will generally bias the positive effect of exporting new products on economic growth downwards.

Figure 4.3: Product Maturity - Most Volatile Products



4.2.2 Measuring the Export Maturity of Countries

The overall maturity associated with a country's export basket, M_{jt}^{All}, in turn can now be defined as

$$M_{jt}^{All} = \sum_i s_{ijt} M_{it} = \sum_i \frac{exp_{ijt}}{exp_{jt}} M_{it} \tag{4.3}$$

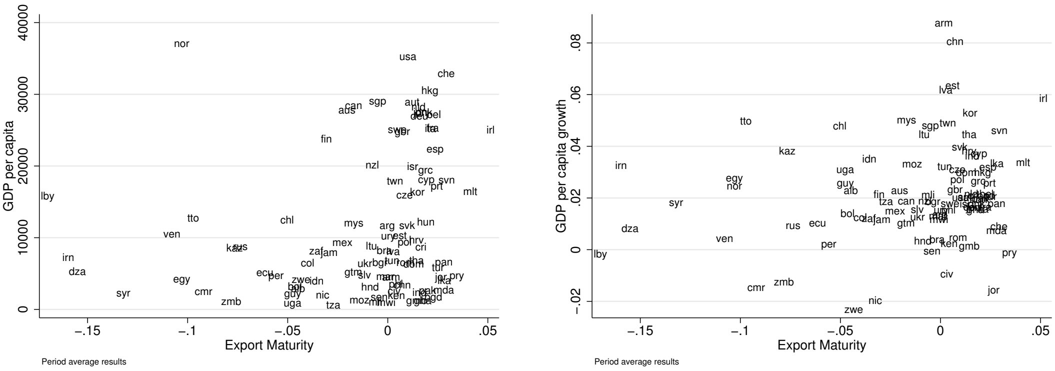
where M_{jt}^{All} is a weighted average of product maturity M_{it} (at the global level) across all products for country j over time t. The weights are the export shares of these products in country j's total exports. We retrieved the product-country level export data for all 430 products identified above in 98 countries during 1988-2005 from COMTRADE to calculate the overall maturity of a country's export mix M^{All}. Figure 4.4 plots the weighted maturity measures against GDP per capita and GDP per capita growth to get a first impression of the data. From these scatter plots it seems that a weak positive relation exists between the maturity index (higher values indicate younger products) and the level and growth rate of per capita GDP. The scatter plots also suggests that outliers may be a problem, in particular for the relationship to growth.

To check the robustness of our measure M^{All}, we therefore computed four other country-level maturity indices by considering sub-samples of products.

First, we compute the measure $M1$ by excluding all the oil-related products, i.e. those for which the four digit product code begins with 3. Second, we

Figure 4.4: GDP Per Capita, Growth and Export Maturity

(a) GDP Per Capita and Export Maturity **(b)** Growth and Export Maturity



compute $M2$ by only looking at manufacturing products, i.e. those for which the first digit is between 6 and 9. Third, Sutton & Trefler (2010) find that the income difference between the richest and poorest exporters of the same product, i.e the product-income range, is huge, questioning the informativeness of Hausmann *et al.* (2007)'s product-specific sophistication measure based on the income of the *average* exporter. They define *informative* products as those that lie in the upper right or bottom left in Figure (4.A.1) in the Appendix. In other words, a large share of products that appear in the upper left corner of the graph are considered uninformative as they are exported by both rich and poor countries.[14] Based on their definition, we identify 191 informative products out of 430 in our sample and calculated the maturity using these 191 products. Finally, Rauch (1999) develops a classification of products into differentiated, homogeneous and an intermediate category. Subsequent research has used this classification to explore how trade in homogeneous and differentiated products differ (e.g. Besedes & Prusa (2006)). Thus, we remove all differentiated products and calculate $M4$ on basis of the other two categories. Table 4.2 reports pairwise and ranking correlations of all of our five differently constructed measures. We find that these measures are positively and signifi-

[14] More precisely, the (ln) minimum GDP per capita of the country that produces this good is smaller than 8.26 and the (ln) maximum GDP per capita is 9.99.

cantly correlated using both pairwise correlation and ranking correlation.

Table 4.2: Correlation Matries for the Export Maturity Indices (Pooled Data)

Pairwise Correlation (N=1696)					
	M^{All}	$M1$	$M2$	$M3$	$M4$
M^{All}	1.000				
$M1$	0.373*	1.000			
$M2$	0.593*	0.539*	1.000		
$M3$	0.497*	0.324*	0.838*	1.000	
$M4$	0.893*	0.241*	0.472*	0.454*	1
Spearman Ranking Correlation (N=1696)					
	M^{All}	$M1$	$M2$	$M3$	$M4$
M^{All}	1.000				
$M1$	0.486*	1.000			
$M2$	0.806*	0.568*	1.000		
$M3$	0.705*	0.378*	0.836*	1.000	
$M4$	0.854*	0.270*	0.608*	0.591*	1.000

Note: *Significant at 1 percent.

We conclude from these results that our time varying, continuous measure of export maturity reflects something that is correlated with the alternative measures suggested in the literature, is easy to compute based on conventional trade data and is founded in well established empirical regularities over the product life cycle. The proof of the pudding, however, is in the eating. Our measure picks up something of substance if we can show it has explanatory power in a panel growth regression, to which we turn below. For our purpose, we will use M^{All} in the main analysis and use the other four maturity measures in our robustness analysis.

4.2.3 Empirical Methodology

A general investigation of the relationship of export maturity and economic growth starts with the following standard growth regression:

$$g_{jt} = \beta_0 + \beta_1 M_{jt}^{All} + \beta' Z_{jt} + \varepsilon_{jt} \tag{4.4}$$

Where j denotes country and t denotes time; g is per capita GDP growth; M^{All} measures the maturity of a country's export basket; β' is a $1 \times n$ parameter vector; Z is an $n \times 1$ vector of control variables that contains the usual determinants of economic growth. Levine & Renelt (1992) find that most of the independent variables in standard growth regressions are fragile. Since the effect of export maturity on growth, i.e.β_1, is our primary interest, we minimize the data mining biases for the other variables by closely mimicking the regression in Hausmann *et al.* (2007). We thus include a country's initial level of GDP per capita (gdp_0) to capture beta-convergence, the capital to labour ratio (KL), the level of human capital(HC) and rule of law index (Law), a *de jure* trade openness index ($Trade$) and a trade concentration index (HHI) in Z; finally, ε is an i.i.d. error term.

One major drawback of equation (4.4) is that the relationship between the maturity of exports and economic growth is now assumed to be identical across countries. Therefore, the estimated parameters, e.g., β_1 and β' are common to all countries *by construction*. In practice, it may well be the case that this relationship is not homogeneous and equation (4.4) masks potentially important parameter heterogeneity across countries.

We therefore adopt a flexible modeling framework in which the export maturity-growth relationship is allowed to be heterogeneous across different groups of countries (or growth regimes), depending on the stage of economic development. Two strands of literature motivate our choice of relying on GDP per capita as a proxy of economic development. The first strand has examined the heterogeneity of growth experience of countries in general and has well established the substantial differences in the determinants of growth between developing and developed countries. These studies (e.g., Canova, 2004; Durlauf & Johnson, 1995; Papageorgiou, 2002) typically use the initial level of GDP per capita as a regime splitting variable to examine multiple growth regimes. However, such an ex ante classification is somewhat arbitrary and subject to debate since the appropriate cut-off point is not always clear. In contrast, our approach endogenizes the cut-off points and is thus much more flexible. The second strand has established a non-linear relationship between export structure (specialized vs. diversified) and economic growth (Aditya & Roy, 2007; Cadot *et al.*, 2007; Hesse, 2008; Imbs & Wacziarg, 2003). These papers typically find that the relationship is differs by the development stage of countries as proxied by GDP per capita.

We thus treat the stage of development as a latent variable, and use a latent class model to endogenize the sorting of countries into different growth regimes. To model the latent variable, we use a multinomial logit sorting equation, and include the stage of development, proxied by real GDP per capita, to estimate the likelihood of being in a particular growth regime. Our conditional latent class model consists of a system of two equations: an equation to estimate the maturity-growth nexus for each regime, and a multinomial sorting equation where the regime membership is a function of the development stage, i.e. GDP per capita.

To allow for endogenous sorting into regimes $k(=1,...K)$, we can rewrite equation (4.4) as follows:

$$g_{jt|k} = \beta_k + \beta_{1|k} M_{jt}^{All} + \beta_k' Z_{jt} + \varepsilon_{jt|k} \tag{4.5}$$

where $k = 1, ..., K$ indicates the regime and K refers to the (endogenous) total number of regimes. Each regime has its own parameter vector β. In other words, β_0, β_1, β' are allowed to differ across regimes.

To estimate equation (4.5), we must first find the suitable number of K. As this is not a parameter to be estimated directly from equation (4.5) Greene (2007) suggests a "test-down" strategy to identify the correct number of regimes. A specification with $K+1$ regimes is inferior to one with K regimes if the parameters in any two of the $K+1$ classes are equal (statistically indistinguishable). If the true K is unknown, it is possible to test down from $K+n$ to K

using a log likelihood ratio test.[15]

Our aim is then to sort each observation jt into a discrete regime k. This is done by specifying the contribution of each observation jt to the likelihood function, conditional on its regime membership. The unconditional likelihood for each observation jt is obtained as a weighted average of its regime-specific likelihood using the prior probability being in regime k as weights. Since we do not observe directly which regime will contain a particular observation jt, the group membership probability θ_{jt} must be estimated. In our conditional latent class framework, we make this probability conditional on GDP per capita ($GDPPC$) and parameterize θ_{jt} by means of a multinomial logit model:

$$\theta_{jt} = \frac{\exp(GDPPC_{jt}\theta_k)}{\sum_{k=1}^{K} \exp(GDPPC_{jt}\theta_k)} \tag{4.6}$$

where θ_{jt} measures the odds of being in regime k, conditional on $GDPPC$. The likelihood for the entire sample, which is the sum of all unconditional likelihood over all jt resulting from equation (4.5) and (4.6), can then be maximized with respect to the parameter vector $\beta = (\beta_1, ...\beta_K)$ and the latent class parameter vector $\theta = (\theta_1, ...\theta_K), \theta_K = 0$ using a conventional maximum likelihood estimator, following Greene (2007). With the parameter vector β and θ in hand, a posterior estimate of the regime membership probability for each observation jt, can be computed using Bayes' theorem. Each observation can then be assigned to the regime with the largest posterior probability.

One distinctive feature of our approach is that we allow countries to switch between regimes over time, following e.g. Bos *et al.* (2010). We do want to avoid countries close to a switching point, however, to switch back and forth between regimes all the time. We therefore split our sample in 4 time periods (the first three periods consists of 5 years, while the last one consists of 3 years): 1988-1992,1993-1997,1998-2002 and 2003-2005 allow countries to only switch regime between these four periods. Essentially we pooled together the

[15]Theoretically, the maximum number of regimes is only restricted by the number of cross-sections, i.e. the number of observations in the data. However, empirically the overspecification problem limits the estimation of a large number of regimes.

observations from the time periods and treated observations within these periods as independent draws from the same regime. This implies that one country can be allocated to one particular regime k in period 1 (1988-1992) and another one in period 2 (1993-1997), but no switches occur within these periods by construction. This adds flexibility into our modeling framework by avoiding the imposed assumption of persistent regime allocation and provides additional insights into regime switches. We can thus study the dynamics of the maturity-growth relation as countries move along their development path at different speeds.

To summarize our empirical strategy, we employ a conditional latent class model to examine for the possible non-linear relationship between export maturity and growth in K endogenously determined regimes. The regime membership probabilities are conditional on the stage of economic development.

4.2.4 Data

To estimate a growth regression we obviously require, in addition to our country level export maturity measure, the standard set of variables. Economic growth (g), measured as the change of the real GDP per capita is taken from the Penn World Table, version 6.3 (PWT 6.3). To prevent simultaneity or reverse causality, we take the initial level of all export maturity measures at the beginning of four different time periods defined above (i.e. at 1988, 1993, 1998 and 2003). The vector Z includes the usual suspects. The initial level of GDP per capita gdp_0 (2005 international purchasing power parity (PPP) dollars chain index) is set equal to the start of the different periods. The capital to labor ratio (KL) is computed as the physical capital stock divided by the total number of workers. We construct the capital stock (K) applying the perpetual inventory method as in Hall & Jones (1999).[16] Human capital (HC), is measured as the average years of schooling of the population that is at least 25 years old

[16] We estimate the initial stock of capital, K_{t0} as $\frac{I_{t0}}{G+\delta}$, where I is investment, t_0 refers to the year 1988, G is the average geometric growth rate of investment. We use the average growth rate over the first 9 years (the first half of our sample) to determine the country-specific average growth rate. The depreciation rate δ is assumed to be 6 percent. The subsequent value of capital stock is computed following $K_t = (1-\delta)K_{t-1} + I_t$.

and is obtained from the Barro & Lee (2010) database on educational attainment.[17] The rule of law index (*Law*), ranging from 0.5 (low institutional quality) to 6 (high institutional quality) is retrieved from the International Country Risk Guide (ICRG) and our de jury trade openness measure ($Jure$) is taken from Wacziarg & Welch (2008). It takes a value of one when a country's trade regime is liberalized, and zero otherwise. We measure trade concentration as the Hirschman-Herfindahl index, which is computed using the COMTRADE data. The conditioning variable that we rely on to estimate the latent class model is the stage of economic development for which we proxy by using the level of GDP per capita ($GDPPC$), retrieved from PWT 6.3. Table 4.3 summarizes the definitions, sources and descriptive statistics of country-level variables used in our analysis.

4.3 Empirical Results

We first determine the number of regimes in our data following the suggestion by Greene (2007). The test results in the top row in Table 4.4 favor a specification with three regimes over the one with two regimes. We refer to these regimes as developing, emerging and advanced for reasons we will explain later. Moreover, the second row shows that the unconditional latent class model must be rejected in favor of the conditional one. Next, we test whether the parameter estimates differ significantly across regimes by means of Wald tests for joint equality. The results indicate that the equality of all parameters should be rejected at the 1 percent significance level across regimes. Finally, we test whether the effect of export maturity on growth is significantly different across regimes. The Wald tests here reveal that the effects are jointly significantly different across the three regimes, except between the developing and advanced regime.

[17] Since the data is only available at a five-year interval, we use a linear interpolation to fill in missing annual data.

Table 4.3: Descriptive Statistics - Growth Regression

	Description	Unit	Source	Mean	Min	Max	SD	Obs
g	GDP per capita growth	percentage	PWT 6.3	0.037	-0.455	0.358	0.078	1580
M^{All}	Initial export maturity, all products	index	COMTRADE	-0.017	-0.344	0.123	0.066	1580
M1	Initial export maturity, non-oil products	index	COMTRADE	-0.002	-0.273	0.124	0.051	1580
M2	Initial export maturity, manufacturing products	index	COMTRADE	0.008	-0.220	0.119	0.044	1580
M3	Initial export maturity, Sutton	index	COMTRADE	-0.015	-0.278	0.143	0.062	1580
M4	Initial export maturity, Rauch	index	COMTRADE	-0.047	-0.554	0.113	0.072	1580
g	GDP per capita growth	percentage	PWT 6.3	0.037	-0.455	0.358	0.038	1580
gdp_0	Initial GDP per capita	2005 PPP dollars	PWT 6.3	11414	601	42490	8168	1580
KL	Capital/labor ratio	2005 PPP dollars	PWT 6.3	122.179	0.615	749.560	133.732	1580
HC	Average year of schooling	year	BL2010	7.087	0.642	13.086	2.84	1580
Law	Rule of law index	index	ICRG	3.959	0.5	6	1.468	1580
Jure	De jure openness measure	index	WW2008	0.801	0	1	0.399	1580
HHI	Trade concentration index	index	COMTRADE	0.111	0.001	0.843	0.146	1580
GDPPC	GDP per capita	2005 PPP dollars	PWT 6.3	11966	620	44141	10303	1580

BL2005 refers to Barro & Lee (2010); WW2008 refers to Wacziarg & Welch (2008); ICRG refers to International Country Risk Guide.

Table 4.4: Hypothesis Test

Testing	Test	Test Statistic	P-value	Conclusion
Class Fit				
Three-regime conditional vs. Two-regime conditional	LRT	152.281	0.000	rejected
Three-regime conditional vs. Three regime unconditional	LRT	41.263	0.000	rejected
Equality of All Parameters				
Regime Developing vs. Emerging	Wald	97.405	0.000	rejected
Regime Emerging vs. Advanced	Wald	202.182	0.000	rejected
Regime Developing vs. Advanced	Wald	28.705	0.000	rejected
Regime Developing, Emerging and Advanced	Wald	257.298	0.000	rejected
Equality of Export Maturity				
Regime Developing vs. Emerging	Wald	9.467	0.002	rejected
Regime Emerging vs. Advanced	Wald	47.246	0.000	rejected
Regime Developing vs. Advanced	Wald	0.001	0.975	not rejected
Regime Developing, Emerging and Advanced	Wald	49.895	0.000	rejected

Note: LRT represents the likelihood ratio test.

From this table we conclude that a three regime, conditional latent class specification is most suitable for our purpose. Then we turn to the effect of the maturity of a country's export portfolio on economic growth across these regimes by looking at the conditional latent class estimation results in Table 4.5.

First observe in the lower part of the table that the first regime has a low average GDP per capita, the most mature export bundle and the lowest average growth rate. We therefore labeled this regime "developing". The second "emerging" regime has still low but slightly higher average levels of GDP per capita, a considerably higher average growth rate and an intermediate average maturity. The "advanced" regime has a high average level of GDP per capita, moderate growth rates and the lowest average maturity of exports. Note that we have labelled the regimes after the model classified the observations and we based our labels on these average characteristics, not the other way around.

Most interesting from our perspective, however, is the impact of maturity

Table 4.5: Main Empirical Results

Regime	Developing	Emerging	Advanced
Initial export maturity	0.096	-0.127***	0.095***
	(0.070)	(0.027)	(0.018)
Initial GDP per capita	-0.019***	0.018***	-0.002
	(0.007)	(0.003)	(0.002)
Capital/labour ratio	-0.010	-0.010***	-0.001*
	(0.009)	(0.002)	(0.001)
Human capital	0.007***	0.001	0.001
	(0.002)	(0.001)	(0.001)
Rule of law	0.013***	0.005***	0.001
	(0.004)	(0.002)	(0.001)
Trade openness	0.019**	-0.008**	0.006
	(0.009)	(0.004)	(0.004)
Trade concentration	0.080***	-0.125***	0.039***
	(0.029)	(0.016)	(0.008)
Constant	-0.012	0.014***	0.438**
	(0.025)	(0.007)	(0.283)
Regime Membership Probability			
Constant	0.438**	0.643***	Reference
	(0.283)	(0.280)	
GDP per capita	-0.011***	-0.007***	Reference
	(0.002)	(0.002)	
Prior Classification Probability	0.191	0.358	0.455
Observations	298	542	740
Mean growth rate of GDP per capita	0.013	0.028	0.02
Mean maturity level	-0.044	-0.014	-0.007
Mean level of GDP per capita	7084	8755	16283

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

on the growth rate itself. In emerging countries, a higher maturity index, i.e. a less mature export bundle, *reduces* growth. This strongly contrasts with the advanced country regime, where a less mature export mix *increases* growth. For the developing countries, the relationship is insignificant, implying that the maturity of the export bundle does not have a clear cut impact on the growth performance of these countries. Given that many commodities were classified as young products due to the peculiarities of resource and commodities trade in the 90s, the insignificant effect could perhaps be attributed to the fact that developing countries often find themselves exporting some mature manufactures but also commodities.[18]

Our results extend and complement recent literature that examines the linkages between the product characteristics of exports and economic growth (An & Iyigun, 2004; Bensidoun *et al.*, 2002; Feenstra & Rose, 2000; Hausmann *et al.*, 2007; Lee, 2010). Table 4.5 not only shows that export maturity as we have measured it, matters for growth. It also shows that this effect depends on the stage of economic development and is significantly non-linear in the level of GDP per capita. This finding is contrary to the common conclusion that emerges from this literature, as it typically postulates a linear monotonic relationship between specific characteristics of exports and growth in spite of notable differences in measures, specifications and econometric techniques used. Consistent with the notion that "what you export matters", our findings suggest that when in your development process you export it matters too.

It is worth noting that the endogeneity of export maturity does not pose a serious problem in our analysis for three reasons. First, since we construct the product-specific maturity measure using the global data, it is less prone to the endogeneity issue than using country-level data. This approach captures some exogenous product characteristics and does not rely on the product information at the country level. Second, we use lagged export maturity, defined as the level at the beginning of each period (i.e. 1988, 1993, 1998, 2003) in our estimations, to alleviate the reverse causality problem. And third, the identification of the negative coefficient between export maturity and growth in the emerging regime suggests that reverse causality cannot be an issue. As countries enjoying higher growth are less likely to export mature products that are

[18] The sales volumes of these commodities and resources depend more on the extraction and transport capacity and global demand than production costs. If, as was the case in the 1990s and early 2000s, demand for food, resources and commodities is volatile, then such supply and capacity constraints drive (relative) prices and consequently our measure classifies these non-manufactured products as mature or young as a result of such external market conditions. Possible additional volatility due to speculation in these markets makes this effect even stronger.

in the declining stage, we feel that the causality running from export maturity to growth is more plausible.

The conventional determinants in our growth regressions also show interesting differences over the regimes. The developing country regime exhibits beta-convergence (among developing countries). The importance of human capital and the rule of law for developing countries are also well established and confirmed in our results. In addition, trade openness and export appears to positively associate with growth. In the emerging regime, countries show strong divergence and a negative impact of a higher capital-labor ratio. This reflects the high returns to capital stock such as infrastructure and reliable power supply in these emerging economies. The accumulation of human capital does not appear significant partially, we would argue, because it is not that important in economies that grow based on exporting mature products. For emerging countries, where inflows of foreign direct investment have been shown to be important, the significance of rule of law is as expected. We also find that export concentration carries a growth penalty for emerging countries and this confirms the finding that a more diversified export structure reduces the vulnerability to adverse terms of trade shocks and is growth promoting. For the advanced economies, we do not find strong evidence of the accumulation of physical and human capital as the driver of growth consistent with economies in their steady states. Also improving openness and rule of law have no significant impact as this regime consists of rather homogeneous countries in openness (actually all are open) and rule of law. However, these countries do seem to perform better with export concentration, in line with the earlier non-linear effect of export diversification on growth found in the literature (Aditya & Roy, 2007; Cadot *et al.*, 2007; Hesse, 2008). We add to this literature by showing that diversifying exports into a wider range of *mature* products is probably most effective and relevant for developing and emerging countries, whereas concentrating exports on a range of *new* products has a positive connection to growth for advanced countries.

To check the robustness of our results, we also used the four alternative country-level maturity measures based on sub-samples of products. Table

4.A.4, Table 4.A.6, Table 4.A.8 and Table 4.A.10 in the Appendix used maturity measure $M1$ by excluding oil-related products, $M2$ by including only manufacturing products, $M3$ for the informative products and $M4$ for the homogeneous products, respectively. The specification tests are shown in Table 4.A.5, Table 4.A.7, 4.A.9 and 4.A.11 in the Appendix. The results show that the three-regime specification is a very robust feature of our data. Moreover, the non-linear effect between export maturity and economic growth over three development stages is found to be very similar to those reported in Table 4.5. Overall, our results do not seem to be driven by the choice of a particular subset of products.

There are three reasons why we conclude that our latent class specification does not merely sort country-time observations in such a way that these results endogenously emerge. First the significantly negative coefficient on GDP per capita in the regime membership probability estimation signifies that lower GDP per capita increases the probability of moving from the reference group to the emerging and developing regimes, respectively, where the latter effect is stronger. This implies that countries with high GDP per capita tend to be sorted into the advanced regime, whereas countries with medium GDP per capita sort into the emerging regime and low income countries end up in the developing regime.[19] In an unconditional latent class specification the three regimes might simply emerge because the model fits the data better if one sorts the observations for which a negative, positive and indeterminate effect applies. The fact that GDP per capita has predictive power in the sorting suggests, however, that there is more to these regimes.

Second, in Table 4.6 we present the regime classifications over time for selected countries. It can be verified that most of the G7 countries are in the advanced growth regime, most of the time, with an occasional switch to the emerging regime and back. The newly industrialized countries in South East Asia, South Africa and Brazil are classified in most periods into the emerging regime and occasionally move between the developing and emerging regimes

[19] Of course we have named these regimes accordingly ex post and based on this outcome. The model endogenously identifies three statistically distinct classes/growth regimes.

(with the exception of Singapore which moves from the advanced to developing regime. Financial services, re-exports and port logistics may well have driven this outlier).[20] Interestingly, the exports of mature products by e.g. China may constitute an important factor to explain the recent rapid growth and strong convergence of the newly industrialized countries. Our classification is not completely in line with our priors (e.g., Japan classified as emerging in 1988-1992 or Brazil as advanced since 1998), but on the whole the classification looks roughly fine, considering that this classification is in no way based on ex ante assumptions and exogenous thresholds or cut-off points.

Table 4.6: Classification-Selected Countries

	Country	1988-1992	1993-1997	1998-2002	2003-2005
	Canada	Advanced	Advanced	Advanced	Advanced
	Germany	Advanced	Advanced	Advanced	Advanced
	France	Advanced	Advanced	Advanced	Advanced
G7	Italy	Advanced	Advanced	Advanced	Advanced
	Japan	Emerging	Advanced	Advanced	Advanced
	United Kingdoms	Advanced	Advanced	Advanced	Advanced
	United States	Advanced	Advanced	Advanced	Advanced
	Brazil	Emerging	Emerging	Advanced	Advanced
	China	Emerging	Developing	Emerging	Emerging
	Hongkong	Emerging	Advanced	Developing	Emerging
Newly	India	Emerging	Emerging	Emerging	Emerging
Industrialized	Korea	Developing	Emerging	Developing	Advanced
	Malaysia	Developing	Emerging	Developing	Emerging
	Thailand	Developing	Emerging	Developing	Emerging
	Taiwan	Emerging	Emerging	Advanced	Advanced
	Singapore	Emerging	Emerging	Developing	Emerging
	South Africa	Advanced	Advanced	Advanced	Advanced

A final distinctive feature of our model is that a country may change regimes over time. Thus, we can examine the stability of the regime classification by

[20] The full classification of countries in growth regimes is presented in Table 4.A.3 in the Appendix.

Table 4.7: Transition Matrix

		To			
		A-Developing	B-Emerging	C-Advanced	Total
	A-Developing	15	30	10	55
		(27.27)	(54.55)	(18.18)	(100)
From	B-Emerging	16	39	36	91
		(17.58)	(42.86)	(39.56)	(100)
	C-Advanced	34	15	42	117
		(6.84)	(15.38)	(77.78)	(100)
	Total	39	87	131	263
		(41.83)	(33.46)	(24.71)	(100)

Numbers denote the transition cases. The transition probability is in the parentheses.

considering regime switches over time. Table 4.7 presents the regime transition matrix, including the absolute number of regime allocation changes and the frequency between any two time periods.[21] We can see that the diagonal elements carry the largest percentages as would be expected. However, there is quite some transitions from emerging to advanced and back. Transitions between the advanced and the developing regime are more rare, as is to be expected. Transitions from developing to emerging and back are much more frequent than between developing and advanced. The emerging regime thus seems to be the stepping stone towards the advanced country growth regime. The occasional switches from developing to advanced and back can also be due in part to the disrupting effects of resource and commodities trading, as was argued above. This, however, requires much more detailed analysis of the transition dynamics in our data. A useful first step in that direction would be to redo our analysis without products that can be classified as primary sector products. We feel, however, that at this stage it is useful to leave these products in the sample. This has stacked the odds against us finding the results we feel are most important to report in this paper. That is, even in their presence our maturity measure picks up something of significance, both in the statistical and the economic sense. We now turn to our conclusions, to discuss the significance of that result.

[21]Since we distinguish four time periods, we have three transition matrices. We opt to present the aggregate, unconditional transition probabilities, following Bos *et al.* (2010).

4.4 Conclusions

In this paper we set out to develop a new measure of product maturity using old knowledge about the product life cycle. A typical product will diffuse in global trade (if at all) approximately following an S-shaped diffusion curve, where total market volume increases fast, than slower and eventually goes into decline. In global markets a product was thus defined as mature when export growth declines. Using this empirical regularity of the product life cycle we developed a continuous maturity measure and showed that our classification of four-digit products in global trade is positively correlated but certainly not equivalent to other classification methods in the literature. As our empirical analysis went on to show, our measure has something sensible and novel to say about countries' growth performance.

We showed in a conditional latent class growth estimation that countries can find themselves in three distinct growth regimes. That is, the vector of parameters differs significantly between three endogenously determines groups of country-year observations in our data set. In addition we showed that GDP per capita, as a proxy for the level of development of a country, is a good predictor of class membership and our model distinguishes between low, middle and high income level countries. This too is quite similar to classifications used in the literature, but our classification has the added benefit, that we do not impose group membership or have to rely on inherently arbitrary cut-off points.

Finally, we showed that our maturity measure has a non-linear impact on economic growth over the development stages our countries find themselves in. In the low-income *developing* stage the maturity of exports has no significant impact on growth and such traditional variables as capital-labor ratio's and institutional quality pick up most of the cross-country, within period variation. This implies that for developing countries getting into or out of more or less mature export products is not expected to affect their growth performance in a predictable direction. In part this may be due to the fact that some resources and commodities were classified as early stage products as a result of the late 1990s resource boom. This would offset the otherwise positive (or negative) impact of manufactured early stage products, but we feel it is more likely we would have found a significant coefficient in either direction if such biases had been strong. Slightly richer *emerging* countries, in contrast have a robust and clearly negative impact of exporting early stage products on growth. They do better exporting mature (manufactured) products and moving into large but globally saturated or declining markets. This gives them the opportunity to grow fast, capturing market share of others. But as in the *advanced* country stage the sign switches and export maturity becomes a drag on growth, the challenge is clearly to grow fast on mature products but at the same time prepare for the final stage in which early stage innovative exports become the engine of growth.

This is clearly a huge policy challenge. As recent theoretical and empirical studies have shown, institutions are of paramount importance in generating sustainable economic growth. And our results once more confirm this. The existence of distinct growth regimes and sign-switches between them imply that institutions that drive growth in one stage may put a drag on growth in the next. The institutions that fit the emerging country stage best (e.g. lax intellectual property standards, autocratic control over e.g. infrastructures and bank credit) may well be less than perfect for the same county when it enters a more advanced stage. And institutions usually resist change. The institutions that bred success in the past thus easily become a liability. The advanced industrialized countries are currently still making their transition from an industrial, managed society to an entrepreneurial society (Audretsch & Sanders, 2007). The challenge for emerging countries like China, India and Brazil is to build institutions that are strong yet flexible enough to take the country to the next stage of development and then keep it at the frontier. What institutions will pass that test is an empirical matter and left for further research.

Appendix

Table 4.A.1: Top 50 Least Mature Products

Name	Percentage of World Export	Maturity (year=2005)	Rank (year=2005)	Maturity (year=1988)	Rank (year=1988)
2112-Calf skins, raw	0.011	0.810	427	-0.139	72
8841-Lenses,prisms and mirrors	0.338	0.749	426	0.009	193
8432-Suits and costumes	0.041	0.724	425	0.073	305
4232-Soya bean oil	0.067	0.709	424	-0,114	88
2234-Linseed	0.005	0,539	423	-0,366	11
0012-Sheep and goats (live)	0.016	0,537	422	0,154	399
0616-Natural honey	0.010	0.512	421	-0.082	108
6760-Rails and railway track construction mater	0.029	0.465	420	0.037	242
4239-Other soft fixed vegetable oils	0.029	0.447	419	-0.021	159
0619-Other sugars	0.035	0.437	418	0.059	282
4313-Fatty acids, acid oils and residues	0.071	0.422	417	-0.015	166
4111-Fats and oils of fish and marine mammals	0.008	0.404	416	-0.016	165
0411-Durum wheat (unmilled)	0.021	0.402	415	-0.118	85
0142-Sausages	0.032	0.388	414	0.140	385
4249-Fixed vegetable oils	0.273	0.388	413	-0.028	154
0565-Vegetables (prepared or preserved)	0.136	0.382	412	0.047	260
0612-Refined sugars	0.107	0.371	411	-0.008	176
3221-Anthracite	0.606	0.361	410	-0.037	139
3231-Briquet and ovoids	0.003	0.356	409	0.153	398
0730-Chocolates	0.278	0.348	408	0.005	188
5417-Medicaments	2.668	0.347	407	0.133	379
2481-Railway or tramway sleepers	0.003	0.343	406	-0.019	161
7188-Engines and motors	0.109	0.329	405	-0.033	147
2815-Iron ore and concentrates (not agglomerated)	0.255	0.328	404	0.008	190
6783-Other tubes and pipes	0.294	0.322	403	-0.049	130
0611-Sugars	0.069	0.318	402	-0.384	9
3354-Petroleum bitumen,petrol and coke	0.134	0.318	401	-0.117	86
6130-Furskins (tanned or dressed)	0.022	0.316	400	-0.193	48
6781-Tubes and pipes	0.013	0.314	399	0.248	424
8928-Printed matter	0.309	0.312	398	0.052	270
8741-Surveying,hydrographic and compasses	0.140	0.305	397	0.057	280
2320-Natural rubber latex	0.127	0.291	396	-0.319	18
2332-Reclaimed rubber	0.004	0.290	395	-0.107	90
2222-Soya beans	0.202	0.284	394	-0.048	132
7211-Agricultural	0.047	0.284	393	-0.131	77
2879-Ores and concentrates	0.162	0.281	392	-0.596	3
0813-Oil-cake and other residues	0.165	0.277	391	-0.037	138
6973-Domestic-type,non-electric heating and cooking	0.100	0.277	390	0.188	415
6611-Quicklime,slaked lime and hydraulic lime	0.006	0.276	389	0.163	405
5416-Glycosides,glands or other organs	0.409	0.264	388	0.154	400
0980-Edible products and preparations	0.391	0.264	387	0.192	416
6359-Manufactured articles of wood	0.181	0.262	386	0.013	198
0460-Meal and flour of wheat and flour	0.032	0.260	385	0.052	269
8483-Fur clothing and articles made of furskins	0.030	0.258	384	-0.090	101
0574-Apples (fresh)	0.050	0.257	383	-0.019	160
0470-Other cereal meals and flours	0.034	0.256	382	-0.055	127
4113-Animal oils, fats and greases	0.020	0.253	381	-0.159	63
2119-Hides and skins	0.011	0.253	380	-0,447	6
5415-Hormones (natural or reproduced)	0.096	0.251	379	0,135	380
8459-Other outer garments	0.452	0.249	378	0.076	311

Table 4.A.2: Top 50 Most Mature Products

Name	Percentage of World Export	Maturity (year=2005)	Rank (year=2005)	Maturity (year=1988)	Rank (year=1988)
3341-Motor spirit and other light oils	0.001	-4.096	1	0.091	333
3343-Gas oils	0.001	-3.605	2	0.139	384
6351-Wooden packing cases,boxes and crates	0.007	-1.352	3	0.157	401
3345-Lubricating petrol and oils	0.067	-1.319	4	0.212	418
6412-Printing paper and writing paper	0.124	-1.101	5	-0.100	95
2235-Castor oil seeds	0.000	-0.668	6	-0.267	32
8710-Optical instruments and apparatus	0.515	-0.643	7	0.069	298
7641-Electric lines	0.572	-0.600	8	-0.007	179
2614-Silk worm cocoons	0.001	-0.546	9	-0.059	124
2683-Fine animal hair (not carded or combed)	0.010	-0.542	10	-0.240	35
2771-Industrial diamonds (sorted)	0.007	-0.491	11	0.520	427
2872-Nickel ores and concentrates	0.069	-0.469	12	-0.290	25
6812-Platinum and other metals of the platinum	0.189	-0.453	13	-0.292	24
0451-Rye (unmilled)	0.003	-0.413	14	-0.106	91
3330-Petrol oils and crude oils	9.535	-0.380	15	-0.188	49
2890-Ores and concentrates of precious metals	0.049	-0.372	16	-0.115	87
2440-Cork,natural,raw and waste	0.003	-0.369	17	-0.030	151
0483-Macaroni,spaghetti and similar products	0.030	-0.294	18	0.177	411
8452-Dresses,skirts,suits etc.	0.044	-0.285	19	0.057	277
8442-Under garments	0.013	-0.284	20	0.238	422
2511-Waste paper (paperboard)	0.066	-0.282	21	-0.417	8
7788-Other electric machinery and equipment	0.983	-0.279	22	0.048	261
2225-Sesame seeds	0.011	-0.259	23	-0.198	46
2517-Chemical wood pulp (soda or sulphate)	0.216	-0.255	24	-0.376	10
2640-Jute and other textile bast fibres	0.001	-0.253	25	-0.085	106
7284-Mach and appliances	1.404	-0.248	26	0.019	211
6831-Nickel and nickel alloys	0.107	-0.245	27	-0.315	20
8813-Photographic and cinematographic apparatus	0.370	-0.243	28	0.013	197
2232-Palm nuts and palm kernels	0.001	-0.242	29	-0.869	2
6863-Zinc and zinc alloys	0.012	-0.237	30	0.053	271
6415-Paper and paperboard	0.240	-0.235	31	-0.130	78
7281-Mechanical tools	0.157	-0.231	32	0.001	184
7754-Shavers and hair clippers with motor	0.029	-0.225	33	-0.008	175
8811-Photographic,cameras,parts and accessories	0.078	-0.224	34	0.062	284
2512-Mechanical wood pulp	0.025	-0,211	35	-0,236	36
7512-Calculating machines and cash registers	2.510	-0.211	36	0.020	215
6542-Fabrics,woven and contain	0.062	-0.194	37	0.073	304
8939-Miscellaneous art	0.760	-0.179	38	0.096	345
2223-Cotton seeds	0.003	-0.176	39	0.298	426
7642-Microphones,loudspeakers and amplifiers	0.153	-0.168	40	0.096	344
6861-Zinc and zinc alloys (unwrought)	0.074	-0.166	41	-0.094	97
7442-Lifting,handling and conveyors	0.491	-0.164	42	-0.009	173
6573-Coated/impregnated textile fabrics	0.129	-0.155	43	0.081	321
8433-Dresses	0.050	-0.148	44	-0.010	172
2516-Chemical wood pulp and dissolving grades	0.017	-0.144	45	-0.277	30
2784-Asbestos	0.004	-0.141	46	-0.101	94
2111-Bovine and equine hides	0.041	-0.141	47	-0.223	41
6822-Copper and copper alloys	0.423	-0.137	48	-0.089	102
2472-Sawlogs and veneer logs	0.063	-0.132	49	-0.068	116
7591-Parts of and accessories	0.161	-0.127	50	0.052	268

Figure 4.A.1: Informativeness of Products

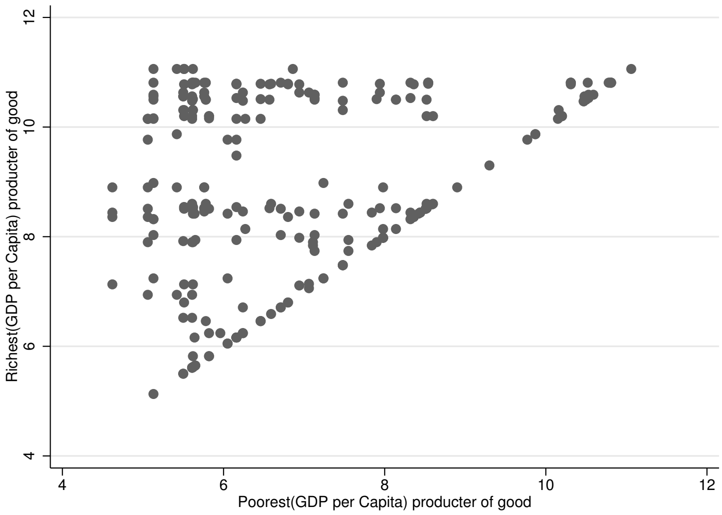


Table 4.A.3: Country Division (Main Specification)

Code	Country	1988-1992	1993-1997	1998-2002	2003-2005
Africa					
CIV	Cotedivoire	A	A	A	B
CMR	Cameroon	A	B	C	C
DZA	Algeria	A	A	C	C
EGY	Egypt	B	C	C	A
GHA	Ghana	C	B	A	C
GMB	Gambia	B	B	B	C
KEN	Kenya	B	B	B	C
LBY	Libya	C	A	A	A
MAR	Morocco	B	A	C	C
MLI	Mali	B	A	B	B
MOZ	Mozambique	A	A	A	A
MWI	Malawi	B	A	B	C
SEN	Senegal	B	B	C	C
TUN	Tunisia	C	C	C	B
TZA	Tanzania	A	B	C	C
UGA	Uganda	C	A	C	C
ZAF	South Africa	C	C	C	C
ZMB	Zambia	B	B	B	C
ZWE	Zimbabwe	A	B	A	A
Europe					
ALB	Albania	A	A	A	A
AUT	Austria	C	C	C	C
BEL	Belgium	C	C	C	C
CHE	Switzerland	C	C	C	C
CYP	Cyprus	B	B	C	C
CZE	Czech Republic	C	C	C	C
DEU	Germany	C	C	C	C
DNK	Denmark	C	C	C	C
ESP	Spain	C	C	B	C
FIN	Finland	A	B	B	C
FRA	France	C	C	C	C
GBR	Great Britain	C	C	C	C
GRC	Greece	C	C	C	C
HUN	Hungary	A	C	B	C
IRL	Ireland	B	B	B	C
ITA	Italy	C	C	C	C
MLT	Malta	B	C	B	C
NLD	Netherlands	C	C	C	C
NOR	Norway	C	B	C	C
POL	Poland	A	B	C	B
PRT	Portugal	B	C	C	C
SVK	Slovakia	B	C	B	C
SWE	Sweden	C	C	C	C
TUR	Turkey	B	A	A	B
Former USSR					
ARM	Armenia			A	A
EST	Estonia			B	B
KAZ	Kazakhstan			A	A
LTU	Lithuania			B	B
LVA	Latvia			B	B
HRV	Croatia			C	B
SVN	Slovenia			C	C
Asia					
CHN	China	B	A	B	B
BGD	Bangladesh	C	B	C	C
HKG	Hong Kong	B	C	A	B
IDN	Indonesia	B	B	A	B
IND	India	B	B	B	B
IRN	Iran	C	A	C	C
ISR	Israel	B	C	B	C
JOR	Jordan	A	B	C	C
JPN	Japan	B	C	C	C
KOR	Korea	A	B	A	C
LKA	Sri Lanka	C	C	C	A
MYS	Malaysia	B	B	A	B
PAK	Pakistan	C	C	C	B
PHL	Philippines	B	B	A	B
SGP	Singapore	B	B	A	B
SYR	Syria	C	A	B	B
THA	Thailand	A	B	A	B
TWN	Taiwan	B	B	C	C
North America					
CAN	Canada	C	C	C	C
USA	The United States	C	C	C	C
Oceania					
AUS	Australia	C	C	C	C
NZL	New Zealand	C	C	C	C
South and Central America					
ARG	Argentina	A	C	A	B
BOL	Bolivia	C	C	C	C
BRA	Brazil	A	C	C	C
CHN	Chile	B	B	C	C
COL	Colombia	C	C	C	C
CRI	Costa Rica	C	B	C	C
DOM	Dominican Republic	A	C	A	B
ECU	Ecuador	B	C	B	C
GTM	Guatemala	C	C	C	C
GUY	Guyana	A	A	B	B
HND	Honduras	B	B	B	C
JAM	Jamaica	B	B	B	B
MEX	Mexico	C	A	C	C
NIC	Nicaragua	B	B	C	C
PAN	Panama	A	B	C	B
PER	Peru	B	A	B	C
PRY	Paraguay	A	B	B	B
TTO	Trinidad and Tobago	C	A	B	B
URY	Uruguay	A	B	A	B
VEN	Venezuela	A	B	B	A

A-Developing B-Emerging C-Advanced

Table 4.A.4: Empirical Results-Non-oil Products

Regime	Developing	Emerging	Advanced
Initial export maturity (non-oil)	0.284***	-0.095***	0.089***
Initial GDP per capita	-0.023***	0.028***	-0.005***
Capital/labor ratio	-0.004	-0.019***	0.000
Human capital	0.007***	0.000	0.001
Rule of law	0.009**	0.003**	0.002***
Trade openness	0.009	-0.005	0.005
Trade concentration	0.044	-0.106***	0.032***
Constant	0.024	-0.062***	0.022***
Regime Membership Probability			
Constant	0.430	0.519	Reference
GDP per capita	-0.010***	-0.007***	Reference
Observations	317	521	742

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

Table 4.A.5: Hypothesis Test-Non-oil Products

Testing	Test	Test Statistic	P-value	Conclusion
Class Fit				
Three-class conditional vs. Two-class conditional	LRT	139.085	0.000	rejected
Three-class conditional vs. Three-class unconditional	LRT	42.011	0.000	rejected
Equality of Export Maturity				
Class A vs. B	Wald	16.888	0.002	rejected
Class B vs. C	Wald	23.894	0.000	rejected
Class A vs. C	Wald	5.088	0.024	(not) rejected
Class A, B and C	Wald	30.360	0.000	rejected
Equality of All Parameters				
Class A vs. B	Wald	92.072	0.000	rejected
Class B vs. C	Wald	231.775	0.000	rejected
Class A vs. C	Wald	37.710	0.000	rejected
Class A, B and C	Wald	287.684	0.000	rejected

Note: LRT represents the likelihood ratio test.

Table 4.A.6: Empirical Results-Manufacturing Products

Regime	Developing	Emerging	Advanced
Initial export maturity (manuf.)	0.266***	-0.086**	0.076***
Initial GDP per capita	-0.019***	0.026***	-0.005***
Capital/labor ratio	-0.004	-0.018***	0.001
Human capital	0.007***	0.000	0.000
Rule of law	0.011***	0.003*	0.003***
Trade openness	0.008	-0.003	0.002
Trade concentration	0.045	-0.099***	0.029***
Constant	0.002	-0.058***	0.021***
Regime Membership Probability			
Constant	0.677**	0.655**	Reference
GDP per capita	-0.011***	-0.006***	Reference
Observations	362	537	681

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

Table 4.A.7: Hypothesis Test-Manufacturing Products

Testing	Test	Test Statistic	P-value	Conclusion
Class Fit				
Three-class conditional vs. Two-class conditional	LRT	139.937	0.000	rejected
Three-class conditional vs. Three-class unconditional	LRT	42.965	0.000	rejected
Equality of Export Maturity				
Class A vs. B	Wald	23.940	0.000	rejected
Class B vs. C	Wald	13.105	0.000	rejected
Class A vs. C	Wald	8.450	0.004	rejected
Class A, B and C	Wald	26.412	0.000	rejected
Equality of All Parameters				
Class A vs. B	Wald	111.039	0.000	rejected
Class B vs. C	Wald	253.736	0.000	rejected
Class A vs. C	Wald	51.091	0.000	rejected
Class A, B and C	Wald	319.959	0.000	rejected

Note: LRT represents the likelihood ratio test.

Table 4.A.8: Empirical Results-Sutton's Measure

Regime	Developing	Emerging	Advanced
Initial export maturity (Sutton)	0.248***	-0.132***	0.122***
Initial GDP per capita	-0.021***	0.019***	-0.002
Capital/labor ratio	-0.007	-0.009**	-0.002
Human capital	0.007***	0.001	0.001***
Rule of law	0.008**	0.008***	-0.001
Trade openness	0.009	-0.005	0.006**
Trade concentration	0.034	-0.094***	0.033***
Constant	0.031	-0.060***	0.020***
Regime Membership Probability			
Constant	0.338	0.456	Reference
GDP per capita	-0.010	-0.009	Reference
Observations	321	426	833

Note: Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.A.9: Hypothesis Test-Sutton's Measure

Testing	Test	Test Statistic	P-value	Conclusion
Class Fit				
Three-class conditional vs. Two-class conditional	LRT	134.378	0.000	rejected
Three-class conditional vs. Three-class unconditional	LRT	40.878	0.000	rejected
Equality of Export Maturity				
Class A vs. B	Wald	26.122	0.000	rejected
Class B vs. C	Wald	40.938	0.000	rejected
Class A vs. C	Wald	3.645	0.056	(not) rejected
Class A, B and C	Wald	46.948	0.000	rejected
Equality of All Parameters				
Class A vs.B	Wald	78.489	0.000	rejected
Class B vs.C	Wald	185.099	0.000	rejected
Class A vs. C	Wald	31.502	0.000	rejected
Class A, B and C	Wald	232.598	0.000	rejected

Note: LRT represents the likelihood ratio test.

Table 4.A.10: Empirical Results-Rauch's Measure

Regime	Developing	Emerging	Advanced
Initial export maturity (Rauch)	0.054	-0.128***	0.099***
Initial GDP per capita	-0.017**	0.016***	0.000
Capital/labor ratio	-0.010	-0.009***	-0.003***
Human capital	0.007***	0.001	0.001
Rule of law	0.013***	0.005***	0.001
Trade openness	0.022**	-0.010***	0.009***
Trade concentration	0.072**	-0.126***	0.039***
Constant	-0.019	-0.034	0.009
Regime Membership Probability			
Constant	0.397	0.588	Reference
GDP per capita	-0.011	-0.007	Reference
Observations	293	528	759

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

Table 4.A.11: Hypothesis Test-Rauch's Measure

Testing	Test	Test Statistic	P-value	Conclusion
Class Fit				
Three-class conditional vs. Two-class conditional	LRT	158.945	0.000	rejected
Three-class conditional vs. Three-class unconditional	LRT	40.878	0.000	rejected
Equality of Export Maturity				
Class A vs. B	Wald	9.674	0.001	rejected
Class B vs. C	Wald	65.453	0.000	rejected
Class A vs. C	Wald	0.659	0.417	not rejected
Class A, B and C	Wald	62.535	0.000	rejected
Equality of All Parameters				
Class A vs. B	Wald	96.874	0.000	rejected
Class B vs. C	Wald	248.152	0.000	rejected
Class A vs. C	Wald	25.148	0.000	rejected
Class A, B and C	Wald	305.133	0.000	rejected

Note: LRT represents the likelihood ratio test.

Chapter 5

Structural Dissimilarity and Cross-border Equity Investments

5.1 Introduction

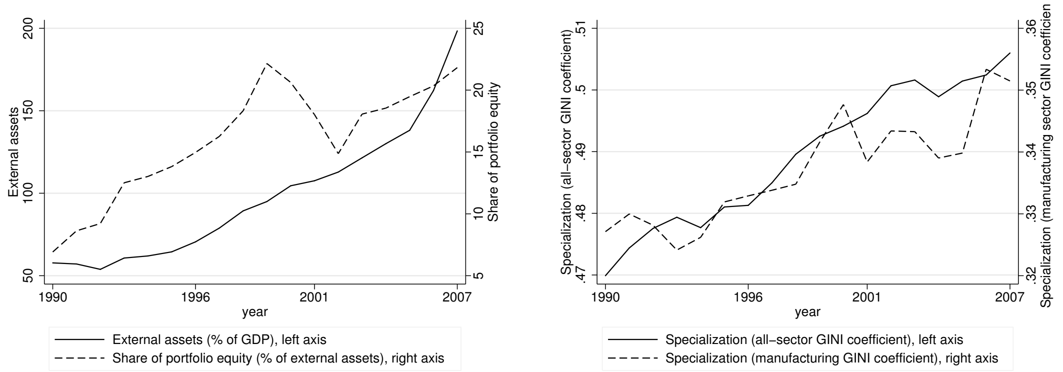
The past two decades have seen an accelerated pace of financial globalization, mirrored by the proliferation of external asset holdings across a large number of countries (Lane & Milesi-Ferretti, 2007, 2008). External financial assets have expanded dramatically on average from 50 percent to 200 percent of GDP since the early 1990s. In addition, portfolio equity has become an increasingly important type of asset and its share in total assets has shown a five-fold rise as shown in Figure (5.1a). At the same time, countries have experienced considerable structural changes. Figure (5.1b) plots that industrial specialization, i.e. the concentration of industries in the economy has steadily increased over the same period. Such a trend is pronounced when we look at specialization across the entire range of economic activities and specialization within the manufacturing sector.

An interesting question that arises, is what are the linkages between industrial specialization and financial integration? This issue has attracted considerable attention in the recent literature. A handful of studies (Basile & Girardi, 2010; Kalemli-Ozcan *et al.*, 2003) emphasize that financial integration promotes industrial specialization through risk-sharing. Open and integrated financial

Figure 5.1: Developments in external assets and industrial specialization

(a) Development of external assets and portfolio assets

(b) Development of industrial specialization



Note: All graphs are weighted by the country size, based on authors' own calculations from a sample of 34 countries.

markets offer a broader range of financial instruments and permit the diversification of ownership via both *ex ante* and *ex post* insurance. The former allows domestic residents to hold claims on the output of other countries, then the dividend, interest, and rental income derived from these holdings contribute to smoothing the effects of output shocks across countries. The latter permits households in each country to adjust their asset portfolios following the occurrence of shocks to achieve consumption smoothing. Countries that are better protected against idiosyncratic shocks, can therefore afford to specialize more. The seminal study of Kalemli-Ozcan *et al.* (2003) finds a robust positive link between risk sharing from financial integration to production specialization among the US regions, as well as across some OECD countries. Basile & Girardi (2010) find a similar positive relationship across European regions.

While there is a vast literature analyzing how financial integration affects specialization, far less attention has been paid to the reverse linkage. The role of industrial structure in driving the dynamics of financial integration is less well-studied. Production specialization exposes an economy to external shocks that are idiosyncratic to specific industries. With uninsured production risk, specialization may result in higher output volatility and entails a welfare loss that may outweigh the benefits. Consequently, countries with a more specialized production structure have more incentive to hold foreign assets to diversify their idiosyncratic output risks. Therefore, any shifts in industrial structures in response to (improved) risk sharing arising from financial integration also impact global linkages and in particular can be expected to reshape the patterns of cross-border portfolio investments.

The purpose of this paper is to fill in this gap by examining the effects of ongoing changes in industrial structures on cross-border portfolio investments for a large number of OECD countries. I explicitly test to what extent investors tilt their foreign equity portfolio towards countries with (dis)similar industrial structures and thereby gain or forego diversification benefits in a country-pair setting. The growing availability of bilateral portfolio data from the Coordinated Portfolio Investment Surveys (CPIS) by the IMF and detailed production data from the EU KLEMS database and Structural Analysis Databased by the OECD allows me to obtain new empirical evidence by differentiating situations in which a home country holds portfolio assets across heterogeneous destination countries. I conduct my analysis in a gravity framework that is commonly used in the international finance literature to analyze the bilateral portfolio equity holdings (Lane & Milesi-Ferretti, 2008; Portes & Rey, 2005). My sample consists of 23 NACE one- and two-digit industries that cover all economic activities, 30 source and 34 destination countries over the period 2000-2007.

The channel I explore in this paper is a diversification or risk-sharing motive in foreign equity holdings. Substantial research has shown that investors do not exploit such diversification opportunities as they allocate a disproportionately larger fraction of their wealth to domestic equities than the optimal allocation suggested by the standard portfolio theory, a phenomenon commonly referred to as the "home bias".[1] However, the surge in financial globalization in the last two decades has been accompanied by a significant decline in in equity (and debt) home bias with a corresponding increase in international

[1] See for example, Lewis (1999) and Coeurdacier & Rey (2013) for an extensive overview of the home bias literature.

risk-sharing, especially for developed countries (Artis & Hoffmann, 2007; Kose *et al.*, 2009b; Sørensen *et al.*, 2007). A strand of literature has demonstrated that home bias and international risk sharing are closely related phenomena. These studies typically find that countries with low home bias through diversifying their portfolios internationally tend to obtain more risk sharing in international market, and consequently display smoother income and consumption patterns (Artis & Hoffmann, 2007; Holinski *et al.*, 2012; Sørensen *et al.*, 2007).

Whether the motivation to diversify idiosyncratic home country risk constitutes an important driver of cross-border portfolio investments has been analyzed in a number of studies. While there is by now a considerable literature exploring the presence of a diversification motive, the empirical evidence is ambiguous. Portes & Rey (2005) build on a general equilibrium model with endogenous asset formation by Martin & Rey (2004) and estimate a gravity specification of asset trade. For a sample of 14 countries over 1989-1996, they employ three risk diversification variables (i.e., covariance of the stock market indices, covariances of the GDP growth rates and covariances between consumption growth rate and stock market returns) in their empirical framework and find weak evidence of a diversification motive, i.e. the covariance carries a negative sign only after controlling for information frictions, proxied by bilateral distance. Lane & Milesi-Ferretti (2008) analyze patterns and drivers of bilateral portfolio equity holdings using bilateral pairs on 50 source and 132 destination countries in 2001. They include three measures, similar to Portes & Rey (2005), to take into account the role of stock markets of designation countries in potentially hedging against home country output fluctuations. They also find little evidence of a diversification motive. On the contrary, Coeurdacier & Guibaud (2011) find that controlling for many determinants of international portfolios and for the endogeneity of stock return correlations, investors do tilt their foreign holdings towards countries which offer better diversification opportunities, measured by the lower correlation with their home stock market. Vermeulen (2013) examines the relationship between foreign equity holdings and stock market return correlations before and during the financial crisis for 22 source and 42 destination countries. He finds a significant negative relationship during the crisis and no relationship before the crisis, implying that during the crisis investors have overexposure to equities which are less correlated with domestic market. Therefore, the actual foreign equity positions help to stabilize the wealth of investors in the crisis.

While the above mentioned studies have delivered conflicting results when using stock market return correlations as risk diversification variables, I depart from this literature by developing structural dissimilarity measures to capture the diversification motive. Naturally, countries with different industrial structures are subject to different industry-specific risks. For example, countries that are highly concentrated on manufacturing activities are more exposed to risks that are common to the world manufacturing sectors compared to countries with high concentration on the service sectors. Consequently, stock market return correlations may critically depend on the differences in industrial structures across countries. My paper is thus closely related to a few studies that postulate the role of industrial structures as a fundamental factor in affecting the stock market return correlations. Dutt & Mihov (2008) find that the difference in industrial structures is an important factor in explaining the pairwise stock market return correlations. Countries with similar industries (or similar export structures) have stock markets that exhibit high correlation of returns. Tavares (2009) shows that (export) structural dissimilarity decreases the cross-country co-movements in stock returns. More broadly, my paper builds on a large stand of earlier literature on the relative importance of industry vs. country factors in determining the correlation of stock market returns. The seminal study by Roll (1992) suggests that industrial composition can explain substantial variation in national equity returns. On the contrary, Heston & Rouwenhorst (1994) and Griffin & Andrew Karolyi (1998) find that industrial structure accounts for a very small proportion of variation in national equity returns and country factors appear to be the main driver of stock market co-movements. More recently, industry factors have become increasingly important or even surpassed the country effects along with the economic integration (Brooks & Del Negro, 2004; Campa & Fernandes, 2006). The important point to note for the objective of this paper is that I do not intend to answer whether industry or country factors are prevalent, rather we are interested in how structural changes in industrial composition across countries shape the patterns of bilateral holdings of portfolio assets and uncover whether investors take into account the diversification motive when investing in foreign equities.

My paper belongs to the growing literature that has sought to identify the empirical determinants of bilateral asset holdings. These studies have emphasized the role of geography, culture and information frictions (Portes & Rey, 2005; Portes *et al.*, 2001), trade flows (Aviat & Coeurdacier, 2007; Lane & Milesi-Ferretti, 2008), external pull factors (e.g, low interest rates and economic downturns in developed countries, etc) and internal pull factors, such as institutional development (Alfaro *et al.*, 2008; Papaioannou, 2009), financial market development (di Giovanni, 2005; Lane & Milesi-Ferretti, 2008) and capital account liberalization as important determinants of the pattern of international financial transactions. I add to this literature by examining an important missing element, namely the role of industrial structure in affecting bilateral portfolio investments while controlling for the determinants stressed in the aforementioned studies.

My results are easy to summarize. By estimating a gravity model controlling for country-pair fixed effects and time fixed effects, I find that structural dissimilarity appears to be an important determinant of bilateral holdings of portfolio assets. In contrast to conventional wisdom and previous empirical studies, I demonstrate a significant negative relationship between structural dissimilarity and bilateral holdings of portfolio assets, suggesting that investors tend to hold more foreign equities in countries with similar industrial structures. The diversification motive therefore does not seem to play a role. This finding is robust to a wide range of alternative measures, different specifications, various samples and the endogeneity of structure dissimilarity. My findings can be explained by a preference for familiarity when investing abroad. For example, Massa & Simonov (2006) find that investors do not primarily engage in hedging, but invest in stocks closely related to their non-financial income. They argue that the familiarity, that is, the tendency to concentrate holdings in stocks to which the investor is geographically or professionally close or he has held for a longer time may explain their findings. I extend this to the logically equivalent argument that investors prefer to invest in similar countries.

The remainder of the paper proceeds as follows. Section 5.2 discusses econometric specifications and estimation procedures. Section 5.3 presents the data and measures proposed. Section 5.4 discusses the empirical results. Finally, Section 5.5 summarizes and concludes.

5.2 Methodology

5.2.1 Econometric Specification

The purpose of this paper is to investigate whether structural dissimilarity influences bilateral holdings of portfolio equity and thereby uncover whether investors take into account the diversification opportunities. I start my analysis by estimating the following gravity specification:

$$ln(F_{odt}) = \alpha_{od} + \alpha_t + \eta_1 S_{odt} + \beta' Z_{odt} + \epsilon_{odt} \tag{5.1}$$

where o denotes the source country, d denotes the destination country, and t denotes time; lnF is the natural log of the bilateral holdings of portfolio equities;[2] S is a time-varying measure capturing the (dis)similarities of economic structures between each country pair o and d. If the diversification motive is present, we expect a positive relationship between the structural dissimilarity measure and portfolio asset holdings as investors hedge home country-specific risk by seeking foreign equities in countries whose industrial structures are different to their own, i.e., a positive η_1 . β' is a $1 \times n$ parameter vector. Z_{odt} is an $n \times 1$ vector of control variables that capture other determinants of bilateral asset holdings. These variables include the bilateral trade and the standard gravity determinants, such as population, GDP per capita, distance, common border and common language. ϵ is a normally distributed random error term

[2] I also use the natural log of the bilateral FDI holdings as the dependent variable to study their link with structural dissimilarity. However, the results are rather mixed and remain unreported here. This issue is left for future research.

that has a zero mean and a constant variance. I include country-pair fixed effects α_{od} and year fixed effects α_t in my specification. These fixed effects control for hard-to-measure time-invariant factors such as cultural ties, endowments, and time-varying global common factors that could potentially drive the patterns of structural dissimilarity and portfolio equity holdings.

5.2.2 Estimation Procedure

I adopt both cross-section and panel-based econometric procedures to estimate equation (5.1). Each estimation procedure complements, rather than substitutes the other procedure. I first use pure cross-sectional OLS estimates that pool the time-series observations across all country pairs. This between-country-pair estimator removes the time dimension by averaging the dependent and independent variables over the period 2000-2007. Therefore, for these estimates, I have one single observation for each country pair. [3]

While these estimates help me determine to what extent the cross-sectional variation in the size of bilateral equity holdings can be attributed to differences in industrial structures, it has at least two drawbacks. First, the estimator does not utilize the time-series dimension of our data, and thus it does not provide the possibility to investigate whether the within country-pair variation plays a role, i.e., whether a changing degree of dissimilarities between countries is associated with the changes in portfolio composition. Second, the cross-sectional estimator does not control for country-pair fixed effects, which may bias my estimates. To overcome these problems, I further employ panel-based estimation strategies that exploit both time-series as well as cross-section variations and control for country-pair and time fixed effects, thus yielding more efficient estimates.

[3]Note that in most cases there are two observations (country o to country$d$ and country d to country o) for the same pair of countries. I did not average them. In the panel setting, I regard them as the same pair, i.e. share the same country-pair fixed effects.

5.3 Data and Measures

A number of data considerations govern the choice of my sample. First, having a sufficiently large set of country pairs is important to ensure sufficient variation in bilateral portfolio asset holdings. A second consideration for the purpose of our analysis is the fact that I require a sufficiently disaggregated set of industries to construct the structural dissimilarity measures. In other words, at a higher level of aggregation, countries' industrial structures appear alike by construction. Third, industrial structures are relatively slow to adjust, therefore, a longer time span is desirable to uncover the dynamics between industrial structures and portfolio asset holdings.

My empirical analysis covers an unbalanced panel of 10 sectors spanning all economic activities as well as 13 industries within the manufacturing sector for 30 source countries and 34 destination countries during the period 2000-2007, the longest period for which (production) data are available for the largest amount of countries. I construct bilateral structural differences across all sectors and as well as structural differences across manufacturing industries.

Below, I present the construction of my variables and their sources.

Bilateral Holdings of Portfolio Assets

To construct the dependent variable, I use annual data on cross-border portfolio equity holdings, retrieved from the Coordinated Portfolio Investment Survey (CPIS) provided by the International Monetary Fund (IMF). The CPIS reports data on year-end cross-border security holdings for a large number of home and destination countries and territories. Though CPIS suffers from a number of measurement errors (Lane & Milesi-Ferretti, 2008), the reporting of holdings by developed countries is in general of high quality (Coeurdacier & Guibaud, 2011). In particular, the geographical distribution of CPIS aggregate data is shown to be strongly correlated with micro data on international mutual funds equity holdings (Hau & Rey, 2008).

I collect figures on portfolio security holdings, measured in US dollars for 30 home countries and 34 destination countries over the period 2000-2007. Furthermore, to ensure sufficient time-series variation, country pairs are removed from our sample if less than three observations are available over the entire period.

Structural Dissimilarity

Following Kalemli-Ozcan *et al.* (2003), Krugman (1991) and Imbs (2004), my primary measure of bilateral structural dissimilarity is specified as follows:

$$S_{odt} = \sum_{j=1}^{n} |s_{jot} - s_{jdt}| \tag{5.2}$$

where j denotes the industry, n denotes the number of industries, o denotes home country, d denotes destination country, and s represents the share of each industry in each country. In other words, this index summarizes the absolute differences of all sector shares between each pair of country o and d. It measures the extent to which country o differs from country d in terms of industrial composition. S reaches its maximum value of two if no industry is in common between o and d.

For the robustness purpose, I employ two additional measures. First, I compute a variation of S as follows:

$$S'_{odt} = \sum_{j=1}^{n} (s_{jot} - s_{jdt})^2 \tag{5.3}$$

One aspect worth noting is that S' summarizes the square of bilateral differences in sector shares, instead of the absolute differences in equation (5.2). This index puts more weight on industries with large bilateral differences. The industry shares s are computed using the same data source on industry value added.

Second, I take a measure that is based on the absolute differences of the Gini coefficients of each country pair Spe as follows:

$$Spe_{odt} = |Gini_{ot} - Gini_{dt}| \tag{5.4}$$

The Gini coefficient measures the degree of concentration or inequality of the distribution of sector shares in an economy, which is commonly used in the empirical literature to measure the (absolute) specialization.[4] All value added data is taken from the EU-KLEMS database and OECD (2008) STAN database.

For all these three structural dissimilarity measures, I first compute it using sector-level value added data for 10 broad sectors covering all economic activities. Then I compute the same measure using value added data for 13 NACE 2-digit manufacturing industries.

To deal with the endogeneity problem, I use three measures of infrastructure provision, namely total length of the road network in miles, the number of telephone lines in use and the electrical power-generating capacity to instrument structural dissimilarity measures. I normalize them by the size the labor force, following Yeaple & Golub (2007).[5] All three measures of infrastructure provisions are taken from the World Bank (2008) *World Development Indicators* (WDI).

Other Variables

I control for other determinants of bilateral equity holdings identified in earlier studies.

To control for bilateral trade flows $lntrade$, I use the log of bilateral exports plus imports, measured in current US dollars. Data on bilateral imports and exports are taken from the IMF Direction of Trade (DOT) database.

I control for standard gravity determinants, including the stage of development and country size of home and destination countries. The former is

[4]It's important to note that Spe captures the difference in the degree of specialization between each country pair, rather than the difference in industrial structures as in S and S'. It may very well be the case that the degree of Gini coefficient is the same between a country pair, i.e. Spe equals zero, but the industrial composition is different, i.e. S and S' may not equal to zero accordingly. Although all these three measures are highly correlated, the correlation coefficients are much higher between S and S' (i.e., 0.818) than between S and Spe (i.e., 0.37) and S' and Spe (i.e., 0.225).

[5]Ideally, the infrastructure variables should capture some elements of quality (failed telephone calls, power outages, etc). However, such data does not exist in the necessary panel setting. Therefore, I purely rely on the quantity measures.

measured by GDP per capita at constant 2000 US dollars, whereas the latter is measured by the total number of population. Furthermore, *lndist* is the natural log of the distance between a country pair, defined as distance between the major cities in two countries. *border* is the contiguity dummy that takes the value of one if country o and d share a land border. *language* is a dummy variable equal to one when country o and d speak a common language. All gravity variables are taken from the CEPII database.

Table 5.1 summarizes the definitions, sources and descriptive statistics of main variables as well as those used in robustness analysis, respectively. The presentation and discussion of the empirical findings is the task of the next section.

5.4 Empirical Results

This section presents the empirical results.

Cross-Sectional Results

I start by investigating the effect of structural dissimilarity on the size of bilateral portfolio investments in a cross-sectional setting. The average size of portfolio investments between each country pair is regressed against the average of specialization indices and other gravity variables. Columns (I), (II) and (III) consider the role of dissimilarity across all sectors, columns (IV), (V) and (VI) examine the role of dissimilarity within the manufacturing sector. Lastly, columns (VII), (VIII) and (IX) take into account both aspects of dissimilarity. For every specification, I first report the unconditional correlations columns (I), (IV) and (VII). I then proceed to columns (II), (V) and (VIII) where a number of standard gravity variables are added. Lastly, columns (III), (VI) and (IX) further control for the bilateral trade flows as existing studies have shown that bilateral asset holdings and trade in goods are strongly correlated (Aviat & Coeurdacier, 2007; Lane & Milesi-Ferretti, 2008).

Table 5.1: Descriptive Statistics

Variable	Description	Source	Mean	Sd	Min	Max	Obs
portfolio	portfolio investments, million USD	CPIS	0.018	0.060	0.000	1.142	5231
S(all)	structural dissimilarity, all sectors	own calculation	0.298	0.102	0.064	0.676	5231
S(manuf)	structural similarity, manuf. industries	own calculation	0.526	0.188	0.140	1.133	5231
S′(all)	alternative structural dissimilarity, all sectors	own calculation	0.025	0.024	0.001	0.171	5231
S′(manuf)	structural similarity, manuf. industries	own calculation	0.526	0.188	0.140	1.133	5231
Spe(all)	differences in Gini coefficients, all sectors	own calculation	0.060	0.043	0.000	0.224	5231
Spe(manuf)	differences in Gini coefficients, manuf. industries	own calculation	0.082	0.073	0.000	0.440	5231
pop_o	population(home), in 1000 persons	CEPII	35680	59412	393	301200	5231
pop_d	population(destination), in 1000 persons	CEPII	37680	58924	961	301200	5231
$gdppc_o$	GDP per capita (home)	CEPII	21512	10306	4421	41904	5231
$gdppc_d$	GDP per capita (destination)	CEPII	20743	10584	3505	41904	5231
trade	Imports and exports, million USD	DOT	11156	30898	0.950	503363	5231
dist	bilateral distance between two major cities, in kilo meters	CEPII	4602.183		5020.481	59.617	19586.18
border	common border	CEPII	0.077	0.266	0.000	1.000	5231
language	common language	CEPII	0.079	0.270	0.000	1.000	5231
road	differences in total length of road network per worker, in miles	WDI	1.193	1.104	0.001	4.539	4616
telephone	differences in the number of telephone lines in use per worker	WDI	14.388	10.577	0.000	61.100	4870
electricity	differences in electricity power-generating capacity per worker	WDI	5.200	5.297	0.010	27.392	4870

Table 5.2: Does structural differences matter for the portfolio investments? - Cross-Sectional Results

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
S(all)	-8.173***	-2.740***	-2.043***				-6.876***	-3.127***	-2.429***
	(0.984)	(0.503)	(0.498)				(0.977)	(0.496)	(0.492)
S(manuf)				-3.718***	1.317***	1.324***	-2.805***	1.583***	1.530***
				(0.553)	(0.326)	(0.317)	(0.547)	(0.319)	(0.311)
log of population (source)		0.522***	0.115*		0.618***	0.159**		0.596***	0.194***
		(0.035)	(0.069)		(0.040)	(0.072)		(0.040)	(0.072)
log of population (destination)		0.819***	0.447***		0.905***	0.486***		0.882***	0.516***
		(0.038)	(0.065)		(0.041)	(0.068)		(0.041)	(0.067)
log of GDP per Capita (source)		2.654***	2.292***		2.636***	2.239***		2.645***	2.290***
		(0.098)	(0.116)		(0.099)	(0.116)		(0.097)	(0.117)
log of GDP per Capita (destination)		1.571***	1.170***		1.626***	1.170***		1.576***	1.182***
		(0.074)	(0.092)		(0.078)	(0.096)		(0.074)	(0.093)
log of distance		-0.799***	-0.367***		-0.890***	-0.397***		-0.836***	-0.410***
		(0.049)	(0.077)		(0.048)	(0.080)		(0.049)	(0.078)
border		-0.121	-0.289		-0.012	-0.202		-0.010	-0.179
		(0.191)	(0.176)		(0.199)	(0.178)		(0.191)	(0.174)
language		0.811***	0.600***		0.853***	0.604***		0.787***	0.580***
		(0.152)	(0.136)		(0.158)	(0.139)		(0.153)	(0.136)
log of trade			0.479***			0.530***			0.470***
			(0.076)			(0.076)			(0.078)
Observations	813	813	813	813	813	813	813	813	813
R-squared	0.077	0.783	0.796	0.055	0.780	0.797	0.106	0.790	0.803

This table reports cross-sectional (between) coefficients based on one observation per each country pair averaged over time. The dependent variable is the log of bilateral portfolio equity holdings. S(all) is the structural dissimilarity index that summarizes the differences of all sector shares between each country pair. S(manuf) summarizes the differences of manufacturing industries between each country pair. Log of population (home), log of population (destination), log of GDP per capita (home) and log of GDP per capita (destination) refer to standard gravity determinants that capture the size and economic development of home and destination countries. Log of trade is the log of bilateral imports plus exports. Log of distance is the log of bilateral distance between two capital cities of each country pair. Border is a contiguity dummy that takes the value of 1 if a country pair share a common border, 0 otherwise. Language is a dummy that takes the value of 1 if a country pair speaks the same official language. Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The coefficients on both structural dissimilarity variables appear to be quite informative. As can be seen from columns (I), (II) and (III), structural dissimilarity is negatively correlated with bilateral portfolio investments, suggesting that countries that have similar economic structures also have higher bilateral portfolio equity holdings. This effect remains significant at 1 percent level even after I control for gravity variables and bilateral trade, albeit the magnitudes decrease considerably. The effect of dissimilarity across manufacturing industries is rather different. Columns (V) and (VI) reveal a significant positive relationship between differences in manufacturing industries and portfolio investments once gravity variables and bilateral trade are controlled for. Columns (VII), (VIII) and (IX) confirm the findings in columns (I)-(VI). Structural dissimilarities appear to be important factors in explaining bilateral portfolio equity holdings. Two dissimilarity variables alone explain approximately 10 percent of cross-sectional variations. I show a significant negative link between structural dissimilarity across all sectors and portfolio asset holdings, and a positive one between dissimilarity across manufacturing industries and portfolio asset holdings. The latter is consistent with the diversification motive.

In line with past evidence, I find positive and significant coefficients for population and GDP per capita in both source and destination countries, trade flows and common language and a significant negative coefficient on distance, suggesting that larger size and higher levels of economic development of both source and destination countries, higher volumes of trade, lower distance and speaking the same language are associated with larger bilateral portfolio investments. In line with Aviat & Coeurdacier (2007), I find that controlling for trade significantly reduces the impact of distance on asset holdings.

Panel Fixed Effect Results

To explore the time series variation of the data and overcome the shortcomings of the cross-sectional estimator, I re-estimate equation (5.1) in a panel setting. Table 5.3 reports results for specifications similar to those in Table 5.2, but I add country-pair fixed effects and time fixed effects. As a result, time invariant country-pair covariants, such as distance, border and common language are absorbed into the pair fixed effects. In addition, I cluster the standard errors (and all subsequent results) at the country-pair level to alleviate the concern of possible heteroskedasticity and autocorrelation. Columns (I), (II) and (III) show that the estimates on structural dissimilarity across all sectors continue to enter with a significant negative sign even after taking into account the gravity determinants and trade flows. These results imply that a higher degree of structural dissimilarity is associated with a lower level of portfolio investments. In other words, investors tilt their foreign equity portfolio towards countries with similar, rather than dissimilar structures. In contrast to the cross-sectional results, I find that the positive relationship between dissimilarity across manufacturing industries and portfolio asset holdings is no longer present in the panel setting. Rather, columns (IV), (V) and (VI) demonstrate a similar negative relationship between dissimilarity across manufacturing industries and portfolio asset holdings, although the coefficient becomes largely insignificant once we add control variables in columns (V) and (VI). The contrast between cross-sectional and panel estimates indicates that cross-sectional estimates may suffer from the omitted variable bias, arising from ignoring the global time-varying effects and country-pair fixed effects. Columns (VII), (VIII) and (IX) further confirm my findings in columns (I)-(VI) that countries with increasing structural similarities tend to hold more portfolio assets. And the changes in dissimilarity across manufacturing industries do not seem to play a role. Regarding the control variables, most gravity variables continue to be positively associated with bilateral equity investments. The source country population variable (i.e. the size of the source country) is the exception.

To summarize, several key findings emerge from my analysis so far. First, structural dissimilarity appears to be an important factor in explaining bilateral portfolio equity holdings even if standard gravity determinants and trade flows are taken into account. Second, I demonstrate a significant negative relationship between structural dissimilarity and portfolio investments, indicating

Table 5.3: Does structural differences matter for the portfolio investments? - Panel Results

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
S(all)	-8.424***	-3.997***	-2.541***				-7.121***	-3.668***	-2.441**
	(0.980)	(0.928)	(0.888)				(0.976)	(0.941)	(0.946)
S(manuf)				-3.832***	-1.337*	-0.607	-2.876***	-0.654	-0.227
				(0.561)	(0.772)	(0.666)	(0.552)	(0.755)	(0.690)
log of population		0.371***	0.013		0.331***	-0.034		0.333***	0.003
(source)		(0.084)	(0.099)		(0.103)	(0.107)		(0.094)	(0.104)
log of population		0.553***	0.229**		0.525***	0.190*		0.521***	0.221**
(destination)		(0.083)	(0.099)		(0.101)	(0.105)		(0.092)	(0.102)
log of GDP per Capita		2.770***	2.376***		2.917***	2.420***		2.792***	2.388***
(source)		(0.192)	(0.217)		(0.208)	(0.225)		(0.188)	(0.214)
log of GDP per Capita		1.470***	1.084***		1.630***	1.135***		1.495***	1.096***
(destination)		(0.180)	(0.208)		(0.196)	(0.216)		(0.175)	(0.204)
log of trade			0.361***			0.397***			0.357***
			(0.078)			(0.078)			(0.079)
Country-pair FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	5231	5231	5225	5231	5231	5225	5231	5231	5225
R-squared	0.073	0.916	0.919	0.051	0.914	0.918	0.100	0.916	0.919

This table reports the panel fixed effect (within) coefficients based on an annual country-pair sample that include a vector of country-pair fixed effects and a vector of year-fixed effects. All standard errors are adjusted for country-pair-level heteroskedasticity and autocorrelation, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variable is the log of bilateral portfolio equity holdings. S(all) is the structural dissimilarity index that summarizes the differences of all sector shares between each country pair. S(manuf) summarizes the differences of manufacturing industries between each country pair. Log of population (home), log of population (destination), log of GDP per capita (home) and log of GDP per capita (destination) refer to standard gravity determinants that capture the size and economic development of home and destination countries. Log of trade is the log of bilateral imports plus exports.

that countries with similar economic structures tend to hold more portfolio assets. This finding is present in both cross-sectional and panel estimates. Third, I find some evidence of portfolio diversification motive reflected by a significant positive coefficient on dissimilarity across manufacturing industries and portfolio asset holdings in the cross-sectional setting, but this result disappears in the panel framework. Lastly, conventional gravity determinants, such as country size and economic development, and bilateral trade flows are important in explaining the bilateral holding of portfolio assets across specifications.

Further Robustness Analysis

I conduct a series of robustness analyses based on column (IX) (or equation 5.3) and demonstrate that our results are insensitive to alternative measures, different specifications, various samples and the endogeneity of specialization in Table 5.4.

I first consider alternative measures of structural dissimilarity. Column (I) employs a variant of dissimilarity measure S' which summarizes the square of bilateral differences in industrial structure, whereas column (II) uses spe which is the absolute differences of the Gini coefficients between each country pair. Again, we consider both dissimilarity across all sectors and dissimilarity across the manufacturing industries. As shown, results are quite similar to those reported in columns (IX) in Table 5.3. The negative relationship between dissimilarity in overall economic structures and bilateral equity holdings remains significant at 1 percent level, whereas the finding for the manufacturing dissimilarity is mixed. Overall, my results do not seem to be driven by the choice of a particular dissimilarity measure.

Next, I check whether the results are driven by the econometric specifications. Instead of adding country-pair fixed effects and time fixed effects, we combine source country fixed effects, destination country fixed effects and time fixed effects and find quantitatively similar results in column (III). In a similar vein, I exploit the combination of source country time-varying fixed effects and destination country time-varying fixed effects in column (IV). The population and GDP per capita of source and destination countries are thus absorbed by

Table 5.4: Does structural differences matter for the portfolio investments? - Panel Results

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
	Alter.Measures		Alter. Specifications		EU	Euro	1-year lag	2-year lag	IV
S(all)			-1.305**	-1.310**	-2.241**	-3.111**	-2.034**	-2.057**	-4.964***
			(0.565)	(0.609)	(0.991)	(1.205)	(0.919)	(0.991)	(1.704)
S(manuf)			-0.678**	-0.655*	-0.333	1.641	-0.207	-0.290	-2.299
			(0.323)	(0.342)	(0.723)	(1.072)	(0.681)	(0.691)	(2.585)
S′(all)	-5.994***								
	(1.931)								
S′alt(manuf)	-3.877***								
	(1.471)								
Spe(all)		-6.624***							
		(2.557)							
Spe(manuf)		1.357							
		(0.964)							
log of population	-0.038	0.023	3.854***		-0.037	0.189	-0.014	-0.008	-0.053
(source)	(0.048)	(0.099)	(1.484)		(0.108)	(0.158)	(0.109)	(0.113)	(0.120)
log of population	0.183***	0.235**	5.304***		0.204*	0.128	0.199*	0.211*	0.183*
(destination)	(0.047)	(0.097)	(1.579)		(0.106)	(0.148)	(0.108)	(0.111)	(0.099)
log of GDP per Capita	2.461***	2.367***	4.798***		2.229***	2.815***	2.378***	2.291***	2.434***
(source)	(0.103)	(0.201)	(0.649)		(0.220)	(0.361)	(0.218)	(0.224)	(0.153)
log of GDP per Capita	1.174***	1.073***	1.588**		1.074***	1.045***	1.088***	1.039***	1.206***
(destination)	(0.096)	(0.189)	(0.748)		(0.208)	(0.228)	(0.209)	(0.214)	(0.158)
log of distance			-0.190**	-0.196**					
			(0.081)	(0.084)					
border			-0.035	-0.044					
			(0.136)	(0.140)					
language			-0.057	-0.067					
			(0.131)	(0.135)					
log of trade flows	0.378***	0.420***	0.631***	0.631***	0.397***	0.910***	0.377***	0.357***	0.246***
	(0.035)	(0.072)	(0.068)	(0.071)	(0.082)	(0.111)	(0.081)	(0.082)	(0.066)
Country-pair FE	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Home country FE	No	No	Yes	No	No	No	No	No	No
Destination country FE	No	No	Yes	No	No	No	No	No	No
Home time-varying FE	No	No	No	Yes	No	No	No	No	No
Destination time-varying FE	No	No	No	Yes	No	No	No	No	No
Observations	5225	5225	5225	5225	4289	2103	5456	4756	4610
R-squared	0.918	0.919	0.874	0.883	0.922	0.950	0.917	0.920	0.922

This table reports the further robustness checks on basis of column (IX) in Table 3. All standard errors are adjusted for country-pair-level heteroskedasticity and autocorrelation, *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of bilateral portfolio equity holdings. S(all) is the structural dissimilarity index that summarizes the differences of all sector shares between each country pair. S(manuf.) summarizes the differences of manufacturing industries between each country pair. S′(all) and S′(manuf) are the variant of S(all) and S(manuf), respectively. These two measures summarize the square of bilateral differences in all sector shares and manufacturing industries shares, respectively. Spe(all) and Spe(manuf) are the absolute differences in (absolute country) Gini coefficients across all sectors and manufacturing industries, respectively. Log of population (home), log of population (destination), log of GDP per capita (home) and log of GDP per capita (destination) refer to standard gravity determinants that capture the size and economic development of home and destination countries. Log of distance is the log of bilateral distance between two capital cities of each country pair. Border is a contiguity dummy that takes the value of 1 if a country pair share a common border, 0 otherwise. Language is a dummy that takes the value of 1 if a country pair speaks the same official language. Log of trade is the log of bilateral imports plus exports.

the time-varying fixed effects. Note that column (IV) serves another important purpose here. This specification is in line with Okawa & van Wincoop (2012) who develop a theory for bilateral asset holdings that takes a gravity form. They propose to include time-varying source and destination country dummies to capture the (time-varying) multilateral resistance effect, analogous to that derived by Anderson & van Wincoop (2003) for goods trade. Overall, I find no changes to my main findings. The structural dissimilarity measures appear highly significant in both specifications. I note that the manufacturing dissimilarity measure also carries negative signs, although the significant levels are only at 5 percent and 10 percent level, respectively. In all, my results are robust to alternative specifications.

An additional concern is that the choice of country group might drive our results. To further examine this issue, I construct two sub samples. One includes only source countries in the EU, whereas the other one only includes source countries in the Eurozone. I check whether the negative relationship between differences in production structure and portfolio investments are different across these two country groups. The results are shown in columns (V) and (VI). I find that the estimated relationship is very similar using the first sub sample of EU countries compared with our benchmark results in columns (IX) in Table 5.3. A notable difference using the second sample of Eurozone countries is that the magnitude of difference in production structure is somewhat larger, albeit still highly significant.

So far, there has been no discussion of the endogeneity problems. One possible source of bias in my estimates is the possibility of reverse causality. This type of bias may arise if bilateral portfolio asset holdings are also affecting structural dissimilarity. For example, Kalemli-Ozcan *et al.* (2003) emphasize that financial integration promotes industrial specialization through risk-sharing. Countries are better protected against idiosyncratic shocks, can therefore afford to specialize more.

I alleviate this endogeneity concern in two ways. First, I repeat the main analysis using one-year and two-year lagged values of structural dissimilarity, respectively, and consequently examine the predictive power of structural dissimilarity for future portfolio asset holdings. The results, reported in columns

(VII) and (VIII) are quantitatively similar to those in column (IX) in Table 5.3. Second, it is necessary to find relevant instruments (i.e. correlated with endogeneous variable) that are not correlated with the error term (instrument exogeneity). I use the differences in the infrastructure provision (i.e., total length of the road networks, the number of telephone lines in use and the electrical power-generating capacity) to instrument two measures of structural dissimilarity, following Yeaple & Golub (2007). I employ various diagnostic tests to ensure the validity of our Instrumental Variable (IV) estimations. First, we perform a Durbin-Wu-Hausman (DHW) endogeneity test to examine whether the two structural dissimilarity measures are indeed endogeneous. The DHW statistic barely rejects the null hypothesis (i.e., p-value: 0.098) that introducing instruments has no effect on the estimated coefficients, indicating that the endogeneity problem is not very severe here. Furthermore, I investigate the relevance of the instruments by examining the F-statistics of the first stage regressions. The F-statistics for the regressions with the structural dissimilarity and manufacturing dissimilarity as a dependent variable are 701.57 and 46.98, respectively. Since an F-statistic of 10 is often regarded as a rule of thumb to examine the instrument relevance, I conclude that these instruments are indeed relevant. The key exogeneity assumption is that differences in infrastructure provision are not correlated with the disturbance term. The usage of multiple instruments allows me to perform a Hansen test of over-identifying restrictions. According to the test statistic (p-value: 0.112), I do not reject the null hypothesis that the instruments are valid. I report the IV estimates in column (IX) and find that the negative coefficient on structural dissimilarity remains highly significant. However, the magnitude of the coefficient is twice as large as the OLS estimates in column (IX) of Table 5.3. I find that after taking into account the endogeneity problem, the manufacturing dissimilarity is no longer significant.

In summary, I demonstrate a significant negative effect of bilateral differences in overall production structure on bilateral portfolio asset holdings, suggesting that the increase in bilateral portfolio investments is driven by the increasing similarity, rather than dissimilarity of production structures. This effect is robust to a wide range of measures, specifications, sub samples and endogeneity.

5.5 Conclusion

This paper investigates the relationship between structural dissimilarity and bilateral portfolio asset holdings and uncover whether a diversification motive can be found. By estimating a gravity model controlling for standard gravity determinants, country-pair fixed effects and time effects, I find that structural dissimilarity plays an important role in explaining the patterns of bilateral portfolio asset holdings. Contrary to conventional wisdom and past studies, I demonstrate a strong negative relationship between structure dissimilarity and bilateral portfolio investments, indicating that investors tilt their foreign portfolio towards countries with similar industrial structures. I did not find consistent evidence of a diversification motive. My findings are in line with the familiarity argument that investors prefer to invest in similar countries in terms of the industrial structure. It would be interesting to extend the analysis during the crisis period and examine whether the results still hold.

Appendix

Table 5.A.1: Industries and NACE Codes

Industry	NACE code
Agriculture, hunting, forestry and fishing	A-B
Mining and quarrying	C
Manufacturing	D
Electricity, gas and water supply	E
Construction	F
Retail and wholesale trade	G
Hotels and restaurants	H
Communication	I
Financial intermediation	JtK
Education, services	LtQ
Manufacturing	
Food, beverages and tobacco products	15-16
Textiles, leather and footwear	17-19
Wood and of wood and cork	20
Pulp, paper, printing and publishing	21-22
Coke, refined petroleum and nuclear fuel	23
Chemicals and chemical	24
Rubber and plastics	25
Other non-metallic mineral	26
Basic metals and fabricated metal	27-28
Machinery, nec	29
Electrical and optical equipment	30-33
Transport equipment	34-35
Manufacturing nec, recycling	36-37

Chapter 6

Conclusion

6.1 Motives and Main Findings

Throughout this thesis, I examine the causes, processes and consequences of industrial specialization. Specifically, I address three sets of questions. First, how do trade and financial openness affect industrial specialization across countries? Second, how does trade openness affect industrial composition across industries and how do firm-level dynamics play an important role? Third, what are the macroeconomic consequences of specialization? In particular, how does specialization matter for economic growth and cross-border portfolio investments?

I start in chapter 2 with an investigation of the roles of trade and financial openness, separately and in conjunction with each other in affecting industrial specialization. While the existing literature has studied their effects on specialization in isolation, I analyze them in one empirical framework.

First, I show that both trade and financial openness have a positive relationship with industrial specialization, in line with existing findings (Basile & Girardi, 2010; Imbs, 2004; Kalemli-Ozcan *et al.*, 2003), suggesting that trade and financial openness are important determinants of specialization. Furthermore, it appears that trade openness has a bigger impact on specialization in countries with a low degree of intra-industry trade, whereas financial openness leads to a larger effect on specialization in countries with more developed financial systems. In a second step, I demonstrate that the effect of trade (financial) openness on specialization is enhanced by the level of financial (trade) openness, suggesting that they are complementary in their effects on specialization. More specifically, I find that trade openness always has a positive relationship with specialization, independent of the level of financial openness. However, a threshold effect is present for trade openness as a moderator for the effect of financial openness on specialization, meaning that the positive relationship between financial openness and specialization only exists when countries are sufficiently open to trade.

A main implication of my analysis is the importance of simultaneously deepening trade and financial integration. Countries that exploit integration along both lines can expect to benefit the most from opening up, while insuring themselves against idiosyncratic shocks. However, in the presence of asymmetric shocks, there is still a need for better risk-sharing mechanisms (via cross-holding of foreign assets, international borrowing and lending or fiscal transfers), particularly in response to common policy objectives, such as in the Eurozone.

Given the evidence of a trade-specialization nexus found in chapter 2, chapter 3 takes a closer look at which industries are driving the trade-specialization nexus, and how firm-level dynamics play a critical role. Drawing insights from the recent theoretical and empirical literature on international trade featuring firm heterogeneity (Bernard *et al.*, 2006; Eslava *et al.*, 2009; Melitz, 2003; Pavcnik, 2002; Trefler, 2004; Tybout & Westbrook, 1995), I argue that industries need 'room to move' in order for increasing trade openness to translate into increased specialization. The true drivers of the trade-specialization nexus are productive firms, who benefit from the increase in trade-openness and can appropriate resources from less productive firms. This causes the industry in which they operate to expand, at the expense of other industries, in which there is no room to make such moves. In order words, the intra-industry potential for reallocation determines whether there is a trade-specialization nexus.

I find support of the existence of two distinctive groups of industries. On the one hand, in industries with little potential for reallocation, increased trade openness has no or a negative effect on that industry's share of total manufacturing value added. One the other hand, in industries with large potential for reallocation, I show an inverted-U shape relationship between trade openness and industry size, indicating that trade openness induces specialization at a decreasing rate. Taken together, the trade-specialization nexus is indeed driven by a small number of industries with large potential for reallocation, who nevertheless have a significant impact on industry concentration patterns of countries.

Among the key implications derived from these results is the notion that reallocation is a key channel through which industries can benefit from trade openness. Therefore, policies aimed at removing barriers in the factor and product markets are likely to enhance the reallocation of economic activity. The resulting gains in scale and efficiency appear to be an important source of long-run competitiveness and economic growth in the EU.

While chapters 2 and 3 focus on the determinants and processes of industrial specialization, chapters 4 and 5 examine its macroeconomic consequences. In chapter 4, I approach specialization from the export side and examine how export specialization matters for economic growth, furthermore how it matters differently over development stages. I am motivated by the increasing availability of detailed export data across a wide range of countries and the growing literature on studying the specific characteristics of exports in relation to economic performance (An & Iyigun, 2004; Bensidoun *et al.*, 2002; Feenstra & Rose, 2000; Hausmann *et al.*, 2007; Lee, 2010). In doing so, I first propose a proxy for the maturity of a country's export bundle based on one of the well established empirical regularities found in the product life cycle theory, namely total sales of a product in the global market first increase at an increasing rate, then at a decreasing rate and finally decline, tracing out an S-shaped diffusion curve (Audretsch, 1987; Hirsch, 1967; Klepper, 1996). I therefore develop a measure of maturity at the product level by looking at the dynamics in trade volume at the global level. I then construct an aggregate export maturity measure for a country's export bundle by weighting the product maturity by the shares of these products in a country's exports. With this measure, I am thus able to explore whether the maturity of a country's export matters for its economic growth performance.

I analyze Statistics Canada's version of the UN-COMTRADE database that contains the export data on 430 Standard International Trade Classification (SITC) four-digit products for 93 countries over the period 1988-2005. Employing a conditional latent class model, I find that the effect of export maturity on growth is very different across three endogenously determined clusters of countries. The class membership is conditional on real GDP per capita, which is a proxy for the development stage of a country. In the most developed cluster, countries tend to grow more rapidly when they export new and innovative products that are in an early stage of the product life cycle. In contrast, I also identify a cluster of emerging countries that appears to grow faster by exporting more mature products that are in the later stages of their life cycle. Finally, the effect of export maturity on growth seems insignificant in the cluster of developing countries. These results suggest that what you export matters (Hausmann *et al.*, 2007), but more importantly when you export them over subsequent development stages seems to matter too.

My findings imply that industry policies should be tuned to the development stages. Countries in early stages of development should focus on acquiring market share in mature markets with routine technologies whereas emerging economies face the challenge of at some point switching from mature to new products as they approach the global technology frontier. At that frontier they must join the advanced economies who continuously switch into (increasingly) less mature innovative products to stay ahead of increasing competition from abroad.

While chapter 2 has established the finding that financial openness promotes specialization through risk-sharing, the reverse linkage is less well-studied. Production specialization exposes an economy to external shocks that are idiosyncratic to specific industries. With uninsured production risk, specialization may result in higher output volatility and entails a welfare loss that may outweigh the benefits. Consequently, countries with a more specialized production structure may have more incentive to hold foreign portfolio assets to diversify their idiosyncratic output risks. Chapter 5 fills this gap by investigating the effects of ongoing changes in industrial structure on cross-border portfolio investments in a bilateral setting. More specifically, I explicitly test to what extent investors tilt their foreign equity portfolio towards countries with (dis)similar industrial structures and thereby gain or forego diversification benefits.

I point out that structural dissimilarity plays an important role in explaining the patterns of cross-border portfolio investments. Contrary to conventional wisdom and past studies, I demonstrate a strong negative relationship between structure dissimilarity and bilateral portfolio investments, indicating that investors tilt their foreign portfolio towards countries with similar industrial structures. The diversification motive therefore does not seem to play a role.

One implication of these findings is that investors have a preference for familiarity when investing abroad. For example, Massa & Simonov (2006) find that investors do not primarily engage in hedging, but invest in stocks closely related to their non-financial income. They argue that the familiarity, that is, the tendency to concentrate holdings in stocks to which the investor is geographically or professionally close or he has held for a longer time may explain their findings. I extend this to the logically equivalent argument that investors prefer to invest in similar countries.

6.2 Caveats and suggestions for future research

The analyses presented in this thesis are subject to a number of limitations. Recognizing these limitations helps understand the results and provides a good basis for some future research.

A first limitation concerns the definition of specialization. For the purpose of my analysis, I choose absolute specialization measures in chapter 2. These measures describe a country's absolute level of specialization, i.e., concentration. A country would be considered specialized if a small number of industries exhibit high shares of the country's overall value added. This type of measures provides evidence on how the economic structure of one specific country evolves, regardless of the development of other countries. In a similar vein, chapter 3 employs the industry's value added shares as the specialization measure. Chapter 4 also takes into account products' export shares in each country. In contrast, chapter 5 makes use of relative specialization measures, which I label as 'structural dissimilarity'. This type of measures is derived relative to the industrial composition of the benchmark country. As noted earlier in this thesis, there are a large number of alternative indices in the literature to measure specialization. Each is with its own advantages, disadvantages and statistical properties. Although the literature has shown that the empirical results are sensitive to the choice of these indices, yet, there seems to be no agreement concerning which index is best to describe specialization. The purpose of this thesis is not to address this issue either. I did not intend to provide an extensive analyses using vastly different specialization measures. Rather, my view is more pragmatic. The purpose of the analysis should govern the choice of a particular index.

Another limitation relates to the scope of my analyses, which is reflected in several aspects.

First, due to the availability of production data, I limit myself in chapters 2, 3 and 5 to focusing on the experience of developed countries. As the emerging countries have become more involved in international trade and cross-border capital flows, an interesting avenue of future research is to explore how trade and financial openness drive structural changes and the consequences of such changes in these countries. Chapter 4 represents a step towards this direction. I make use of detailed export data across a large number of developed, emerging and developing countries. I point out that trade-induced structural changes have a wider applicability for a large range of countries and show that the relationship between the maturity of a country's export mix and economic growth is very different across these three groups of countries. Such knowledge can inform the industry policy of developing countries and thereby provide additional insights beyond the lessons taught by the experience of developed countries. However, an important caveat to bear in mind in chapter 4 is that my unit of analysis is a product. I did not take into account the unbundling of production tasks due to the emergence of the global supply chain

(Baldwin, 2012). It might be the case that a (developing) country's exports are not necessarily a good indication of what they are actually producing. It can merely be about their position in an advanced economy's supply chain. In light of current development in international trade, future research may aim at exploring the relationships between the (un)bundling of economic activity, structural changes in exports and economic performance.

Second, in terms of industries covered in the analyses, chapters 2 and 3 are limited to the manufacturing industries based on the premise that these industries, in contrast to services, are involved in trade, and are therefore more responsive to trade openness. Towards chapters 4 and 5, I begin to relax this restriction, where I examine a broad range of commodities in chapter 4, and take into account the shifts in overall economic structures, beyond manufacturing only in chapter 5. I find for example in chapter 5 that the results are significantly different whether I look at the dissimilarity of overall structures or the dissimilarity of manufacturing structures. Thus, understanding the determinants and consequences of a broader shift in industrial structures might prove to be a fruitful avenue for future research.

Third, recent theoretical and empirical literature has emphasized the importance of investigating firm-level adjustments in response to trade openness. Chapter 3 is in line with this development in the literature. However, the channels through which financial openness affects industrial composition have not been analyzed extensively in this thesis. This is an interesting area for research on its own. Another direction may focus on how trade and/or financial openness affect the composition of firms within industries, for example, how does the number of firms, average firm size, and overall firm-size distribution, entry and exit dynamics, respond to trade and/or financial openness? The combination of macro and micro aspects will yield a more complete understanding of the effects of trade and financial openness.

Lastly, regarding the time span, my analyses are based on the evidence prior to the year 2008. Although I am constrained by the availability of recent production data, this choice raises an intriguing issue: what is the role of a crisis in reshaping the dynamics between openness, structural changes and economic performance. Is a crisis a force of "creative destruction" or "plain destruction"? Are the structural impacts of crises temporary or permanent? Do countries, industries and firms respond differently to crises? What kind of characteristics matter? Answering these questions represents another extension of this thesis, which will further add our knowledge about the determinants, processes and consequences of industrial specialization.

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Nederlandse Samenvatting

Dit proefschrift beantwoordt drie vragen met betrekking tot de oorzaken, ontwikkelingen en gevolgen van industriële specialisatie. Ten eerste, hoe beïnvloedt industriële specialisatie het vrije verkeer van goederen en kapitaal tussen landen? Ten tweede, hoe beïnvloedt handelsvrijheid de economische structuur en wat is de rol van dynamische interactie tussen bedrijven? Ten derde, wat zijn de macro-economische consequenties van specialisatie? De focus ligt voornamelijk op de effecten in relatie tot economische groei en grensoverschrijdende investeringen. Daarnaast worden de economische effecten van specialisatie onderzocht.

In hoofdstuk 2 worden de effecten van het vrij verkeer van kapitaal en goederen op specialisatie geanalyseerd. De studie richt zowel op de afzonderlijke effecten van kapitaal en goederen alsook de gezamenlijke effecten. De resultaten laten zien dat de mate van vrij verkeer van kapitaal en goederen een positief effect heeft op industriële specialisatie. Dit betekent dat de mate waarin het verkeer van kapitaal en goederen is vrijgegeven een belangrijke oorzaak is van specialisatie. Bovendien heeft handelsvrijheid een grotere invloed op specialisatie in landen met lager niveau van handel tussen industrieën terwijl de mate van vrijheid van kapitaal een groter effect heeft op specialisatie in landen met een beter ontwikkeld financieel systeem.

Daarnaast toont hoofdstuk 2 het belang van het gezamenlijk effect van vrij verkeer van kapitaal en goederen op specialisatie. De effecten van handelsvrijheid op specialisatie zijn sterker wanneer het niveau van vrij verkeer van kapitaal hoger is. Resultaten laten tevens zien dat handelsvrijheid altijd een positieve relatie heeft met specialisatie. Dit resultaat is onafhankelijk van het niveau van vrij verkeer van kapitaal. Echter, de positieve relatie tussen financiële openheid en specialisatie is alleen aanwezig bij landen die voldoende handel drijven. Concluderen dienen zowel handelsintegratie alsook financiële integratie versterkt te worden om zo veel mogelijk van de voordelen van specialisatie te profiteren.

Gegeven dat er in hoofdstuk 2 een relatie tussen handelsvrijheid en specialisatie is gevonden gaat hoofdstuk 3 op zoek naar welke industrieën bepalend zijn voor deze relatie. Daarnaast wordt er onderzocht hoe de dynamiek van handelsspecialisatie een rol speelt op het niveau van het bedrijf. De onderzoeksvraag in dit hoofdstuk is gebaseerd op de recente literatuur over internationale handel waarin de verschillen tussen bedrijven binnen een industrie een prominente rol spelen.

Er wordt beargumenteerd en bewezen dat industrieën 'room to move' nodig hebben om de effecten van handelsvrijheid op specialisatie te realiseren. De drijvende kracht achter de handelsspecialisatie relatie zijn de meest productieve bedrijven in een industrie. Deze bedrijven profiteren het meest van de handelsvrijheid omdat zij middelen kunnen aantrekken van minder productieve bedrijven met als resultaat dat de industrie waarin zij opereren zich uitbreidt. Deze uitbreiding van de industrie gaat echter ten koste van andere industrieën waar minder 'room to move' mogelijkheden zijn. Met andere woorden, de 'room to move' bepaalt in welke type industrie de handelsspecialisatie plaatsvindt. De belangrijkste implicatie van dit resultaat is dat intra-industrie reallocatie een belangrijke wijze is waarop industrieën profiteren van handelsvrijheid. Beleid dat erop gericht is om intra-industrie reallocatie te vergemakkelijken kan daarom in belangrijke mate bijdragen aan het vergroten van de productiviteit van een land en handelszone.

Waar hoofdstuk 2 en 3 zich toespitsen op de determinanten en processen van specialisatie, gaan hoofdstuk 4 en 5 in op de macro-economische consequenties van deze specialisatie.

Hoofdstuk 4 bestudeert de relatie tussen export specialisatie en economische groei en vraagt zich af of deze relatie verandert tijdens de verschillende ontwikkelingsfases van een land. Om de relatie te meten wordt een maatstaf opgesteld die de samenstelling van de export van een land meet over de ontwikkelingsstadia van dat land. De maatstaf is gebaseerd op bevindingen in bestaande literatuur over de levenscyclus van producten.

Samengevat laten de resultaten van het onderzoek zien dat de relatie tussen het ontwikkelingsniveau van de export en economische groei verschilt tussen drie groepen landen. In de groep van meest ontwikkelde landen wordt een hogere groei gerealiseerd wanneer er nieuwe en innovatieve producten worden geëxporteerd. Dit zijn de producten die in een begin stadium zitten van de levenscyclus van producten. Daarentegen hebben de opkomende economieën als eigenschap dat deze sneller groeien wanneer ze producten exporteren in de latere fase van de levenscyclus van producten. Voor de groep van ontwikkelingslanden geldt dat er geen significante relatie is tussen het ontwikkelingsniveau van de export en economische groei. Concluderend zijn zowel de groeifase waarin een land zicht bevindt als de samenstelling van de export van belang om de relatie tussen export en groei te begrijpen.

De beleidsimplicatie die volgt uit deze resultaten is dat de samenstelling van export afgestemd zouden moeten worden op de ontwikkelingsfase waarin een economie zicht bevindt. Ontwikkelingslanden zouden zich moeten concentreren op het verkrijgen van een groter marktaandeel in meer volwassen markten. Echter, om de transitie te maken naar een volwassen economie, zou men op een gegeven moment de export samenstelling moeten aanpassen van producten die zich in een volwassen levensfase bevinden naar nieuwe en innovatieve producten. Ontwikkelde economieën dienen zich te blijven concentreren op nieuwe en innovatieve producten om op deze manier de concurrentie voor te blijven.

Waar hoofdstuk 2 heeft vastgesteld dat financiële openheid de specialisatie bevordert, kijkt hoofdstuk 5 naar de relatie tussen blijvende veranderingen in industriële structuren en internationale investeringen. Er wordt getest in hoeverre investeerders hun beleggingsportefeuille aanpassen voor landen met vergelijkbare industriële structuren als hun land van herkomst, om zo gebruik te maken van diversificatie voordelen. In tegenstelling tot de bevindingen in andere studies laat dit hoofdstuk zien dat beleggers in plaats van minder juist méér investeren in landen met eenzelfde industriële structuur. Het diversificatie motief lijkt daarom geen rol te spelen.

Een van de verklaringen voor de bevindingen in dit hoofdstuk is dat investeerders een voorkeur hebben voor investeringen die voor hun vertrouwd zijn. Bijvoorbeeld, Massa en Simonov (2006) vinden dat investeerders liever investeren in bedrijven waar zijn vertrouwd mee zijn. Het diversificatie motief is hier van ondergeschikt belang. De logica in dit hoofdstuk bouwt hier op voort: investeerders hebben een voorkeur om te investeren in landen die vertrouwd voor hun zijn.

Samengevat draagt dit proefschrift bij aan het begrip van de reële effecten van handel en financiële integratie, door te onderzoeken hoe handelsintegratie en financiële integratie specialisatie beïnvloeden en wat de consequenties zijn van specialisatie. In een breder perspectief laat deze dissertatie zien hoe macro-economische ontwikkelingen wordt beïnvloedt door continue structurele veranderingen op een meso (industrie) en micro (bedrijf) niveau. Daarnaast laat dit proefschrift zien hoe de dynamiek van de ontwikkelingen op een micro niveau (product) tot macro-economische uitkomsten leidt. Er wordt documenteert hoe de onderliggende micro-meso-macro verbanden werken en waar de verbanden vandaan komen. Met de combinatie van macro- en micro-economische aspecten ontstaat een beter raamwerk om de effecten van handel en financiële integratie te begrijpen.

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Curriculum Vitae

Lu Zhang (1982) was born in Qingdao, China. Since 2002 she moved to the Netherlands, where she completed two years Bachelor study in International Business and Management Studies at Saxion Hogeschool Ijsselland, Deventer. Between 2004 and 2006 she studied at Utrecht University School of Economics (USE) and received her Bachelor degree in Economics and Law in 2006. From 2006 she continued to pursue a Master's Degree in International Economics and Business at USE. She wrote her master thesis entitled "Efficiency of Dutch Pension Funds: Risk, Persistence and Determinants" during an internship at De Nederlandsche Bank (Dutch Central Bank) and graduated *cum laude* in 2007. During 2007 to 2009, she was awarded a "Huygens Scholarship Program (HSP)" scholarship by the Netherlands Organization for International Cooperation in Higher Education (NUFFIC) to follow the Research Master's program in Multidisciplinary Economics at USE. She completed it in 2009. In January 2009, she received a prestigious "Mozaiek" grant for four years awarded by the Netherlands Organizations for Scientific Research (NWO) and became a PhD candidate at USE, where she completed her dissertation in 2013. As of March 2013, she works as a postdoctoral researcher at the Department Global Economics and Management of University of Groningen. Her research interests cover the dynamics between bank credit flows, economic growth and financial stability.