Essays in International Trade

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Abstract

This dissertation consists of three chapters in the field of international trade. The first two, jointly written with Matilde Bombardini and Giovanni Gallipoli, explore the role of skill dispersion as a source of comparative advantage. The first chapter presents a tractable multi-country, multi-sector model of trade with search frictions in which comparative advantage derives from (i) cross-sectoral differences in the substitutability of workers' skills and (ii) cross-country differences in the dispersion of skills in the working population. We provide conditions under which higher skill dispersion triggers specialization in sectors characterized by higher substitutability among workers' skills.

The second chapter explores the empirical relevance of skill dispersion as a determinant of the pattern of trade across industries. The analysis relies on micro-data from the International Adult Literacy Survey to construct measures of skill dispersion. Results indicate that the latter has a significant effect on the pattern of trade across industries, of a magnitude comparable to the aggregate endowments of human and physical capital. The result is robust to the controls for other proximate causes of comparative advantage, such as institutional quality and flexibility of labour markets.

The third chapter offers a relatively unconventional approach to the empirical analysis of the factors that determine export decisions at the firm level, by exploring whether the characteristics of firms geographically located close to each other play a role in shaping their individual entry decisions. In particular, I develop an empirical framework to study whether export participation decisions of individual firms are influenced by non-market interactions (e.g. learning or imitation) with firms that belong to a common reference group. The main testable hypothesis is that, in the presence of entry costs, group composition affects the degree of state dependence of individual export decisions. This proposition is tested by applying a dynamic panel data estimator to a data set of Argentine manufacturing firms. The findings show that group composition influences individual export decisions. Most of this effect is channelled through entry costs. Firms benefit from proximity to productive firms but not from proximity to other exporters.

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Chapter 1

Skill Dispersion and Trade with Labour Market Frictions

Synopsis. *This chapter develops a tractable multi-country, multi-sector model of international trade with search frictions in the labour market. Comparative advantage derives from (i) cross-sectoral differences in the substitutability of workers' skills and (ii) cross-country differences in the dispersion of skills in the working population. We establish the conditions under which higher skill dispersion triggers specialization in sectors characterized by higher substitutability of skills across workers.*

1.1 Introduction

One of the mainstays of the theory of comparative advantage is that countries' factor endowments determine the pattern of trade. In this chapter we study an alternative, but closely related, source of comparative advantage: the dispersion of skills (or human capital) in the working population.[1]

Why would the distribution of skills matter for specialization and trade? We argue that industries vary in the degree of complementarity among the skills of workers employed in the production process. In some industries, such as aerospace or engine manufacturing, production requires completing a long sequence of tasks and poor performance at any single stage greatly reduces the value of output. These are industries with high skill complementarity (or *O-Ring*, as in Kremer, 1993), where teamwork is crucial. Efficiency is higher when workers of similar skills are employed in every stage of production. On the contrary, in other industries, such as apparel, teamwork is relatively less important, workers' skills are more easily substitutable and therefore poor performance in some task can be mitigated by superior performance in others. In this chapter, we investigate theoretically whether countries with greater skill dispersion specialize in sectors characterized by higher substitutability of skills across tasks.

The model features monopolistic competition, a single factor of production (skills), many countries and many sectors. Countries only differ in terms of the distribution of skills in the labour force. Sectors only differ in terms of the degree of skill substitutability in the production process.

Importantly, we introduce search frictions in the labour market - as in Helpman and Itskhoki (2009a) and Helpman et al. (2008a; 2008b)- and focus on skills that are not observable ex-ante (i.e. before workers are hired).[2] The latter modelling choice reflects the fact that observable characteristics of workers, including age

[1] Human capital is determined by many factors, among which formal education, family upbringing, underlying ability and on-the-job training. Throughout this chapter we refer to human capital or skills, terms that we use interchangeably, as a set of attributes that are of productive use in the workplace.

[2] The unobservability of skills could also be broadly interpreted as a 'friction'. However, in Chapters 1 and 2 of this dissertation, this term will exclusively be used to refer to the cost that firms incur when searching for workers, which is in line with its usage in the search and matching literature.

and education, account for a minor share of the total variation in work-related literacy scores within countries (see chapter 2, section 2.3.1). It is also consistent with evidence suggesting that firms only gradually learn the skills of their workers (see for example Altonji and Pierret, 2001 and Altonji, 2005). In this context, the model is best interpreted as a mechanism that illustrates how the dispersion of skills among workers with otherwise identical observable characteristics affects comparative advantage. In the rest of chapter 1 and chapter 2 we often refer to such skills as 'residual' skills.

One immediate advantage of our assumptions is that they allow the model to remain tractable in a setting with many countries and many sectors. Essentially, ex-ante unobservability and search frictions imply that firms in our model hire by randomly sampling workers from the endowment of the economy. As a result, firms and industries inherit the skill distribution of the economy -i.e. the distribution of skills of the workers employed in every firm is identical to the distribution of skills in the country.[3]

We show that this mechanism generates differences in output per worker across industries and countries that determine the pattern of international trade. In particular, the central result of the chapter establishes the conditions under which countries with a high dispersion of skills in the labour force will be relatively more productive and therefore export relatively more in sectors where skills are more easily substitutable across tasks.

Our theoretical framework provides a useful guide to derive an appropriate econometric specification to test its main result empirically, a task pursued in chapter 2. In addition, it delivers a direct link between the unobservable degree of com-

[3]Random matching is consistent with recent international evidence (see Iranzo et al., 2008, and Lazear and Shaw, 2008) suggesting that most of the observed dispersion of wages occurs within, rather than between, firms.

plementarity and the observable dispersion of residual wages within industries. In particular, we also show that, in the presence of random matching on residual skills, residual wage distributions at the industry level uniquely reflect the degree of complementarity among skills. Industries with higher complementarity are characterized by more compressed wage distributions because, for example, workers with higher than average skills contribute to surplus relatively less, a fact reflected in their wage.

This paper is related to a recent theoretical literature that has studied how skill distributions may influence the pattern of trade. The hypothesis that skill dispersion may lead to specialization was first put forth by Grossman and Maggi (2000) -henceforth GM- which is a useful point of reference, since their modelling assumptions complement those of this chapter. In particular, GM focused on the case of fully observable skills and competitive labour markets. In a two-country, two-sector model, they show that when both production functions only differ in the degree of complementarity in skills, there is positive assortative matching of workers in every industry. As a result, skill diversity does not generate comparative advantage and there is no trade. They also show that comparative advantage emerges only if there are two sectors, one with supermodular and submodular production functions.[4] These set of results motivate the emphasis on ex-ante unobservability and frictions in the labour market in this chapter.[5]

[4]Trade emerges only conditional on the existence of a supermodular sector, where workers of identical abilities are paired together, i.e. self-matching prevails, and of a submodular sector, where the most skilled workers are paired with the least skilled co-workers, i.e. cross-matching prevails. Supermodularity implies that the marginal product of any worker is increasing in the ability of the co-worker. Submodularity of the production function implies the opposite. In GM, the country with more dispersed skill distribution specializes in the submodular sector.

[5]We expand on an element introduced by GM, who consider imperfect observability of skills. At the end of the paper the authors "note in passing that, with imperfect matching, trade would take place between two countries with different educational processes even if tasks were complementary in all production activities", i.e. all production functions were super-modular, which is the case we consider. We extend this model to many countries and sectors, and derive sharp predictions for the pattern of trade.

Ohnsorge and Trefler (2007) propose a model with two-dimensional worker heterogeneity and show that, when each worker represents a bundle of two skills, the correlation of the two in the population determines comparative advantage. Grossman (2004) starts from the premise that, in some sectors, incomplete contracts make it difficult to tie remuneration to an individual worker's output. In a country with high skill dispersion highly skilled individuals prefer to sort into sectors where individual performance is easier to measure, rather than working in an industry where the common wage is dragged down by workers with relatively low skills. This type of endogenous sorting results in comparative advantage. Finally, in Bougheas and Riezman (2007) comparative advantage emerges from differential returns to skills across sectors. This chapter also contributes to the large and established literature on factor endowments and comparative advantage, a topic which still receives a great deal of attention. For example, in a recent contribution to this literature, Costinot and Vogel (2009) build a model with a continuum of sectors and a continuum of skill levels and investigate the effect of trade on wage inequality in a rich framework.

The paper begins with the analysis of the two-country case. Countries, Home and Foreign, are characterized by different skill distributions. They may also vary in size, but are otherwise identical. The next section introduces the model with a description of consumer preferences, production technologies and the labor market. Section 3 discusses of how different skill distributions generate productivity differences across countries and industries, the source of comparative advantage in the model. Sections 1.4 and 1.5 study the optimization problem of individual firms and the general equilibrium (entry). The following two sections analyze the implications for the pattern of international trade in the two-country and multi-country versions of the model. Section 1.8 characterizes the link between skill complementarity and wage inequality, which is extensively used in BGP. Section 1.9 provides some concluding remarks.

1.2 Setup

1.2.1 Preferences

Countries are denoted with a subscript c where $c \in \{H, F\}$, which is dropped when it does not create ambiguity. Each country c is populated by a measure L_c of individuals. Utility of the representative consumer depends on the consumption of a homogeneous good $Q(0)$ and a continuum of differentiated goods $Q(i)$ with $i \in I$. The utility function U is Cobb Douglas:

$$\log U = \alpha(0) \log Q(0) + \int_{i \in I} \alpha(i) \log Q(i)\, di$$

with $0 < \alpha(i) < 1$ and $\alpha(0) + \int_{i \in I} \alpha(i)\, di = 1$. The aggregate $Q(i)$ is the consumption index over the set $\Omega(i)$ of available varieties of product i and preferences exhibit a constant elasticity of substitution σ across varieties of good i.[6] Under these preferences, demand for a given variety ω is represented by the following equation:

$$d(\omega, i) = \frac{p(\omega, i)^{-\sigma} \alpha(i) E}{P(i)^{1-\sigma}} \tag{1.1}$$

where E is total expenditure, $p(\omega, i)$ is the price of variety ω of i, and $P(i)$ is the ideal CES price index of aggregate $Q(i)$.

[6] More specifically:

$$Q(i) = \left[\int_{\omega \in \Omega(i)} q(\omega, i)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}} \text{ with } \sigma > 1.$$

where $q(\omega, i)$ is the quantity consumed of variety ω of good i.

1.2.2 Production

Good $Q(0)$ is produced under constant returns to scale by perfectly competitive firms. The technology is such that one unit of labour produces one unit of output. We choose $Q(0)$ as our numeraire and we assume that all countries produce the numeraire good in positive quantity, which implies that the wage in sector 0, $w(0)$, is equal to one.

Each differentiated sector i is populated by a continuum of identical firms, each producing a different variety ω. The market is characterized by monopolistic competition among firms, with free entry and a fixed cost of production f. Total output y depends on the skill level of each worker hired a, the measure of workers hired h and the distribution of skills across workers $\tilde{g}(a)$.[7] The distribution of skills matters for production because we assume that different levels of skills are not perfectly substitutable.[8] In particular, the production function of a representative firm in a sector depends on the degree of complementarity λ among workers' skills in that sector and takes the following form:

$$y = \left(\int a^{\lambda} h \tilde{g}(a)\, da \right)^{\frac{1}{\lambda}} \text{ with } \frac{\sigma - 1}{\sigma} < \lambda < 1 \tag{1.2}$$

The parameter λ measures the degree of skill complementarity, since the elasticity of substitution among skills levels, for a fixed mass of workers h, is given by $\frac{1}{1-\lambda}$, which increases with λ. The larger λ, the more substitutable workers of different skill levels are.[9] The key assumption in this model is that each sector i is charac-

[7] For simplicity we only model 'residual' skills and work under the assumption that other observable characteristics are accounted for. In this sense we do allow for selection on observables, but we do not model it explicitly. In Chapter 2 we carefully control for such selection.

[8] One possible interpretation is that the skill of each worker is a differentiated input in the production process. An alternative interpretation, along the lines of the paper by Takii and Tanaka (2009), is that each worker produces a differentiated intermediate good, in quantity proportional to her skills, and intermediate inputs are aggregated by a CES production function.

[9] For a fixed h, this production function is analogous to that in Grossman and Maggi (2000), p.

terized by a different value of λ in production, and therefore by a different degree of complementarity among workers' skill levels. Since λ is the only characteristic that differentiates sectors, in the remainder of the theoretical section we drop the index i and index sectors by their parameter λ.

Two properties of this production function are worth discussing in detail. First, for given mass of workers h, the function is homogeneous of degree one in the skills of workers. This property stresses the relative importance of the shape, rather than location, of the distribution of skills. Second, the production function features increasing returns to the mass of workers, given the distribution of skills.[10] In particular, λ also represents the extent of increasing returns to scale (as well as the degree of complementarity), but this feature plays no substantial role in the model.[11] We restrict the range of λ to guarantee that the firm's maximization problem is concave, as described in section 1.4.

1.2.3 Labour Market

We introduce labour market frictions in the spirit of Helpman and Itskhoki (2009a), although for simplicity we assume that there are no frictions in sector 0. Workers are characterized by different levels of skills and skill is a continuous variable distributed in the workers' population of country c according to a density function $g(a,c)$. The interaction between firms and workers in the labour market has the

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[10]This is easily seen by rewriting the production function as $y = h^{\frac{1}{\lambda}} \left(\int a^{\lambda} \tilde{g}(a)\, da\right)^{\frac{1}{\lambda}}$.

[11]We should note that it is not possible to obtain both constant returns to mass of workers and ability without confounding the quantity and quality of workers, as for example in a production function of the following type: $y = \left(\int (ah\tilde{g}(a))^{\lambda}\, da\right)^{\frac{1}{\lambda}}$. We give priority to maintaining constant returns to ability because we do not want to confound the degree of complementarity with differential returns to aggregate ability in different sectors. Grossman and Maggi (2000) discuss this as another case in which the distribution of ability matters and Bougheas and Riezman (2007) explicitly model this aspect in a different framework.

following timing. First, workers choose whether to look for jobs in the homogeneous sector or in one of the differentiated good sectors. Second, firms in each differentiated sectors pay a cost *bh* to randomly sample a mass *h* of workers from the population of workers searching for a job in that sector. The search cost *b* depends on labour market conditions, as described further below. Third, production takes place. Umatched workers remain unemployed. Fourth, each firm and its employees bargain over the split of revenues into profit.and wages.

Regarding information sets, we follow Helpman and Itskhoki (2009a) and Helpman et al. (2008a) in assuming that individual skills are match-specific and therefore cannot be observed when firms and workers are matched. That is, workers cannot condition their job search on their own skills and firms cannot condition their hiring decisions on skill levels. Individual skills are revealed to all parties only at the production stage. These assumptions on the observability of skills are consistent with the empirical literature in labour economics.[12]

As a result the initial distribution of residual skills in the worker population is inherited by the mass of workers looking for a job in each sector. Moreover, by definition, workers' residual skills are not observable to the firm when hiring. The combination of these assumptions yields no sorting between workers and firms. It's worth noticing that if we allowed skills to be partially observable in our model we would obtain that firms only hire workers of identical *observable* skills. Therefore we can interpret our case of unobservable skills as a residual of overall skills, once the observable component has been accounted for. This has implications for the empirical analysis in the next chapter where, for consistency with the theory, our measure of skill dispersion will be purged of observable individual characteristics.

[12]For example, Altonji and Pierret (2001) find that as employers learn about worker productivity the wage equation coefficients on easily observed characteristics, such as education, fall relative to the coefficients on hard-to-observe correlates of worker productivity.

Although the distribution of workers' skills $\tilde{g}(a)$ could potentially be sector specific, random matching implies that every firm, in every sector λ, in country c inherits the residual skill distribution in the general population:[13]

$$\tilde{g}(a) = g(a,c)$$

1.3 Skill Dispersion as Comparative Advantage

Given that firms and workers match randomly with respect to unobservable skills, in this section we discuss how different skill distributions across countries generate comparative advantage. To facilitate the discussion we rewrite the production function in (1.2) as $y = h^{\frac{1}{\lambda}} A(\lambda, c)$ where $A(\lambda, c)$ is defined as:

$$A(\lambda, c) = \left(\int a^{\lambda} g(a,c) da \right)^{\frac{1}{\lambda}}$$

We loosely refer to $A(\lambda, c)$ as 'productivity', although clearly this is not the result of countries having access to different technologies. The magnitude of $A(\lambda, c)$ depends on a combination of a country-specific skill distribution and a sector-specific level of complementarity across skills. We are interested in how the pattern of comparative advantage, i.e. the relative A's, are affected by the distribution of skills.

The general idea we explore is whether countries with lower dispersion in the distribution of skills have a comparative advantage in sectors with high degree of complementarity, i.e. where it is relatively more important to employ workers with

[13] We do not allow firms to screen workers as in Helpman et al. (2008a). We note that, contrary to the case described by Helpman et al. (2008a), with our choice of production function, firms would not want to screen workers even if the technology to screen were available, because the marginal product of an additional worker is always positive. This is the case in the static problem we are analyzing. In a dynamic framework we would expect firms to lay off unproductive workers and replace them with potentially more productive ones.

similar skills. Since the A's exhibit constant returns to skills, a proportional increase in the skills of all workers increases the A by the same proportion and does not affect comparative advantage. We concentrate on comparing A's across countries that have the same average skills and different dispersion.[14] Without loss of generality countries are ordered so that, if $c < c'$, then country c' is characterized by a skill distribution $g(a, c')$ that is a mean-preserving spread of the skill distribution $g(a, c)$ in country c. We state a general condition, Property 1, for a specific pattern of comparative advantage to emerge as a result of differences in the distribution of skills.

Property 1 $A(\lambda, c)$ is *log-supermodular in* λ *and c, i.e. for* $\lambda < \lambda'$ *and* $c < c'$*:*

$$\frac{A(\lambda, c')}{A(\lambda, c)} < \frac{A(\lambda', c')}{A(\lambda', c)} \tag{1.3}$$

Property 1 states that firms in countries with high skill dispersion will be relatively more productive in low complementarity sectors.

As GM suggest,[15] a general result of this type cannot be established for arbitrary skill distributions. However, since our goal is to derive testable implications of this theory, we are mainly interested in verifying the chapter relevance of Property 1 by employing the distributions of IALS scores observed in the data.

Specifically, we construct $A(\lambda, c)$ replacing $g(a, c)$ with the empirical distribution of scores for 19 countries that participated in the IALS. For a grid of 100 λ's in the $[0, 1]$ interval, we calculate the ratio $\frac{A(\lambda, c')}{A(\lambda, c)}$ where country c' has higher skill dispersion (coefficient of variation of scores) than country c. We then find that, averaging across country pairs, $\frac{A(\lambda, c')}{A(\lambda, c)}$ is increasing in λ for 97% of the grid points. Similar results hold if countries are ranked according to alternative measures of

[14] Note that changes in the average ability that are *not* the result of a multiplicative change in all abilities *will* affect the pattern of comparative advantage.

[15] See p.1271.

scores dispersion.

This evidence suggests that Property 1 provides a reasonable approximation to the patterns of comparative advantage due to differences in skill dispersion. As an alternative approach, In the Appendix, we offer two alternative analytical approaches to studying this problem. First, we show that Property 1 can be established for any distribution if we place a lower bound on λ. Second, we perform comparative statics exercises that do not restrict the range of λ and verify Property 1 for specific parametric skill distributions (Pareto, lognormal, uniform, triangular, gamma, beta and inverse Gaussian).

1.4 The Firm's Problem and Bargaining

This section analyzes the problem of a representative Home firm in a given sector. Analogous expressions can be derived for a Foreign firm. Firms can sell in the domestic market or export, facing a transport cost. The transport cost τ is of the iceberg type, so that firms have to ship $\tau > 1$ units of good in order for one unit to arrive. We denote by $x_{cc'}$ a variable x originating in market c and destined for market c'. We drop the sector index to simplify notation.

A Home firm must decide how much to produce for the Home and Foreign market and, since it maximizes profits, it equates marginal revenues across the two markets. This allows us to write total revenues of a Home firm r_H as a function of total output:

$$r_H = y_H^{\frac{\sigma-1}{\sigma}} \Gamma_H \tag{1.4}$$

where $y_H = y_{HH} + y_{HF}$, $\Gamma_H = \left(B_H^{\sigma} + B_F^{\sigma} \tau^{1-\sigma}\right)^{\frac{1}{\sigma}}$ and $B_c = P_c Q_c^{\frac{1}{\sigma}}$ for $c = H, F$.[16] The

[16]Total revenues are given by $r_H = B_H y_{HH}^{\frac{\sigma-1}{\sigma}} + B_F y_{HF}^{\frac{\sigma-1}{\sigma}} \tau^{\frac{1-\sigma}{\sigma}}$. The equality of marginal revenues across markets, which implies $\frac{y_{HH}}{y_{HF}} = \left(\frac{B_H}{B_F}\right)^{\sigma} \tau^{\sigma-1}$ and some algebraic manipulation lead to (1.4), similarly to Helpman and Itskhoki (2009a).

firm must then simply choose the total amount of output to produce and therefore how many workers to employ. In this decision it takes into account how much workers are paid.

Because of the presence of search frictions, once workers are hired they are not interchangeable with outside workers and we assume that the firm and all workers employed engage in bargaining to share the surplus created. We assume that the intra-firm bargaining is of the type described by Stole and Zwiebel (1996), with the workers having unemployment as outside option, which we assume yields a payoff of zero. Stole and Zwiebel show that the bargaining solution yields payoffs that correspond to the Shapley value. We discuss wages in the following section, while here we show that the bargaining outcome for a firm with revenues r is given by sr, where:

$$s = \frac{\sigma\lambda}{\sigma(1+\lambda)-1} \ . \tag{1.5}$$

Given the expression for total revenues in (1.4), the firm static problem[17] reduces to choosing how many workers to hire (h) to maximize profits π:

$$\max_h \pi \ = \ s\left[A(\lambda,H)\,h^{\frac{1}{\lambda}}\right]^{\frac{\sigma-1}{\sigma}}\Gamma_H - bh - f. \tag{1.6}$$

This is a concave problem because of the restriction placed on λ in (1.2). Since this is a standard problem we refer to the Appendix for details of the derivation, and report here the main results. The total output produced by a Home firm is given by:

$$y_H = A(\lambda,H)\,\phi$$

where $\phi(\lambda) = \left[\frac{f(\sigma-1)}{b(1+(\lambda-1)\sigma)}\right]^{\frac{1}{\lambda}}$. Intuitively, output is increasing in productivity A, the size of the fixed cost f, and the elasticity of demand σ, while it decreases with

[17] For a dynamic extension of this type of framework see Helpman and Itskhoki (2009b).

the hiring cost b.[18] We assume that differences in productivity between Home and Foreign firms in a given sector are not too large, that is:

$$\frac{1}{\tau} \leq \frac{A(\lambda,H)}{A(\lambda,F)} \leq \tau \quad \forall\lambda \tag{1.7}$$

otherwise the amount produced is zero. Under condition (1.7) we can derive how much output is produced for the domestic and export market, y_{HH} and y_{HF} respectively (see Appendix). As standard with iso-elastic demand, the producer price is constant across markets and for a Home firm is equal to $p_H = \frac{\gamma}{\phi A_H}$ where $\gamma(\lambda) = f\frac{\sigma\lambda+\sigma-1}{\sigma\lambda-\sigma+1}$. The consumer price in the export market is the producer price multiplied by τ:

$$p_{HF} = \frac{\gamma\tau}{\phi A_H} \tag{1.8}$$

In the Appendix we derive revenues accruing to firms in all markets. We focus attention here on the relative revenues (i.e. value of output sold) of a Home and Foreign firm in a *given* market, for example Foreign:

$$\frac{r_{HF}}{r_{FF}} = \rho\left(\frac{A(\lambda,H)}{A(\lambda,F)}\right)^{\sigma-1} \tag{1.9}$$

Intuitively, relative revenues increase in relative productivity, as predicted by comparative advantage. In the next section we solve for the mass of firms, which is the final step in the determination of trade flows.

[18] The hiring cost depends on tightness of the labor market x, and is assumed to take the same form as in Helpman and Itskhoki (2009a) and Helpman et al. (2008a): $b = \delta_0 x^{\delta_1}$. We refer to these papers for a discussion. We similarly obtain that in equilibrium the hiring cost is constant across sectors, i.e. $b = \delta_0^{\frac{1}{1+\delta_1}}$.

1.5 Entry

In Section 1.4 we derived the amount of output sold by each firm in the domestic and export market. In order to determine trade flows we need to calculate the equilibrium mass of firms. Here we characterize entry while details of the derivation are presented in the Appendix. We remark that, similarly to other models of monopolistic competition with trade costs (Helpman and Krugman, 1985), the presence of a home-market effect requires that we restrict the degree of asymmetry in country sizes to prevent all firms from locating in one country. Define relative population in Home as $\eta \equiv \frac{L_H}{L_F}$. We impose throughout the restrictions that $\eta_{low} < \eta < \eta_{up}$. If the condition is violated for some industries, we expect to observe no production and no exports.[19] If the condition is satisfied, then the following proposition establishes a link between comparative advantage and equilibrium entry.

Proposition 1 *Under the condition that country sizes are sufficiently similar, i.e.* $\eta_{low} < \eta < \eta_{up}$, *the equilibrium mass of firms in country H relative to country F in sector* λ' *is higher than in sector* λ *if and only if country H has a comparative advantage in sector* λ', *i.e.*

$$\frac{A(\lambda, H)}{A(\lambda, F)} < \frac{A(\lambda', H)}{A(\lambda', F)} \Longleftrightarrow \frac{M_H(\lambda)}{M_F(\lambda)} < \frac{M_H(\lambda')}{M_F(\lambda')}$$

[19] As equations (A-19) and (A-20) establish, the conditions for a positive mass of firms depend on size, but also on comparative advantage. If a country is relatively more productive it can afford to be smaller in size and still have a positive mass of firms. In this sense our model also predicts an extensive margin of trade (whether we observe or not trade between two countries) based on comparative advantage, albeit a very stark one. Differently from models with heterogeneous firms, e.g. Helpman et al. (2008c), in this setup the assumption of identical firms implies that either firms exist and export or they do neither.

1.6 Trade Flows

In this model trade flows are completely determined by the amount sold in the export market by each firm and by the number of firms. Therefore, we now use the results in sections 1.4 and 1.5 to show that the value of exports is relatively higher in comparative advantage industries. In turn, as shown in section 1.3, the latter is determined by a combination of sector characteristics (the degree of complementarity λ) and country characteristics (the dispersion of skills in the population). The following proposition summarizes the previous discussion and represents the main result of this section. We denote the value of total sales by firms from country c in market c', as $X_{cc'}$. Relative total sales of good λ by Home and Foreign firms in a given market, for example Foreign, are then equal to:

$$\frac{X_{HF}(\lambda)}{X_{FF}(\lambda)} = \frac{r_{HF}(\lambda)M_H(\lambda)}{r_{FF}(\lambda)M_F(\lambda)} \tag{1.10}$$

Proposition 2 *Under Property 1, a country with relatively higher dispersion of skills has a comparative advantage, and therefore exports relatively more to any destination, in sectors with high degree of substitutability* λ.

1.7 Multi-Country Extension

The goal of this section is to generalize the model to many countries and provide the conditions under which the main result of the two-country model holds, i.e. countries with relatively higher dispersion of skills have a comparative advantage, and therefore export relatively more, in sectors where the dispersion of wages is higher. This result provides a foundation for the empirical analysis of skill dispersion and comparative advantage, carried out in the next chapter.

Without loss of generality we consider three countries, so that $c \in \{H, F, G\}$. Following HMR, we allow transport costs to be country-pair specific and asymmetric, i.e. $\tau_{HF} \neq \tau_{FH}$. We fix as destination market country F and express the value of exports of good λ by country H relative to country G as follows:

$$\frac{X_{HF}(\lambda)}{X_{GF}(\lambda)} = \frac{r_{HF}(\lambda) M_H(\lambda)}{r_{GF}(\lambda) M_G(\lambda)}$$

While the determination of relative revenues of individual firms r_{HF}/r_{GF} is straightforward, the equilibrium mass of firms can be computed, but not easily characterized, with more than two asymmetric countries. This is a known problem in the home-market effect literature.[20] Therefore in the following proposition we limit ourselves to imposing that the relative mass of firms be non-decreasing in relative productivity. This is reasonable if we believe that, in equilibrium, entry is relatively higher in sectors where a country has a comparative advantage.

Proposition 3 *Under Property 1, if the relative mass of firms $\frac{M_H(\lambda)}{M_G(\lambda)}$ is non-decreasing in relative productivity $\frac{A(\lambda,H)}{A(\lambda,G)}$ then a country with relatively higher dispersion of skills has a comparative advantage, and therefore exports relatively more to any destination, in sectors with higher degree of substitutability λ.*

1.8 Wage Distribution and Complementarity

As a bridge to the empirical analysis in the next chapter, this section discusses how the model provides a proxy for the degree of complementarity, which is not directly observable and for which we have no available estimates. In particular, this section establishes the existence of a one-to-one link between the degree of

[20] Behrens et al. (2009) show that the home-market effect intuition does not easily generalize to the case of more than two countries. Our case of multiple countries with productivity differences further complicates the problem and is beyond the scope of this chapter.

complementarity and the dispersion of wages in sector, which can be measured in the data.

As discussed above, we assume that at the bargaining and production stage workers' skills are revealed, so that workers of different skills receive different wages as a result of intra-firm bargaining. Although the assumption that skill is perfectly revealed only at the production and bargaining stage is stark, we believe it captures some realistic features of the hiring process, where workers' skills in particular tasks are difficult to assess until they start working. Moreover, even if skills were partially revealed at the production stage, as long as the portion revealed were constant across sectors, this would not substantially change the implications discussed below.

Section A.7 in the appendix provides the derivation of the Shapley value for a worker of skill a. Since the average wage also differs across sectors, we normalize the wage of a worker of skill a in sector λ by the average wage in the sector. The normalized wage is $\widetilde{w}(a,\lambda) = \frac{a^{\lambda}}{E\left(a^{\lambda}\right)}$, which reflects the marginal product of a worker of skill a when added to the production team and depends on λ. The higher the substitutability across workers the larger the marginal product of a worker with high skills. In contrast, if λ is low, i.e. complementarity is high, a worker of high skills has a relatively lower marginal product because her skills are very different from the average skills of her team-mates. An implication of this wage structure is that workers with identical skills, but employed in different sectors, generally receive different wages, as returns to skills vary across industries.[21]

Keeping in mind that the distribution of skills is the same in every industry, the distribution of wages within a sector depends, in our framework, exclusively on technological factors that determine the marginal product of workers with different

[21] The point is made by Heckman and Scheinkman (1987), who show that returns to unobservable characteristics are different across sectors.

skills. It therefore does not reflect compositional differences across sectors. The following proposition establishes that the existence of a one-to-one correspondence between the degree of complementarity and several common measures of wage dispersion.

Proposition 4 *For any non-degenerate distribution of skills $g(a,c)$, the following three measures of dispersion of sectoral wages are strictly increasing in the degree of substitutability of workers' skills, λ: (i) the Coefficient of Variation; (ii) the Gini Coefficient and (iii) the Inter-Percentile Ratio*[22]

Proposition 4 establishes that the more complementary workers are, the more compressed the wage distribution is. The intuition follows from our discussion of normalized wages.

1.9 Conclusions

Relative differences in the distribution of production factors are central to the classical theory of international trade. The Heckscher-Ohlin-Samuelson factor proportion model stresses the idea that differences in factor endowments play a major role in predicting trade flows. Comparative advantage is associated with relatively abundant factors of production: the aggregate endowment of some important factor can be a driving force in determining international specialization. In this chapter we push this idea further and argue that the entire distribution of a productive factor, and not just its aggregate endowment, can help in understanding the pattern of trade.

[22] The Interpercentile-Ratio, IPR_{kj}, is defined as $IPR_{kj} = \frac{w_k}{w_j}$, where w_k (w_j) is the wage of the worker at the k^{th}(j^{th}) percentile of the sectoral wage distribution and $j < k$.

We develop a theoretical framework where, because of frictions in the labor market and ex-ante unobservable skills, workers and firms are randomly matched. The skill distribution matters differently across industries because some of them are more capable of substituting skills across production tasks than others. All sectors inherit the distribution of residual skills in the country's population and, as a result, firms in sectors with higher complementarity are relatively more productive in countries with lower skill dispersion. Our model provides an observable proxy for the otherwise unobservable degree of complementarity among workers' skills, that is the dispersion of residual wages at the industry level. This result is exploited in the empirical evaluation of this theory, pursued in the next chapter of this dissertation.

Finally, the theoretical framework developed in this chapter has implications for the impact of trade on overall wage inequality. Our model, taken at face value, implies that a more disperse skill distribution does not just have a direct effect on the income distribution, but also an indirect effect, as countries with higher skill dispersion specialize in sectors with higher residual wage dispersion. Thus, specialization patterns (and, more generally, industry composition) can reinforce or attenuate the effect of the initial skill distribution on wage inequality. Although beyond the scope of this study, the model suggests an interesting link between trade and residual wage inequality that remains to be explored in future research.

Chapter 2

Skill Dispersion and Trade: an Empirical Analysis

Synopsis. *While there is substantial empirical evidence that a country's aggregate endowment of skills is an important source of comparative advantage, this chapter investigates whether the distribution of skills in the labour force plays a role in explaining the pattern of international trade flows of manufacturing goods. In particular, using microdata from the International Adult Literacy Survey to construct measures of skill dispersion, we find that countries with high skill dispersion export relatively more in industries where skills are more easily substitutable across workers. The magnitude of the estimated effect is comparable to that of aggregate endowments of human and physical capital. The result is robust to controlling for alternative sources of comparative advantage and proxies of skill substitutability.*

2.1 Introduction

Numerous empirical studies of the Heckscher-Ohlin-Samuelson factor proportion theory identify quantities such as the stocks of human and physical capital of countries as primary sources of comparative advantage.[1] In this chapter we provide evidence supporting an alternative, and empirically sizeable, source of comparative advantage: the dispersion of skills (human capital) in the working population.[2] We present empirical evidence that diversity is in fact a strong determinant of specialization, a novel finding to the best of our knowledge.

A first glance at the data reveals that cross-country differences in skill dispersion are larger than differences in the average skills of workers. We use the distribution of scores in the International Adult Literacy Survey (IALS), an internationally comparable measure of work-related literacy, as a proxy for the distribution of skills. The coefficient of variation of the standard deviation of scores is 1.64 times larger than that of the average scores. Figure B.1 reports the mean and standard deviation of IALS scores during 1994-1998.

The reasons why countries at similar stages of development differ in their skill distribution are beyond the scope of this study;[3] such differences may be due to the degree of centralization in the education system and curricular control (Stevenson and Baker, 1991), the existence of elite schools, sorting and segregation,[4] early

[1] Among others, Romalis (2004), testing the predictions of the theory about commodity trade, and Bowen et al. (1987), Trefler (1993), Trefler (1995), and Davis and Weinstein (2001), testing the factor content predictions of the theory.

[2] As in chapter 1, we use the terms human capital or skills interchangeably, to refer to a set of individual attributes that are of productive use in the workplace.

[3] What is not beyond the scope of this study is a discussion of how the endogeneity of skill dispersion might affect our empirical results. See Section 2.5.

[4] The existence of peer effects, as documented for example by Hanushek et al. (2003) and Hoxby and Building (2000), implies that segregation and sorting might result in even higher inequality of educational outcomes. An example of this amplification mechanism is provided by Friesen and Krauth (2007).

tracking,[5] local school financing (Benabou, 1996) and the share of private and public schools (Takii and Tanaka, 2009).[6]

The objective of this study is to evaluate the main prediction of the theory presented in chapter 1: countries with more dispersed skill distributions specialize, and therefore export relatively more, in sectors with lower complementarity of skills in production. In order to achieve this goal, we adapt the empirical approach of Helpman et al. (2008c), henceforth HMR, to account for industry-level bilateral trade flows and augment it with our key variable of interest. We show that the interaction of the exporter's skill dispersion with sectoral measures of skill substitutability is a significant and economically large determinant of exports, after controlling for a variety of bilateral trade barriers, exporter and importer-industry fixed effects (as dictated by the theory). We also include determinants of comparative advantage based on aggregate factor endowments as in Romalis (2004) and check that the result is not due to a correlation of country-level skill dispersion with institutional variables, like labor law rigidity and judicial quality, that have been found to influence trade flows in recent research.

Since the degree of substitutability across workers' skills is not directly observable, we take two distinct approaches to its measurement. First, we exploit the structure of the model presented in chapter 1, which delivers a direct link between the unobservable degree of complementarity and the observable dispersion of residual wages within industries. In view of substantial evidence linking firm size and wages (e.g. Oi and Idson, 1999), we are careful to filter out sector-specific firm heterogeneity from our wage dispersion measures. In order to mimic random

[5]Tracking refers to the practice of grouping students in different schools according to their ability. Woessmann et al. (2006) show that when grouping happens before age 10, inequality in education outcomes increases at the country level.

[6]James (1993) argues that the mix of public and private educational services is due, for example, to the degree of religious heterogeneity within a country.

matching we also purge wages of the effect of self-selection of workers into industries. As with IALS scores, in order to bring the empirical analysis in line with the theoretical focus on unobservable skills, we purge individual workers' wages (from the US Census) of the component explained by observable characteristics, to obtain *residual* wages.

Second, we use an alternative set of measures of the degree of skills substitutability. These measures are based on survey data available from the Occupational Information Network (O*NET), which allow us to quantify cross-industry variation in the degree of teamwork, communication and interdependence between co-workers' labor inputs. These measures are not motivated by, and are independent of, the theory in chapter 1 and provide a direct and intuitive way to proxy for complementarity.

Our findings relate to recent work emphasizing less traditional sources of comparative advantage. In this literature the endowment of a country, interpreted in a broad sense, includes institutional features, such as the ability to enforce contracts (Levchenko, 2007, and Nunn, 2007), the quality of the financial system (Manova, 2008a; 2008b) and the extent of labor market frictions (Helpman and Itskhoki, 2009a, Cuï£¡at and Melitz, 2007, Tang, 2008). We view our contribution as related to this 'institutional endowment' view of comparative advantage because human capital dispersion in a country is to a large extent the result of the prevailing educational system and social make-up. The latter, in turn, can be considered, if not immutable, a slow-moving attribute of a country.[7]

Next we present the estimation framework. Section 2.3 describes the data and section 2.4 reports baseline results. Finally, section 2.5 discusses identification and provides robustness checks. The chapter ends with some concluding remarks.

[7]Glaeser et al. (2004) show that education is significantly more persistent than several other institutional features, such as the form of government.

2.2 Estimation Framework

In this section, we build on the theory developed in chapter 1 in order to derive an econometric specification to evaluate its main predictions. As a first step to design an empirical test of Proposition 3, we express the value of total exports of good i from exporter H to importer F as the product of the quantity demanded of an individual variety of i from equation (1.1), the price and the mass of firms/varieties:

$$X_{HF}(i) = d_{HF}(i)\, p_{HF}(i)\, M_H(i) = \frac{[p_{HF}(i)]^{1-\sigma}\,\alpha(i)\,E_F}{[P_F(i)]^{1-\sigma}} M_H(i) \tag{2.1}$$

The price of a variety produced by a Home firm and sold in Foreign, $p_{HF}(i)$, depends positively on transport costs and negatively on productivity, as shown in the Appendix:

$$p_{HF}(i) = \frac{\gamma(i)\,\tau_{HF}}{\phi(i)\,A(i,H)}. \tag{2.2}$$

Once we substitute (2.2) in (2.1) and we take the natural logarithm, we obtain the following expression for the value of (log) exports:

$$\begin{aligned} \log X_{HF}(i) \quad = \quad & (\sigma-1)\log A(i,H) + \log M_H(i) - (\sigma-1)\log\tau_{HF} \qquad (2.3)\\ & +\log\alpha(i) + \log E_F - (\sigma-1)P_F(i) + (\sigma-1)\log\frac{\phi(i)}{\gamma(i)} \end{aligned}$$

where $A(i,H)$ captures comparative advantage of the exporting country, $M_H(i)$ the mass of firms in the exporting country, τ_{HF} transport costs between the two countries, $P_F(i)$ an industry-importer specific price index, E_F the importing country total expenditure and $\phi(i)$, $\gamma(i)$ and $\alpha(i)$ industry-specific constants. Since we consider a discrete number of industries, in the remainder of this section we use subscript i to index variables that vary across industries.

An ideal test of Proposition 3 would require quantifying the effect of a mean-preserving spread in the distribution of residual skills in country H on its relative exports to country F, as a function of the elasticity of substitution in each sector i. These effects operate through A_{Hi} in equation 2.3. Although M_{Hi} is not observable, the model shows it is also a function of A_{Hi}. Therefore, in order to derive an estimation equation for $\log X_{HFi}$, we assume that $(\sigma-1)\log A_{Hi}+\log M_{Hi}$ can be written as an additive function of industry characteristics (δ_i), exporter characteristics (δ_H), an interaction between a measure of skill substitutability in industry i ($Substit_i$) and a measure of skill dispersion in country H ($SkillDisp_H$), plus other unobservable determinants of comparative advantage in country H (ν_{Hi}), that is, $(\sigma-1)\log A_{Hi}+\log M_{Hi}=\beta Substit_i \times SkillDisp_H+\delta_i+\delta_H+\nu_{Hi}$.[8]

Transport costs are allowed to depend linearly on a vector of observable country-pair bilateral trade barriers (d_{HF}) and unmeasured i.i.d. trade frictions (u_{HF}).[9] A set of industry-importer specific fixed effects (δ_{Fi}) controls non-parametrically for the price index P_{Fi}, industry constants $\frac{\phi_i}{\gamma_i}$ and δ_i. Finally, let η_{HFi} capture measurement errors in trade flows and the effect of other unobserved determinants of X_{HFi}.

With this specification, the estimation equation for exports takes the following form:

$$\log X_{HFi}=\beta Substit_i \times SkillDisp_H+\gamma d_{HF}+\delta_H+\delta_{Fi}+\varepsilon_{HFi} \tag{2.4}$$

[8]Note that A_{Hi} may also depend on the mean and other moments of the skill distribution of country H and these could potentially have different effect on productivity in different industries, a possibility that we explicitly consider in the empirical analysis of trade flows. These effects are summarized by ν_{Hi}.

[9]Alternatively, transport costs could have been captured non-parametrically by the inclusion of exporter-importer fixed effects. Note that in this case our interaction of interest would still be identified since it varies at the exporter-industry level. However, for comparability with previous studies, we do not pursue this empirical strategy here. Also, we do not treat unmeasured trade frictions u_{HF} as a random effect when estimating β, since that would require assuming stronger exogeneity conditions than needed. However, we account for the presence of u_{HF} as a cluster effect in the computation of the standard errors.

where $\varepsilon_{HFi} = \nu_{Hi} + u_{HF} + \eta_{HFi}$.

The variable of interest is $Substit_i \times SkillDisp_H$ and estimation of its coefficient β allows us to test Proposition 3. To see why, assume that equation (2.4) correctly specifies a model for the conditional expectation of $\log X_{HFi}$, so that

$$E\left[\varepsilon_{HFi} | Substit_i \times SkillDisp_H, d_{HF}, \delta_H, \delta_{Fi}\right] = 0$$

Then, for any two countries H and G exporting to F, and any two industries i and j, equation (2.4) implies:

$$E\left[\log\left(\frac{X_{HFi}}{X_{GFi}}\right) - \log\left(\frac{X_{HFj}}{X_{GFj}}\right)\right] = \beta \Delta_{ij} Substit \times \Delta_{HG} SkillDisp \qquad (2.5)$$

where $\Delta_{HG}SkillDisp \equiv SkillDisp_H - SkillDisp_G$ and $\Delta_{ij}Substit$ is similarly defined. According to (2.5), Proposition 3 implies $\beta > 0$.

A difficulty in implementing this test of the theory comes from the fact that the elasticity of substitution of individuals' skills at the industry level, $Substit_i$, is not observable in the data and we are not aware of any estimates of the elasticity of substitution for a fine disaggregation of skills. Therefore we take two different approaches to proxy for the elasticity of substitution of workers skills, $Substit_i$. The first is based on a theoretically-founded link between complementarity and residual wage dispersion (chapter 1, section 1.8). The second approach is to construct proxies for complementarity available from occupation-level data. Although these two approaches do not identify the elasticity of substitution, $Substit_i$, they allow us to rank industries in order of increasing $Substit_i$.

2.2.1 Skill Substitutability I: Residual Wage Dispersion Rankings

While we now discuss a heuristic explanation of the link between complementarity and (residual) wage dispersion, section A.8 of the appendix provides the formal proof of the result.

Consistent with empirical evidence, e.g. Altonji and Pierret (2001), suggesting that firms only gradually learn about worker skills, we posit that at least part of the unobservable skills at the time of hiring are revealed to firm and worker once production begins and bargaining takes place. Hence workers of different skills receive different wages. Since our model predicts that each sector inherits the same distribution of unobservable skills, the distribution of residual wages only reflects technological differences across sectors. In particular, the degree of complementarity affects the wage of workers that are far from the average. For example, in a sector with high complementarity, a worker with high skill has a lower marginal product because her skills are very different from the average, compared with a sector with high substitutability, where high skills yield a high marginal product and high wage. Therefore sectors with low complementarity (high substitutability) have a more dispersed wage distribution. Although we do not rely on the model to structurally recover the actual value of $Substit_i$, we use its unambiguous prediction of a monotonic relationship between $Substit_i$ and wage dispersion to identify a ranking of industries in terms of $Substit_i$.

2.2.2 Skill Substitutability II: O*NET Rankings

In our second approach we construct proxies for complementarity using occupation-level data from O*NET. As described in section 2.3.2, this database rates industries in three dimensions which are closely associated to skill complementarity: i) *Teamwork*: team production can naturally be thought of as a particular type of O-Ring production process (Kremer, 1993), in which the quality of final output critically depends on the successful completion of a given number of complementary tasks. (ii) *Impact on co-worker output:* a closely related way of characterizing complementarity is to quantify the extent to which a worker's actions impact the performance of co-workers; a higher impact implies a higher degree of complementarity. (iii) *Communication/Contact*: communication and contact intensity are linked to the importance of coordinating tasks to achieve, for example, a given level of output quality; if co-workers have no need for communication or contact with each other, they are likely to have independent contributions to the final outcome. As for wage dispersion, and because we do not know the exact mapping between the O*NET variables and $Substit_i$, we simply rely on O*NET to identify a ranking of industries in terms of $Substit_i$.[10]

2.3 Data

Before presenting the estimation results we describe the measurement of two key explanatory variables in the empirical analysis, skill dispersion at the country level and skill substitutability at the industry level. A detailed discussion of all data can be found in the Appendix.

2.3.1 Skill Dispersion

We use test scores from the 1994-1998 International Adult Literacy Survey (IALS) to approximate the skill distribution within a country. Collaborators in this household survey administered a common test of work-related literacy skills to a large sample of adults between the ages of 16 and 65 in 19 countries. The IALS fo-

[10]With both wage dispersion and O*NET, regression results are qualitatively unchanged if we employ the value of the proxies instead of their ranking.

cuses on literacy skills that are needed for everyday tasks (e.g. working out a tip, calculating interest on a loan and extracting information), across three different dimensions of literacy: *quantitative*, *prose* and *document* literacy. We combine the results of these three tests into a single average score for each individual, measured on a scale from 0 to 500. The skill distribution is proxied by the distribution of log-scores of individuals participating in the labor market and living in the same country.

To ensure consistency with the theoretical assumption of imperfect skill observability, we construct a measure of *residual* scores dispersion within countries. For an individual k participating in the labor market of country H, we obtain the estimated residual $\widehat{\varepsilon_{kH}}$ from the following regression:

$$\log(s_{kH}) = X_{kH}\beta_H + \varepsilon_{kH} \tag{2.6}$$

where s_{kH} is the IALS score of k and X_{kH} is a vector of individual demographic information from the IALS questionnaire. The residual $\widehat{\varepsilon_{kH}}$ is then used to compute the skill dispersion measures used for the estimation of trade flows. Analyzing the R-squared of these country-by-country regressions, we find that the variation in residual scores $\widehat{\varepsilon_{kH}}$ accounts for a minimum of 46% of the observed variation in log-scores in Canada, for a maximum of 83% in Germany and for 70% in Finland, the median country in the sample.

Table 1 ranks 19 countries according to the coefficient of variation (CV) of IALS scores, and also reports their rank by mean, standard deviation (St Dev) and standard deviation of residual IALS (St Dev Res). The figures show different dispersion in countries at similar stages of development: for example, we observe a more spread distribution of skills in the US, UK and Canada, than in Sweden, the

Netherlands and Germany.[11]

2.3.2 Substitutability

In this section we describe the construction of the two rankings of skill substitutability at the industry level, based on residual wage dispersion and O*NET indices.

Residual Wage Dispersion We use the 5% Public Use Microdata Sample (PUMS) files of the 2000 Census of Population in the United States to construct industry-specific measures of wage dispersion to identify a ranking of industries in terms of the unobserved elasticity of substitution. An advantage of our approach is that we can match individual wage observations to a detailed industry classification, accounting for the entire manufacturing sector[12]. This procedure results in 63 industries for which both wage dispersion and international trade flows can be computed, at a level of aggregation between the 3 and 4 digit levels of the 1997 North American Industry Classification System (NAICS).

As with IALS scores, we focus on residual wage dispersion. We start by removing variation in wages driven by individual characteristics on which firms can typically condition employment decisions. We also adapt the correction method proposed in Dahl (2002) to address the possibly non-random selection of workers into multiple industries. In essence, this procedure controls for selection effects using differences in the probabilities of being observed in a given industry due to

[11] Brown et al. (2007) report similar variation in skill distributions in a comprehensive study using IALS, the 1995, 1999 and 2003 Trends in International Maths and Science Study (TIMSS), the 2000 and 2003 Programme for International Student Assessment (PISA) and the 2001 Progress in International Reading Literacy Study (PIRLS).

[12] This is not feasible for IALS data, since individual observations are assigned a broad sectoral classification (e.g. agriculture, mining, manufacturing, construction, etc), while international trade data is available only for manufacturing industries.

exogenous variation, such as the state of birth of two people who are otherwise similar in terms of education, experience, household structure, race and gender. Details are provided in the Appendix.

For an individual k employed in industry i, we obtain the estimated residual $\widehat{\xi_{ki}}$ from the following regression:

$$\log(w_{ki}) = Z_{ki}\beta_i + \xi_{ki} \tag{2.7}$$

where w_{ki} is the weekly wage of k and Z_{ki} is a vector of observable characteristics (age, gender, etc.). Note that we run these regressions separately for each industry to allow for differences in the return to observable characteristics across industries.[13]

Several studies have shown that firm size affects workers' wages.[14] This implies that wage dispersion might also reflect variation in the distribution of firm size across different industries. Although the model does not incorporate firm heterogeneity, we purge residual wage dispersion of the effect of firm heterogeneity in order to isolate the degree of complementarity. Since the Census does not provide the size of the establishment at which individual workers are employed, we regress measures of dispersion of $\widehat{\xi_{ki}}$ on the coefficient of variation of firm size within industry i, $FirmDisp_i$. The residuals from this regression are employed to construct $WageDisp_i$, a ranking of industries in table 2, where we report the top and bottom 5. For example, in terms of the standard deviation of residual wages, the three lowest ranked sectors are railroad, ship building and aerospace. The three highest ranked are apparel accessories, bakeries and cut and sew apparel.

The use of U.S. estimates as proxies for within-industry wage dispersion (and

[13]Regression results are available upon request.
[14]See Oi and Idson (1999).

skill substitutability) in other countries is warranted if they have access to similar production technologies.[15] Equal access to technology implies that the elasticity of substitution in any given industry will be constant across countries. As a result, the ranking of industries according to wage dispersion will be the same within each country, a hypothesis that is not easy to verify due to the scarcity of publicly available microdata with similar sector classification. However, we do perform this exercise for the U.S. and Canada. We compute the sectoral dispersion of wage residuals in Canada to verify whether the ranking is similar to the one prevailing in the US.[16] To maximize comparability, we are careful to control for the same set of observable characteristics of workers in both countries when computing the residuals, use similar sampling criteria and the same industry classification. Figure B.2 shows industry rankings in terms of the standard deviation of the wage residuals in the two countries. The positive slope of the fitted line is significant at the 1% level. Clearly, the sectoral ranking of residual dispersion in the US is strongly correlated to the one observed in Canada. Sectors like computers and clothing exhibit higher dispersion in both countries, compared to sectors like machinery and paper manufacturing.

Although purging composition effects from the residuals by accounting for worker self-selection and firm size makes $WageDisp_i$ a reasonable proxy for skill substitutability, it is not impossible to think about alternative deteminants of wage rankings. One such example is variation in unionization rates across industries. However, $WageDisp_i$ will remain a valid proxy unless the correlation between

[15]The assumption that industry-specific characteristics computed for the United States also apply to industries in other countries is not an unusual one in the recent empirical trade literature on comparative advantage. Examples include the measurement of financial vulnerability (Manova, 2008b), the importance of relationship-specific investment (Nunn, 2007), firm-specific skill intensity (Tang, 2008) and the variance of firm-specific shocks (Cuï£¡at and Melitz, 2007).

[16]We use the Canadian Labor Force Survey data for May 2000. Details of this exercise are available upon request.

unionization rates and skill substitutability is sufficiently large to affect industry rankings. Also notice that $WageDisp_i$ is robust to cross-country variation in labour market institutions that affect all manufacturing industries to a similar degree, such as miminum wage regulations. If, say, the minimum wage in the US is lower than in Germany, any given industry in the US will display higher wage dispersion than its counterpart in Germany. However, industry rankings are unlikely to be affected.

*O*NET Measures of Complementarity* Sponsored by the Employment and Training Administration of the United States Department of Labor, O*NET provides detailed information on job requirements and worker attributes for 965 occupations in the U.S. Information on 277 descriptors including abilities, work styles, work context, interests, experience and training, is annually updated by ongoing surveys of each occupation's worker population and occupational experts.

As anticipated in section 2.2, our complementarity rankings are based on four selected O*NET (Version 12.0) questions capturing different aspects of skill complementarity: (1) *Teamwork*: How important are interactions that require you to work with or contribute to a work group or team to perform your current job?[17] (2) *Impact*: How do the decisions an employee makes impact the results of co-workers, clients or the company? (3) *Communication*: How important is communicating with supervisors, peers or subordinates to the performance of your current job? (4) *Contact*: How much contact with others (by telephone, face-to-face, or otherwise) is required to perform your current job? Respondents were asked to rate these questions on a scale from 1 to 5. The O*NET database provides average scores for each occupation.

In constructing industry-level proxies of complementarity, O*NET scores were

[17] An alternative measure of teamwork can be obtained from the Detailed Work Activities (a supplemental file to O*NET). Reported results are qualitatively unchanged when this measure is used.

matched to the 2000 Census microdata.[18] In this way, because occupational structures vary across industries, we obtain a different distribution of scores for each industry. Using the median score for each industry we generate $O^{*}NET_i$, a ranking of sectors in terms of substitutability.[19] Industries with higher $O^{*}NET_i$ exhibit lower skill substitutability. Table 2 reports the ranking in terms of $Contact_i$ for the top and bottom 5 industries as ranked according to residual wage dispersion (other O*NET variables produce similar rankings). The table shows that among the lowest ranked sectors in terms of wage dispersion appear the top ranked sectors in terms of O*NET measures. These are the low substitutability sectors. Similarly, among the highest ranked sectors in terms of $WageDisp_i$ we find the bottom $O^{*}NET_i$ sectors (those sectors with high substitutability). This reflects the fact that, as shown in table 3, $O^{*}NET_i$ and $WageDisp_i$ are inversely correlated. Although weakly significant, correlation signs among substitutability rankings are consistent with the expected pattern.

2.4 Baseline Results

This section discusses results of the empirical analysis of trade flows using specification (2.4). The dependent variable in tables 4 to 6 is the log of exports from country H to country F in industry i. Our data set contains the value of exports in year 2000 from 19 exporters to 145 importers in 63 industries. We first report results when $Substit_i$ is proxied by a wage dispersion ranking $WageDisp_i$ and later show similar quantitative findings when we utilize survey-based complementarity rankings from O*NET.

[18] This is possible since the occupational classifications in both O*NET and the Census are based on the Standard Occupational Classification.

[19] The results reported in the empirical section are robust to reweighting by hours worked and to using mean scores instead of medians as complementarity proxies.

2.4.1 Substitutability Proxied by Wage Dispersion Rankings

Table 4 reports estimates of the impact of skill dispersion as proxied by the dispersion of *residual* IALS test scores (defined in section 2.3.1): we identify this effect through an interaction with *residual* wage dispersion rankings (defined in section 2.3.2). For comparability, all tables report standardized coefficients of the explanatory variables.[20] The measures of dispersion employed in table 4 are: the standard deviation in columns (1) and (4), the 95-5 interpercentile range in columns (2) and (5), and the Gini mean difference in columns (3) and (6). Columns (1)-(3) add exporter, importer and industry dummies to our variables of interest; columns (4)-(6) include theoretically consistent exporter and importer-industry dummies, along with a vector of bilateral trade barriers described in the Appendix. We find that $WageDisp_i \times SkillDisp_H$ has a positive and significant effect on exports. We note that the magnitudes of the coefficient are stable across specifications and measures of dispersion. The standardized coefficient of $WageDisp_i \times SkillDisp_H$ varies between 1.4% and 1.9% in the six specifications.

We employ the estimated coefficients to gauge the economic magnitude of this source of comparative advantage. Our baseline estimate is 0.017 (column 4, table 4). Consider two countries, the US and Sweden, and two industries, 'computers' and 'plastics'. These countries and industries are chosen because the skill dispersion in the US is (approximately) one standard deviation higher than Sweden's and $WageDisp_{computers}$ is one standard deviation higher than $WageDisp_{plastics}$. Since the standard deviation of log exports is 2.204 (table 8), the relative ratios of US and Sweden's exports (to an average importer F) in the two sectors are given by

[20] When a regressor is the product of two variables, the latter are standardized before computing the interaction.

$e^{0.017\times 2.204}$, that is:

$$\frac{X_{US,F}\,(computers)}{X_{US,F}\,(plastics)} \Big/ \frac{X_{SWEDEN,F}\,(computers)}{X_{SWEDEN,F}\,(plastics)} = 1.038$$

This implies that all else constant, averaging across destination markets, the relative exports of computers to plastics in the US are 3.8% higher than in Sweden (this figure varies between 3.1% and 4.3% depending on the estimate used from table 4). To put the result in perspective, section 2.5 compares this effect against those of other sources of comparative advantage that have been studied in the literature.

Section B.3 in the Appendix shows that similar results are obtained if raw wages and raw scores are employed in building measures of dispersion, that is wages and scores before we filter out the effect of observables.

2.4.2 Substitutability Proxied by O*NET Rankings

Next, we report estimates of the effect of skill dispersion on trade flows using four alternatives measures of skill complementarity constructed from the O*NET database. Table 5 replicates the structure of columns (4)-(6) of table 4, in terms of the set of fixed effects included and trade barriers used as controls. The variable of interest is the interaction of $SkillDisp_H$ (measured by the standard deviation of residual scores) and the corresponding O*NET ranking: $Teamwork_i$, $Impact_i$, $Communic_i$ and $Contact_i$. Note that since O*NET rankings are proxying for complementarity, the expected sign of the interaction is negative (i.e. countries with a higher skill dispersion export relatively less in industries with high skill complementarity). This is confirmed in every specification of table 5 at the 1% significance level. The estimates of the effect of skill dispersion are quantitatively very similar to the ones generated using $WageDisp_i$. In unreported regressions we check that these results are qualitatively unchanged if (i) $SkillDisp_H$ is measured as either the 95-5 interpercentile range or the Gini mean difference of residual scores; (ii) importer-industry fixed effects are replaced by importer and industry fixed effects; (iii) trade barriers are not included in the estimation and (iv) O*NET rankings are computed using the mean score of occupations in the industry rather than the median.

2.5 Identification and Robustness

In this section we discuss some potential issues related to the identification of the effects quantified in tables 4 and 5. For parsimony we present our robustness analysis using residual wage dispersion rankings to proxy for substitutability. All the results presented below also hold when using the O*NET rankings.[21]

2.5.1 The Extensive Margin of Trade: Selection

Tables 4 and 5 report estimation results which do not take into account the fact that a substantial fraction of bilateral trade flows are zero and that trade flows reflect both an intensive margin (the amount exported by each firm) and an extensive margin (the number of firms exporting, possibly zero). The estimation of (2.4) requires excluding observations for countries which do not trade in specific industries. These amount to 66.5% of the sample (table 8). As discussed in HMR, selection of trading partners induces a negative correlation between observed and unobserved trade barriers (d_{HF} and u_{HF}) that might bias OLS estimates in (2.4), including β.

In order to correct for selection bias, we implement a two-step estimation pro-

[21] Estimation results are available from the authors.

cedure: in the first step we account for the discrete export decision using a linear probability model and obtain the predicted probabilities of observing positive exports, $\widehat{\varphi_{HFi}}$; in the second stage, equation (2.4) is estimated including a flexible polynomial of degree four in $\widehat{\varphi_{HFi}}$ to control for selection bias.[22] For identification not to rely on the non-linearity of $\widehat{\varphi_{HFi}}$ one needs to identify a source of variation which affects the discrete choice of engaging in exports without changing the intensity of trade flows. HMR argue that cross-country variation in start-up regulation costs likely relates to the decision to export, and it has no bearing on the intensive margin. The economic rationale lies in the fact that start-up costs in the exporting country, as well as in the importing one, affect fixed rather than variable costs of trade. Different forces can be at work and the nature and strength of this effect may depend on characteristics of both exporting and importing countries. For example, HMR find that start-up regulation costs are an effective predictor of the extensive export decision and that the interaction between home and foreign regulation costs has a negative gradient on the likelihood to export. On the other hand, De Groot et al. (2004) show that *differences* in institutional factors, including differences in regulation and red tape, have large effects on trade flows; their work unveils an alternative channel through which regulation can affect trade, and stresses the importance of 'similarity' in institutional frameworks.

An analysis of the first-stage bilateral export decisions (see table 7) uncovers strong effects of regulation costs. We use exporter-importer interactions of three proxies of regulation costs: the number of days ($RegDays_H \times RegDays_F$), number of legal procedures ($RegProc_H \times RegProc_F$) and relative cost, as a percentage of

[22] We favor using a linear probability model in the first stage since its two most common alternatives, probit and logit models, suffer different problems in the current application. The probit model with fixed effects yields inconsistent estimates. In turn, estimating a fixed effects logit becomes computationally very costly due to the large number of fixed effects required by our specification of equation (2.4).

GDP per capita ($RegProc_H \times RegProc_F$), for an entrepreneur to start operating a business.[23] We find that these proxies are significant predictors of selection into exporting. [24]

In table 6 we report the second stage obtained using the selection correction. To facilitate comparison, column (1) of table 6 is identical to column (4) of table 4, which is the baseline result using $WageDisp_i$, i.e. we employ only one of the three measures of dispersion, the standard deviation.[25] Columns (2)-(6) report the second stage of the selection-corrected estimation. Column (2) documents the robustness of the effect associated to the interaction $WageDisp_i \times SkillDisp_H$: the standardized coefficient is essentially unchanged at 0.016.

2.5.2 Omitted Determinants of Comparative Advantage

A second potential source of bias is due to the omission of other determinants of comparative advantage, possibly correlated to our variable of interest. Suppose that the true model includes an additional term $n_i Z_H$. If $WageDisp_i$ is correlated with n_i and $SkillDisp_H$ is correlated with Z_H, the OLS estimate of β in equation (2.4) will be inconsistent. As an example, industries with lower dispersion of wages tend to be capital intensive. Similarly, exporters with low skill dispersion tend to be relatively abundant in aggregate physical capital.[26] In this case, comparative advantage

[23] To test the overidentifying restrictions we performed a Hausman test comparing second stage estimates using all three instruments to the corresponding estimates using only a subset of them. We tested all possible combinations of exclusion restrictions and in no case could we reject the null hypothesis that they are valid and, therefore, estimates with different restrictions only differ as a result of sampling error.

[24] In fact, as might be expected, we find that regulatory costs tend to have a direct negative effect on export choices, but also that relative differences across countries do matter, and can lead to positive interaction effects. Additional details available from the authors.

[25] The same qualitative results emerge if we employ the other two measures of dispersion.

[26] In our dataset, the correlation between the coefficient of dispersion of residual wages and physical capital intensity across industries is -0.511. In turn, the correlation between the standard deviation of residual IALS scores and physical capital abundance across exporters is -0.524.

driven by skill dispersion is correlated with comparative advantage deriving from standard factor proportions theory.

Columns (3) to (5) of table 6 show that the estimated effect of the interaction $WageDisp_i \times SkillDisp_H$ is robust to a number of controls for other potential determinants of comparative advantage. Column (3) introduces controls for standard Heckscher-Ohlin sources of comparative advantage: the interaction of factor endowment of a country (in particular, human capital $SkillEndow_H$ and physical capital $KEndow_H$) and factor intensity of the sector (human capital $SkillIntens_i$ and physical capital $KIntens_i$), as in Romalis (2004). Since their 95% confidence intervals overlap, we conclude that the impact of our variable of interest $WageDisp_i \times SkillDisp_H$ on trade flows is quantitatively similar to the effect of interactions $SkillIntens_i \times SkillEndow_H$ and $KIntens_i \times KEndow_H$. In column (4) we control for the interaction between $WageDisp_i$ and institutional features of countries that might be correlated with $SkillDisp_H$. Our concern is that, to the extent that $WageDisp_i$ displays a similar pattern to other characteristics of sectors that make them benefit from those institutional features, our interaction of interest could be capturing alternative channels that have been found empirically relevant in the literature. In particular, we interact $WageDisp_i$ with $LaborRigid_H$ (a measure of labor law rigidity in country H) and with $JudicQual_H$ (a measure of judicial quality). These alternative controls do not substantially affect the magnitude of our variable of interest. In column (5) we introduce the share of individual wages that are top-coded within an industry, $TopCode_i$, interacted with $SkillDisp_H$, to show that our result is not driven by the fact that some sectors rely on 'superstars' (those sectors that have a high share of top-coded wages). This suggests that more than one aspect of the dispersion of the distribution of wages is driving the result, and that the overall shape of the distribution seems to be better captured by broader measures of dispersion.

2.5.3 Reverse Causality

Finally, $WageDisp_i$ and $SkillDisp_H$ might be partly influenced by the pattern of international trade, potentially resulting in reverse causality. We explore this possibility by examining the relationship between each of these two variables and the error term ε_{HFi}. The orthogonality condition needed for consistent estimation of β in equation (2.4) is:

$$E\left(WageDisp_s \times SkillDisp_c \times \varepsilon_{HFi}\right) = 0 \quad \forall s,c \tag{2.8}$$

By the Law of Iterated Expectations, a sufficient condition to obtain identification is:

$$E\left(WageDisp_s \times \varepsilon_{HFi} | SkillDisp_c\right) = 0 \quad \forall s,c \tag{2.9}$$

which requires that, for every exporter in our sample, within-industry wage dispersion be uncorrelated with unobserved determinants of trade. For example, a violation of (2.9) would arise if ε_{HFi} contained the unobserved share of exporting firms in a given sector in H and the proportion of exporters varied across industries and importers. In a model with heterogeneous firms, Helpman et al. (2008a) show that within-industry wage dispersion is a function of the proportion of firms exporting in the industry since, on average, exporters pay higher wages than non-exporters.[27] However, as shown in HMR, the correction for self-selection into the export market discussed in section 2.5.1 effectively removes this potential bias.

Furthermore, since we measure wage dispersion at the industry level using U.S. data, we can check the robustness of our estimates by removing the U.S. from our set of exporters. To the extent that the U.S. wage structure is not significantly affected by bilateral trade flows between other countries, this procedure

[27] Exporters do pay higher wages. See, for example, Bernard et al. (1995) and Bernard and Jensen (1997).

substantially decreases the likelihood of feedback effects running from trade flows to $WageDisp_s$. Column (6) in table 6 shows that, also in this case, the coefficient of our interaction of interest maintains the same magnitude and significance.

An alternative sufficient condition that guarantees (2.8), and therefore identification of β, is

$$E\left(SkillDisp_c \times \varepsilon_{HFi} | WageDisp_s\right) = 0 \quad \forall s, c$$

which means that, for every sector, skill dispersion in every exporting country is uncorrelated with the error term ε_{HFi}. This condition is satisfied if unobserved exporting opportunities captured in ε_{HFi} are not significantly related to the dispersion, and overall distribution, of residual skills in a country. There are several reasons to believe that this is plausible. First, the unobserved exporting opportunities ε_{HFi} must occur at levels other than exporter or importer-industry, which are already captured by our set of dummies. Moreover, since our skill dispersion measures pre-date trade flows by several years, the link between ε_{HFi} and $SkillDisp_c$ introduces bias only if: (i) ε_{HFi} is a highly persistent shock to exporting opportunities which is not captured by our dummies and also affects the long-term, 'residual' skill distribution, and (ii) the skill distribution reacts very quickly in response to export shocks. In this respect Glaeser et al. (2004) show that the education system is a slow-changing characteristic of a country. However, skill dispersion is not only the product of the formal education system, but may change after school through on-the-job training. A number of chapters have established the relatively limited impact of on-the-job training on the overall level of human capital.[28] Nevertheless, we explicitly account for the possibility that re-training is triggered by exporting opportunities through the inclusion, in the derivation of residual skills, of a control

[28] See discussion in Carneiro and Heckman (2003) and Adda et al. (2006).

for whether a worker was re-trained in the previous year.

2.6 Conclusions

This chapter explores the empirical relevance of skill dispersion as a determinant of the pattern of trade across industries. The analysis relies on microdata to construct measures of skill dispersion in the labour force for a set of countries that participated in the IALS. The evidence indicates that exporters with higher residual skill dispersion specialize in low complementarity sectors. The result is robust to a variety of controls for alternative sources of comparative and is also quantitatively large: in fact we find that the magnitude of the effect of skill dispersion on trade flows is comparable to that of the aggregate endowment of human capital. Two alternative measures of skill substitutability produce results that are qualitatively and quantitatively very similar.

Building on the theory developed in chapter 1, the analysis focuses on the impact of *residual* skill dispersion: in the model this means analyzing *unobservable* skills; in the empirical analysis it translates into purging skills and wages of all characteristics that are observable to the econometrician. To the extent that a substantial component of residual wages and skills is observed by firms and workers, but unobservable to the econometrician, two remarks about the interpretation of our evidence are in order.

First, the empirical results are not necessarily inconsistent with a model of observable skills as in GM: we find that countries with high skill dispersion specialize in sectors with high wage dispersion. In our model wage dispersion only reflects the degree of complementarity, and not compositional effects. Conversely, in GM, any differences in the sectoral wage distribution is due exclusively to industries employing workers of different skills: the supermodular sector employs similar workers, the submodular sector employes workers at the tails of the skill distribution. We expect that a multi-country, multi-sector extension of GM could be consistent with the empirical evidence that this chapter presents. We are not aware of such an extension and we believe it would be non-trivial.[29]

Second, we hypothesize that a Heckscher-Ohlin-Samuelson model of factor proportions with a large number of factors and different factor intensities across sectors would potentially yield testable implications similar to our model. Our results indicate that such a model should encompass a much finer level of disaggregation of factors than Heckscher-Ohlin-Samuelson-type models and their empirical tests have employed so far.[30]

[29]As previously noted, trade does not emerge in GM with supermodular sectors and observable skills. Therefore such an extension with n sectors would have to feature $n-1$ submodular industries, that exhibit different degrees of submodularity.

[30]Tests of the factor proportions theory typically involve a dichotomous classification of workers into production and non-production, or college and non-college educated.

Chapter 3

Non-Market Interactions and Entry into Export Markets

Synopsis. *Previous research suggests that firms that penetrate foreign markets reduce entry costs for other potential exporters, generating export spillovers. This chapter continues this line of research by developing a general empirical framework to study whether export participation decisions at the firm level are influenced by the characteristics of firms that belong to a common reference group (defined by industry and geographical region). It is shown that, in the presence of entry costs, group composition affects the degree of state dependence of individual export decisions, thus making its impact contingent on export status. I test this idea applying the dynamic panel data estimator introduced by Blundell and Bond (1998) to a data set of Argentine manufacturing firms. Group composition influences individual export decisions and most of this effect is channeled through entry costs. However, these non-market interactions are not driven by* *export spillovers, but by average firm size at the group level.*

3.1 Introduction

What explains the export behaviour of firms? Most of the research at the micro level has centered on analyzing which characteristics of a firm affect its propensity to export, including productivity (Bernard et al., 1995) and export status, i.e. past export experience (Roberts and Tybout, 1997). However, a number of studies have taken a different approach by focusing on whether the characteristics of firms located close to each other play a role in shaping individual entry decisions. Intuitively, proximity among firms could influence individual export decisions if it enables interactions such as learning or imitation.[1] The literature on *export spillovers* searches for a specific learning interaction generated by exporters and influencing the export decisions of firms belonging to the same reference group. The reference group describes the space of interaction (i.e. who interacts with whom) and is usually defined in terms of product similarity and geographical proximity. In particular, these studies suggest that firms that penetrate foreign markets reduce entry costs for other potential exporters in the same industry and region, either through learning effects or by establishing commercial linkages. However, a recent survey, Greenaway and Kneller (2007, p. 143) concludes that the evidence of export spillovers is "somewhat mixed".

The objective of this chapter is to re-examine the role of group composition (i.e. variation in the characteristics of the reference group) as a determinant of export decisions while addressing three methodological issues that, to the best of my knowledge, have been overlooked in previous research:

[1] Note that, in principle, learning does not require firms to cooperate actively; the observation of the actions of competitors could potentially reveal information that facilitates entry to export markets. Aitken et al. (1997, p. 104) provide an example.

(i) Nine out of the eleven chapters surveyed in Greenaway and Kneller (2007, table 2) apply static estimation frameworks to analyze entry decisions. Modeling the firm's export decision in the presence of entry costs as in Bernard and Jensen (2004), I illustrate the well-known result (Roberts and Tybout, 1997) that a static approach is incompatible with the existence of entry costs in export markets, resulting in misspecified empirical models and complicating the interpretation of the results.

(ii) The remaining two studies reviewed in that survey, Clerides et al. (1998) and Bernard and Jensen (2004) apply dynamic frameworks and find weak evidence of export spillovers.[2] However, a maintained assumption in these studies (and, in general, in the export spillovers literature) is that, once differences in productivity across firms and prior export experience have been controlled for, the influence of group composition on export decisions is the same for every firm belonging to the reference group. A second goal of this chapter is to show that this assumption is inappropriate for testing whether exporter concentration reduces entry costs in export markets. On the contrary, if group composition affects entry costs, its impact on individual decisions should depend on the firm's export status. The intuition behind this result is that any effect of group composition on entry costs should only influence the decision of firms considering whether to *start* exporting or not, and be irrelevant in the export decision of firms with recent experience in export markets (since, by definition, the latter have already incurred entry costs).

(iii) As mentioned, the literature on export spillovers has exclusively focused on whether individual export decisions are driven by the concentration of exporters

[2]Clerides et al (1998) examine the role of exporter concentration within regions and industries on the export decision of Colombian plants. They find only weakly significant evidence that the presence of other exporters makes it easier for domestically oriented firms to break into foreign markets, but find no spillovers reducing marginal costs of exporters. Using a panel of U.S manufacturing firms, Bernard and Jensen (2004) find significant entry costs to foreign markets but negligible market access spillovers from export activity of firms in the same industry or region.

in the reference group. However, interactions could be related to other features of group composition. Therefore, a third objective of this chapter is to provide a general framework to account for alternative sources of non-market interactions. As an example, instead of learning from other exporters, a firm considering entry could plausibly learn from the R&D investment of firms in its reference group (perhaps, by learning new ways to upgrade its products, making them more appealing to foreign consumers). Another alternative is for firms to become more productive (and, as a result, more prone to exporting) by tapping into a group-specific stock of innovations that have already been made by past innovators in the group. The idea of firms catching up to a *technological frontier* is applied by Aghion and Howitt (2006) to study the role of technological spillovers in explaining growth rates across countries, but it can also be used to think about the transfer of knowledge within firms belonging to the same group.

In general, sorting out which features of group composition generate interactions on individual behaviour is likely to have policy implications. As an example, if firms learn from exporters (as suggested in the spillovers literature), government support to any single exporter will generate an indirect benefit for other firms considering entry to export markets. But if firms learn how to export as a result of the R&D investment of other firms located nearby, then resources allocated to export promotion may end up being socially more productive if redirected to R&D support programs.

Overall, exploring the link between individual export decisions and group outcomes is appealing for a number of reasons. First, from a general perspective, because it is in line with a relatively recent and growing interest among economists of various fields in understanding how social factors beyond the marketplace affect individual decisions and outcomes.[3] Second, because it may provide a better

[3]The study of social interactions in economic decision making is also referred to as the *new social*

foundation for evaluating specific policy issues, such as the case of government support to exporters. As shown in Melitz (2003), access to export markets leads to inter-firm resource reallocation towards the more productive firms, contributing to welfare gains from trade liberalization. If entry decisions at the firm level are influenced by non-market interactions, then there is likely to be a positive role for government intervention in, for example, coordinating or promoting entry to export markets.

The firm-level data used for empirical analysis in this chapter is a representative sample of manufacturing firms in Argentina between 1992 and 2001. Argentina has substantially increased its openness to foreign trade during the 1990s and entry into foreign markets has since been seen as a critical issue for the long run success of this policy. Therefore, these data provide an interesting and relevant ground for analyzing entry into export markets.

The econometric approach relies on the GMM dynamic panel data estimator developed by Blundell and Bond (1998) in order to deal with unobserved heterogeneity and the dynamic effects generated by entry costs into export markets. This approach is also convenient for dealing with the potential endogeneity of group composition, including the *reflection* problem that arises in the identification of the effect of group behaviour on individual export decisions (Manski, 1993).

Briefly, the results indicate that variation in group composition plays an important role in the determination of individual export decisions, after controlling for the effect of the firm-level determinants usually emphasized in the empirical micro literature (past export experience and firm heterogeneity). As suggested by the export spillovers literature, most of this effect is channeled through its influence

economics (Durlauf and Young (2001, p.1)). Soetevent (2006) is a recent survey of the empirical literature on social interactions, including neighborhood effects, substance use among teenagers and peer effects among university roommates on entry costs and is, therefore, contingent on export status. However, group composition effects are not driven by the concentration of exporters, but by average firm size in the group. Furthermore, the benefit (in terms of increased likelihood of exporting) of belonging to a group characterized by a higher average firm size is larger for small firms than for large firms. If average firm size at the group level is viewed as proxying for a group-specific stock of past innovations or technological frontier, a possible interpretation of the result is that non-market interactions lead to a "backwardness advantage" -Gerschenkron (1965)- that, ceteris paribus, increases the likelihood of exporting in smaller firms.

The outline of the chapter is as follows. The next section presents a model of entry into export markets with sunk costs in order to characterize export decisions at the firm level and to illustrate different channels through which non-market interactions could exert their influence on individual behaviour. Section 3.3 describes the data set and presents descriptive statistics of the export decisions of manufacturing firms during the 1990s in Argentina. Section 3.4 offers a preliminary exploration of the links between individual export behaviour and group composition that can be found the raw data. Section 3.5 begins with a discussion on the identification of non-market interactions and then sets up the econometric model to formally analyze the determinants of export decisions. Section 3.6 presents the estimation results and section 3.7 concludes.

3.2 A Model of Entry into Export Markets with Sunk Costs

In order to examine whether group composition generates non-market interactions that reduce entry costs to potential exporters, it is crucial to apply an empirical framework designed to identify the effects of entry costs on export participation decision at the firm level. In this section, I present a simple model of export decisions that explicitly incorporates the role of entry costs in export markets, a modified version of the models in Roberts and Tybout (1997) and Bernard and Jensen (2004).[4] As an additional feature, group composition is introduced into the analysis in a stark way with the goal of illustrating its potential impact on export decisions.

The model provides a useful framework that will guide the specification and interpretation of the empirical analysis in sections 3.4 and 3.5. As shown below, a consequence of the existence of entry costs is that the export decision of a firm will exhibit state dependence. This implies that a proper econometric evaluation of the influence of group composition on entry costs requires modelling export decisions in a dynamic framework. An additional feature of the model is that it explicitly separates the role of profit heterogeneity and entry costs. This is convenient to allow for different channels through which non-market interactions could influence individual entry decisions. In particular, the model also shows that the influence of group composition on individual export decisions is contingent on export status, a result that plays a central role in the empirical analysis.

Consider a firm i that in any given period τ can earn profits by selling in the domestic (d) and/or export (f) markets. Let this firm belong to a *reference group* $g \in G$, where g indexes a specific industry and geographical location where the firm carries out its production activities in the domestic market. G is the finite set of all groups producing in this market. Assume that the firm's profit function is separable by letting $\pi^k_{g,\tau}$ represent the profit obtained by selling in market $k = \{d, f\}$ in period τ.[5]

Let the per-period, fixed costs of being an exporter (e.g. dealing with cus-

[4]The description of the model closely follows that in Clerides et al (1998).

[5]Profit separability can be derived from a model of monopolistically competitive firms that can price discriminate between foreign and domestic buyers, and produce at constant marginal costs –see Clerides et al (1998).

toms and intermediaries) be $M_{g,\tau}$. Then, the firm will earn positive profits from exporting in τ whenever $\pi^f_{g,\tau} \geq M_{g,\tau}$. Accordingly, if there were no start-up costs associated with becoming an exporter (and no learning-by-exporting effects) firms would simply participate in foreign markets whenever this condition was satisfied. However, as noted in Bernard and Jensen (2004), the existence of an entry cost (denoted by $\lambda_{g,\tau}$) makes the firm's entry decision forward-looking and opens up the possibility that firms export today in anticipation of cost reductions, or foreign demand increases, later on. In particular, it may be optimal to keep exporting even if $\pi^f_{g,\tau} < M_{g,\tau}$ since, by remaining in the export market, the firm avoids future re-entry costs.

Perhaps the simplest possible way to introduce non-market interactions in this framework is to model λ, M and π^k as functions of a group-specific vector $S_{g,\tau}$ that summarizes characteristics of group g that are thought to generate externalities. As a result, $\lambda_{g,\tau} \equiv \lambda(S_{g,\tau})$, $M_{g,\tau} \equiv M(S_{g,\tau})$ and $\pi^k_{g,\tau} \equiv \pi^k(z^k_{g,\tau}, S_{g,\tau})$ where, in addition, $z^k_{g,\tau}$ captures both individual characteristics of the firm and usual exogenous demand shifters in k (income level, exchange rates and goods' prices). These functions provide a reduced-form link between individual export decisions and group composition through different channels; i.e. through their influence on marginal, fixed and entry costs of exporting.

In empirical studies, $S_{g,\tau}$ is usually a measure of the concentration of exporters in group g, period τ. In general, non-market interactions could be generated by export decisions or by other exogenous characteristics of firms belonging to reference group g (such as the proportion of foreign firms in g). An implicit assumption in this formulation is that firms interact only with firms belonging to the same group. I also assume throughout this section that the number of firms belonging to each group $g \in G$ is large so that, when solving their export decision problem, firms can ignore the impact of their decision on the vector of non-market interactions $S_{g,\tau}$.

In other words, firms take $S_{g,\tau}$ as given, although some of its components could be endogenous variables determined in the general equilibrium -for example, if $S_{g,\tau}$ contains the average export decision of firms in group g. For the purposes of this chapter, however, I will only study the partial equilibrium of this model.

Letting y_τ be a binary indicator equal to one if the firm decides to export in τ, assume that in an initial period t the firm chooses a sequence of export participation decisions $\{y_{t+\tau}\}_{\tau=0}^{\infty}$ in order to maximize the expected value of future discounted profits:

$$
\begin{aligned}
V_t(y_{t-1}, z_{g,t}, S_{g,t}) \quad \equiv \quad & \max_{\{y_{t+\tau}\}_{\tau=0}^{\infty}} E_t \sum_{\tau=0}^{\infty} \delta^{\tau} \{y_{t+\tau}[\pi^f_{g,t+\tau} - M_{g,t+\tau} - (1 - y_{t+\tau-1})\lambda_{g,t+\tau}] \\
& + \pi^d_{g,t+\tau}\}
\end{aligned}
$$

where E_t is an expectations operator conditioned on the set of information available at time t and δ is the one-period discount rate. This formulation implies that producers who exit the market and re-enter face the same start-up costs as producers who never exported.[6] Note that the entry cost, $\lambda_{g,t+\tau}$, is incurred if and only if the firm decides to start exporting in $t+\tau$ without recent export experience -i.e. if and only if $y_{t+\tau} = 1$ and $y_{t+\tau-1} = 0$. The firm's problem can equivalently be viewed as choosing y_t to satisfy Bellman's equation:

$$
\begin{aligned}
V_t(y_{t-1}, z_{g,t}, S_{g,t}) \quad = \quad & \max_{y_t \in \{0,1\}} \{y_t[\pi^f_{g,t} - M_{g,t} - (1 - y_{t-1})\lambda_{g,t}] + \pi^d_{g,t} \\
& + \delta E_t(V_{t+1}(y_t, z_{g,t+1}, S_{g,t+1}))\}
\end{aligned}
$$

After evaluating the right-hand side of this equation at $y_t = 0$ and $y_t = 1$, comparing the resulting expressions and recognizing that h^*_t and $\lambda_{g,t}$ are functionally

[6]This will be assumed in the empirical analysis of this chapter. However, it can be generalized by allowing start-up costs to depend upon previous exporting experience –see Roberts and Tybout (1997).

dependent on $S_{g,t}$, the firm's export decision in period t can be written as

$$y_t = 1[h_t^*(z_{g,t}, S_{g,t}) - [1 - y_{t-1}]\lambda_{g,t}(S_{g,t}) \geq 0] \tag{3.1}$$

where $1[.]$ denotes an indicator function equals 1 if the expression is true and zero otherwise, and

$$\begin{aligned} h_t^*(z_{g,t}, S_{g,t}) \quad \equiv \quad & \pi_{g,t}^f - M_{g,t} + \delta[E_t(V_{t+1}(y_t = 1, z_{g,t+1}, S_{g,t+1}) \\ & -E_t(V_{t+1}(y_t = 0, z_{g,t+1}, S_{g,t+1})] \end{aligned} \tag{3.2}$$

Equation (3.1) implies that incumbent exporters continue exporting whenever current net operating profits from exports plus the expected discounted payoff from remaining an exporter (which includes avoiding the entry cost next period) is positive, and non-exporters begin exporting whenever this sum, net of entry costs, is positive. Therefore, the existence of sunk costs ($\lambda_{g,t} > 0$) generates state-dependence, introducing a dynamic component in the export decision of the firm.

Equation (3.1) suggests two distinct channels through which non-market interactions may influence entry decisions. Firstly, through net profits h_t^*. This effect would arise if, for example, the presence of other exporters in the same group g increases the availability of specialized capital and labour inputs, lowering the firm's marginal cost of production. I'll refer to this channel as a *productivity spillover*. A second channel of externalities operates on the sunk cost of access to export markets, generating an *entry cost spillover*.

This result bears important implications for the empirical analysis of non-market interactions and entry to export markets. First, it shows that in order to conduct a proper evaluation of the existence of entry cost spillovers it is necessary to identify the degree of state dependence on individual export decisions. Second, as opposed to productivity spillovers, only the decisions of firms with no prior export experience can be influenced by entry cost spillovers -since only these firms need to incur the sunk cost to export in period t. In other words, the influence of group composition $S_{g,t}$ on individual export decisions is contingent on export status. These two observations play an important role in the empirical analysis of this chapter.

3.3 Export Decisions in Argentina During the 1990s

The data set used in the empirical analysis comes from a variety of sources that are described in detail in the appendix, section C.1. Briefly, the firm-level data is a random sample of manufacturing firms in Argentina, collected during two Innovation Surveys carried out by I.N.D.E.C. (Argentina's National Statistical Agency). The first survey provides information on 1639 firms in 1992 and 1996, while the second survey collected information on 1688 firms in 1998 and 2001 (Bisang and Lugones 1998, 2003). The rest of this section presents summary statistics of exporters and non-exporters, and documents the persistence of entry decisions in the data.

3.3.1 Exporters and Non-exporters

Table 9 summarizes the characteristics of exporters and non-exporters in the Argentine manufacturing industry after pooling all observations for 1992, 1996, 1998 and 2001. Exporters comprise slightly more that half of the observations in the sample (53%). In line with previous research, exporters are clearly larger and better performing firms, invest more heavily in capital and R&D, and demand relatively more skilled employees than non-exporters. The presence of foreign firms among exporters is substantially larger as well.

Table 10 shows the distribution of firms and exporters across provinces in Argentina. The activity of firms is highly concentrated in the three most populated provinces, Buenos Aires, Cordoba and Santa Fe. These provinces account for 64% of the country's population in 2001, over 85% of the observations and almost 90% of the exporters in the data set.

3.3.2 Transitions In and Out of Exporting and the Persistence of Entry Decisions

Figure B.3 shows the magnitude of the flows in and out of exporting that occurred in the manufacturing industry during the 1990s. While most of the firms where non-exporters in 1992, the reverse occurred later in the sample. The number of exporters peaked in 1996, driven by both high entry and very low exit rates. The reduction in the number of exporters in 1998 comes more from a rise in exits than a decline in entry. On average, 15.6% of exporters were entrants in any given year (i.e. they were non-exporters in the previous sample year). Similarly, 12.1% of non-exporters were, on average, previous exporters. The degree of variation in export decisions displayed in this sample is similar to that reported in Bernard and Jensen (2004, p. 563) for U.S. manufacturing firms during 1984-1992 -their average entry and exit rates are 13.9% and 12.6%, respectively.

Though a substantial number of firms enter and exit the export market each year and exporting became more prevalent over time, there is still a large degree of persistence in the export status of individual plants. Columns (1) and (2) of table 11 report the fractions of exporters and non-exporters in 1992 who were exporters in subsequent years. Among plants that exported in 1992, 84% were exporting in 2001. Non-exporters show a smaller persistence: 68% remained with the same export status in 2001. Columns (3) and (4) of table 11 report the predicted rates of persistence if exits and entrants were chosen randomly according to the calculated annual transition rates. At all horizons, the predicted persistence is substantially lower than that observed in the sample. From this we conclude that there is a high degree of reentry by former exporters, that is, they have a higher probability of reentering export markets. Similarly, former non-exporters have a higher probability to continue producing exclusively for the domestic market. This is consistent with the predictions of the export decision model presented in section 3.2. The empirical analysis intends to examine whether this persistence in exporting results from firm heterogeneity or from sunk costs, and the extent to which these sources of persistence are affected by the characteristics of reference groups.

3.4 Why do Firms Behave Similarly?

3.4.1 A Look at the Raw Data

I now turn to exploring the link between individual entry decisions and group export behaviour in the raw data. To characterize the latter, I'll measure the concentration of exporters in reference group g by $Y_{(-i)gt}$, the proportion of exporters in group g and year t excluding firm i,

$$Y_{(-i)gt} \equiv \Big(\sum_{j \in g, j \neq i} y_{jgt} \Big) / (N_g - 1)$$

where N_g is the number of firms in g.[7] Alternatively, $Y_{(-i)gt}$ can be interpreted as the average export decision in group g. How are groups defined? In this chapter, I follow the usual practice in the literature and assume that non-market interactions operate within groups of firms that produce similar products and are located close

[7] $Y_{(-i)gt} \equiv 0$ if $N_g = 1$

to each other. Product similarity is measured at the 3-digit ISIC level of aggregation and geographical locations are defined by provincial boundaries.[8]

A starting point in the analysis is the observation that a firm's decision to enter export markets is positively correlated with the decisions of firms belonging to the same group. Column (1) in table 12 shows the results of the linear projection of individual entry decisions on group behaviour, obtained by means of an OLS estimation of equation 3.3,

$$y_{igt} = \delta_t + \beta_y Y_{(-i)gt} + u_{igt} \tag{3.3}$$

where δ_t is a time-varying intercept common to all groups and u_{igt} captures variation in export decisions that is orthogonal to $Y_{(-i)gt}$. The results indicate a strong positive correlation between y_{igt} and $Y_{(-i)gt}$. Figure B.4 plots the fitted values of this regression against $Y_{(-i)gt}$.

The finding that members of the same group tend to behave similarly is an empirical regularity observed in different contexts in the social sciences.[9] As mentioned, a maintained assumption in the export spillovers literature is that the influence of group composition on export decisions is the same for every firm belonging to a given group. However, the analysis presented in section 3.2 showed that it is inappropriate for testing whether exporter concentration reduces entry costs in export markets. If group composition affects entry costs, its impact should depend on a firm's export status. The intuition behind this result is that any effect of group composition on entry costs should only influence the decision of firms considering

[8] The findings of this section are robust to changing the level of industry aggregation to 2 and 4 digits of ISIC.

[9] Researchers have hypothesized that this observation could be driven by interactions in which the propensity of an agent to behave in some ways varies positively with the prevalence of this behaviour in the group. As noted in Manski (2000), according to the context, these interactions may be alternatively called "peer influences", "neighborhood effects" or "herd behaviour", among others.

whether to start exporting or not, and be irrelevant in the export decision of firms with recent experience in export markets. In other words, we should expect the correlation illustrated in figure B.4 to be contingent on export status.

As a first step towards analyzing this hypothesis more formally, it is interesting to verify if it can be observed in the raw data. This requires introducing y_{igt-1}, export status, in equation 3.3 and allowing its coefficient λ_{gt} to depend on the average export decision in group g; that is,

$$\lambda_{gt} = \lambda_0 + \lambda_y Y_{(-i)gt}$$

In this way, the effect of $Y_{(-i)gt}$ on y_{igt} can now operate through a direct and an indirect channel, captured by λ_y and β_y, respectively. Substituting λ_{gt} in equation 3.3 yields,

$$y_{igt} = \alpha_t + \lambda_0 y_{igt-1} + \lambda_y y_{igt-1} Y_{(-i)gt} + \beta_y Y_{(-i)gt} + u_{igt} \tag{3.4}$$

The results of the OLS estimation of equation 3.4 are presented in column (2) of table 12. The coefficient of interest, λ_y, is negative and highly significant. This has two main implications. First, consistent with the analysis in section 3.2, the correlation illustrated in figure B.4 is contingent on export status. In particular, a higher concentration of exporters is correlated with a smaller influence of export status on export decisions. This is illustrated in figure B.5, a plot of the fitted values of this regression against $Y_{(-i)gt}$, contingent on export status. The vertical distance between the fitted lines illustrates how the persistence of export decisions at the firm level, λ_{gt}, decreases with export concentration. Second, a negative sign of λ_y together with the fact that β_y is positive and significant also implies that the export decision of firms considering whether to *start* exporting in period t is more sensitive to changes in export concentration than the decision of firms that exported in period $t-1$.[10] Note in figure B.5 that the fitted line for $t-1$ exporters is almost flat. In fact, a Wald test of $\lambda_y + \beta_y = 0$ in equation 3.4 cannot be rejected at conventional significance levels.[11]

3.4.2 Three Challenges for the Empirical Analysis

Overall, a simple examination of the raw data points to the importance of allowing the influence of group behaviour to be contingent on export status and, as a consequence, to operate indirectly through its effect on the degree of persistence in export decisions. The literature on export spillovers, on the other hand, has focused on studying the uncontingent effect (i.e. independent of export status), albeit after controlling for export status as in Clerides et al. (1998) and Bernard and Jensen (2004).

The primary objective of the empirical analysis is to assess whether the geographical concentration of exporters in the same industry generates non-market interactions on individual export decisions. Are the correlations between individual and group behaviour shown in figures B.4 and B.5 evidence of this hypothesis? Not necessarily. An appropriate test of this hypothesis has to meet three basic challenges.

First, it must disentangle persistence in export decisions due to state dependence (export status) from persistence due to unobserved heterogeneity in firm characteristics.[12] The analysis in section 3.2 implies that entry costs generate state dependence. The econometric analysis thus needs to isolate this source of persis-

[10] This follows because $\frac{\partial y_{igt}}{\partial Y_{(-i)gt}} = \beta_y + \lambda_y y_{igt-1}$ in equation 3.4.

[11] The p-value for this hypothesis is 0.1541.

[12] In a series of papers, Heckman (1978, 1981b, 1981a) discusses these two sources of serial persistence.

tence as a prior condition to evaluating the relevance of export spillovers on entry costs.

A second task is to isolate an exogenous source of variation in group export propensity (and, in general, in group composition). Although export spillovers within provinces would generate feedback loops in export decisions that stimulate the agglomeration of exporters such as in figures B.4 and B.5, other alternative mechanisms could be at work. A most natural alternative is to imagine that some provinces provide firms with institutional and economic environments that are more conducive to exporting than others. This could be driving the agglomeration of firms described in table 10. In this story, the geographical characteristics of provinces and the quality of both local public goods and provincial governments are likely to play key roles. Alternatively, the co-movement of export decisions could be simply reflecting firms adjusting to changes in fundamentals across industries, such as export prices or transport costs. These issues are discussed in detail in section 3.5.2.

Conditional on the previous two, a final task of the empirical analysis is to identify the source of non-market interactions. The concentration of exporters may still be driven by non-market interactions, but of a different kind than suggested in the export spillovers literature. Exporter agglomeration may be related to features of group composition other than export propensity. Instead of learning from other exporters, a firm considering entry could plausibly learn from the R&D investment of firms in the same group (perhaps, by learning new ways to upgrade its products, making them more appealing to foreign consumers). Another plausible alternative is for firms to become more productive (and, as a result, more prone to exporting) by tapping into a stock of innovations that have already been made by past innovators belonging to a given group, catching up to a group-specific *technological frontier*. There is no reason to rule out these possibilities a priori and, as suggested in the introduction, sorting out which features of group composition generate interactions on individual behaviour is likely to have policy implications.

As a summary of this section, stripped to its basics, the correlations shown in figures B.4 and B.5 could be driven by (Manski (2000)):

a) Endogenous interactions, wherein the export propensity of a firm varies with the export propensity at the group level -the export spillovers hypothesis.

b) Exogenous interactions, wherein the export propensity of a firm varies with other exogenous characteristics of group composition.

c) Correlated effects, wherein firms in the same group tend to behave similarly because the have similar individual characteristics or face similar institutional environments (including market fundamentals).

Notice that while endogenous and exogenous effects represent genuine non-market interactions between firms of the same group, correlated effects operate entirely at the individual level and, therefore, should not be regarded as any form of interaction.

3.5 Econometric Analysis

In this section, I start by presenting the econometric framework for analyzing export decisions at the firm level. I then turn to a discussion of the identification of non-market interactions that leads to the empirical strategy used in this chapter.

3.5.1 A Linear Specification

As a first step in setting up the econometric model, I follow Bernard and Jensen (2004) and Bernard and Jensen (2004) and express y_t^* in equation 3.2 as a reduced linear form of observable firm and group-specific (including group composition) characteristics and unobservable idiosyncratic firm effects. Furthermore, as shown in section 3.2, if non-market interactions influence entry costs λ_{gt}, its effect on individual entry decisions is contingent on the export status of a firm. Therefore, I allow λ_{gt} to depend linearly on group composition. As a result, the firm's export decision in equation 3.1 can be expressed as

$$y_{igt} = 1[\lambda_{gt} y_{igt-1} + {z_{igt}}^T \eta + {S_{gt}}^T \beta + {x_{gt}}^T \gamma + \delta_t + u_{igt}] \geq 0 \tag{3.5}$$

for $t = 1, ..., T$, where

$$\lambda_{gt}(S_{gt}) = \lambda_0 + {S_{gt}}^T \lambda_1 \tag{3.6}$$

As in previous sections, reference groups $g \in G$ are defined by product similarity and geographical proximity. Therefore, $G \equiv \{(industry, location)\}$, where $industry$ is defined by 3-digit industries of the ISIC classification and $location$ is defined by Argentine provinces. Since the Innovation Surveys provide data on export decisions for 1992, 1996, 1998 and 2001, then $T = 3$ for the model in equation 3.5.

Using the notation in section 3.2, y_{igt} is the export decision of firm i, in group $g \in G$ and period t; (z_{igt}, u_{igt}) are firm-specific attributes that directly affect y_{igt}; x_{gt} are attributes characterizing group g in period t; δ_t controls for aggregate time effects; S_{gt} describes the composition of the set of firms in group g during period t. In particular, as mentioned in the previous section, non-market interactions arising from group composition S_{gt} can comprise both endogenous and exogenous effects. While endogenous effects are generated by the export decisions of firms belonging to group g, exogenous effects are generated by the predetermined characteristics z_{igt} of these firms. In order to capture these features of group composition explicitly, I define[13]

$$S_{gt} \equiv [E(y_{gt}|g), E(z_{gt}|g)]^T$$

Also, let $\beta \equiv [\beta_y, \beta_z]^T$ and $\lambda_1 \equiv [\lambda_y, \lambda_z]^T$ be the coefficients of $[E(y_{gt}|g), E(z_{gt}|g)]$ in equations 3.5 and 3.6, respectively.

The unobserved term, u_{igt}, is assumed to have the following structure:

$$u_{igt} = \alpha_i + \varepsilon_{igt} \tag{3.7}$$

where α_i captures time invariant unobserved characteristics of the firm, including geographical location and industry effects (since these two characteristics are time invariant in the data set used in this chapter). Geographical effects that could influence export decisions include the institutional environment and accessibility to major markets. Industry effects include factor endowments and other time-invariant determinants of comparative advantage. ε_{igt} is an error term that I'll describe in detail below.

In this setup, $\lambda_y \neq 0$ implies that exporter concentration in group g affects entry costs for firms with no prior export experience, thus generating entry cost spillovers. If $\beta_y \neq 0$, exporter concentration affects export decisions independently of export status; in light of equation 3.1, this is interpreted as a spillover on productivity. Both λ_y and β_y thus capture endogenous interactions. λ_z and β_z have similar interpretations, but they measure the effect of exogenous interactions on export decisions. If $\gamma \neq 0$ in equation 3.5, the model expresses correlated effects: firms in group g tend to behave similarly because they face similar institutional

[13] The use of expected average choice rather than the realized average choice is made for analytical convenience. As noted in Blume and Durlauf (2006), the assumption makes most sense for larger groups where the behaviors of the rest of group are not directly observable. The assumption that individuals react to expected rather than actual behaviors is not critical for the identification analysis I describe below.

environments and market fundamentals.[14]

The specification of $(z_{igt}, x_{gt}, S_{gt})$ for the empirical analysis of manufacturing firms in Argentina is the following:

z_{igt} includes: firm size (log of total number of employees), output per worker (log of total sales of goods produced by the firm per employee), foreign ownership dummy (equal to 1 if the majority of the firm's shares are held by non-Argentine residents), skilled labour (proportion of employees with completed college or higher education) and R&D intensity (share of R&D expenditures in total sales).

x_{gt} includes industry and location time-varying controls. Industry controls: producer price index in ISIC industry, export price index in ISIC industry, total exports in ISIC industry. Location controls: province population, share of public employees in province population and provincial government's per capita expenditure in education, health and infrastructure services.[15]

Regarding group composition, $E(y_{gt}|g)$ and $E(z_{gt}|g)$ are estimated non-parametrically using sample data by

$$Y_{(-i)gt} \equiv (\textstyle\sum_{j\in g, j\neq i} y_{jgt})/(N_g - 1) \quad \text{and} \quad Z_{(-i)gt} \equiv (\textstyle\sum_{j\in g, j\neq i} z_{jgt})/(N_g - 1) \tag{3.8}$$

respectively, where N_g is the number of firms in g.[16] Excluding firm i's decision (y_{igt}) or characteristic (z_{igt}) does not affect the consistency of $Y_{(-i)gt}$ or $Z_{(-i)gt}$ and avoids a mechanic positive correlation between individual and group outcomes.

Equations 3.5 through 3.7 define a dynamic binary choice decision model with unobserved heterogeneity that characterizes export decisions in the presence of

[14] Actually, γ captures correlated effects arising from group characteristics that change over time. Time-invariant correlated effects are, in turn, captured by α_i.

[15] See section C.1 for details on data sources.

[16] $Y_{(-i)gt} \equiv 0$ and $Z_{(-i)gt} \equiv 0$ if $N_g = 1$

entry costs and non-market interactions. There are several potential estimation strategies for this type of models. A first decision is whether to use a linear or non-linear estimation framework to model export decisions. Linear probability models are robust to arbitrary correlation between the unobserved heterogeneity α_i and the regressors, and can be used to eliminate the incidental parameters associated with the unobserved heterogeneity in fixed effects probit models. Random effects probit models, which parameterize the distributions of α_i and ε_{igt}, rely more strongly on the functional form assumptions made, are computationally more demanding and require dealing with the problem of specifying the initial conditions of the dynamic process.[17] For these reasons, the estimation approach in this chapter is to use a linear probability model.[18]

Substituting equations 3.6 and 3.7 into a linear probability model specification of equation 3.5 yields the estimating equation for the econometric analysis of this chapter:

$$\begin{aligned} y_{igt} &= \lambda_0 y_{igt-1} + y_{igt-1}[E(y_{gt}|g)\ E(z_{gt}|g)]^T \lambda_1 + z_{igt}{}^T \eta \\ &\quad + [E(y_{gt}|g)\ E(z_{gt}|g)]^T \beta + x_{gt}{}^T \gamma + \alpha_i + \delta_t + \varepsilon_{igt} \end{aligned} \tag{3.9}$$

It will be useful to write this equation in a compact way. Letting $\psi \equiv (\lambda_0, \lambda_1, \eta, \beta, \gamma)^T$ and W_{igt} denote the vector of explanatory variables,

$$W_{igt} \equiv (y_{igt-1}, y_{igt-1}E(y_{gt}|g), y_{igt-1}E(z_{gt}|g), z_{igt}, E(y_{gt}|g), E(z_{gt}|g), x_{gt}, \delta_t)$$

[17]For example, implementing Heckman (1981c) would first require assuming a density of the initial condition y_{ig0} for given covariates and α_i and then specifying the conditional density of α_i given the covariates. Misspecification of of these densities generally results in inconsistent estimates of the parameters of interest. Wooldridge (2005) suggests an alternative quasi maximum likelihood approach that avoids specifying a density for the initial conditions but still requires restricting the distribution of the unobserved heterogeneity.

[18]Bernard and Jensen (2004) also rely on linear probability models in their econometric analysis.

equation 3.9 can be reformulated as

$$y_{igt} = W_{igt}{}^{T}\psi + \alpha_i + \varepsilon_{igt} \tag{3.10}$$

3.5.2 Identification

Next, I study the identification of non-market interactions in equation 3.9. Although most of the discussion is centered on dealing with the endogeneity of export status and group composition, it is essential to begin with a comment on what the causal effect of interest is. An important point to acknowledge is that, in general, group composition may influence individual export decisions *directly* through non-market interactions such as learning or imitation processes, or *indirectly* through its effect on market prices in the general equilibrium. While the direct channel is emphasized in the spillovers and social interactions literatures, Melitz (2003) provides an example of the indirect channel by showing how average firm productivity within industry determine aggregate price and income indices that, in turn, affect entry into export markets in the general equilibrium.[19] Since the objective of this chapter is to learn whether group composition generates non-market interactions that influence individual export decisions, the focus is to isolate the effect of the direct channel. Therefore, even if the variation in group composition were completely exogenous in my sample it would be necessary to control for market prices as a necessary step in interpreting the correlation between export decisions and group composition as evidence of non-market interactions. This motivates the inclusion of domestic and export prices and aggregate expenditure at the industry level controls in vector x_{gt} in the empirical analysis (see page 66).

The causes of the endogeneity of group composition in equation 3.9 can be

[19] See Melitz (2003, p. 1700).

grouped into two broad categories (see Moffitt, 2001):[20]

(i) the simultaneity problem

(ii) the correlated unobservables problem

The simultaneity problem complicates the identification of non-market interactions because group composition is itself determined by the behaviour of group members. Hence, data on outcomes do not necessarily reveal whether group behaviour actually affects individual behaviour, or group behaviour is simply the aggregation of individual behaviour. This problem was formally analyzed in Manski (1993), and has since been also known as the 'reflection problem'. To illustrate Manski's argument, consider a version of equation 3.9 where, for the sake of the argument, there are no spillovers on entry costs; i.e. $\lambda_1 = 0$,

$$y_{igt} = \lambda_0 y_{igt-1} + {z_{igt}}^T \eta + \beta_y E(y_{gt}|g) + E(z_{gt}|g)^T \beta_z + x_{gt}^T \gamma + \alpha_i + \delta_t + \varepsilon_{igt} \quad (3.11)$$

Assume, for the moment, that 3.11 represents a structural equation for y_{igt}, so that

$$E[\varepsilon_{igt}|y_{igt-1}, z_{igt}, x_{gt}, \alpha_i, g] = 0$$

It follows that, for a given $g \in G$, the mean regression of y_{igt} on $(y_{igt-1}, z_{igt}, x_{igt}, \alpha_i)$ has the linear form

$$\begin{aligned} E(y_{igt}|y_{igt-1}, z_{igt}, x_{gt}, \alpha_i, g) \quad = \quad & \lambda_0 y_{igt-1} + {z_{igt}}^T \eta + \beta_y E(y_{gt}|g) + E(z_{gt}|g)^T \beta_z \\ & + {x_{gt}}^T \gamma + \alpha_i + \delta_t \end{aligned}$$

Integrating this expression with respect to $(y_{igt-1}, z_{igt}, x_{gt})$ reveals that $E(y_{igt}|g)$

[20]Actually, Moffitt (2001) adds a third category, the endogenous group membership problem, which arises from the self-selection of firms into groups due to factors that are also correlated with the dependent variable. However, endogenous membership can be considered as a particular case of the correlated unobservables problem -see Moffitt (2001, p. 65).

solves the following equilibrium equation in every period $t = 1, ..., T$

$$E(y_{gt}|g) = \lambda_0 E(y_{gt-1}|g) + \beta_y E(y_{gt}|g) + E(z_{gt}|g)^T(\beta_z + \eta) + x_{gt}{}^T\gamma + E(\alpha|g) + \delta_t$$

Therefore, assuming $\beta_y \neq 1$,

$$\begin{aligned} E(y_{gt}|g) &= \frac{\lambda_0}{(1-\beta_y)}E(y_{gt-1}|g) + E(z_{gt}|g)^T\frac{(\beta_z+\eta)}{1-\beta_y} + x_{gt}{}^T\frac{\gamma}{1-\beta_y} \\ &\quad + \frac{E(\alpha|g)}{1-\beta_y} + \frac{\delta_t}{1-\beta_y} \end{aligned}$$

Therefore, $E(y_{gt}|g)$ is a linear function of $[E(y_{gt-1}|g), E(z_{gt}|g), x_{gt}, d_t, d_g]$, where dt and d_g denote time-varying and group-specific intercepts. Identification of non-market interactions in equation 3.11 is not possible if either $\lambda_0 = 0$ or $E(y_{gt-1}|g)$ is included as an additional explanatory variable, since in these cases $E(y_{gt}|g)$ becomes perfectly collinear to the rest of the explanatory variables in equation 3.11. When $\lambda_0 = 0$, the model becomes a static linear case similar to that analyzed in Manski (1993).[21]

The last observation suggests that the existence of dynamic effects, in this case arising from the presence of entry costs, may help to mitigate the simultaneity problem. However, this will be true as long as $E(y_{gt-1}|g)$ is (correctly) excluded from equation 3.11. Intuitively, if excluded, $E(y_{gt-1}|g)$ acts as an instrument for $E(y_{gt}|g)$ breaking the reflection in the same way as exclusion restrictions are used to solve standard simultaneous equations in econometrics. This idea is formalized in the next section. Briefly, the identifying restriction is that individual export decisions are not *directly* influenced by $E(y_{gt-1}|g)$; that is, y_{igt-1} does not generate non-market interactions in period t once $E(y_{gt}|g)$ has been controlled for.[22] The

[21] Manski (1993) considers the case with no unobserved heterogeneity; i.e. $\alpha_i = 0$.

[22] As noted by Moffitt (2001), this example shows that there might be a larger class of exclusion restrictions consisting of characteristics of firms that can be argued on some basis to not have a direct

assumption becomes more plausible if the value of non-market interactions depreciates rapidly over time. This appears to be a reasonable approximation to the case I study in this chapter, considering that the average time gap between the available data points (1992, 1996, 1998 and 2001) is 3 years and the fact that, during the 1990s, manufacturing firms in Argentina were in the midst of a radical process of structural change and adjustment to increased competition stemming from trade liberalization and a reduction of government intervention in the economy.

In turn, the problem of correlated unobservables arises if there is some individual or group-specific component of the error term ε_{igt} that is correlated with the explanatory variables in equation 3.9. Thus, it is equivalent to a standard omitted variable problem in econometrics. The unobservables may arise from unobserved product attributes or managerial ability at the firm level or may represent group effects. As mentioned in section 3.3, some provinces are likely to provide firms with institutional and economic environments that are more conducive to exporting than others. Alternatively, the co-movement of export decisions could simply reflect firms adjusting to changes in fundamentals across industries, such as export prices or transport costs, or other idiosyncratic shocks to comparative advantage. In these cases, unobservable determinants of the export decision are also correlated with z_{igt}, $E(y_{gt}|g)$ or $E(z_{gt}|g)$.

The empirical strategy for dealing with correlated unobservables in this chapter is the following. First, I will use an estimator that allows for arbitrary correlation between time-invariant unobservables (α_i) and the explanatory variables. This feature covers some important cases mentioned above such as geographic and, to the extent they remain roughly constant over time, industry effects and managerial ability. Second, I will control for several sources of time-varying correlated unobservables, including local government performance and demand shocks at the

influence on others.

industry level (see details in page 3.5.1). Finally, in order to deal with any residual correlation in the error term ε_{igt}, I will use an instrumental variables strategy similar to the one outlined in the context of the simultaneity problem. Next, I turn to describing this approach.

3.5.3 Estimation Framework

Consistent estimation of the parameters in equation 3.9 requires dealing with the presence of a lagged dependent variable (export status) as a regressor and, as analyzed previously, with the endogeneity of group composition.

It is well known that OLS and standard panel data estimators yield inconsistent estimates in the presence of a lagged dependent variable and unobserved heterogeneity -see Cameron and Trivedi (2005, p. 764). The consistency of OLS estimators depends on the assumption that firm heterogeneity α_i is uncorrelated with the regressors in W_{igt}. This assumption is violated by equation 3.9, due to the presence of export status y_{igt-1} as an explanatory variable. Thus, a first step in obtaining consistent estimates is to eliminate α_i. The 'within' panel data (or fixed-effects) estimator transforms equation 3.9 to express the original observations as deviations from their firm-specific means. OLS is then used on the transformed equation. Consistent estimation requires the right-hand side variables of equation 3.9 to be strictly exogenous.[23] That is, strict exogeneity requires $E(\varepsilon_{igt}|W_{ig1},...,W_{igT},\alpha_i) = 0$. This implies $E(W_{igs}.\varepsilon_{igt}) = 0$ for $s,t = 1,...,T$ and $g \in G$, an assumption that is violated in equation 3.10 since $y_{igt} \in W_{igt+1}$.

In general, strict exogeneity rules out feedback effects from the dependent variable y_{igt} to future values of W_{igt}. In the context of this chapter, this is not only incompatible with the existence of entry costs in export markets, but it also rules out

[23] The random effects estimator also requires strict exogeneity in order to achieve consistency. These results are shown in Wooldridge (2002, chapter 10).

other phenomena of interest such learning by exporting, which involves the effect of exporting activity on future firm productivity.[24] In other words, in the presence of either entry costs or learning by exporting effects, the fixed-effects estimator is inconsistent.

An alternative GMM-based approach can be applied by first removing unobserved firm heterogeneity α_i and then searching for instrumental variables. I start by relaxing strict exogeneity and introducing a set of *sequential moment conditions*

$$E(\varepsilon_{igt}|W_{igt}, W_{igt-1}, ..., W_{ig1}, \alpha_i) = 0, \text{ for } t = 1, ..., T \tag{3.12}$$

That is, the explanatory variables in equation 3.10 are sequentially exogenous in the sense of being uncorrelated with current and future values of ε_{igt}. However, no restriction is imposed on their correlation with past values of ε_{igt}. Below, I explain how to treat endogenous regressors, such as group composition, that are likely to be contemporaneously correlated with ε_{igt}.

Given the model in equation 3.10, assumption 3.12 is equivalent to

$$E(y_{igt}|W_{igt}, W_{igt-1}, ..., W_{ig1}, \alpha_i) = E(y_{igt}|W_{igt}, \alpha_i) = W_{igt}^T \psi + \alpha_i, \text{ for } t = 1, ..., T \tag{3.13}$$

The first equality makes it clear what sequential exogeneity implies about the explanatory variables: after W_{igt} and α_i have been controlled for, no past values of W_{igt} affect the expected value of y_{igt}. In other words, under sequential exogeneity, the model in equation 3.10 is assumed to be *dynamically complete* conditional on α_i. It means that one lag of y_{igt} is sufficient to capture the dynamics in the condi-

[24]The empirical relevance of learning by exporting is far from being settled. Clerides et al (1998), Bernard and Bradford Jensen (1999), Isgut (2001) and Delgado et al. (2002) are firm level studies that do not find evidence of learning by exporting. An exception is Van Biesebroeck (2005), who finds that past export experience has a causal effect on the performance in a panel of sub-Saharan African firms.

tional expectation of export decisions; neither further lags of y_{igt} nor lags of other components of W_{igt} are important once W_{igt} and α_i have been controlled for. The second equality is an implication of equation 3.10.

First differencing equation 3.10 to remove unobserved firm heterogeneity α_i gives

$$\Delta y_{igt} = \Delta W_{igt}{}^T \psi + \Delta \varepsilon_{igt} \tag{3.14}$$

Note that ΔW_{igt} is necessarily endogenous in this equation since, in any period t, $\Delta y_{igt-1} = y_{igt-1} - y_{igt-2} \in \Delta W_{igt}$ is correlated with $\Delta \varepsilon_{igt} = \varepsilon_{igt} - \varepsilon_{igt-1}$. Group composition is also likely to be endogenous for the reasons given in the previous section. Next, note that sequential exogeneity implies

$$E(W_{igs} \varepsilon_{igt}) = 0, \text{ for } s = 1, ..., t$$

and $t = 1, ..., T$. Therefore,

$$E(W_{igs} \Delta \varepsilon_{igt}) = 0, \text{ for } s = 1, ..., t-1 \tag{3.15}$$

This implies that, in period t, W^0_{igt-1} can be used as potential instruments for ΔW_{igt} in equation 3.14, where

$$W^0_{igt} \equiv (W_{ig0}, W_{ig1}, ..., W_{igt})$$

The moment conditions in equation 3.15 form the basis of the Arellano and Bond (1991) GMM 'difference estimator' for dynamic panel data, that uses lagged levels of the explanatory variables W^0_{igt-1} as instruments in the estimation of equation 3.14. A convenient feature of this framework is that it can easily accommodate for endogenous regressors. If some component of W_{igt}, such as group composition, is presumed to be correlated with unobservables influencing export decisions in period t, then W^0_{igt-2} can be used in place of W^0_{igt-1} as an instrument for W_{igt}.

The difference estimator has the statistical shortcoming that if the regressors in equation 3.9 are persistent, then lagged levels of W_{igt} are weak instruments, that is, they are not highly correlated with the regressors, and so the estimated coefficients may be biased. This problem is particularly serious the shorter the length of the panel is (that is, the smaller T is), see Baltagi (2005). To overcome these problems, Arellano and Bover (1995) and Blundell and Bond (1998) developed a 'systems estimator' that combines the differenced model in 3.14 with the levels model in equation 3.10. In order to be able to use lagged differences of the variables on the right-hand side of equation 3.14 as valid instruments for the regression in levels, the following identifying assumptions are introduced:

$$E(\Delta W_{igt}\alpha_i) = 0 \tag{3.16}$$

which imply that there is no correlation between the differences of the regressors and the country-specific effect; in other words, the firm-specific effect and the regressors are still allowed to be arbitrarily correlated, but this correlation should be constant over time. Given 3.16, the following moment conditions can be added to those specified above in equation 3.15[25]:

$$E(\Delta W_{igt}\varepsilon_{igt}) = 0 \tag{3.17}$$

Endogenous regressors can be treated in a similar way as in the difference estimator, by using ΔW_{igt-1} as an instrument for W_{igt}.

In a nutshell, where Arellano and Bond (1991) instrument differences with lev-

[25] Using 3.7 and 3.16, we have $E(\Delta W_{igt}u_{igt}) = E(\Delta W_{igt}(\alpha_i + \varepsilon_{igt})) = E(\Delta W_{igt}\varepsilon_{igt}) = 0$

els, Blundell and Bond (1998) suggest instrumenting levels with differences. The Blundell-Bond estimator stacks the data for the levels and the difference equations (numbers 3.10 and 3.14, respectively) and estimates them simultaneously in a GMM framework using the moment conditions in 3.15 and 3.17. Further details can be found in Roodman and Floor (2006).

3.6 Estimation Results

Table *13* reports the estimation results of different specifications of equation 3.9, using Blundell and Bond's (1998) GMM system estimator for dynamic panel data.[26] Every specification uses instruments for export status and group composition as explained above, two-period and deeper level lags in the difference equation and one-period and deeper difference lags in the levels equation. Although not reported, all estimations include time dummies, export prices, and total industry exports. Industries are defined at the 3-digit ISIC level, but the results are qualitatively robust to changes in the level of aggregation.

The first two columns present an endogenous interactions model that borrows two distinctive features from usual specifications found in the spillovers literature. First, I assume that the impact of average export intensity at the group level is the same for every firm belonging to a given group -i.e. it is not contingent on export status. However, I do control for export status -as in Clerides et al. (1998) and Bernard and Jensen (2004). Second, I do not consider the influence of other features of group composition (exogenous interactions). In terms of the notation in equation 3.9, I assume $\lambda_1 \equiv [\lambda_y, \lambda_z]^T = [0,0]^T$ and $\beta \equiv [\beta_y, \beta_z]^T = [\beta_y, 0]^T$.

As in Clerides et al. (1998) and Bernard and Jensen (2004), the evidence on

[26] All estimations were implemented in Stata 9.0, using the program 'xtabond2'. A detailed description of this command can be found in Roodman (2006).

export spillovers is very weak. In column (1), the effect of export intensity on individual export decisions, β_y, is statistically insignificant. In line with the empirical literature that has analyzed the determinants of exporting at the micro level, export status and heterogeneity in firm characteristics (output per worker, firm size and R&D investment) are highly significant. In particular, the significance of export status provides evidence of the importance of entry costs in export markets.[27] Column (2) repeats this specification, but instrumenting for firm-level characteristics. The results are qualitatively invariant to this modification -except in the case of R&D investment.

Columns (3), (4) and (5) explore the consequences of introducing the interaction between export status and exporter concentration at the group level to allow for a contingent effect of the latter on export decisions. For the moment, I still rule out exogenous interactions (that is, $[\lambda_z, \beta_z]^T = [0,0]^T$ is maintained) and focus on the vector of endogenous interactions $[\lambda_y, \beta_y]$. These specifications differ in terms of the inclusion of both location controls (see page 66) and IVs for firm-level controls.

The results show that the coefficient of the interaction λ_y is negative and becomes significant at the 5% level when location controls and IVs for firm-level controls are included. This implies that the influence of export status declines in groups where the proportion of exporters is larger. In the context of the model of section 3.2, this is equivalent to stating that a higher export propensity at the group level reduces entry costs into export markets. The fact that β_y is insignificant in all three specifications actually means that the proportion of exporters at the group level does not affect the export decisions of firms with export experience in period $t-1$. These results provide evidence supporting endogenous spillovers on entry

[27] Actually, the magnitude of the estimated coefficient for export status in these specifications is very similar to the point estimate in Bernard and Jensen (2004, table 5, page 567).

costs and against endogenous spillovers on productivity.

With respect to the influence of firm characteristics, the results in columns (3) to (5) show that export status, output per worker and firm size remain significant determinants of export decisions. The binary indicator for foreign firms becomes highly significant in (4) and (5).

In column (6), I allow for general group composition effects by allowing every individual characteristic of a firm to potentially generate exogenous interactions on the export decisions of other firms in the same group. These group variables are denoted with a subscript *g* in table *13* to distinguish them from firm-level controls. For example, $Size_g$ is the within-group average firm size. As in (3) to (5), the impact of group composition is allowed to be contingent on export status.

The results change considerably when exogenous interactions are explicitly introduced in the analysis. Endogenous interactions from other exporters are no longer significant. Spillovers on entry costs are now driven by both average firm size and the share of foreign firms at the group level. Interestingly, there's no evidence of spillovers on productivity, which were also absent in previous specifications. Therefore, the impact of group composition is channeled through entry costs rather than productivity. Note that the estimated coefficients of average firm size and the share of foreign firms have opposite signs. A negative sign in the coefficient of the interaction with export status λ_z implies that larger average firm size generates positive spillovers on entry costs. On the other hand, a higher proportion of foreign firms at the group level generates negative spillovers on entry costs.

The first two columns in table *14* show that the results derived from the last specification in table *13* are largely robust to the level of industry aggregation -in columns (1) and (2) industries are defined at 2 and 4 digits of the ISIC classification, respectively. So, why do export spillovers vanish when other features of group composition are controlled for? Columns (3) to (6) in table *14* examine the sensitivity of endogenous interactions to the inclusion of average firm size and the share of foreign firms at the group level. Columns (3) and (4) show that if average firm size ($Size_g$) is excluded, endogenous spillovers reappear. This does not occur if only the share of foreign firms in the group is excluded -columns (5) and (6). Therefore, the positive effect of exporter concentration present in columns (4) and (5) of table *13* was actually driven by average firm size at the group level.

As mentioned in the introduction, average firm size at the group level can be viewed as a proxy for a stock of past innovations or technological frontier,[28] a group-specific public good that firms can access to upgrade their products. In this interpretation, it becomes interesting to evaluate whether the intensity of the exogenous interactions generated by average firm size on export decisions increases in smaller firms. This hypothesis is reminiscent of Gerschenkron's (1965) 'advantage of backwardness'. In the present context, the advantage for a smaller firm could arise from the fact that implementing innovations allows it to make larger quality improvements the further it has fallen behind the frontier.[29] The thought experiment is the following: we would like to evaluate the effect of shifting the group's technological frontier while holding the size of the firm constant; that is, to evaluate an increase in the firm's 'distance to the frontier'. Furthermore, we'd like to assess whether this effect is stronger in smaller firms. To implement this test, I augment specification (6) in table *13* by allowing the effect of average firm size to depend on the individual size of a firm. This requires a triple interaction between export status, $Size_g$ and *Size*. An additional interaction between *Size* and export status is also included to allow entry costs to vary with firm size. The last column of table *14* presents the estimation results. Smaller firms face higher entry costs

[28] After all, firm size can be naturally viewed as a measure of a firm's past success.

[29] Aghion and Howitt (2006) applly Gerschenkron's analysis to study the role of technological spillovers in explaining growth rates across countries.

(significant at 5%) and the positive estimated coefficient of the interaction between export status, *Size_G* and *Size* suggests that the exogenous interactions on entry costs are weaker for larger firms. This result provides support for the advantage of backwardness hypothesis at the 10% level.

Overall, the picture that emerges from tables 13 and 14 is that group composition plays an important role in the determination of individual export decisions, beyond the effect of the firm level determinants that have been usually emphasized in the micro literature (past export experience and firm heterogeneity). Group composition generates non-market interactions that influence individual export decisions. As suggested by the export spillovers literature, most of this effect is channeled through its influence on entry costs and is, therefore, contingent on export status. However, group composition effects are not driven by the average export propensity at the group level, but by average firm size and the share of foreign firms.

3.7 Conclusions

This chapter examined the role of group composition in shaping export decisions at the firm level. Particular attention was given to the hypothesis that exporters belonging to the same group reduce entry costs for other firms considering entry. Theory indicates that the influence of group composition on entry costs changes the degree of state dependence of individual export decisions.

A proper empirical evaluation of this implication required disentangling the effect of state dependence from other sources of persistence in export decisions and obtaining a source of exogenous variation in group composition. I used a dynamic panel data approach that relies on sequential moment conditions to achieve identification. It would be interesting to search for other identification strategies in order to provide more robust evidence on the findings. Nevertheless, the methodological contribution of the chapter is independent of the effectiveness of the identification strategy used.

The results show that group composition influences individual export decisions and that most of this effect is channeled through entry costs. This holds after controlling for the key determinants of export participation emphasized in recent research, past export experience and firm heterogeneity. Interestingly, these non-market interactions are not driven by export spillovers, but by other features of group composition, namely average firm size and the share of foreign firms at the group level. I have provided a tentative interpretation for the effect of average firm size as a proxy for a group-specific technological frontier, in which non-market interactions generate a "backwardness advantage" that, ceteris paribus, increases the likelihood of exporting in smaller firms. In this story, firms become more productive (and, as a result, more prone to exporting) by tapping into the stock of innovations that have already been made by past innovators belonging to the same group. The results show that once this effect is controlled for, spillovers arising from exporters to other firms considering entry become statistically insignificant. Of course, nothing in this interpretation rules out a mechanism where spillovers from exporters could still impact export decisions by generating a shift in the group-specific technological frontier which, in my argument, was taken to be exogenously determined. These issues are beyond the scope of this paper and are left to future research.

Tables

CV Rank	Exporter	*Mean* Rank		*St Dev* Rank		*St Dev Res* Rank	
1	Denmark	3	5.671	1	0.150	1	0.134
2	Germany	6	5.654	2	0.162	3	0.151
3	Netherlands	4	5.666	3	0.167	2	0.149
4	Norway	2	5.684	4	0.171	4	0.156
5	Finland	5	5.666	5	0.181	5	0.162
6	Sweden	1	5.717	6	0.184	6	0.168
7	Czech Republic	7	5.636	7	0.190	7	0.171
8	Hungary	15	5.546	8	0.204	9	0.192
9	Belgium	8	5.632	9	0.221	10	0.199
10	New Zealand	10	5.597	10	0.240	13	0.222
11	United Kingdom	11	5.595	11	0.262	19	0.318
12	Ireland	14	5.569	12	0.266	12	0.222
13	Switzerland	13	5.573	13	0.269	8	0.189
14	Canada	9	5.628	14	0.274	11	0.216
15	Italy	16	5.499	15	0.285	16	0.256
16	United States	12	5.587	16	0.289	14	0.227
17	Chile	19	5.355	17	0.302	15	0.230
18	Slovenia	17	5.446	18	0.314	17	0.260
19	Poland	18	5.415	19	0.333	18	0.312

Table 1: Summary Statistics - IALS Log-Scores

	$WageDisp_i$ St Dev Res Rank	$O^{*}NET_i$ $Contact_i$ Rank
Lowest $Substit_i$		
Railroad rolling stock	1	60
Ship and boat building	2	40
Aircraft, aerospace products and parts	3	28
Engines, turbines, and power trans. equipment	4	42
Nonferrous metals, exc. aluminum	5	59
Highest $Substit_i$		
Leather tanning and products, except footwear	59	21
Seafood and other miscellaneous foods, n.e.c.	60	31
Apparel accessories and other apparel	61	2
Bakeries	62	32
Cut and sew apparel	63	1

Table 2: Substitutability Rankings

	$WageDisp_i$		$O*NET_i$			
	$\frac{StDev}{Mean}$	$St\ DevRes$	$Contact_i$	$Communic_i$	$Impact_i$	$Teamwork_i$
$\frac{StDev}{Mean}$	1					
$St\ Dev\ Res$	0.8497	1				
	0.000					
$Contact_i$	-0.2061	-0.1756	1			
	0.1052	0.1688				
$Communic_i$	-0.1414	-0.0755	0.5818	1		
	0.2689	0.5565	0.000			
$Impact_i$	-0.2414	-0.097	0.668	0.7467	1	
	0.0567	0.4496	0.000	0.000		
$Teamwork_i$	-0.1606	-0.1666	0.7943	0.614	0.7254	1
	0.2087	0.1919	0.000	0.000	0.000	

p-values in italics

Table 3: Correlations of Substitutability Proxies

Measure of Dispersion	(1) St Dev	(2) 95-5 IPR	(3) Gini MD	(4) St Dev	(5) 95-5 IPR	(6) Gini MD
$WageDisp_i \times SkillDisp_H$	0.017**	0.019**	0.016**	0.017**	0.018**	0.014**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Trade Barriers	No	No	No	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Importer-Industry FE	No	No	No	Yes	Yes	Yes
Observations	58124	58124	58124	58124	58124	58124
R-squared	0.54	0.54	0.54	0.70	0.70	0.70

The dependent variable is the natural logarithm of exports from country H to country F in industry i. Standardized beta coefficients are reported. †, * and ** indicate the coefficient is significant at the 10%, 5% and 1% levels. Bootstrap standard errors clustered by importer-exporter pair in parenthesis (50 replications).

Table 4: Estimates Using Residual Wage Dispersion Rankings and Residual Score Dispersion

Measure of Complementarity	(1) $O^*NET_i =$ $Teamwork_i$	(2) $O^*NET_i =$ $Impact_i$	(3) $O^*NET_i =$ $Communic_i$	(4) $O^*NET_i =$ $Contact_i$
$O^*NET_i \times$ $SkillDisp_H$	-0.016** (0.004)	-0.016** (0.004)	-0.016** (0.005)	-0.014** (0.003)
Trade Barriers	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes
Imp-Ind FE	Yes	Yes	Yes	Yes
Observations	58124	58124	58124	58124
R-squared	0.70	0.70	0.70	0.70

Bootstrap standard errors clustered by importer-exporter pair in parenthesis (50 replications).

Table 5: Estimates using O*NET Rankings and Residual Score Dispersion (St Dev)

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline (St Dev)	HMR Selection	Heckscher Ohlin	Institution Controls	Top Coding	Without US
$WageDisp_i \times SkillDisp_H$	0.017**	0.016**	0.020**	0.013**	0.023**	0.017**
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.003)
$KIntens_i \times KEndow_H$			0.028**			
			(0.008)			
$SkillIntens_i \times SkillEndow_H$			0.034**			
			(0.005)			
$WageDisp_i \times JudicQual_H$				-0.008*		
				(0.004)		
$WageDisp_i \times LaborRigid_H$				-0.007†		
				(0.004)		
$TopCode_i \times SkillDisp_H$					-0.015*	
					(0.007)	
Trade Barriers	Yes	Yes	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58124	52455	41301	51166	52455	48129
R-squared	0.69	0.69	0.73	0.70	0.70	0.68

The dependent variable is the natural logarithm of exports from country H to country F in industry i. Standardized beta coefficients are reported. †, * and ** indicate the coefficient is significant at the 10%, 5% and 1% levels. Bootstrap standard errors clustered by importer-exporter pair in parenthesis (50 replications). Column (6) is the same specification of column (2) excluding the observations involving US as exporter. The regression includes a polynomial in the probability to export, obtained from the first stage, which is significant and we do not report.

Table 6: Estimates - Selection and Other Controls

	(1)	(2)	(3)	(4)	(5)
	HMR Selection	Heckscher Ohlin	Institution Controls	Top Coding	Without US
$WageDisp_i \times SkillDisp_H$	0.004**	0.010**	0.005**	0.009**	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$RegCosts_H \times RegCosts_F$	0.008**	0.001	0.007*	0.008**	0.004†
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)
$RegDays_H \times RegDays_F$	0.007*	0.009†	0.006	0.007*	0.006*
	(0.003)	(0.005)	(0.004)	(0.003)	(0.002)
$RegProc_H \times RegProc_F$	0.008**	0.021**	0.009**	0.008**	0.008**
	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
$KIntens_i \times KEndow_H$		0.002†			
		(0.001)			
$SkillIntens_i \times SkillEndow_H$		-0.004*			
		(0.001)			
$WageDisp_i \times JudicQual_H$			0.002†		
			(0.001)		
$WageDisp_i \times LaborRigid_H$			-0.003*		
			(0.001)		
$TopCode_i \times SkillDisp_H$				-0.012**	
				(0.002)	
Trade Barriers	Yes	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes
Importer-Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	132867	94794	125874	132867	124740
R-squared	0.58	0.59	0.58	0.58	0.58

Columns (1)-(5) report the first stage estimation results corresponding to Columns (2)-(6) of Table 6. The dependent variable equals one if exports from country H to country F in industry i are positive, zero otherwise. Standardized coefficients reported. †, * and ** indicate statistical significance at 10%, 5% and 1%. Bootstrap s.e. clustered by importer-exporter pair in parenthesis (50 replications).

Table 7: Estimates - First Stages

Variable	Obs	Mean	Std. Dev	Min	Max
Exports dummy	173565	0.335	0.472	0	1
Exports volume (X_{HFi})	58124	7.866	2.204	0	17.906
Language	2755	0.193	0.395	0	1
Legal	2755	0.217	0.412	0	1
Religion	2755	0.196	0.257	0	0.973
Land Border	2755	0.019	0.135	0	1
Currency Union	2755	0.002	0.047	0	1
Distance	2755	4.136	0.806	0.882	5.661
FTA	2755	0.017	0.131	0	1
Colonial Ties	2755	0.022	0.146	0	1
Gatt / WTO	2755	1.489	0.578	0	2
Island	2755	0.291	0.494	0	2
Landlock	2755	0.309	0.509	0	2
$RegProc_F$	112	9.679	3.491	2	19
$RegDays_F$	112	49.402	38.593	2	203
$RegCosts_F$	112	90.065	165.785	0	1268.4
$RegProc_H$	19	5.947	2.818	2	10
$RegDays_H$	19	23.842	16.433	3	61
$RegCosts_H$	19	7.874	7.190	0	22.9
$SkillEndow_H$	14	-3.435	0.402	-4.522	-2.957
$JudicQual_H$	18	0.832	0.115	0.615	0.972
$LaborRigid_H$	19	0.473	0.155	0.205	0.667
$KEndow_H$	14	-0.530	0.662	-1.377	0.925
$SkillIntens_i$	61	0.381	0.116	0.166	0.757
$KIntens_i$	61	0.859	0.464	0.235	2.535
$TopCode_i$	63	0.009	0.005	0.004	0.030

Table 8: Additional Variables

	Non-exporters	Exporters
Sales (thousands of pesos)	10652	56221
	26093	157565
Labor	109	377
	204	650
Investment K (thousands of pesos)	428	3501
	2182	34637
Skilled labor (share)	0.043	0.075
	0.077	0.088
Foreign Ownership (dummy)	0.052	0.293
	0.222	0.455
R&D (thousands of pesos)	17.30	133.44
	118.27	1069.63
Observations	1565	1771

Pooled data for 1992, 1996, 1998, 2001

Table 9: Descriptive Statistics - Mean and S.D. (in italics)

Geographical distribution of firms and exporters - Pooled data

Province	Population in 2001	Firms		Exporters		
		Number	% in total	Number	% in prov	% in total
Buenos Aires	16,485,462	2,357	70.59	1,364	58	77.02
Cordoba	3,052,747	216	6.47	79	37	4.46
Santa Fe	2,975,970	291	8.72	143	49	8.07
Mendoza	1,573,671	70	2.10	43	61	2.43
Tucuman	1,331,923	47	1.41	13	28	0.73
Entre Rios	1,152,090	31	0.93	13	42	0.73
Salta	1,065,291	24	0.72	5	21	0.28
Chaco	978,956	8	0.24	4	50	0.23
Misiones	961,274	45	1.35	28	62	1.58
Corrientes	926,989	12	0.36	3	25	0.17
Santiago	795,661	12	0.36	0	0	0.00
San Juan	617,478	35	1.05	10	29	0.56
Rio Negro	549,204	12	0.36	2	17	0.11
Formosa	489,276	4	0.12	0	0	0.00
Neuquen	471,825	7	0.21	0	0	0.00
Chubut	408,191	29	0.87	14	48	0.79
San Luis	367,104	96	2.88	41	43	2.32
Catamarca	330,996	20	0.60	2	10	0.11
La Pampa	298,772	12	0.36	2	17	0.11
La Rioja	287,924	4	0.12	0	0	0.00
Tierra del Fuego	100,313	7	0.21	5	71	0.28
ARGENTINA	**35,221,117**	**3,339**	**100.00**	**1,771**	**53**	**100.00**

Pooled data for 1992, 1996, 1998, 2001

Table 10: Geographical Distribution of Firms and Exporters

Fraction of 1992 plants with the same export status (%)

	Actual		Expected	
	(1)	(2)	(3)	(4)
Year	Exporters	Non-Exporters	Exporters	Non-Exporters
1996	0.97	0.69	0.97	0.69
1998	0.82	0.70	0.76	0.60
2001	0.84	0.68	0.72	0.53

Table 11: Persistence in Export Decisions

OLS estimation - Equations 3.3 and 3.4		
	(1)	(2)
Export Status (y_{igt-1})		0.747
		(0.022)**
Export Status * Exporter Concentration		-0.095
		(0.040)*
Exporter Concentration ($Y_{(-i)gt}$)	0.338	0.129
	(0.023)**	(0.032)**
Time dummies	Yes	Yes
Observations	3336	2444
R-squared	0.07	0.52

The dependent variable (y_{igt}) is a dummy that equals 1 if firm i in group g exports in period t. Robust s.e. in parentheses. * and ** indicate significance at 5% and 1%, respectively.

Table 12: Correlations between Individual and Group Behaviour

Blundell and Bond (1998) estimator - Equation 3.9. (continues on next page)

Dependent Var: Export decision y_{igt}

	(1)	(2)	(3)	(4)	(5)	(6)
Entry Cost Spillovers						
$y_{igt-1} * Y_{(-i)gt}$			-0.294	-0.373	-0.416	-0.064
			(0.189)	(0.201)†	(0.207)*	(0.280)
$y_{igt-1}*$ Output/worker$_g$						-0.075
						(0.056)
$y_{igt-1}*$ Investment K$_g$						-0.006
						(0.008)
$y_{igt-1}*$ Skilled$_g$						2.602
						(1.810)
$y_{igt-1}*$ R&D$_g$						-0.027
						(0.281)
$y_{igt-1}*$ Foreign$_g$						1.130
						(0.490)*
$y_{igt-1}*$ Size$_g$						-0.232
						(0.096)*
Productivity Spillovers						
$Y_{(-i)gt}$	-0.006	0.053	0.158	0.235	0.279	0.174
	(0.100)	(0.112)	(0.138)	(0.154)	(0.172)	(0.199)
Output/worker$_g$						0.007
						(0.006)
Investment K$_g$						-1.675
						(1.462)
Skilled$_g$						0.085
						(0.233)
R&D$_g$						-0.022
						(0.039)
Foreign$_g$						-0.415
						(0.281)
Size$_g$						0.056
						(0.065)

Blundell and Bond (1998) estimator - Equation 3.9. (continued) Dependent Var: Export decision y_{igt}						
	(1)	(2)	(3)	(4)	(5)	(6)
Firm-level controls						
y_{igt-1}	0.380	0.414	0.525	0.603	0.627	0.656
	(0.042)**	(0.044)**	(0.107)**	(0.114)**	(0.117)**	(0.222)**
Output/worker	0.031	0.062	0.027	0.053	0.050	0.035
	(0.015)*	(0.029)*	(0.015)†	(0.029)†	(0.030)†	(0.030)
Size	0.119	0.062	0.117	0.059	0.058	0.076
	(0.020)**	(0.026)*	(0.020)**	(0.026)*	(0.026)*	(0.027)**
Foreign	0.036	0.104	0.044	0.128	0.136	0.163
	(0.045)	(0.056)†	(0.045)	(0.056)*	(0.057)*	(0.059)**
Investment K	-0.000	0.001	-0.000	0.001	0.001	0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Skilled	0.323	0.046	0.339	0.079	0.102	0.092
	(0.203)	(0.211)	(0.205)†	(0.206)	(0.208)	(0.220)
R&D	-0.005	0.003	-0.004	0.006	0.008	0.009
	(0.002)*	(0.031)	(0.002)†	(0.032)	(0.033)	(0.030)
Observations	2440	2440	2440	2440	2440	2440
IV for firm-level controls	No	Yes	No	Yes	Yes	Yes
Location controls	No	No	No	No	Yes	Yes

Robust standard errors in parentheses, ** p<0.01, * p<0.05, † p<0.1. All regressions include firm fixed-effects, time dummies, export prices and total exports in ISIC sector. Group variables are defined by province and industry -at the 3-digit ISIC level.

Table 13: Dynamic Panel Data Estimation - Main Results

Blundell and Bond (1998) estimator - Equation 3.9. (continues on next page)

Dependent Var: Export decision y_{igt}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Entry Cost Spillovers							
y_{igt-1}*Y_{gt}	-0.189	-0.045	-0.422	-0.457	0.060	0.128	0.020
	(0.279)	(0.224)	(0.255)†	(0.241)†	(0.335)	(0.305)	(0.278)
$y_{igt-1}*$ Output / worker$_g$	-0.073	-0.094	0.037	0.029	-0.016	-0.020	-0.056
	(0.055)	(0.053)†	(0.036)	(0.035)	(0.051)	(0.050)	(0.055)
$y_{igt-1}*$ Investment K$_g$	-0.006	0.000	-0.013	-0.014	-0.003	-0.003	-0.004
	(0.007)	(0.008)	(0.008)†	(0.007)†	(0.007)	(0.007)	(0.008)
$y_{igt-1}*$ Skilled$_g$	4.323	1.751	3.607	3.552	4.816	4.736	2.941
	(2.409)†	(1.422)	(2.100)†	(2.003)†	(1.818)**	(1.619)**	(1.924)
$y_{igt-1}*$ R&D$_g$	0.739	-0.016	0.090	0.034	0.172	-0.019	-0.078
	(0.518)	(0.159)	(0.336)	(0.299)	(0.331)	(0.288)	(0.285)
$y_{igt-1}*$ Foreign$_g$	0.968	0.946	0.716	0.678			0.946
	(0.454)*	(0.394)*	(0.546)	(0.478)			(0.495)†
$y_{igt-1}*$ Size$_g$	-0.186	-0.249			-0.163	-0.161	-0.560
	(0.093)*	(0.091)**			(0.092)†	(0.089)†	(0.222)*
$y_{igt-1}*$ Size							-0.467
							(0.198)*
$y_{igt-1}*$ Size$_g$ $*$ Size							0.077
							(0.044)†
Productivity Spillovers							
Y_{gt}	0.371	0.145	0.244	0.445	0.006	0.028	0.126
	(0.184)*	(0.163)	(0.170)	(0.212)*	(0.260)	(0.230)	(0.200)
Output / worker$_g$	-0.014	0.011	-0.057	-0.099	-0.013	-0.015	-0.008
	(0.044)	(0.034)	(0.026)*	(0.034)**	(0.037)	(0.037)	(0.040)
Investment K$_g$	0.004	0.002	0.010	0.011	0.003	0.003	0.005
	(0.006)	(0.007)	(0.006)†	(0.006)†	(0.005)	(0.005)	(0.006)
Skilled$_g$	-2.770	-0.464	-2.580	-2.401	-2.888	-3.143	-2.010
	(1.758)	(1.090)	(1.537)†	(1.562)	(1.409)*	(1.352)*	(1.493)
R&D$_g$	-0.596	0.002	-0.002	0.047	-0.073	0.084	0.146
	(0.413)	(0.145)	(0.266)	(0.245)	(0.276)	(0.241)	(0.239)
Foreign$_g$	-0.309	-0.644	-0.236	-0.094		0.096	-0.393
	(0.265)	(0.235)**	(0.298)	(0.286)		(0.186)	(0.285)
Size$_g$	0.054	0.072		-0.103	0.070	0.055	0.206
	(0.069)	(0.061)		(0.058)†	(0.064)	(0.067)	(0.164)
Size$_g$ * Size							-0.034
							(0.033)

Blundell and Bond (1998) estimator - Equation 3.9. (continued)							
Dependent Var: Export decision y_{igt}							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm-level controls							
y_{igt-1}	0.415	0.635	0.600	0.583	0.729	0.686	2.805
	(0.318)	(0.173)**	(0.226)**	(0.226)*	(0.230)**	(0.222)**	(0.887)**
Output / worker	0.051	0.045	0.037	0.031	0.053	0.046	0.023
	(0.032)	(0.030)	(0.031)	(0.031)	(0.033)	(0.032)	(0.030)
Size	0.078	0.053	0.070	0.077	0.081	0.086	0.275
	(0.027)**	(0.029)†	(0.027)**	(0.027)**	(0.025)**	(0.025)**	(0.152)
Foreign	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Investment K	0.007	0.274	0.117	0.076	0.023	0.029	-0.009
	(0.227)	(0.216)	(0.234)	(0.237)	(0.243)	(0.248)	(0.253)
Skilled	0.185	0.256	0.154	0.157	0.165	0.145	0.204
	(0.059)**	(0.076)**	(0.062)*	(0.060)**	(0.058)**	(0.056)**	(0.062)**
R&D	-0.036	0.023	0.015	0.007	0.013	0.012	-0.012
	(0.042)	(0.030)	(0.030)	(0.030)	(0.031)	(0.030)	(0.028)
Observations	2440	2421	2440	2440	2440	2440	2440
IV for firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, ** $p<0.01$, * $p<0.05$, † $p<0.1$. All regressions include firm fixed effects, time, dummies, export prices and total exports in ISIC sector. Group variables are defined at the 3-digit ISIC level. In columns(1) and (2), ISIC industries are defined at 2 and 3 digits of aggregation, respectively. Columns (3) to (6) examine the sensitivity of the results column (7) of Table 13 by excluding average firm size and proportion of foreign firms at the group level. In column (7), entry time costs and spillovers are allowed to depend on firm size.

Table 14: Dynamic Panel Data Estimation - Sensitivity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Dispersion	$\frac{\text{St Dev}}{\text{Mean}}$	$\frac{\text{95-5 IPR}}{\text{Mean}}$	Gini RMD	$\frac{\text{St Dev}}{\text{Mean}}$	$\frac{\text{95-5 IPR}}{\text{Mean}}$	Gini RMD
$WageDisp_i \times SkillDisp_H$	0.013**	0.009*	0.010*	0.015**	0.010*	0.010*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Trade Barriers	No	No	No	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Importer-Industry FE	No	No	No	Yes	Yes	Yes
Observations	58124	58124	58124	58124	58124	58124
R-squared	0.54	0.54	0.54	0.70	0.69	0.69

The dependent variable is the natural logarithm of exports from country H to country F in industry i. Standardized beta coefficients are reported. †, * and ** indicate the coefficient is significant at the 10%, 5% and 1% levels. Standard errors clustered by importer-exporter pair in parenthesis.

Table 15: Normalized Raw Scores and Wage Rankings

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Dispersion	St Dev	95-5 IPR	Gini MD	St Dev	95-5 IPR	Gini RMD
$WageDisp_i \times SkillDisp_H$	0.024**	0.013*	0.022**	0.024**	0.013*	0.022**
	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.008)
$WageMean_i \times SkillMean_H$	0.145**	0.156**	0.164**	0.145**	0.156**	0.164**
	(0.007)	(0.007)	(0.009)	(0.007)	(0.007)	(0.009)
$WageMean_i \times SkillDisp_H$	0.075**	0.090**	0.093**	0.753**	0.090**	0.093**
	(0.007)	(0.006)	(0.008)	(0.007)	(0.006)	(0.008)
$WageDisp_i \times SkillMean_H$	0.023**	0.011	0.025**	0.023**	0.011	0.025**
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
Trade Barriers	Yes	Yes	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer FE	No	No	No	No	No	No
Industry FE	No	No	No	No	No	No
Importer-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58124	58124	58124	58124	58124	58124
R-squared	0.70	0.70	0.70	0.70	0.70	0.70

The dependent variable is the natural logarithm of exports from country H to country F in industry i. Standardized beta coefficients are reported. †, * and ** indicate the coefficient is significant at the 10%, 5% and 1% levels. Standard errors clustered by importer-exporter pair in parenthesis.

Table 16: Non-Normalized Interactions

Figures

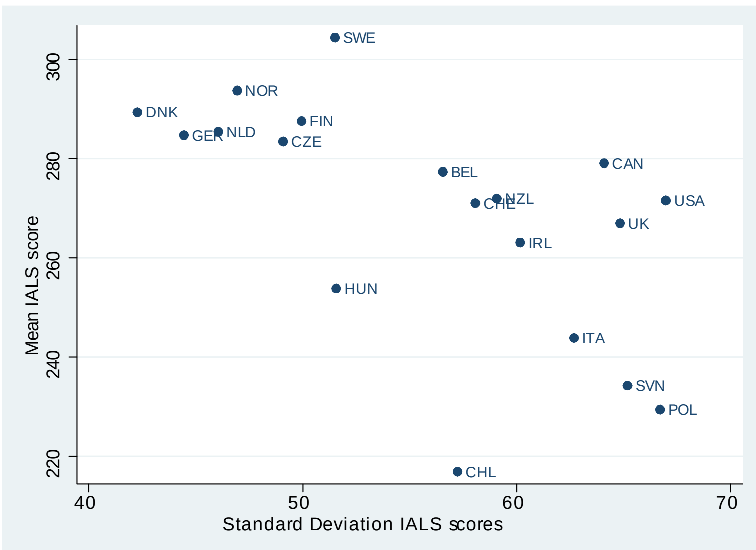


Figure 1: Mean and Standard Deviation - IALS scores

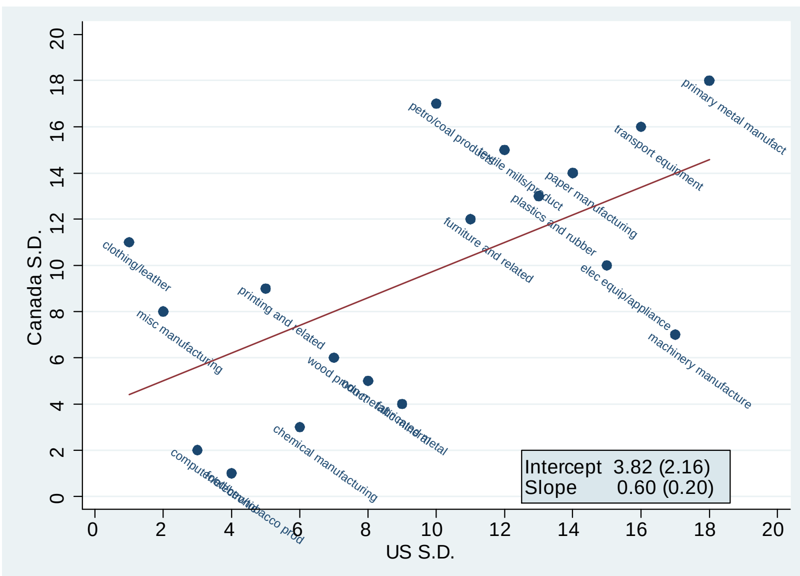
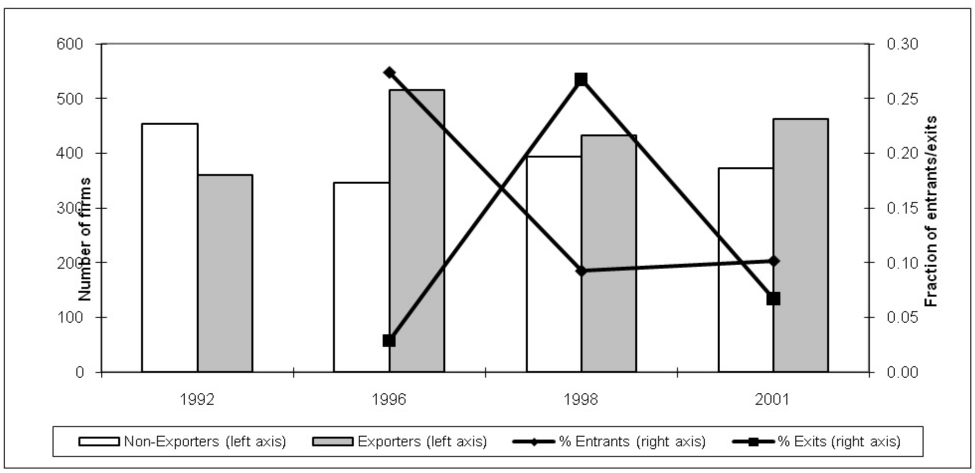
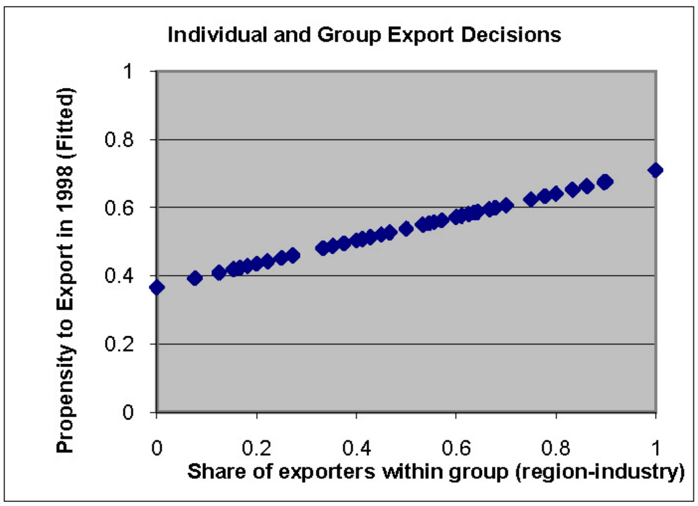


Figure 2: Industry Rankings by Standard Deviation of Residual Wages



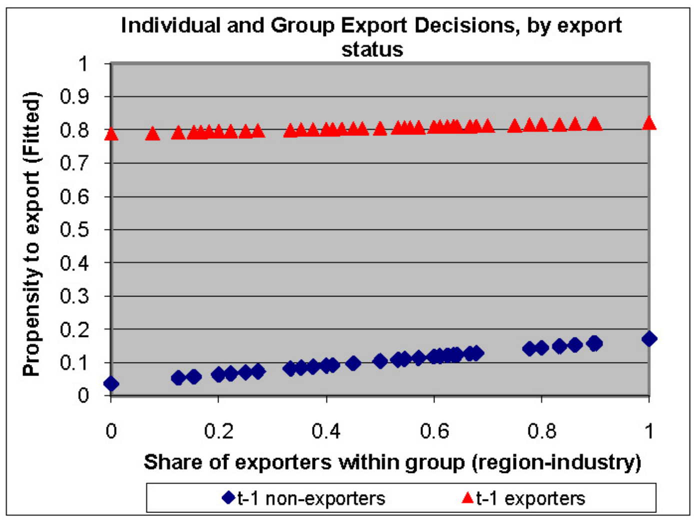
The number of exporters and non-exporters each year are represented by the bar graph (left-hand axis). The fraction of firms exiting or entering the export market are shown by the lines (right-hand axis)

Figure 3: Transitions In and Out of Exporting



Plot of the relationship between the share of exporters within group, $Y_{(-i)gt}$, and the fitted values obtained in from column (1) of table 12

Figure 4: Individual and Group Export Decisions



Plot of the relationship between the share of exporters within group, Y_{(-i)gt}, and the fitted values obtained in from column (2) of table12.

Figure 5: Individual and Group Export Decisions, by Export Status

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Appendix A

Appendix to Chapter 1

A.1 Sufficient Conditions for Property 1

This section reports analytical conditions which guarantee that Property 1 holds. We show that comparative advantage can be established for any distribution if we place bounds on the degree of complementarity λ. Moreover, we perform comparative statics assuming specific distributions of skills.

Our first approach yields a general result based on restrictions on the degree of complementarity and on the upper bound of the support of the skill distribution.[1]

Proposition A-1 *Property 1 holds, i.e. a country c' with a more dispersed skill distribution than country c has a comparative advantage in sectors with lower complementarity (higher λ) under the following sufficient conditions:*

(i) Skill is bounded from above by $a_{\max}$

(ii) The degree of complementarity is low enough: $\lambda > \overline{\lambda}$ where $\overline{\lambda}$ is defined by the following condition

$$\log a_{\max} = \frac{2\overline{\lambda} - 1}{\left(1 - \overline{\lambda}\right) \overline{\lambda}}$$

Proof. By definition of log-supermodularity we need to prove that, if $g(a, c')$

[1] Imposing an upper bound on a is realistic because it means we do not admit the existence of infinitely productive workers.

is a mean-preserving spread of $g(a,c)$ then:

$$\frac{\partial \log A(\lambda, c)}{\partial \lambda} \leq \frac{\partial \log A(\lambda, c')}{\partial \lambda}.$$

The partial derivative has the following expression:

$$\frac{\partial \log A(\lambda, c)}{\partial \lambda} = \frac{1}{\lambda} \frac{\int a^{\lambda} \log a \, g(a,c) da}{\int a^{\lambda} g(a,c) da} - \frac{1}{\lambda^2} \log \left(\int a^{\lambda} g(a,c) da \right) \tag{A-1}$$

A mean-preserving spread of $g(a,c)$ increases the second term of the right-hand side of (A-1) by definition, since a^{λ} is a concave function. A sufficient condition for the first term of (A-1) to increase with a mean-preserving spread in $g(a,c)$ is that $k(a) = a^{\lambda} \log a$ is a convex function which is verified if its second derivative with respect to a is positive for every value of a. i.e. $\log a < \frac{2\lambda - 1}{(1-\lambda)\lambda}$. Since the right-hand side of this inequality is continuous and increasing in λ, it is equal to zero for $\lambda = \frac{1}{2}$ and $\lim_{\lambda \to 1} \frac{2\lambda - 1}{(1-\lambda)\lambda} = \infty$ then, if a is bounded above by $a_{\max}$, then there exists a value $\overline{\lambda} < 1$ such that $\log a_{\max} = \frac{2\overline{\lambda} - 1}{(1-\overline{\lambda})\overline{\lambda}}$. If $\lambda > \overline{\lambda}$ then $\frac{\partial \log A(\lambda, c)}{\partial \lambda}$ increases with a mean preserving spread of $g(a,c)$. ■

In our second approach to studying Property 1 we relax the conditions on complementarity at the cost of concentrating on specific distributions. We can only consider continuous distributions that are characterized by at least two parameters (in order to be able to consider mean-preserving increases in dispersion) and are defined on a positive support.

Proposition A-2 *If skills are distributed according to a Pareto or Log-normal distribution then, if country c and c' are characterized by skill distributions $g(a,c)$ and $g(a,c')$ such that $g(a,c')$ has equal mean and higher variance than $g(a,c)$ and if $\lambda < \lambda'$ then Property 1 holds, i.e. country c' has a comparative advantage in λ'.*

(i) *Pareto Distribution* - Under the assumption that skills follow a Pareto distribution with mean μ and standard deviation σ, A takes the following expression:[2]

$$A = \frac{\mu^2+\sigma^2-\sigma\sqrt{\mu^2+\sigma^2}}{\mu}\left(\frac{\sigma+\sqrt{\mu^2+\sigma^2}}{\sigma+\sqrt{\mu^2+\sigma^2}-\lambda\sigma}\right)^{\frac{1}{\lambda}}.$$

Since A is twice differentiable in σ and λ, the result in Proposition 1.3 is equivalent to A being log-supermodular in λ and σ, that is $\frac{\partial^2 \log A}{\partial\sigma\partial\lambda} > 0$. The expression for the cross partial derivative is the following:

$$\frac{\partial^2 \log A}{\partial\sigma\partial\lambda} = \frac{\sigma\left(\sqrt{\mu^2+\sigma^2}-\sigma\right)}{\sqrt{\mu^2+\sigma^2}\left[\sigma(1-\lambda)+\sqrt{\mu^2+\sigma^2}\right]} \tag{A-2}$$

and $\lambda < 1$ so A is log-supermodular in λ and σ.

(ii) *Log-Normal Distribution* - If the distribution of skills a is lognormal on the support $[0,\infty]$ with mean μ and standard deviation σ then A takes the following form:

$$A = e^{\log\mu - \frac{1-\lambda}{2}\log\left(\frac{\sigma^2}{\mu^2}+1\right)}$$

It is easy to show that under this distribution, A is log-supermodular since the following expression is always positive:

$$\frac{\partial^2 \log A}{\partial\sigma\partial\lambda} = \frac{\sigma}{\mu^2+\sigma^2}$$

[2] The Pareto distribution is characterized by a shape parameter k and location parameter $a_{\min}$, i.e. the cumulative distribution of ability is given by $G(a) = 1-\left(\frac{a_{\min}}{a}\right)^k$ with $a_{\min} > 0$ and $k > 2$. We could have written A as a function of those parameters:

$$A = a_{\min}\left(\frac{k}{k-\lambda}\right)^{\frac{1}{\lambda}}$$

Since we are interested in a mean-preserving increase in variance, we express the A as a function of μ and σ, which are related to shape and location parameters according to the following equations:

$$\begin{aligned} a_{\min} &= \frac{\mu^2+\sigma^2-\sigma\sqrt{\mu^2+\sigma^2}}{\mu} \\ k &= \frac{\sigma+\sqrt{\mu^2+\sigma^2}}{\sigma} \end{aligned}$$

While Proposition A-2 establishes an analytical result, we have also numerically computed the A's for the following distributions: uniform, triangular, gamma, beta and inverse Gaussian. For all these distributions, and for a wide range of parameters, we cannot find a violation of the ranking in (1.3).[3]

A.2 Output, Prices and Revenues

In this section we provide details about the solution to the firm problem.

Revenues (1.4)

First, we show how to derive the expression for total revenues in (1.4). Total revenues of a firm in Home are given by:

$$r_H = B_H y_{HH}^{\frac{\sigma-1}{\sigma}} + B_F y_{HF}^{\frac{\sigma-1}{\sigma}} \tau^{\frac{1-\sigma}{\sigma}} \tag{A-3}$$

For a profit-maximizing firm marginal revenues have to be equal across markets. Rearranging the equality of marginal revenue condition leads to the following:

$$\frac{y_{HH}}{y_{HF}} = \left(\frac{B_H}{B_F}\right)^{\sigma} \tau^{\sigma-1} \tag{A-4}$$

From (A-4) y_{HH} can be expressed as a function of y_{HF} and replaced in (A-3) to find:

$$r_H = B_F y_{HF}^{-\frac{1}{\sigma}} \tau^{\frac{1-\sigma}{\sigma}} \left(y_{HH} + y_{HF}\right) \tag{A-5}$$

From (A-5) and its analogous for y_{HH} we can find the two following equations:

$$y_{HH} = r_H^{-\sigma} B_H^{\sigma} \left(y_{HH} + y_{HF}\right)^{\sigma} \tag{A-6}$$

$$y_{HF} = r_H^{-\sigma} B_F^{\sigma} \left(y_{HH} + y_{HF}\right)^{\sigma} \tau^{1-\sigma} \tag{A-7}$$

[3] A violation of the ranking can be engineered using a result by Ross (1981). The intuition is the following. Ross (1981) shows that, if we adopt the Arrow-Debreu definition of risk aversion, then, starting from a given lottery, we might find the counterintuitive result that a more risk-averse individual is willing to pay less than a less risk-averse individual to avoid an an increase in risk in the sense of a mean-preserving spread. We can view our A as the certainty equivalent of lottery g for an individual with Bernoulli utility $u(a) = a^{\lambda}$, $0 < \lambda < 1$. Individuals with lower λ are more risk averse in the Arrow-Pratt sense. In our case we can show, using the example proposed by Ross (1981) that, with a mean-preserving spread, the certainty equivalent of a more risk averse individual drops proportionately by less than for a less risk averse individual. Details are available from the authors.

Adding up (A-6) and (A-7) and rearranging them leads to the expression for revenues reported in (1.4):

$$r_H = (y_{HH} + y_{HF})^{\frac{\sigma-1}{\sigma}} \left(B_H^{\sigma} + B_F^{\sigma}\tau^{1-\sigma}\right)^{\frac{1}{\sigma}}$$

Output and Prices

The first order condition of problem (1.6) can be written as a function of revenues r_H as follows:

$$s\frac{\sigma-1}{\sigma\lambda b}r_H = h_H$$

This first order condition, together with the zero profit condition derived from free entry, implies:

$$sr_H - bh_H - f = 0$$

delivers total revenues and employment:

$$\begin{aligned} r_H &= \frac{f\sigma\lambda}{s(\sigma\lambda-\sigma+1)} \\ h_H &= \frac{f(\sigma-1)}{b(\sigma\lambda-\sigma+1)} \end{aligned}$$

Given the production function, the expression for total output follows:

$$y_H = A(\lambda, H)\left[\frac{f(\sigma-1)}{b(\sigma\lambda-\sigma+1)}\right]^{\frac{1}{\lambda}} \tag{A-8}$$

Next, we determine how output is divided across the domestic and export market. We employ (A-6) and (A-7) and their analogous for the Foreign firm to find the relative output of firms *selling* in the same market:

$$\frac{y_{HH}}{y_{FH}} = \frac{r_H^{-\sigma}(y_{HH}+y_{HF})^{\sigma}}{r_F^{-\sigma}(y_{FF}+y_{FH})^{\sigma}\tau^{1-\sigma}} \tag{A-9}$$

$$\frac{y_{FF}}{y_{HF}} = \frac{r_F^{-\sigma}(y_{FF}+y_{FH})^{\sigma}}{r_H^{-\sigma}(y_{HH}+y_{HF})^{\sigma}\tau^{1-\sigma}} \tag{A-10}$$

The expressions above can be simplified using the fact that total revenues are constant in a given sector: $r_H = r_F = r$. Together with (A-8) and its foreign equivalent, (A-9) and (A-10) deliver the amount of output sold by a Foreign and a Home firm in every market. The amounts of output sold in the two markets by a Home firm are given by:

$$y_{HH} = \frac{\phi A(\lambda,H)}{1-\rho^2}\left[1-\rho\left(\frac{A(\lambda,H)}{A(\lambda,F)}\right)^{\sigma-1}\right] \quad \text{(A-11)}$$

$$y_{HF} = \frac{\phi\rho A(\lambda,H)}{1-\rho^2}\left[\left(\frac{A(\lambda,H)}{A(\lambda,F)}\right)^{\sigma-1}-\rho\right] \quad \text{(A-12)}$$

where $\rho=\tau^{1-\sigma}$, while the corresponding Foreign firm expressions are:

$$y_{FF} = \frac{\phi A(\lambda,F)}{1-\rho^2}\left[1-\rho\left(\frac{A(\lambda,H)}{A(\lambda,F)}\right)^{1-\sigma}\right] \quad \text{(A-13)}$$

$$y_{FH} = \frac{\phi\rho A(\lambda,F)}{1-\rho^2}\left[\left(\frac{A(\lambda,F)}{A(\lambda,H)}\right)^{\sigma-1}-\rho\right] \quad \text{(A-14)}$$

Finally we derive relative revenues for a Home and a Foreign firm in a given market (1.9) by expressing it first as a function of relative output $\frac{r_{HF}}{r_{FF}}=\left(\frac{y_{HF}}{y_{FF}}\right)^{\frac{\sigma-1}{\sigma}}\tau^{\frac{1-\sigma}{\sigma}}$, and then replacing the expressions for y_{HF} and y_{FF}.

Intuitively, relative revenues increase in relative productivity, as predicted by comparative advantage. As standard with iso-elastic demand, the producer price is constant across markets and for a Home firm is equal to $p_H=\frac{\gamma}{\phi A_H}$ where $\gamma(\lambda)=f\frac{\sigma\lambda+\sigma-1}{\sigma\lambda-\sigma+1}$. The consumer price in the export market is the producer price multiplied by τ; i.e. $p_{HF}=\frac{\gamma\tau}{\phi A_H}$.

A.3 Mass of Firms

Previously we derived the amount of output sold by each firm in the domestic and export market. In order to determine trade flows we need to calculate the equilibrium mass of firms for country c and sector λ, $M_c(\lambda)$. Having determined the revenues of a firm in each market, the mass of firms in each country has to be such that, total expenditure on good λ in a given country is equal to total revenues accruing to all firms operating in that market. The two equations below express these equilibrium conditions for sector λ:

$$\alpha(\lambda) L_H = M_H(\lambda) r_{HH}(\lambda) + M_F(\lambda) r_{FH}(\lambda) \tag{A-15}$$

$$\alpha(\lambda) L_F = M_F(\lambda) r_{FF}(\lambda) + M_H(\lambda) r_{HF}(\lambda) \tag{A-16}$$

It is convenient to rewrite conditions (A-15) and (A-16) as a function of output, rather than of revenues:

$$\begin{aligned} \alpha L^H &= M_H \frac{\gamma}{\phi A(\lambda, H)} y_{HH} + M_F \frac{\gamma}{\phi A(\lambda, F)} y_{FH}, \\ \alpha L^F &= M_F \frac{\gamma}{\phi A(\lambda, F)} y_{FF} + M_H \frac{\gamma}{\phi A(\lambda, H)} y_{HF}. \end{aligned}$$

The solution to this linear system is given by the following expressions for M_H and M_F:

$$M_H = A(\lambda, H) \frac{\alpha\phi(L_H y_{FF} - L_F y_{FH})}{\gamma(y_{FF} y_{HH} - y_{HF} y_{FH})}, \tag{A-17}$$

$$M_F = A(\lambda, F) \frac{\alpha\phi(L_F y_{HH} - L_H y_{HF})}{\gamma(y_{FF} y_{HH} - y_{HF} y_{FH})}. \tag{A-18}$$

First, we show that the denominator of M_H and M_F is always positive. Define Home productivity advantage $z(\lambda) = \frac{A(\lambda,H)}{A(\lambda,F)}$. The denominator is positive if and only if $\frac{y_{HH}}{y_{FH}} > \frac{y_{HF}}{y_{FF}}$, a condition we can rewrite as $z^\sigma \frac{1}{\rho} > z^\sigma \rho$ and that is always satisfied since $\rho < 1$.

We remark that, similarly to other models of monopolistic competition with trade costs (Helpman and Krugman, 1985), the presence of a home-market effect requires that we restrict the degree of asymmetry in country sizes to prevent all firms from locating in one country. Define relative population in Home as $\eta \equiv \frac{L_H}{L_F}$. The mass of Home firms M_H is positive if and only if $L_H y_{FF} - L_F y_{FH} > 0$. This condition places a lower bound on the relative population, since $M_H > 0$ if and only if:

$$\eta > \frac{\rho\left(\frac{1}{z^{\sigma-1}} - \rho\right)}{1 - \frac{\rho}{z^{\sigma-1}}} = \eta_{low} \tag{A-19}$$

Equivalently, M_F is positive if and only if $L_F y_{HH} - L_H y_{HF} > 0$, a condition that places an upper bound on the relative population η, i.e. $M_F > 0$ if and only if:

$$\eta < \frac{1-\rho z^{\sigma-1}}{\rho\left(z^{\sigma-1}-\rho\right)} = \eta_{up} \tag{A-20}$$

Both η_{low} and η_{up} are positive under the condition that we imposed in order to guarantee that a positive amount of output is produced for every market: $\rho < z^{\sigma-1} < \frac{1}{\rho}$. We impose throughout the restrictions that $\eta_{low} < \eta < \eta_{up}$. If the condition is violated for some industries, we expect to observe no production and no exports.[4] If the condition is satisfied, then proposition 1 establishes a link between comparative advantage and equilibrium entry.

A.4 Proof of Proposition 1

We define the mass of Home relative to Foreign firms in sector λ as $m(\lambda) \equiv \frac{M_H}{M_F}$. We investigate how m changes with z, assuming that we are operating in the parameter space where $\eta_{low} < \eta < \eta_{up}$. We rewrite the relative mass of firms, using (A-17), (A-18), the expressions for Home firm outputs, (A-11) and (A-12), and the corresponding expressions for the Foreign firm:

$$m = \frac{z^{1-\sigma}(1+\eta)\rho - \left(\eta+\rho^2\right)}{z^{\sigma-1}(1+\eta)\rho - \left(1+\eta\rho^2\right)}$$

The first derivative of m with respect to z takes the following form:

$$\frac{\partial m}{\partial z} = \frac{1}{z^{\sigma+2}}(\sigma-1)(1+\eta)\frac{-2z^{1+\sigma}(1+\eta)\rho + z^{2\sigma}\left(\eta+\rho^2\right) + z^2\left(1+\eta\rho^2\right)}{\left(\rho z^{\sigma-1} - \eta\rho^2 + \eta\rho z^{\sigma-1} - 1\right)^2}$$

This derivative is positive if the numerator is positive and the numerator can be divided in two parts, which we show are both positive. The first part, denoted by

[4] As equations (A-19) and (A-20) establish, the conditions for a positive mass of firms depend on size, but also on comparative advantage. If a country is relatively more productive it can afford to be smaller in size and still have a positive mass of firms. In this sense our model also predicts an extensive margin of trade (whether we observe or not trade between two countries) based on comparative advantage, albeit a very stark one. Differently from models with heterogeneous firms, e.g. Helpman et al. (2008c), in this setup the assumption of identical firms implies that either firms exist and export or they do neither.

ψ_1 is:

$$\psi_1 = -z^{1+\sigma}(1+\eta)\rho + z^{2\sigma}\left(\eta+\rho^2\right),$$

while the second part denoted by ψ_2 is:

$$\psi_2 = -hz^{1+\sigma}(1+\eta)\rho + z^2\left(1+\eta\rho^2\right).$$

It is straightforward to show that $\psi_1 > 0$ if and only if $\eta > \eta_{low}$ and that $\psi_2 > 0$ if and only if $\eta < \eta_{up}$, conditions we have imposed throughout.

A.5 Proof of Proposition 2

The result follows directly since we have proven that both components of relative sales (1.10), relative revenues per firm $\frac{r_{FH}(\lambda)}{r_{HH}(\lambda)}$ and relative mass of firms $\frac{M_F(\lambda)}{M_H(\lambda)}$ are increasing in relative productivity $\frac{A(\lambda,F)}{A(\lambda,H)}$ (see (1.9) and Proposition 1) and relative productivity depends the degree of complementarity λ (proxied by the dispersion of wages according to Proposition 4) and the dispersion of skills according to the discussion in Section 1.3.

A.6 Proof of Proposition 3

Since the derivation is analogous to the two-country case we simply report the expression relative revenues:[5]

$$\frac{r_{HF}}{r_{GF}} = \left(\frac{A(\lambda,H)}{A(\lambda,G)}\right)^{\sigma-1}\left(\frac{\tau_{HF}}{\tau_{GF}}\right)^{1-\sigma}.$$

It follows that, if the relative mass of firms is non-decreasing in relative productivity, relative exports are higher in comparative advantage sectors, similarly to the two-country case in Proposition

[5] Details are available from the authors upon request.

A.7 Derivation of the Shapley Value

In this section we provide details on how to derive the share of revenues accruing to the firm and the wages paid to workers. Stole and Zwiebel (1996) have proved the equivalence of their bargaining solution to the Shapley value of the corresponding cooperative game not only for the case of identical workers, but also for the case of heterogeneous workers,[6] therefore we calculate the Shapley value directly.[7] The Shapley value of the firm is heuristically derived as its marginal contribution averaged over all possible orderings of employees and the firm itself. The case of heterogeneous employees is easy to handle under our assumption of a continuum of workers because no matter how the firm is ordered, it is preceded by a mass of workers whose skill distribution mirrors the overall skill distribution in the workers population, so the only variable we have to keep track of is the mass of workers preceding the firm, define it n, which varies from zero to h. As discussed in Acemoglu et al. (2007), since the firm is an essential input its marginal contribution is equal to revenues when n workers are employed in production $r_H(n) = \left(n^{\frac{1}{\lambda}}A\right)^{\frac{\sigma-1}{\sigma}}\Gamma_H$. The Shapley value of the firm S_{firm} is therefore:

$$S_{firm} = \int_0^h \frac{1}{h}\left(n^{\frac{1}{\lambda}}A\right)^{\frac{\sigma-1}{\sigma}}\Gamma_H \, dn = sr_H$$

where s is defined by (1.5). As discussed in Acemoglu et al. (2007) the share of revenues accruing to the firm depends on the curvature of the revenue function, due to characteristics of the demand function (σ) and the production function (λ).

In a similar fashion we calculate the Shapley value of a worker of skill a, by averaging its marginal contribution across all possible orderings. When a mass n of workers is employed, revenues of the firm are:

$$r(n) = \Gamma_H \left[\int_a a^{\lambda} n(a,c)da\right]^{\frac{\sigma-1}{\sigma\lambda}}$$

where $n(a,c) = ng(a,c)$. The marginal contribution of a worker of skills a is given by the marginal revenue from an increase in the mass of workers of skill a, $n(a,c)$, conditional on the firm being ordered before the worker (otherwise the marginal

[6] See their Theorems 8 and 9, p. 393.

[7] The analogous of the Shapley value for a continuum of players is derived in Aumann and Shapley (1974).

contribution is null):

$$\frac{\partial r(n)}{\partial n(a)} = \Gamma_H \frac{\sigma-1}{\sigma\lambda} \left[\int_a n\tilde{g}(a) a^{\lambda} da \right]^{\frac{\sigma-1}{\sigma\lambda}-1} a^{\lambda}$$

The Shapley value and wage of worker of skill a in industry λ is:

$$w(a,\lambda) = \frac{1}{h}\int_o^h \frac{n}{h}\frac{\partial r(n)}{\partial n(a)} dn = \Gamma_H A(\lambda,c)^{\frac{\sigma-1-\sigma\lambda}{\sigma}} \frac{\sigma-1}{\sigma-1+\sigma\lambda} h^{\frac{\sigma-1}{\sigma\lambda}-1} a^{\lambda}$$

Since the average wage also differs across sectors, we normalize wages by the average wage in the sector $E[w(a,\lambda)]$. The normalized wage is denoted by $\widetilde{w}(a,\lambda) = \frac{w(a,\lambda)}{E[w(a,\lambda)]}$ and takes the following form:

$$\widetilde{w}(a,\lambda) = \frac{a^{\lambda}}{E\left(a^{\lambda}\right)}$$

A.8 Proof of Proposition 4

We consider three measures of wage dispersion:

(i) the Coefficient of Variation of wages $w(a,\lambda)$, directly related to the variance of the normalized wage $\widetilde{w}(a,\lambda)$, $Var(\widetilde{w}(a,\lambda))$, which is given by:

$$Var(\widetilde{w}(a,\lambda)) = \frac{E\left(a^{2\lambda}\right)}{E\left(a^{\lambda}\right)^2} - 1, \tag{A-21}$$

(ii) the Gini Coefficient, defined with respect to the Lorenz Curve for normalized wages at the sector level $\Lambda(w,\lambda)$,

(iii) the Inter-Percentile Ratio IPR_{kj} defined as:

$$IPR_{kj} = \frac{w_k}{w_j},$$

where w_k (w_j) is the wage of the worker at the k^{th}(j^{th}) percentile of the sectoral wage distribution and $j < k$.

(i) *Coefficient Of Variation*

Since the variance of normalized wages is equal to the square of the coefficient of variation we prove the result for the former. We start by rewriting (A-21) in an explicit form, dropping the country index c to simplify notation:

$$Var(\widetilde{w}(a,\lambda)) = \frac{\int a^{2\lambda}\tilde{g}(a)\,da}{\left(\int a^{\lambda}\tilde{g}(a)\,da\right)^2} - 1 \tag{A-22}$$

The derivative of (A-22) with respect to λ is non-negative if an only if the following inequality is satisfied:

$$\left(\int_0^\infty a^{2\lambda}\log a\,\tilde{g}(a)\,da\right)\left(\int_0^\infty a^{\lambda}\,\tilde{g}(a)\,da\right) \tag{A-23}$$

$$\geq \left(\int_0^\infty a^{\lambda}\log a\,\tilde{g}(a)\,da\right)\left(\int_0^\infty a^{2\lambda}\,\tilde{g}(a)\,da\right) \tag{A-24}$$

The left-hand side of (A-23), which we denote by Φ_L can be rewritten as:

$$\Phi_L = \int_0^\infty\int_0^\infty a^{2\lambda}\log a\,\tilde{g}(a)\,b^{\lambda}\,\tilde{g}(b)\,dadb$$

We can divide the region of integration in two parts, delimited by the 45 degree line in the plane $[0,\infty]\times[0,\infty]$. It follows that Φ_L can be rewritten as:

$$\Phi_L = \int_0^\infty\left(\int_0^a b^{\lambda}\,\tilde{g}(b)\,db\right)a^{2\lambda}\log a\,\tilde{g}(a)\,da + \tag{A-25}$$

$$\int_0^\infty\left(\int_a^\infty b^{\lambda}\,\tilde{g}(b)\,db\right)a^{2\lambda}\log a\,\tilde{g}(a)\,da \tag{A-26}$$

We change the order of integration in the second component of Φ_L so that we can rewrite (A-25) it as:

$$\Phi_L = \int_0^\infty\left(\int_0^a b^{\lambda}\,\tilde{g}(b)\,db\right)a^{2\lambda}\log a\,\tilde{g}(a)\,da + \tag{A-27}$$

$$\int_0^\infty\left(\int_0^b a^{2\lambda}\log a\,\tilde{g}(a)\,da\right)b^{\lambda}\,\tilde{g}(b)\,db \tag{A-28}$$

Finally, a change of variable in the second component of (A-27) allows us to express Φ_L as:

$$\begin{aligned}\Phi_L &= \int_0^\infty \left(\int_0^a b^\lambda\ \tilde{g}(b)\,db\right) a^{2\lambda}\log a\ \tilde{g}(a)\,da + \\ &\quad \int_0^\infty \left(\int_0^a b^{2\lambda}\log b\ \tilde{g}(b)\,db\right) a^\lambda\ \tilde{g}(a)\,da\end{aligned}$$

If the same decomposition is performed on the right-hand side of (A-23) we can rewrite the inequality as follows:

$$\int_0^\infty \left(\int_0^a a^\lambda b^\lambda \left[\left(a^\lambda - b^\lambda\right)(\log a - \log b)\right] \tilde{g}(b)\tilde{g}(a)\,db\right) da \geq 0$$

which is always satisfied since $\left(a^\lambda - b^\lambda\right)(\log a - \log b) \geq 0$.

(ii) *Gini Coefficient*

We proceed by deriving the Lorenz Curve for sectoral normalized wages and showing that increasing λ produces a downward shift in the curve at all points. This is a sufficient condition for the Gini coefficient to increase with an increase in λ. The Lorenz Curve $\Lambda(w,\lambda)$ of normalized wages in sector λ is given by the following expression:

$$\Lambda(w,\lambda) = \frac{\int_0^w a^\lambda \tilde{g}(a)\,da}{\int_0^\infty a^\lambda \tilde{g}(a)\,da}$$

The first derivative with respect to λ , $\frac{\partial \Lambda(w,\lambda)}{\partial \lambda}$ is non-positive if and only if the following condition is satisfied $\forall w$:

$$\begin{aligned}&\left(\int_0^w a^\lambda \log a\ \tilde{g}(a)\,da\right)\left(\int_0^\infty b^\lambda \tilde{g}(b)\,db\right) \\ \leq\ &\left(\int_0^w a^\lambda \tilde{g}(a)\,da\right)\left(\int_0^\infty b^\lambda \log b\ \tilde{g}(b)\,da\right)\end{aligned}$$

The region of integration can be divided into two part on both sides of the inequality, so that the inequality can be rewritten as follows:

$$
\begin{aligned}
& \left(\int_0^w \left(\int_0^w b^\lambda \tilde{g}(b)\, db\right) a^\lambda \log a\, \tilde{g}(a)\, da\right) + \\
& \int_0^w \left(\int_w^\infty b^\lambda \tilde{g}(b)\, db\right) a^\lambda \log a\, \tilde{g}(a)\, da \\
\leq \quad & \left(\int_0^w \left(\int_0^w b^\lambda \log b\, \tilde{g}(b)\, db\right) a^\lambda \tilde{g}(a)\, da\right) + \\
& \int_0^w \left(\int_w^\infty b^\lambda \log b\, \tilde{g}(b)\, db\right) a^\lambda \tilde{g}(a)\, da
\end{aligned}
$$

Simplifying and factorizing leads to the following inequality:

$$
\int_0^w \int_w^\infty b^\lambda a^\lambda \ (\log a - \log b)\ \tilde{g}(b)\ \tilde{g}(a)\ db da \leq 0
$$

which is always satisfied since the range of integration of a is $[0,w]$ while the range of integration of b is $[w,\infty]$.

(iii) *Inter-Percentile Ratio*

It is straightforward to show that IPR_{kj} increases with λ since for any percentile the ratio of wages is given by:

$$
IPR_{kj} = \left(\frac{a_k}{aj}\right)^\lambda
$$

where $a_k(a_j)$ is the skill of the worker at the $k^{th}(j^{th})$ percentile.

Appendix B

Appendix to Chapter 2

B.1 Main Variables

B.1.1 Measuring Skill Dispersion

The IALS microdata used for this chapter was compiled by Statistics Canada using the original data sets collected between 1994 and 1998 in each of the participating countries. Tuijnman (2000) describes the three dimensions of literacy used to approximate skills. *Prose literacy* represents the knowledge and skills needed to understand and use information from texts including editorials, news stories, brochures and instruction manuals. *Document literacy* represents the knowledge and skills required to locate and use information contained in various formats, including job applications, payroll forms, transportation schedules, maps, tables and charts. *Quantitative literacy* represents the knowledge and skills required to apply arithmetic operations, either alone or sequentially, to numbers embedded in printed materials, such as balancing a chequebook, figuring out a tip, completing an order form or determining the amount of interest on a loan from an advertisement.

We employ the logarithm of scores (in conjunction with the log of wages) because the standard deviation of the logarithm of a random variable is scale invariant. When extracting residual scores in equation (2.6), using log-scores on the left-hand side is consistent with the common practice of obtaining residual wages from a regression of log-wages, as in equation (2.7). The results of the empirical analysis are qualitatively similar if we use levels instead of logs.

Only individuals participating in the labor market are included in the estimation of equation (2.7). These individuals were either: (i) employed or unemployed at some time in the 12 months previous to the survey or (ii) not searching for a job due to skill upgrading (school or work programs) or a temporary disability.

The right-hand side vector X_{kH} in equation (2.6) includes a number of observable individual characteristics. Education is among them: we include indicators for 7 levels of educational attainment as defined by the International Standard Classification of Education (ISCED). The levels considered in IALS are: ISCED 0 Education preceding the first level; ISCED 1 Education at the first level; ISCED 2 Education at the second level, first stage; ISCED 3 Education at the second level, second stage; ISCED 5 Education at the third level, first stage (leads to an award not equivalent to a first university degree); ISCED 6 Education at the third level, first stage (leads to a first university degree or equivalent; ISCED 7 Education at the third level, second stage (leads to a postgraduate university degree or equivalent); ISCED 9 Education not definable by level. The vector X_{kH} also includes 5 age intervals 16-25, 26-35, 36-45, 46-55 and 56-65, gender, immigrant status and participation in adult education or training programs 12 months prior to the survey date. The latter filters out the effect of skill upgrading on individual residual scores. As explained in section 2.5, this is an important issue for the identification of the effect of skill dispersion on trade flows as (unobserved) trade shocks might have an impact on aggregate skill dispersion by changing incentives for skill upgrading at the individual level. Residual scores $\widehat{\varepsilon_{kH}}$ are constructed as $\widehat{\varepsilon_{kH}} = \log(s_{kH}) - X_{kH}\widehat{\beta_H}$, where $\widehat{\beta_H}$ is estimated by OLS.

As a result of focusing on log-scores, the scale of measurement of IALS scores does not affect the standard deviation of $\widehat{\varepsilon_{kH}}$ or $\log(s_{kH})$. Also note that, since X_{kH} in (2.6) contains a constant, the distribution of $\widehat{\varepsilon_{kH}}$ has the same (zero) mean in each country. For this reason, we do not normalize the standard deviation (or any inter-percentile range) by the mean in order to make cross-country comparisons of residual scores dispersion.

B.1.2 Measuring Wage Dispersion

Wage inequality measures are computed from a sample of full-time manufacturing workers, 16-65 years old, not living in group quarters, reporting positive wages and industry affiliation.[1] Following Dahl (2002), individuals were considered as 'full-time employed' if in 1999 they: (i) were not enrolled full time in school, (ii) worked for pay for at least ten weeks, and (iii) earned an annual salary of at least 2,000 dollars. We focus on the log of weekly wages, calculated by dividing wage and salary income by annual weeks worked. We use weekly wages as opposed to hourly wages, because it requires fewer assumptions to calculate it. In the 2000 Census, hours worked are reported as 'usual hours'. Using this variable to convert weekly wages into hourly wages would almost certainly result in the introduction of a source of measurement error. Incomes for top-coded values are imputed by multiplying the top code value ($175,000) by 1.5.[2]

In equation (2.7), vector Z_{ki} includes indicators for 4 categories of educational attainment,[3] a quartic polynomial in age, race and gender dummies (plus their interaction), Hispanic and immigrant dummies (plus their interaction) and state of residence dummies. Residual wages are constructed as $\widehat{\xi_{ki}} = \log(w_{ki}) - Z_{ki}\widehat{\beta}_i$, where $\widehat{\beta}_i$ is estimated by OLS.

Correcting for self-selection into industries is important in estimating equation (2.7), as the assumption that workers do not selectively search for jobs according to comparative advantage or unobservable tastes is relevant for Proposition 4. In the presence of self-selection the distribution of residual wages in any given industry would reflect not only the degree of skill substitutability in production but also workers' skill composition. For this reason, we use a selection estimator proposed by Dahl (2002). In equation (2.7), correcting for self-selection is complicated by the fact that individuals could choose to search for a job in any of the 63 industries of the manufacturing sector, potentially making the error mean, i.e. $E(\xi_{ki}|k$ *is observed in* $i)$, a function of the characteristics of all the alternatives. In this case, Dahl (2002) argues that under a specific sufficiency assumption,[4] the error mean is only a function of the probability that a person born in the same state as k would make the choice that k actually made (i.e. selecting into industry i), which can be estimated. The sufficiency assumption can be relaxed by including functions of additional selection probabilities; for this reason, Z_{ki} includes a cubic polynomial in

[1]Manufacturing employment excludes workers in private non-profit and government organizations.

[2]Since top codes vary by state, we follow Beaudry et al. (2007) and impose a common top-code value of $175,000.

[3]These are: (i) High school dropout, (ii) high school graduate, (iii) some college but no degree, (iv) college degree or higher.

[4]See Dahl (2002), page 2378.

the estimated first-best selection probability and in the highest predicted probability for k. Identification in this approach is based on the exclusion of state of birth by industry of employment interactions from equation (2.7).

To estimate selection probabilities, we group individuals into cells defined by state of birth[5] and a vector of discrete characteristics: 4 categories of education attainment, 4 age intervals (16-30, 31-40, 41-50, 51-65), race, gender and 2 binary indicators of family status (family/non-family household and presence of own child 18 or younger in the household). As in Dahl (2002), for every individual k, we estimate his selection probability into each industry j using the proportion of individuals within k's cell that are observed working in j, denoted by $\widehat{p_{kj}}$. Individual k's estimated first-best selection probability is $\widehat{p_{ki}}$ and k's highest predicted probability is given by $\widehat{p_{kj_*}}$, where j_* is such that $\widehat{p_{kj_*}} = \max\{\widehat{p_{kj}}\}\ \forall j$.

For the empirical analysis, the Census industry classification was matched to NAICS. It was not possible to match the trade data to Census codes directly, since the former is originally coded according to the Standard International Trade Classification (SITC rev.2). However, it is possible to use NAICS as a bridge between the two classifications. We construct a one-to-one mapping between the Census classification and NAICS by re-coding two or more 4 digit NAICS codes into a single industry (which does not necessarily match a 3 digit level). This re-coding also involves cases where two Census codes map perfectly into two NAICS codes -although originally there was no one-to-one matching between them. Importantly, the resulting mapping (available upon request) exhausts all manufacturing sectors in NAICS. Finally, the trade data was matched to wage inequality data using a concordance between SITC rev. 2 and NAICS, available through the NBER online database.

B.2 Additional Data

In this Appendix we provide a description of additional data sources used in the empirical analysis. Descriptive statistics for each variable can be found in table 8.

Bilateral export volumes at the industry level: From Feenstra et al. (2005), for the year 2000. Sector-level bilateral exports data are categorized at the 4-digit SITC (4-digit rev. 2) level. The mapping from SITC to NAICS required the concordance

[5] As in Beaudry et al. (2007), we keep immigrants in the analysis by dividing the rest of the world into 14 regions (or 'states' of birth).

available at the NBER website.[6]

Bilateral trade barriers: From HMR. This is a set of exporter-importer specific geographical, cultural and institutional variables. 1) *Distance*, the distance (in km.) between importer's and exporter's capitals (in logs). 2) *Land border*, a binary variable that equals one if and only if importer and exporter are neighbors that meet a common physical boundary. 3) *Island*, the number of countries in the pair that are islands. 4) *Landlocked*, the number of countries in the pair that have no coastline or direct access to sea. 5) *Colonial ties*, a binary variable that equals one if and only if the importing country ever colonized the exporting country or vice versa. 6) *Legal system*, a binary variable that equals one if and only if the importing and exporting countries share the same legal origin. 7) *Common Language*, a binary variable that equals one if and only if the exporting importing countries share a common language. 8) *Religion*, computed as (% Protestants in exporter $\times$ % Protestants in importer)+(% Catholics in exporter $\times$ % Catholics in importer)+(% Muslims in exporter $\times$ % Muslims in importer). 9) *FTA*, a binary variable that equals one if exporting and importing countries belong to a common regional trade agreement, and zero otherwise. 10) *GATT/WTO*, the number of countries in the pair that belong to the GATT/WTO.

Start-up regulation costs: From HMR. We use exporter-importer interactions of three proxies of regulation costs: the number of days ($RegDays_H \times RegDays_F$), number of legal procedures ($RegProc_H \times RegProc_F$) and relative cost as a percentage of GDP per capita ($RegProc_H \times RegProc_F$), for an entrepreneur to start operating a business.

Factor endowments: Physical capital endowment, $KEndow$, and human capital endowment, $SkillEndow$, are taken from Antweiler and Trefler (2002). A country's stock of physical capital is the log of the average capital stock per worker. The stock of human capital is the natural log of the ratio of workers that completed high school to those that did not. The measures used are from 1992, the closest year of which data are available. There's no data on factor endowments for four countries in our sample: Switzerland, Czech Republic, Hungary and Poland.

Factor intensities: From Nunn (2007). Originally coded as 1997 I-O industries, the mapping to NAICS required a concordance available from the Bureau of Economic Analysis.[7] Physical capital intensity, $KIntens$, is the total real capital stock divided by value added of the industry in the United States in 1996. Skill

[6] http://www.nber.org/lipsey/sitc22naics97/

[7] http://www.bea.gov/industry/xls/1997import_matrix.xls

intensity, *SkillIntens*, is the ratio of non-production worker wages to total wages at the industry level in the United States in 1996. There's no data on factor intensities for two industries: 'Furniture and related products manufacturing' and 'Sawmills and wood preservation'.

Proportion of top-coded wages: From the 2000 Census of Population in the U.S. For each industry, *TopCode* is calculated as the proportion of workers earning a wage exceeding the top code value of $175,000.

Firm size dispersion: From the 1997 Census of manufacturing in the U.S. For each industry, we calculate *FirmDisp*, the coefficient of variation in the average shipments per establishment across bins defined by employment size. The employment bins defined in the Census are: 1-4, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-999, 1000-2499 and 2500 employees or more.

Quality of the judicial system: From Nunn (2007) *JudicQual* is based on the "rule of law" measures originally from Kaufmann et al. (2003).

Labor law rigidity: From Tang (2008) *LaborRigid* is an index that summarizes firing and employment contract adjustment costs combined with measures of the power of labor unions. These measures are originally from Botero et al. (2004).

B.3 Additional Results

Table 15 reports estimates of the impact of skill dispersion as proxied by the dispersion of (raw) test scores: we identify this effect through an interaction with a (raw) wage dispersion ranking.[8] We show results based on three alternative measures of dispersion: the 95-5 interpercentile range divided by the average in column (1), the Gini relative mean difference (i.e. twice the Gini coefficient) in column (2) and the coefficient of variation in column (3).[9] Columns (1)-(3) add exporter, importer and industry dummies to our variables of interest; columns (4)-(6) include theoretically consistent exporter and importer-industry dummies, along with a vector of bilateral trade barriers described above.

[8] Raw measures are not purged of the effect of observable characteristics.

[9] We note that all three measures have a common structure in that the numerator is a measure of dispersion (the 95-5 interpercentile range, the standard deviation and the Gini mean difference) while the denominator is the average of the variable. Since we are using the logarithm of variables, the reason why we employ measures of dispersion divided by the average is not for rescaling, but rather to parsimoniously control for the effect that the interaction of the averages might have on trade flows.

In all specifications the estimated interaction $WageDisp_i \times SkillDisp_H$ shows a positive effect on exports, significant throughout at the 5% level. The reported coefficients imply that a one standard deviation increase in the value of the interaction raises log exports by anywhere between 3.5% and 6.5% standard deviations.[10]

Table 16 reproduces the structure of table 15 in terms of controls, but it separately reports the effect of the interaction $WageDisp_i \times SkillDisp_H$ (where the measure of dispersion is not divided by the average), as well as those of the interaction of average scores and average wages, $WageMean_i \times SkillMean_H$, and of the other two interactions, $WageDisp_i \times SkillMean_H$ and $WageMean_i \times SkillDisp_H$. The interaction of the averages is expected to capture standard factor proportions effects: on average, countries with more skilled workers specialize in sectors that employ skilled workers and have higher average wages. The interaction $WageMean_i \times SkillDisp_H$ is a flexible way to control for possible bias, due to differences in sectoral average wages, in the estimated effect of our interaction of interest. The interaction $WageDisp_i \times SkillMean_H$ plays a similar role.[11] In general, columns (1)-(6) suggest that the coefficient of $WageDisp_i \times SkillDisp_H$ is robust to the inclusion of all interactions: all estimates are similar to the ones in table 15 and, when trade barriers and importer industry dummies are included, significant at the 5% level. As for the other interactions, as expected $WageMean_i \times SkillMean_H$ has a strong and positive impact on trade flows. Moreover $WageMean_i \times SkillDisp_H$ is consistently positive, significant and large, while $WageDisp_i \times SkillMean_H$ is positive, but not always significant, particularly in columns (1)-(3). We note that the magnitudes of the impact of our variable of interest are similar in tables 15 and 16 to the ones in tables 4 and 5, indicating a substantial degree of robustness in our results.

[10] In regressions we do not report, we interacted all three measures of dispersion for wages and scores with one another obtaining results qualitatively and quantitatively similar to columns (1)-(6).

[11] This interaction relates to the theoretical prediction that increases in average skills not resulting from proportional changes also have an effect on comparative advantage. This effect depends on the degree of complementarity, approximated by $WageDisp_i$.

Appendix C

Appendix to Chapter 3

C.1 Data Sources

The data set used in the empirical analysis comes from a variety of sources. The firm-level data is comprised of manufacturing firms in Argentina, sampled in two Innovation Surveys carried out by I.N.D.E.C. (Argentina's National Statistical Agency). The first survey provides information for 1639 firms in 1992 and 1996, while the second survey collected information for 1688 firms in 1998 and 2001 (Bisang and Lugones 1998, 2003). These samples were randomly drawn from the National Economic Census of 1993 and from the Input–Output Matrix survey of 1997, respectively. The surveys provide information on sales of goods produced in the firm, educational attainment of employees, investments in innovation activities (including R&D) and ownership for the years 1992, 1996, 1998, 2001. There is also information on the geographical location (i.e. Argentine provinces) and the industry to which firms belong (at a 4-digit ISIC level).

I also use geographical data to account for differences in the institutional and economic environment in which firms carry out their activities and interact with each other. The data was collected by the Ministry of Economy and Production of Argentina, it is publicly available through the internet and includes population levels and several indicators of overall performance of the provincial economy and local government (see page 66).[1]

Finally, I constructed series of export prices for 4-digit ISIC industries using

[1] http://www.mecon.gov.ar/hacienda/dncfp/index.html

the NBER-U.N. Trade Data compiled by Robert C. Feenstra.[2] Since the latter was coded according to the SITC classification, the task also required matching SITC to ISIC industries. This was done with the help of a concordance provided by the O.E.C.D., available at Jon D. Haveman's website.[3] Following Schott (2004), the unit value of an SITC product was computed by dividing import value by import quantity.[4]

Before moving on to the description of the data, it is important to point out that the empirical analysis in this chapter is restricted to the subset of firms that were sampled in both surveys, 827 firms. The reason is that the estimation of a dynamic model of export decisions that accounts for unobserved firm heterogeneity requires the availability of at least three data points (see section 3.5), while each survey provides only two. As described above, the importance of previous export experience and firm heterogeneity as determinants of entry in export markets is well documented in the recent empirical literature.

However, restricting the analysis to a balanced panel may raise concerns of potential inferential biases due to ignoring both the attrition of firms from the First Survey and the appearance of a set of firms in the Second Survey that were not previously surveyed.[5] This trade-off is attenuated in this study due to the fact that, by design, the set of firms sampled in each survey were randomly drawn from two different sources (as mentioned above), a situation which resembles that of rotating panels. As shown in see Wooldridge (2002, p. 569), in rotating panels where the decision to rotate units out of the panel is made randomly, the identifying conditions required for obtaining consistent panel data estimators are the same regardless of whether the selected or a full (unrestricted) sample are used in the estimation. Additionally, the empirical analysis in this chapter is robust to systematic selection based on time-invariant and other observable characteristics of firms.

[2] The data is available at http://cid.econ.ucdavis.edu/

[3] http://www.macalester.edu/research/economics/PAGE/HAVEMAN/Trade.Resources /TradeConcordances.html

[4] For some years and products there are multiple country observations of value and quantity. In those cases, I follow Schott (2004) in defining the unit value to be a value-weighted average of the observations. Availability of unit values ranges from 77 percent of product-country observations in 1972 to 84 percent of observations in 1994.

[5] This issue appears to have received little attention in recent research. Clerides et al (1998) and Bernard and Jensen (2004) apply estimation methods that are similar to this paper, but using longer panels than in this study. However, both papers restrict their analyses to the set of firms sampled in every year, ignoring potential selection bias.