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Abstract

My dissertation consists of three chapters on topics in development, specifically education, and international trade.

In Chapter 1, I study how regional variation in information about the returns to a college education contributes to variation in college attainment across regions within the United States. There is a large dispersion in college attainment rates across regions in the US. In this paper, I show that the share of college educated in the local labor force acts as an information channel through which college age individuals learn about the returns to a college education. Using richly detailed individual level panel data I show that the responsiveness of the college attainment decision to the local college premium varies significantly with the existing share of college educated in the local labor force. This effect persists even when accounting for other channels studied in the literature like school quality. To understand the implications of local learning on the aggregate supply of skill, I present a model of endogenous skill acquisition with uncertainty and learning about the returns to skill from the existing share of skilled in the local labor force. Using this framework, I numerically show how this local learning channel can give rise to persistent dispersion in rates of skill acquisition across regions. Low skill traps arise when initial beliefs are low compared to the actual realization of the high skill wage.

In Chapter 2 of my dissertation, I study how non-tariff barriers to international trade affect the quality of exports from developing countries. Specifically, I study the impact of a change in the Rules of Origin imposed by the European Union (EU) on apparel exports from Bangladesh to the EU. Rules of Origin are a trade policy instrument that allows for tariff-free (or lower tariff) entry of exports from certain countries conditional upon those exports meeting a minimum value added requirement in the origin country. The change in the Rules of Origin imposed by the EU relaxed the sourcing restrictions on material inputs in the apparel sector. I find that instead of resulting in lower output prices as might initially be expected, there was an increase in the price of apparel exports from Bangladesh to the EU. I explain this observation in a setting that takes into account the quality of material inputs. Instead of lowering prices, firms upgraded the quality of material inputs sourced. Thus my work shows how stringent Rules of Origin can prevent firms in developing countries with limited

access to high quality inputs from upgrading the quality of their output, and climbing the quality ladder.

Chapter 3 of my dissertation is joint work with Marisol Rodríguez Chatruc at the Inter-American Development Bank. There is a growing literature which shows that shocks to international trade can have heterogenous effects across regions within a country. This literature takes two broad approaches. The first approach is reduced-form and consists of regressing changes in regional outcomes on measures of regional exposure to trade. The variation in these measures of regional exposure is primarily driven by variation in sectoral employment shares across regions. The second approach estimates structural general equilibrium models and quantifies the changes in regional outcomes in response to a trade shock through counterfactual exercises. We show that the reduced-form measures of regional exposure cannot be derived from a general equilibrium model even when only considering the partial equilibrium effect. Using Brazilian data on sub-country trade flows, we show that these analytical differences between the reduced form and theoretical measures of exposure translate into quantitative differences in the measures' correlation with model-based equilibrium wage changes in response to a trade cost shock. We also show that the rank correlation between the different measures of regional exposure are sensitive to the source country of the import cost shock. The results presented caution against relying too heavily on reduced-form exposure measures to recover partial elasticities of regional wages to an international trade shock.

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The research in Chapter 1 of the dissertation was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here do not necessarily reflect the views of the BLS.

Dedication

To Munnu.

Chapter 1

Regional variation in education attainment: The role of information about the returns to skill

1.1 Introduction

There is a large dispersion in college attainment rates across regions in the US[1]. Recent work finds that children's future education attainment outcomes are significantly affected by the neighborhood they grow up in (Chetty and Hendren (2018a,b)). How do neighborhoods where children grow up affect their future education outcomes? In this paper, I study how regional variation in information about the returns to a college education contributes to the observed variation in college attainment rates across regions in the US. Using richly detailed individual panel data, I provide evidence supporting that children learn about the returns to a college degree from the college educated workers in the region where they grow up. The more skilled workers in a region, the more children who grow up there learn about the returns to a college degree. This in turn has an impact on the children's own college investment and attainment decisions. I then build a model of endogenous skill acquisition with uncertainty about the returns to skill, where prior to the skill acquisition decision

[1] Disclaimer: This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here do not necessarily reflect the views of the BLS.

young workers learn about the returns to skill from the skilled old workers around them. Using this model, I show how local learning about the returns to skill can result in persistent regional dispersion in skill acquisition rates and rationalize the pattern we see in the data.

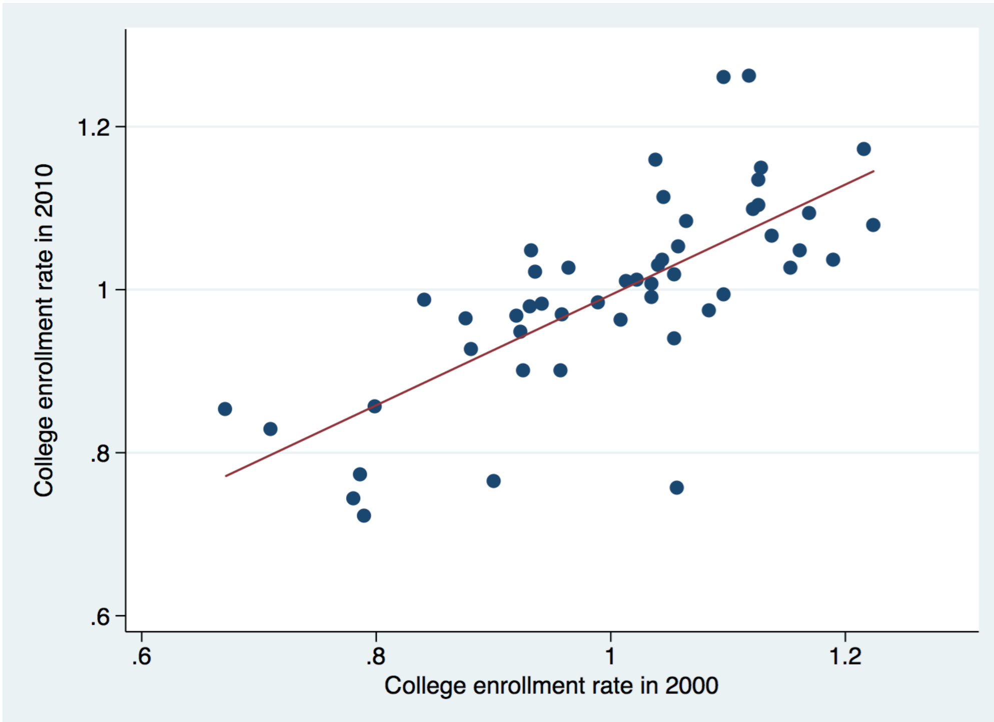
How do different regions in the US compare in terms of the production of college graduates? The focus of this paper is how different regions compare in terms of the future educational attainment of people who grew up there and not just the variation in educational composition of the working age population across regions. However, the data available to answer this question is sparse. There is substantial variation in college attainment rates of youth from different US states. In 2000, the share of high school graduates from a state that enrolled in college anywhere in the US was less than 45% in the bottom decile of US states and more than 65% in the top decile. While the college enrollment rate of high school graduates for the US as a whole has increased over time, from 56% in 2000 to 62% in 2010, the pattern of regional dispersion persists. Figure 1.1 is a scatter plot of the college enrollment rate of high school graduates from each state (relative to the US average) in 2000 and 2010. The state level college enrollment rates are highly correlated between 2000 and 2010, with a rank-rank correlation of 0.76 between the two years (NCHEMS Information Center).

Large spatial dispersion in future college attainment rates is observed even at lower geographies. Conditional on individual parent income, Chetty et al. (2014) find that the probability of college attendance ranges from less than 23% for a child from a commuting zone[2] in the bottom percentile to more than 68% for a child from a commuting zone in the top percentile[3]. Further, follow up work finds that the commuting zones themselves have a significant effect on the future outcomes of the children who grow up there (Chetty and Hendren (2018a,b)). That is, there are substantial effects on future education outcomes coming from the neighborhood where a child grows up. The question remains, *how* do neighborhoods where children grow up affect their future educational attainment?

[2]A commuting zone is an aggregation of counties that were constructed using commuting data to span the area where people live and work (Tolbert and Sizer (1996); David et al. (2013)). It is a widely used definition of a local labor market within the US.

[3]The probability of college attendance is the probability of college attendance for a child whose parent is at the 25th percentile of the national income distribution.

Figure 1.1: State level college enrollment rates in 2000 and 2010



There is a vast body of literature that thinks about the neighborhood effect on future outcomes of local children as arising from local human capital spillovers (Benabou (1996); Fogli and Guerrieri (2018)). That is, the skill composition in a region itself has an impact on the skill acquisition choices of local youth. These local human capital spillovers have primarily been modeled as either financial or social (Fogli and Guerrieri (2018)).

The financial channel models human capital spillovers as generating regional variation in school quality, which in turn generates regional variation in college attainment rates. School quality is an important determinant of college enrollment and attainment (Deming et al. (2014)). Public schools in the US are primarily funded through local property taxes. Higher income and better educated parents sort into neighborhoods with higher housing prices, and as a result, their children attend better schools which in turn has a positive impact on future college attainment.

The social channel refers to the direct or non-financial effect of the local skill composition on regional college attainment. These spillover effects have either been thought of as arising from a preference to adhere to local norms (Akerlof and Kranton (2002)) or from the existing skill composition itself being an input into the production of skill (Kim and Loury (2014); Benabou (1996)). In this paper I explore yet another channel through which the existing skill composition in a region has an impact on the skill acquisition choices - namely by providing *information* about the returns to a college education.

Recent work has found that the information about the returns to education is an important determinant of education investment decision. The perceived returns to education has a significant impact on actual educational investment decisions (Jensen (2010); Attanasio and Kaufmann (2014); Belfield et al. (2016)). Further, it has been documented that there is substantial heterogeneity in beliefs about returns to a college degree in the US and nearly 75% of household heads across the US underestimate the average returns to a college degree (Bleemer and Zafar (2018)). Bleemer and Zafar (2018) also find that providing information about the benefits of a college degree has a significant impact on college attendance expectations.

In this paper, I argue that one specific way in which local human capital spillovers can contribute to spatial variation in college attainment is by generating spatial variation in information about college returns. The existing share of high skilled in a local labor market itself acts as a channel that provides information about the returns to skill. The college investment decision responds to the skill premium in a local labor market (Charles et al. (2018)). The probability of college enrollment and attainment is larger, the larger the returns to college in the local labor market. This can be thought of as the local *college premium effect* on college attainment. When there is uncertainty about the skill premium, the impact of the local skill premium on college attainment would be weaker than otherwise. If children are learning about the local skill premium from the high skilled workers in the region where they grow up, then this would in turn make their skill acquisition decision *more* responsive to the local skill premium when they are of college going age. Using detailed individual level data, I show that this is indeed the case. That is, I show that the effect of the college premium on college attainment is larger when the share of college educated in the local region is higher. Individuals' college decision is more responsive to college returns when they grow up in a region with a higher existing share of college educated in the working age population.

In thinking about the effects of where children grow up on their future educational outcomes, it is important to observe both residential location at younger ages as well as future educational attainment. The primary dataset I use in my analysis is the restricted use version of the National Longitudinal Survey of Youth 1997 (NLSY97) collected by the Bureau of Labor Statistics. This allows me to observe the residential location of respondents at younger ages, their future educational attainment as well as a rich set of individual characteristics. I find that the impact of college returns on educational attainment is stronger when individuals grow up in a region with a higher existing share of college educated in the working age population even when controlling for individual factors that are important to the college investment decision and other widely studied channels through which local human capital spillovers manifest.

If college age individuals learn about the returns to skill from high skilled people in their local region, what does this imply for the relative supply of skill in a region? Can local learning about the returns to skill explain part of the observed persistence in the production of skill across regions? In order to understand the implications of a local learning effect on endogenous skill acquisition decision, I present a model of endogenous skill acquisition in the presence of uncertainty where, prior to the skill acquisition decision, workers in a region learn about the returns to skill from the existing share of high skilled in their region. The key element of this model is that workers are uncertain about the returns to skill and learn about it from the existing high skilled workers around them. I then present some numerical exercises to show how local learning about the returns to skill can result in the persistence of regional variation in skill acquisition (or skill production).

Why is it important to understand *how* local skill composition in a region affects the future education outcomes of children who grow up in that region? Understanding better the different mechanisms through which local skill composition affects education outcomes of local youth is important since each mechanism has different implications for welfare and policy analysis. Consider if the social channel of local human capital spillovers only works as is currently modeled in the literature, through peer effects, networks or some other interpretation that treats local skill composition as an input to the production of skill. In this case, the regional variation in education outcomes that arise as a result of social spillovers would be viewed as efficient. Policies that seek to reduce the regional variation in educational attainment might not be unambiguously welfare improving. If instead, as I argue in this paper, the local skill composition also provides college age individuals with information about the returns to skill, then policies that provide college age individuals with information about the returns to skill would reduce regional variation in education outcomes and be welfare improving.

Related Literature: This paper draws on insights from a growing body of experimental work that finds that the *perceived* returns to education has a significant impact on the educational investment decision. In a survey of eighth graders in the Dominican Republic, Jensen (2010) finds that the returns to secondary schooling as perceived by students are low relative to measured returns. A randomized intervention that provided information about the measured returns to schooling increased both the perceived returns as well as years of schooling completed. Similarly, a study conducted in Madagascar, Nguyen (2008) found that providing information about the returns to schooling improved school performance and test scores on average, and more so for students whose perceived returns were below measured returns. In the context of Mexico, Attanasio and Kaufmann (2014) also find that expected returns and risk perceptions are important determinants of actual schooling decisions. In the context of the US, Bleemer and Zafar (2018) find that baseline perceptions about college costs and benefits are substantially biased with larger biases among lower-income and non-college educated households. Overall, nearly two-thirds of household heads underestimate the college premium and providing information about the college premium has a significant impact on both revised beliefs about the college premium and college attendance expectations. In other work, Hoxby and Turner (2013) show that providing students with semi-customized information about application process and colleges' net costs causes high achieving low-income students to apply and be admitted to more colleges, especially those with high graduation rates and generous instructional resources.

This paper is also related to the vast literature that studies the relationship between regional variation in outcomes and local externalities. The local spillovers have been modeled in different ways. Fogli and Guerrieri (2018) models the local spillovers as a black box that can be interpreted as being driven as a financial or a social channel. Benabou (1996) builds a model of human capital accumulation to study the effect of school funding policies where local externalities take the form of both the financial channel (decentralized school expenditure) and a social channel which was modeled as young's acquisition of skills being affected by the social mix of neighboring families. Benabou (1996) stresses that disentangling the effects of the financial channel from the social spillovers is important, especially when considering the welfare effects of different school financing policies. Zheng (2017) studies the effect of different public school allocation mechanisms on intergenerational mobility in the presence of local spillovers that again arise from school quality and peer effects (social channel). While these and other papers in the literature (Fernandez and Rogerson (1998)) do distinguish between financial and social spillovers, the social spillover itself has been modeled either to represent an amalgam of or interpreted as different forms of social capital - peer effects, role models, norms and networks (Benabou (1996); Akerlof and Kranton (2002); Zheng (2017)). In contrast, this paper focuses on a very specific non-fiscal channel - namely how local skill composition has an impact on skill acquisition choices by providing information about the returns to skill.

Finally, Figueiredo (2018) also focuses on the role of uncertainty about the skill premium and local information transmission in governing skill acquisition choices. However, in her empirical results she uses college enrollment rates at the school district level. In contrast, I use detailed individual level data to show that the response of the skill acquisition decision to the skill premium varies with the share of high skill in a local region even when controlling for important individual level determinants of educational attainment such as race, gender, ethnicity, parental educational attainment and measures of parental income. Further, in my model I show that the local learning channel itself can generate persistent differences in skill acquisition rates across regions.

The paper is organized as follows. In section 1.2, I present my empirical evidence. Section 1.3 presents a model of endogenous skill acquisition in the presence of uncertainty and local learning about the returns to skill. I then present some numerical exercises to show how this information channel can give rise to persistence of regional variation in skill acquisition. The last section concludes.

1.2 Empirical Evidence

In this section I provide evidence to support the hypothesis that one way in which the local skill composition affects college attainment is by providing information about the returns to skill. That is, individuals learn more about the returns to college education when they grow up in regions where the existing share of college educated is high. While it is a challenge to identify the presence of an information channel explicitly in the data, I use richly detailed individual panel data that allows me to account for traditionally studied channels of local human capital spillovers such as school quality and important determinants like parental educational attainment. Further, with this data I am able to observe individuals both in the regions where they grow up as well as their future educational attainment irrespective of subsequent migration choices. I first briefly discuss the data I use and provides some descriptive statistics of relevant variables. I then present empirical evidence in support of my hypothesis.

1.2.1 Data Sources

The primary source of data I use is the restricted use version of the National Longitudinal Survey of Youth 1997 (NLSY97) collected by the Bureau of Labor Statistics, U.S. Department of Labor (2018). This individual-level longitudinal panel data set initially surveyed a random sample of 8,984 American youth born between 1980 and 1984. The respondents were age 13-17 at the time of the first interview in 1997. The survey collects data on a range of topics including educational attainment, income, employment, family characteristics and geography. The longitudinal nature of the dataset allows me to observe the educational attainment of the respondents at older ages. The restricted use version provides the geographic location of respondents for every round of the survey, which allows me to observe individuals' residential locations from younger ages, starting from at least 17 years old. Observing the residential location at younger ages, future educational attainment and a rich set of individual covariates allows me to isolate the effect of skill share in a location as an information channel about the skill premium. To construct measures of skill premium and share of college educated for each region, I use data from the Census Integrated Public Use Micro Samples (IPUMS) for the year 2000 (Ruggles et al. (2018)). I also use data on school expenditure per student, college tuition and number of colleges from the National Center for Education Statistics (Common Core of Data (NCES-CCD) and Integrated Post Secondary Education Data System (NCES-IPEDS)).

1.2.2 Definitions

In this section I define terms that are important for my subsequent analysis.

Local Labor Market: I define a local labor market within the US as a commuting zone. A commuting zone is a commonly used definition of a local labor market within the US since they have been constructed to span the area where people live and work (Autor et al. (2013a); Greenland and Lopresti (2016)). A commuting zone is an aggregation of counties created using county-level commuting data from the 1990 Census (Tolbert and Sizer (1996)). Across the US, there are 741 commuting zones that are characterized by strong commuting ties within CZs and weak commuting ties across CZs (Autor et al. (2013a)). I restrict my analysis to the 722 CZs that cover the entire mainland US.

Skilled Workers: I use two alternative definitions of skilled workers in the following analysis, depending on the skill acquisition that I am studying. I define skilled workers as those who have at least a 2-year associate degree and unskilled as those who have less education than that. I alternatively define skilled workers as those who have at least a 4-year bachelors degree and unskilled as those who have less education than that.

Composition adjusted skill premium: I use IPUMS data to construct the composition adjusted college premium in each commuting zone in 2000. I use wages per hour of workers aged 24 - 54 years old who are not self employed and worked atleast 40 weeks in the past year. To get the composition adjusted wages and college premium, I regress log wages on worker characteristics for each commuting zone and skill level.

$$\log(w_{ics}) = \beta_{cs} + \Gamma_{cs} X_{ics} + \epsilon_{ics}$$

where the dependent variable is log wage per hour of worker i in commuting zone c. X_{ic} is a vector of individual characteristics - indicators for race, gender, US born, ethnicity and age. I divide workers into age bins : 24-30, 31-40, 41-50, 51-55. Using the estimates from these regressions, I then construct the composition adjusted skill premium in each commuting zone.

Childhood commuting zone: A key requirement to see the effect of childhood location on future educational attainment is to observe *both* where a child grows up as well as his future educational attainment. The NLSY97 data allows me to observe the location of each individual in my sample starting earliest at age 13. In the following analysis, I define childhood commuting zone as the commuting zone of residence when the respondent is first interviewed in 1997, i.e. between the ages of 13-17. As I will discuss later, the results presented are robust to alternative definitions of origin commuting zones.

1.2.3 Empirical Results

In this section I show that one way in which the local skill composition affects children's college attainment is by providing information about the returns to skill. Existing literature documents that the probability that an individual goes to college is larger, the larger the skill premium in the local labor market when the individual is around college going age (Charles et al. (2018)). Further, Charles et al. (2018) show that the local skill premium at college going age has not only an impact on immediate college going probability, but also a persistent impact on future college attainment.

I find that the effect of local skill premium (at college going age) on an individual's college attainment probability additionally varies with the existing share of skilled in the local labor market where the individual grew up. That is, the larger the existing share of skilled in the local labor market, the more responsive is local youth's skill

acquisition decision to the local skill premium. Using richly detailed individual level data, I show that individual's college decision is more responsive to the skill premium when they grow up in a region with a higher existing share of skilled workers.
To illustrate my point clearly, I run and compare the following regression specifications:

$$\mathbb{1}(\text{college by 23})_{ic_o} = \alpha_0 + \alpha_1 \log\left(\frac{w_{Hc_o}}{w_{Lc_o}}\right) + \alpha_2 \log\left(\frac{H_{c_o}}{P_{c_o}}\right) + \Gamma X_{ic_o} + \epsilon_{ic_o}$$

$$\begin{aligned}\mathbb{1}(\text{college by 23})_{ic_o} &= \hat{\alpha}_0 + \hat{\alpha}_1 \log\left(\frac{w_{Hc_o}}{w_{Lc_o}}\right) + \hat{\alpha}_2 \log\left(\frac{H_{c_o}}{P_{c_o}}\right) \\ &\quad + \hat{\alpha}_3 \log\left(\frac{w_{Hc_o}}{w_{Lc_o}}\right) \times \log\left(\frac{H_{c_o}}{P_{c_o}}\right) + \hat{\Gamma} X_{ic_o} + \epsilon_{ic_o}\end{aligned}$$

The dependent variable is an indicator of whether an individual i with childhood or origin commuting zone c_o has completed a college degree (associates or bachelors degree) by age 23. $\log\left(w_{Hc_o}/w_{Lc_o}\right)$ is the log of the degree specific skill premium in commuting zone c_o, in the year 2000 - when the individuals in my sample are around college going age - 16-20 years old. $\log\left(H_{c_o}/P_{c_o}\right)$ is the log of the share of skilled in the local labor force in commuting zone c_o in the year 2000. The key focus of the above specifications is to discern how these specific conditions in the labor market where children grow up affect their future educational attainment while also taking into account other channels that affect the probability of college attainment. X_{ic_o} is a vector of individual and region level controls that are correlated with educational attainment and help me account for the other channels that affect the probability of college attainment. I will further describe X_{ic} as I present the results.

In the specification without the interaction term, the coefficient α_1 captures the average effect of the skill premium in the origin commuting zone c_o when individual is college going age on the probability of future degree attainment of an individual who grew up in that commuting zone. α_2 captures the average effect that the share of high skilled people in a commuting zone might have on the future degree attainment of children who grow up in that commuting zone.

However, in the specification with the interaction term, the coefficient $\hat{\alpha}_1$ captures the effect of the skill premium in the origin commuting zone c_o when the existing share of high skilled in that commuting zone is equal to 1, i.e. $H_{c_o}/P_{c_o} = 1$, $\log(H_{c_o}/P_{c_o}) = 0$. Analogously, the coefficient $\hat{\alpha}_2$ captures the effect of the existing share of high skilled in the origin commuting zone on the probability of college attainment when the existing local skill premium is equal to 1, i.e. $(w_{Hc_o}/w_{Lc_o}) = 1$, $\log(w_{Hc_o}/w_{Lc_o}) = 0$. The primary object of interest is $\hat{\alpha}_3$, the coefficient of the interaction term between local skill premium and local skill share. A value of α_3 significantly different from zero indicates that the effect of the origin skill premium around college going age on future educational attainment additionally varies with the existing share of high skilled in that region. A positive value of α_3 indicates that the effect of the origin skill premium around college going age is stronger when the share of high skilled in that region is larger.

If children are learning about the local skill premium from the high skilled workers in the labor market where they grow up (around college age), making their skill acquisition decision more responsive to the local skill premium (at college going age), then $\hat{\alpha}_3$ would be positive and significantly different from zero. In other words, individuals' college decision is more responsive to the existing skill premium during their college decision age when they grow up in a region with a larger share of high skilled in the local labor force.

Table 1.1 above presents the results of the linear specification of the above two regressions. In columns (1) and (2) the dependent variable is an indicator that equals one if individual i with origin commuting zone c_o completed at least an associate degree by the age of 23. In columns (3) and (4) the dependent variable is an indicator that equals one if individual i completed at least a bachelor's (4-year) degree by age 23. In each case, I regress the degree specific dependent variable (for individual i with origin commuting zone c_o) on the degree specific skill premium and skill share in the origin commuting zone c_o in the year 2000, when individual i is between $16-20$ years of age[4].

In Panel A of Table 1.1 I control for baseline individual level covariates. I control for race, gender and ethnicity. As a proxy for individual ability, I include individuals's

[4] I calculate the degree specific skill premium as follows. If the dependent variable is the indicator for at least a bachelors degree, then skilled workers are those with at least a bachelors degree and unskilled workers are those with less education than that.

Table 1.1: Probability of degree attainment - OLS specification

Dependent Variable: Indicator for degree attainment by age 23				
	$\mathbb{1}(\geq$ associate's degree)		$\mathbb{1}(\geq$ bachelors degree)	
	(1)	(2)	(3)	(4)
Panel A: Baseline controls				
log(skill premium$_{c_o}$)	0.200**	1.127***	0.236***	1.266***
	(0.092)	(0.302)	(0.081)	(0.274)
log(skill share$_{c_o}$)	0.028	$-$0.284***	0.011	$-$0.289***
	(0.031)	(0.096)	(0.020)	(0.073)
log(skill premium$_{c_o}$)× log(skill share$_{c_o}$)		0.945***		0.799***
		(0.298)		(0.202)
# of observations	8353	8353	8353	8353
Panel B: Baseline and school quality controls				
log(skill premium$_{c_o}$)	0.185*	1.168***	0.299***	1.207***
	(0.097)	(0.317)	(0.076)	(0.264)
log(skill share$_{c_o}$)	0.014	$-$0.303***	$-$0.011	$-$0.288***
	(0.025)	(0.098)	(0.018)	(0.069)
log(skill premium$_{c_o}$)× log(skill share$_{c_o}$)		0.989***		0.751***
		(0.295)		(0.191)
# of observations	7439	7439	7439	7439

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;
Standard errors are clustered at state level

percentile score on the Armed Services Vocational Aptitude Battery which was administered to respondents in the NLSY97 sample in Round 1 of the survey[5]. This

[5]In Round 1 of the survey, respondents in the NLSY97 sample were aged 13-17 years old. The ASVAB was uniformly administered to all respondents in the sample. However, respondents could opt out of the test. Test scores are not available for 21% of the total sample. I include an indicator

is a summary percentile score variable constructed from results on four subtests which cover both verbal and math abilities[6]. Additionally, in the baseline, I control for the educational attainment of each respondent's parent (less than high school, high school completed, 1-3 years of college and ≥ 4 years of college).

In columns (1) and (3) of Panel A, local skill premium has a positive and significant effect on degree attainment even when controlling for both parental educational attainment and individual ability. In particular, a 10% increase in the local skill premium (degree specific), is associated with a 1.9 percentage point increase in the probability of completing at least an associate degree by age 23 and a 2.2 percentage point increase in the probability of completing at least a bachelors degree by age 23. Note that in columns (1) and (3), the estimate captures the *average* effect of local skill premium on the probability of future degree attainment across all commuting zones.

However, in columns (2) and (4) of Table 1.1 Panel A, I allow for the effect of local skill premium on future degree attainment to vary with the existing share of skilled workers in the commuting zone. Here the coefficient on the interaction term is positive and significant in both cases. The effect of origin skill premium around college going age on individual's future degree attainment is larger, the larger the existing share of skilled workers in the commuting zone. The existing skill share in the origin commuting zone amplifies the effect of the origin skill premium on an individual's probability of degree attainment. For a 10% increase in local skill premium, the probability of completing at least an associate degree (bachelors degree) by age 23 rises by ~ 2.9 (~ 2.68) percentage points more when individuals grow up in commuting zones at the 75th percentile compared to the 25th percentile of the skill share distribution across commuting zones[7]. I see that this amplification effect persists, even when controlling for each individual's ability (proxied by ASVAB test score) and the educational attainment of parents.

One concern with the results in the baseline specification of Panel A is that the

for missing ASVAB test score in my regressions.

[6]The four subtests are on Mathematical Knowledge (MK), Arithmetic Reasoning (AR), Word Knowledge (WK) and Paragraph Comprehension (PC).

[7]75th percentile compared to the 25th percentile of the degree specific skill share across all 722 commuting zones in the mainland US.

positive effect on the interaction term (i.e. the amplification effect) could reflect an alternative explicit channel through which the existing share of skilled workers in a commuting zone affects the probability of future degree attainment of children from that commuting zone - namely by affecting school quality. School quality is an important determinant of future college attainment (Deming et al. (2014)). A higher quality school might not only improve academic achievement but also do a better job of informing students about the costs and benefits of their various career options which in turn would make their college attainment decision more sensitive to the existing skill premium. Public schools in the US are primarily funded through local property taxes. If better educated and wealthier parents sort into communities with higher housing values, then it could be that the positive interaction term in the baseline specification of Panel A is actually picking up the effect of higher school quality on the probability of future degree attainment. To account for this channel, I control for school quality using three main measures - county level school expenditure per student, individual level school type (public, private, parochial or other) and the teacher to student ratio in the individual's school by age 16. The results of the specification that includes school quality controls is given in Panel B of Table 1.1. The magnitudes and significance level of the coefficients of interest are unchanged. Even when controlling for individual level school quality, the effect of the origin commuting zone skill premium on future degree attainment of children who grew up in that commuting zone is larger when the existing share of skilled workers in that commuting zone is larger. The existing share of skilled workers in a commuting zone amplifies the effect of local skill premium on future degree attainment of children who grew up in that commuting zone.

The results presented in Table 1.1 above are from a linear probability specification. The results are robust to the logit specification as well. To make the interpretations of the results clear, the figures below provide a visual representation of how the effect of the skill premium in the origin commuting zone on the future degree attainment of children from that commuting zone varies with the existing share of skilled workers in the commuting zone. The results in Figure 1.2 are from the logit specification of the regressions. The coefficient estimates of the logit specification are provided in Appendix (A.1.2).

Figure 1.2: Marginal effects of skill premium on the probability of college attainment

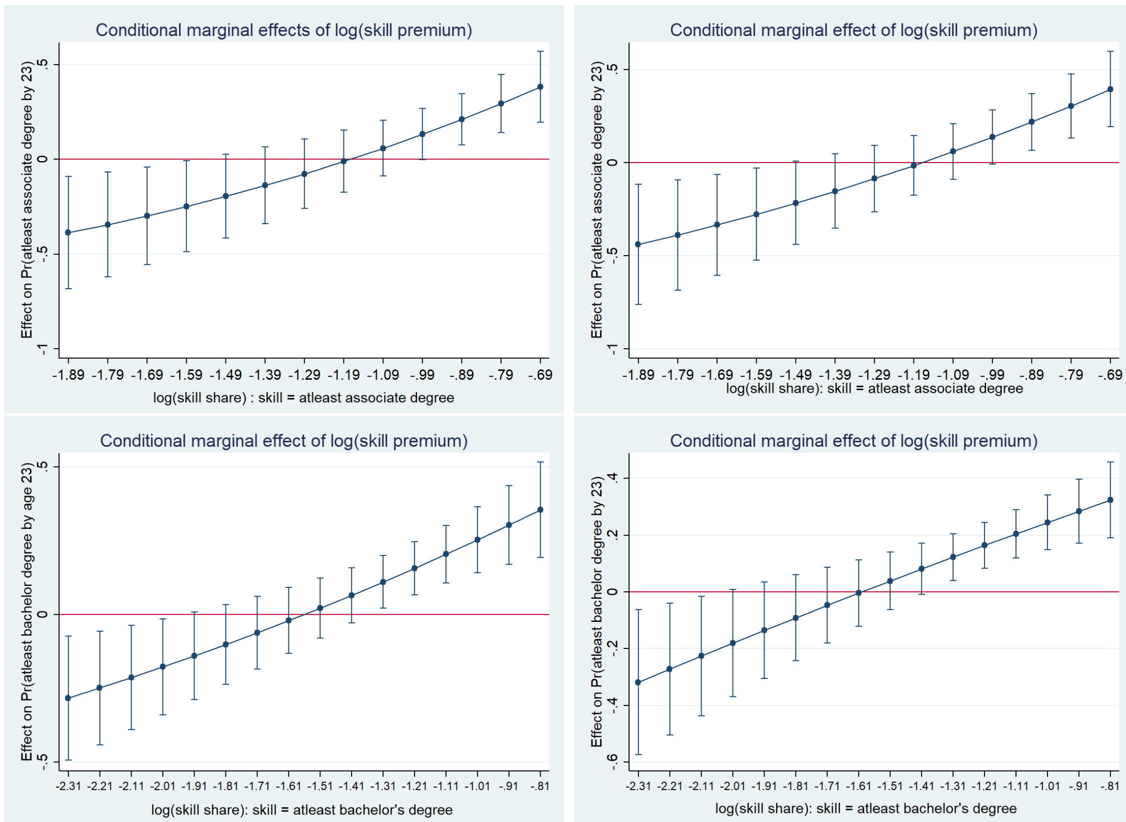


Figure 1.2 presents the marginal effect of origin commuting zone skill premium on the probability of future degree attainment for each level of existing share of skilled workers in that commuting zone, holding other covariates at sample means. Subfigures (a) and (b) in the first row present results when the dependent variable is an indicator of having completed at least an associate degree by the age of 23. Subfigures (c) and (d) in the second row of Figure 1.2 present results when the dependent variable is an indicator of having completed at least a bachelors' degree by the age of 23. The subfigures in the left column ((a) and (c)) present the estimates from the baseline specification described in Panel A of Table 1.1 and the figures in the right column ((b) and (d)) present the estimates from the specification in Panel B of Table 1.1, which includes school quality controls.

In all the subfigures one clear pattern emerges. The marginal effect of origin region skill premium on the probability of degree attainment is increasing in the existing share of skilled workers in the region and strictly positive and significant for larger values of existing local skill share. Further, in both cases, the magnitude of the effect is similar even when I control for measures of school quality (compare left and right column). Thus, even when controlling for individual level school quality, the existing share of skilled workers in a region seems to amplify the effect of the skill premium on the probability of degree attainment of individuals who grow up in that region.

When the dependent variable of interest is the probability of completing at least associate's degree by age 23, the threshold level skill share above which the marginal effect of the skill premium is positive and significantly different from 0 is approximately 41%[8]. The amplification effect of the existing share of skilled prevails even when the dependent variable is the probability of completing at least a bachelors' degree by age 23. Here, the marginal effect of the origin skill premium is not significantly different from zero for low values of existing skill share. However, when the existing share of skilled workers is above 27% (approximately the 75th percentile of the skill share distribution across commuting zones in the US), then the marginal effect of the origin skill premium on the probability of completing at least a bachelors degree by age 23 is positive and significantly different from zero. The figures corroborate that the the responsiveness an individual's college attainment decision to the local skill premium (when the individual is around college going age), is increasing in the existing share of skilled workers in the region. Importantly, this effect persists even when controlling for a rich set of individual level covariates that are positively associated with the probability of degree attainment and also accounting for a widely studied channel of human capital spillovers - namely school quality.

Table 1.2 below shows that my results are robust even when accounting for alternative channels of human capital spillovers and other factors that affect the probability of degree attainment. One of the factors that can affect the probability of degree attainment is access to colleges. If the local availability of post secondary education is low and young people have to move to a different commuting zone in order to go to college, then this would in turn reduce the probability of degree

[8] $\exp(-0.89) \approx 0.41$

attainment. Additionally, the college attainment decision can also be influenced by a preference to adhere to local norms - which is one way in which the literature models social spillovers or the direct effect of local skill composition on regional college attainment. As a proxy for these peer effects, I use individual level expectations about the percentage of peers who would go to college[9]. I control for the local availability of post secondary education or college using Chetty et al. (2014) measure of number of colleges per capita at the county level[10]. Additionally I also include a coarse measure - indicator of parental home ownership - to control for parental income. From Table 1.2 below one can see that the estimates of the coefficient on the interaction term remains positive and significant. Thus, the effect of local (origin) skill premium on the probability of degree attainment continues to vary with the existing share of skilled workers in the local (origin) region.

Table 1.2: Probability of Degree Attainment

Dependent Variable: Indicator for degree attainment by age 23				
	$\mathbb{1}(\geq$ associate's degree)		$\mathbb{1}(\geq$ bachelors degree)	
	(1)	(2)	(3)	(4)
Panel C: Baseline, school quality, college access, parent income and peer effects				
log(skill share$_{c_o}$)	0.208^{**}	1.167^{***}	0.241^{***}	1.220^{***}
	(0.098)	(0.334)	(0.076)	(0.264)
log(skill share$_{c_o}$)	0.035	-0.275^{**}	0.000	-0.276^{***}
	(0.030)	(0.107)	(0.020)	(0.078)
log(skill premium$_{c_o}$)× log(skill share$_{c_o}$)		0.961^{***}		0.748^{***}
		(0.312)		(0.207)
# of observations	7439	7439	7439	7439

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;

[9]These responses were collected in Round 1 of the NLSY97 survey when respondents were between 13-17 years old

[10]This is constructed using NCES data

1.2.4 Discussion

In the section above, I show that the effect of skill premium in a commuting zone on the probability of college attainment of individuals who grew up in that commuting zone additionally varies with the existing share of skilled workers in that commuting zone. Notably, I show that this effect persists even when controlling for important individual level determinants of post secondary educational attainment. This pattern in the data, particularly when controlling for individual ability and parent education attainment, cannot be reconciled by existing literature that studies the effect of local skill composition on local college attainment. As mentioned in the introduction, the two main ways in which existing literature models the effect of local skill composition on local college attainment is either through the financial channel, by having an impact on school quality or through the social channel, where the local skill composition is modeled as itself being an input into the production of skill or through arising from a preference to adhere to local norms (Fogli and Guerrieri (2018); Figueiredo (2018)). However, even when accounting for the financial channel (i.e. individual level school quality), I find that this effect persists. While the social channel should be captured by just the existing share of high skilled in a region, I further proxy for it by controlling for individual expectations about peers' future college attainment.

The fact that the responsiveness of an individual's college decision to the local skill premium at college going age varies with the existing share of skilled workers in that region can be explained if the individual learns about the skill premium from high skilled workers in her region. That is, if children are learning about the local skill premium from high skilled workers in the region where they grow up, this would in turn make their skill acquisition decision *more* responsive to the local skill premium when they are at college going age.

Why is it important to understand *how* the local skill composition in a region affects the future educational attainment of children who grow up in that region? Understanding better the different mechanisms through which the local skill composition affects future educational attainment of children who grow up in that region and hence generates spatial variation in educational attainment is important since the different mechanisms have different implications for policy analysis. Benabou (1996) shows how it is important to disentangle the effects of school quality (i.e. financial spillovers) from direct or social spillovers since the relative importance of the two mechanisms have different implications for optimal school finance reform (Fogli and Guerrieri (2018)). Further unpacking social spillovers is similarly important.

Suppose that the social channel of human capital spillovers only works as is currently treated in the literature, as the existing local skill composition itself being an input to the production of skill, either by raising individual ability or by lowering the cost of skill acquisition. Here, the resulting regional variation in educational attainment would be viewed as efficient. If the objective of policy is to reduce spatial variation in education attainment, then the mechanism described above would imply investing in improving individual ability (i.e. by improving school quality) or reducing the cost of skill acquisition in regions that are disadvantaged. However, when local skill composition acts as an information channel about the returns to skill, as indicated by the evidence above, then some part of the observed spatial variation in education attainment arises from the variation in information about college returns. In this case, one way to reduce spatial variation in educational attainment is to reduce spatial variation in *information* about college returns. Thus, the presence of this information channel calls for investing in policies that provide information to college age individuals about the returns to college. Moreover, interventions that seek to improve information about college returns could possibly be undertaken at lower cost than those that seek to raise academic achievement (i.e. by improving school quality). For instance, Hoxby and Turner (2013) find that interventions that provide students with semi customized information on the college application process and net costs, costs about $6 per student. Thus understanding how the local skill composition in a region impacts the probability of college attainment is important, since each mechanism has different implications for policy analysis.

For the results provided in the main text of the paper, the analysis was conducted at the commuting zone level. As mentioned before, a commuting zone is an aggregation of counties constructed using county-level commuting data from the 1990 Census (Tolbert and Sizer (1996)). It is a commonly used definition of a local labor market in the US. I use commuting zones as the geographic unit of analysis because the object of interest is the effect of the skill premium in the local labor market where an individual grew up on individual's future educational attainment. Given that commuting zones were constructed to span the area where people live and work, commuting zone level skill premium is the most appropriate one facing an individual making a skill acquisition decision.

Further, by using the share of skilled workers in the local labor market as an information channel through which college age individuals learn about the skill premium, I additionally allow college age individuals to learn about the skill premium from their low skilled parents who might work in skill intensive industries in the local labor market (i.e. at the commuting zone level).

Another alternative definition of local labor markets in the US is the MSA. I do not use this as the geographic unit of analysis in the main text since approximately 22% of my sample resides outside an MSA at the start of the data in 1997. That, coupled with the availability of records on individual covariates would restrict my sample to too few observations, precluding meaningful detailed analysis at the MSA level. However, the baseline results presented in the main text are robust to analysis at the MSA level. The results of the MSA level analysis are presented in Appendix A.1.3.

Further, in order to maximize the number of observations used in analysis, in the main text I define childhood or origin commuting zone as the individual's commuting zone of residence at the time of the first interview in 1997. However, the results are robust to stricter definitions of origin commuting zone. The results go through even when I restrict analysis to individuals who have resided in the same commuting zone from the time of the first interview until age 16. The results are presented in Appendix A.1.4.

1.3 A Model of Skill Acquisition Under Uncertainty

The empirical evidence from the previous section supports the hypothesis that one way in which local skill share impacts the production of new skill is by providing young workers with information about the returns to skill. Specifically, even when controlling for important individual and community level determinants of the skill acquisition decision, the existing skill share in a region amplifies the effect of the skill premium on the skill acquisition decision.

If college age individuals learn about the returns to skill from the high skilled people in their local region, what does this imply for the relative supply of skill in a region? Does this local learning channel contribute to explaining the observed persistent regional variation in college attainment rates? To understand the implications of this local learning channel on the future supply of skilled workers in a region, I present a model of endogenous skill acquisition with uncertainty and local learning about the returns to skill that can rationalize the pattern observed in the data.

1.3.1 Environment

The model is set in discrete time with periods indexed by t. Consider an economy with $\mathcal{R}$ regions. Workers can be of two types, high skilled (H) and low skilled (L). In the rest of this section I will use H and L to denote both the type of worker and the mass of workers of each type. Each region $r \in \mathcal{R}$ produces only one product which combines both high and low skill labor in a linear production function. Workers are lived for two periods. In the first period of life, workers are young. Young workers make skill acquisition decision, supply labor and consume. In the second period of life, workers are old and retired. They do not supply labor and also do not consume anything. Their existence only determines what young workers learn about the high skill wage.

1.3.2 Production

Each region $r \in \mathcal{R}$ produces a good Y by combining both low and high skill labor in a linear production function.

$$Y_r = A_{Lr}E^L + A_{Hr}E^H \tag{1.1}$$

where E^L and E^H are effective units of low and high skilled labor respectively. A_{Lr} is the productivity of one effective unit of low skilled labor in region r and is fixed (and known by everyone). A_{Hr} is the productivity of one effective unit of high skill labor in region r. A_{Hr} is a one time productivity draw from a log normal distribution with mean μ_H and variance σ_H^2, i.e. $\log(A_{Hr}) \sim N(\mu_H, \sigma_H^2)$. I denote the *realized* high skill productivity draw as A_{Hr}^*.

With a linear production function, and competitive labor (and goods) markets, in equilibrium:

$$w_{Lr} = A_{Lr} \qquad w_{Hr} = A_{Hr}^* \qquad p = \text{marginal cost} = 1 \tag{1.2}$$

where w_{Lr} is the wage per effective unit of low skill labor and w_{Hr} is the wage per effective unit of high skill labor. Since productivities A_{Lr} and A_{Hr}^* are constant over time in this setup, in equilibrium wages and prices will also be constant over time. The simplification of the production side allows us to focus on the effect of local learning about returns to skill on the endogenous skill acquisition decision in a tractable manner. On the production side, a region is thus characterized by the low skill labor productivity A_{Lr} and a one time draw of high skill labor productivity A_{Hr}^*, drawn from $\log N(\mu_H, \sigma_H^2)$[11].

1.3.3 Workers' Problem

At the start of period t, each region $r \in \mathcal{R}$ has a mass H_{rt}^o and L_{rt}^o respectively of high and low skilled old workers, and a mass M_{rt} of low skilled young workers, where:

$$M_{rt} = H_{rt}^o + L_{rt}^o$$

That is, the mass of young workers in period t is equal to the total mass of old workers. There is no population growth in the model. Young workers are "born" low skilled and have to make a skill acquisition decision (whether to become high skilled or not) and a consumption decision. The preferences of the worker are:

$$U(c) = \frac{c^{1-\eta} - 1}{1 - \eta} \tag{1.3}$$

[11] An alternative way of saying this is that every region r has a fixed low skill wage w_{Lr} and draws a wage w_{Hr}^* from a distribution $w_{Hr} \sim \log N(\mu_H, \sigma_H^2)$.

where c is the consumption of the good. The utility function is CRRA with risk aversion parameter η. Given good price p and total income I, the optimal indirect utility of a worker is given by:

$$V(I,p) = \frac{(I/p)^{1-\eta} - 1}{1-\eta} \tag{1.4}$$

Young workers are born low skilled and draw an ability $\gamma \sim G(.)$. The ability distribution $G(.)$ is Pareto with scale parameter ξ and shape parameter ψ.

$$G(\gamma) = 1 - \left(\frac{\xi}{\gamma}\right)^{\psi}$$

The ability of the worker (γ) determines the cost of becoming high skilled. Young workers know that if they choose to be low skilled, they supply one effective unit of labor and earn total income w_{Lr}. However, if they choose to become high skilled, they supply $1/c(\gamma)$ effective units of labor (where $0 \leq (1/c(\gamma)) \leq 1$) and earn the high skill wage per effective unit of labor supplied. However, while making the skill acquisition decision young workers are uncertain about the high skill wage in region r (w_{Hr}) and learn about it from the high skilled old workers in the region. Workers then form expectations of the utility from being high skilled and make a skill acquisition decision. In the next section, I describe in detail how young workers learn about the high skill wage and form expectations about the return to being high skilled.

1.3.3.1 Learning about the high skill wage

In each period t, prior to the skill acquisition decision, young workers in region r are uncertain about the high skill wage realization in their region (w_{Hr}). Young workers in region r have initial beliefs that high skill wage is distributed log normal with mean μ_H and variance σ_H^2, i.e. $\omega_{Hr} \sim N(\mu_H, \sigma_H^2)$, where $\omega_{Hr} = \log(w_{Hr})$.

Each young worker in region r then learns something about the high skill wage in their region. Specifically, each young worker observes an idiosyncratic signal s_{Hr} of the high skill wage realization, where the signal $s_{Hr} \sim N(\omega_{Hr}^*, \sigma_{srt}^2)$ and $\omega_{Hr}^* = \log(A_{Hr}^*)$. That is, the signal distribution is centered around the log of the realized high skill labor productivity A^*_{Hr} (recall $w^*_{Hr} = A^*_{Hr}$). I assume that the variance of the signal distribution in a region, σ^2_{srt} is decreasing in the share of high skilled old workers in the region in period t. That is, the larger the share of high skilled among old workers, the lower the variance of the signal distribution and the more informative the signal received by young workers about the high skill wage realization. Thus, in region $r \in \mathcal{R}$ in each period t, the signal s_{Hr} is distributed:

$$s_{Hr} \sim N(\omega^*_{Hr}, \sigma^2_s(h^o_{rt}))$$

where $h^o_{rt} = \frac{H^o_{rt}}{M^o_{rt}}$ and $\frac{\partial \sigma^2_s(h^o_{rt})}{\partial h^o_{rt}} < 0$.

Upon receiving the idiosyncratic signal s_{Hr}, young workers update their beliefs about the high skill wage realization using Bayes' rule. Given initial beliefs, and signal s_{Hr}, a young worker in region r in period t has posterior belief that the high skill wage in region r is distributed log normal with mean $\hat{\mu}_{Hrt}$ and variance $\hat{\sigma}^2_{Hrt}$, i.e. $\hat{\omega}_{Hrt} \sim N(\hat{\mu}_{Hrt}, \hat{\sigma}^2_{Hrt})$ where:

$$\hat{\mu}_{Hrt} = \frac{\sigma^2_s(h^o_{rt})}{\sigma^2_H + \sigma^2_s(h^o_{rt})}\, \mu_H + \frac{\sigma^2_H}{\sigma^2_H + \sigma^2_s(h^o_{rt})}\, s_{Hr} \tag{1.5}$$

$$\hat{\sigma}^2_{Hrt} = \left[\sigma^{-2}_H + (\sigma_s(h^o_{rt}))^{-2}\right]^{-1} \tag{1.6}$$

Given the signal structure and process of learning by young workers, each region r in period t can be summarized by θ_{rt} where:

$$\theta_{rt} = \left\{A_{Lr}, A^*_{Hr}, \mu_H, \sigma^2_H, h^o_{rt}\right\}$$

In each period t, region is characterized by the productivity of low and high skill labor in the region (A_{Lr} and A^*_{Hr}), the distribution of initial beliefs of the young workers (summarized by μ_H and σ^2_H) and the share of high skilled in the mass of old workers (h^o_{rt}) which governs the variance of the signal distribution.

However, as mentioned before, prior to making the skill acquisition decision, young workers are uncertain about the high skill wage in region r (w_{Hr}). Thus the information set of young workers in region r can be summarized by θ^y_{rt} where:

$$\theta^y_{rt} = \left\{A_{Lr}, \mu_H, \sigma^2_H, h^o_{rt}\right\}$$

How young workers learn and form expectations about the returns to skill, prior to making the skill acquisition decision, is summarized in the Figure 1.3.

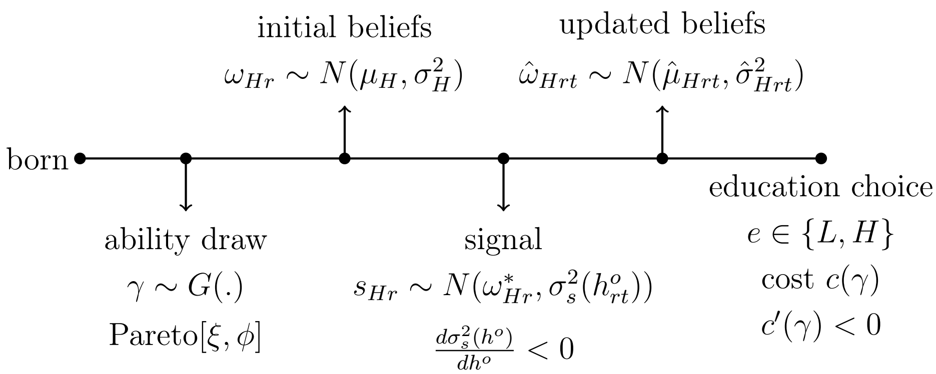


Figure 1.3: Timing of Workers' Problem

1.3.3.2 Expectations about the returns to skill

After receiving a signal s_{Hr} about the realized high skill wage w^*_{Hr}, the expected utility from being high skilled for a worker with ability γ in region r in period t is given by:

$$\begin{aligned}
\mathbb{E}_{\hat{w}_{Hr}}\left[V^H\left(\gamma, \hat{w}_{Hr}, p\right)\middle| s_{Hr}, \theta^y_{rt}\right] &= \mathbb{E}_{\hat{w}_{Hr}}\left[\frac{1}{1-\eta}\left(\left(\frac{\hat{w}_{Hr}}{c(\gamma)p}\right)^{1-\eta} - 1\right)\middle| s_{Hr}, \theta^y_{rt}\right] \\
&= \frac{1}{1-\eta}\left[\frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}|s_{Hr}, \theta^y_{rt}\right]}{\left[c(\gamma)p\right]^{1-\eta}} - 1\right]
\end{aligned}$$

where[12] $\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}|s_{Hr}, \theta^y_{rt}\right] = \exp\left((1-\eta)\hat{\mu}_{Hr}(s_{Hr}, \theta_{rt}) + \frac{(1-\eta)^2\left(\hat{\sigma}_{Hr}(s_{Hr}, \theta_{rt})\right)^2}{2}\right).$

[12] See Appendix A.2 for derivation

The expected utility from being high skilled depends on the worker's own ability, the signal received s_{Hr} and also on what the worker knows about the region characteristics θ^y_{rt}. In every period t and region r, a young worker with ability γ who receives signal s_{Hr} will choose to become high skilled if expected utility from being high skilled is greater than the expected utility from being low skilled. That is if expected returns to skill is greater than or equal to 0, where the expected returns to skill can be written as:

$$\begin{aligned} R^{skill}(\gamma, s_{Hr}|\theta^y_{rt}) &= \mathbb{E}_{\hat{w}_{Hr}}\left[V^H(\gamma, \hat{w}_{Hr}, p)|s_{Hr}, \theta^y_{rt}\right] - V^L(\gamma, w_{Lr}, p) \\ &= \frac{1}{1-\eta}\left[\frac{\hat{m}_H(s_{Hr}, \theta^y_{rt})}{c(\gamma)^{1-\eta}} - w_{Lr}^{1-\eta}\right] \end{aligned} \tag{1.7}$$

The above setup gives us the following predictions about how the returns to skill varies with worker ability γ, the regional characteristics θ_{rt} and the information/ signal received s_{Hr}:

Prediction 1: Given region characteristics θ_{rt} and signal s_{Hr} and cost function $c(\gamma)$ where $c'(\gamma) < 0$ (i.e. cost of skill acquisition is decreasing in ability), expected returns to skill is increasing in worker ability.

Proof. (see Appendix A.2 for the proof) □

This follows directly from the assumption that the cost of skill acquisition is decreasing in worker ability. Thus, given the same information (signal s_{Hr}) and known regional characteristics (θ^y_{rt}), the higher the worker's ability, the larger the expected returns to skill.

Prediction 2: Given known region characteristics θ^y_{rt} and worker ability γ, expected returns to skill is increasing in signal (s_{Hr}) received about the high skill wage realization.

Proof. (see Appendix A.2 for the proof) □

This depends crucially on the fact that both known regional characteristics (θ^y_{rt}) and worker ability are fixed. A young worker knows the variance of the distribution from which the signal s_{Hr} is drawn. Thus, whatever signal s_{Hr} a young worker receives, the weight on the signal relative to the prior will be the same (when updating the mean of the posterior $\hat{\mu}_{Hr}$). Thus, the higher the signal received, the higher the mean of the workers' posterior beliefs and hence the larger the expected returns to skill. That is, if a young worker knows the informativeness of the signal received, then the larger the signal received about the high skill wage, the larger the expected returns to becoming high skilled.

Prediction 3: Given signal s_{Hr} and worker ability γ, expected returns to skill is decreasing in signal variance if the signal received s_{Hr} is "high enough", that is if $s_{Hr} > \log \left[\mathbb{E}\left(w_{Hr}^{1-\eta}\right)\right]^{\frac{1}{1-\eta}}$ and is increasing otherwise.

Proof. (see Appendix A.2 for the proof) □

Whether the expected returns to skill is increasing or decreasing in signal variance depends on the relationship between the signal received (s_{Hr}) and a function of the prior expectation about high skill wages. Prediction 3 can be intuitively thought about as follows. If the signal received by a young worker about high skill wage is greater than the function of the prior expectation about high skill wages, then an increase in the variance of the signal itself implies that the worker believes this large signal less and puts more weight on the lower prior. Hence expected returns to skill decreases. Otherwise, an increase in the signal variance implies that the worker puts more weight on the higher prior than the signal received and expected returns to skill increases. Thus, given low skilled wage (w_{Lr}), worker ability and initial beliefs about high skilled wages, what a young worker learns about high skill wages from high skilled old workers (i.e. the signal s_{Hr}) and how much they believe it (i.e. σ_s^2), is very important to his skill acquisition decision. In other words, the idiosyncratic signal (s_{Hr}) received *and* the variance of the signal distribution itself are crucial to the skill acquisition decision. Prediction 2 states that given young worker's ability γ and known regional characteristics θ_{rt}, the expected returns to skill is increasing in signal s_{Hr}. That is, the larger the signal a young worker observes, the higher the expected returns to skill. This and properties of the expected returns to skill imply Prediction 4 of the model.

Prediction 4: For each worker with ability γ in region r with known characteristics θ^y_{rt}, there exists a threshold signal $s^*(\gamma, \theta^y_{rt})$ such that worker will choose to become high skilled for all signals $s_{Hr} \geq s^*(\gamma, \theta_{rt})$ where $s^*(\gamma, \theta_{rt})$ solves:

$$R^{skill}(\gamma, s^*(\gamma, \theta^y_{rt})|\theta^y_{rt}) = \ 0$$

and is given by

$$s^*(\gamma, \theta_{rt}) = \frac{\sigma^2_s(h^o_{rt}) + \sigma^2_H}{\sigma^2_H} \left[\log(c(\gamma)) + \log(A_{Lr}) - \frac{(1-\eta)\hat{\sigma}^2_H}{2}\right] - \frac{\sigma^2_s(h^o_{rt})}{\sigma^2_H}\mu_H \quad (1.8)$$

Proof. (see Appendix A.2 for the proof) □

A young worker with ability γ in region r with known characteristics θ^y_{rt} will choose to become high skilled if her expected return to skill is greater than zero. Given ability and known regional characteristics, a worker's expected returns to skill is increasing in the idiosyncratic signal she observes (s_{Hr}). As seen in equation (1.8), the threshold signal additionally depends on the initial beliefs of the worker (summarized by μ_H and σ_H) and the variance of the signal distribution. Further from equation (1.8) it is evident that the threshold signal is decreasing in worker ability γ. The lower the idiosyncratic ability of the worker, the larger the minimum (or threshold) signal the young worker needs to observe in order to choose to become high skilled.

As we will see in the next section, the threshold signal above which a young worker will choose to become high skilled is key to computing the aggregate supply of high skill labor in a region r in period t.

1.3.4 Aggregate Labor Supply and Law of Motion

As seen in the previous section, a young worker with ability γ in region r and period t will choose to become high skilled if her expected returns to becoming skilled are greater than or equal to zero. Prior to the skill acquisition decision, young workers are uncertain about the high skill wage realized in their region. Each young worker receives an idiosyncratic signal of the high skill wage realization (w^*_{Hr}) and updates her initial beliefs about w_{Hr}. Given ability and initial beliefs, the larger the signal received about the high skill wage realization, the larger the expected returns to becoming high skilled. As shown in the previous section, for each worker with ability γ in region r with known characteristics θ^y_{rt}, there is a threshold signal $s^*(\gamma, \theta^y_{rt})$, such that the worker will choose to become high skilled if she observes a signal s_{Hr} greater than the threshold signal, i.e. if $s_{Hr} \geq s^*(\gamma, \theta^y_{rt})$.

Thus given young workers' initial beliefs, how they learn about the high skill wage realization and the actual high skill wage realized w^*_{Hr}, the aggregate mass of young workers that choose to become high skilled in a region r in period t (H^y_{rt}) is given by:

$$H^y_{rt} = H^y(\theta_{rt}) = \left[\int_{\xi}^{\infty} \Pr\left(s_H \geq s^*(\gamma, \theta^y_{rt}) \mid \theta_{rt}\right) dG(\gamma)\right] M_{rt} \tag{1.9}$$

$\Pr\left(s_H \geq s^*(\gamma, \theta^y_{rt}) \mid \theta_{rt}\right)$ is the probability that a young worker with ability γ in a region with characteristics θ_{rt} will choose to become high skilled. That is, it is the probability that a worker with ability γ will observe a signal large enough (i.e. above the signal threshold) to choose to become high skilled. While the threshold signal itself depends only on the regional characteristics known to the young worker, θ^y_{rt}, the probability of observing a signal above the threshold depends on the actual high skill wage realized and also on the variance (or informativeness) of the signal distribution. Recall that the signal s_{Hr} is distributed normal with mean $\omega^*_{Hr} = \log(A^*_{Hr})$ and variance $\sigma^2_s(h^o_{rt})$. M_{rt} is the total mass of young workers region r in period t. Analogously, the aggregate mass of low skilled workers in region r at time t is given by:

$$L^y(\theta_{rt}) = \left[\int_{\xi}^{\infty} \Pr\left(s_H < s^*(\gamma, \theta^y_{rt}) \mid \theta_{rt}\right) dG(\gamma)\right] M_{rt} = M_{rt} - H^y(\theta_{rt}) \tag{1.10}$$

There is no migration between the regions $r \in \mathcal{R}$. Thus the share of high skilled in the mass of young workers in a region r in period t is the share of high skilled among old workers in the region at the beginning of period $t+1$. The law of motion for share of high skilled among old is given by the following difference equation:

$$h^{o}_{r,t+1} = \frac{H^{o}_{r,t+1}}{M^{o}_{r,t+1}} = \frac{H^{y}_{rt}}{M^{y}_{rt}} = h^{o\prime}(\theta_{rt}) = \int_{\xi}^{\infty} \Pr\left(s_H \geq s^{*}_{Hr}(\gamma, \theta^{y}_{rt}) \mid \theta_{rt}\right) \frac{1}{c(\gamma)} dG(\gamma) \tag{1.11}$$

where each region r in period t is characterized by $\theta_{rt} = \{A_{Lr}, A^{*}_{Hr}, \mu_H, \sigma^2_H, h^{o}_{rt}\}$ - the wages per effective unit of low and high skilled labor, the initial beliefs of the young workers and the share of high skilled among old workers in region r in period t.

1.3.5 Equilibrium

Given characteristics of region r in period 0 summarized by $\theta_{r0} = \{A_{Lr}, A^{*}_{Hr}, \mu_H, \sigma^2_H, h^{o}_{r0}\}$, preferences, production function and signal structure, an equilibrium is characterized by a sequence of region r characteristics $\{\theta_{rt}\}_{t=1}^{\infty}$ such that :

1. Young workers in region r period t make optimal consumption decisions. Given income and prices, young workers' indirect utility satisfies (1.4)

2. Given ability γ, a young worker will become high skilled if she observes a signal s_{Hr} above the threshold signal ($s^{*}(\gamma, \theta^{y}_{rt})$) defined by equation (1.8).

3. The aggregate mass of high and low skilled young workers satisfies (1.9) and (1.10)

4. The share of high skilled in mass of old workers in period $t+1$ is given by (1.11)

5. Goods market clear.

$$w_{Lr} = A_{Lr} \qquad\qquad w^{*}_{Hr} = A^{*}_{Hr} \qquad\qquad p = 1$$

1.4 Illustrative Numerical Exercise

In the previous section, we see that young workers' skill acquisition decision depends on the initial beliefs of the worker about the high skill wage, the signal received about the true high skill wage and also the informativeness of the signal received (i.e. the variance of the signal distribution). However, the worker does not know the actual high skill wage realization when making the skill acquisition decision. After receiving the signal, worker forms expectations about the returns to skill and on the basis of that makes the skill acquisition decision.

The aggregate supply of high skill labor does depend on the actual high skill wage realization since the signal distribution is centered around it, i.e. $s_{Hr} \sim N(\omega^*_{Hr}, \sigma^2_s(h^o_{rt}))$, where $\omega^*_{Hr} = \log(A^*_{Hr})$. Further, for a given true high skill wage A^*_{Hr}, the aggregate skill supply also depends on the informativeness of the signals received by young workers. That is, given true high skill wage, the aggregate skill supply in a region also depends upon how much young workers learn about the high skill wage realized. How the aggregate skill supply changes with the variance of the signal distribution depends crucially on the initial beliefs of young workers relative to the actual high skill wage realization A^*_{Hr}.

What implication does the local learning effect in the model have for the aggregate supply of high and low skill labor in a region? This can be better understood with an illustrative numerical exercise.

For the numerical exercise I assume the following functional form for the cost of becoming high skilled:

$$c(\gamma) = \frac{1}{\gamma - \xi} + 1$$

Cost of becoming skilled is decreasing in ability γ. As $\gamma \to \xi$ cost goes to infinity and as $\gamma \to \infty$, cost goes to one. Young workers in the model are born with one effective unit of labor. To become high skilled, they must pay a cost in terms of units of labor. Thus, young workers that choose to become high skilled can supply $(1/c(\gamma))$ effective units of high skill labor where $0 \leq (1/c(\gamma)) \leq 1$. The model above assumes that the variance for the signal distribution is decreasing in the share of high skilled in the mass of old workers in region r in period t (h^o_{rt}). In the numerical exercise I assume the following functional form for the variance of the signal distribution:

$$\sigma_s(h^o) = \left(\frac{1}{h^o} - 1 \right) \tag{1.12}$$

The functional form specification for signal variance above implies that the variance of the signal distribution goes to zero as the share of high skilled in the mass of old workers goes to 1 and the variance of the signal distribution goes to infinity as the share of high skilled in the mass of old workers goes to zero. The main parameters of the model along with the values I assume for illustrative exercise are given in Table 1.3 below.

Table 1.3: Parameter Values used in numerical exercise

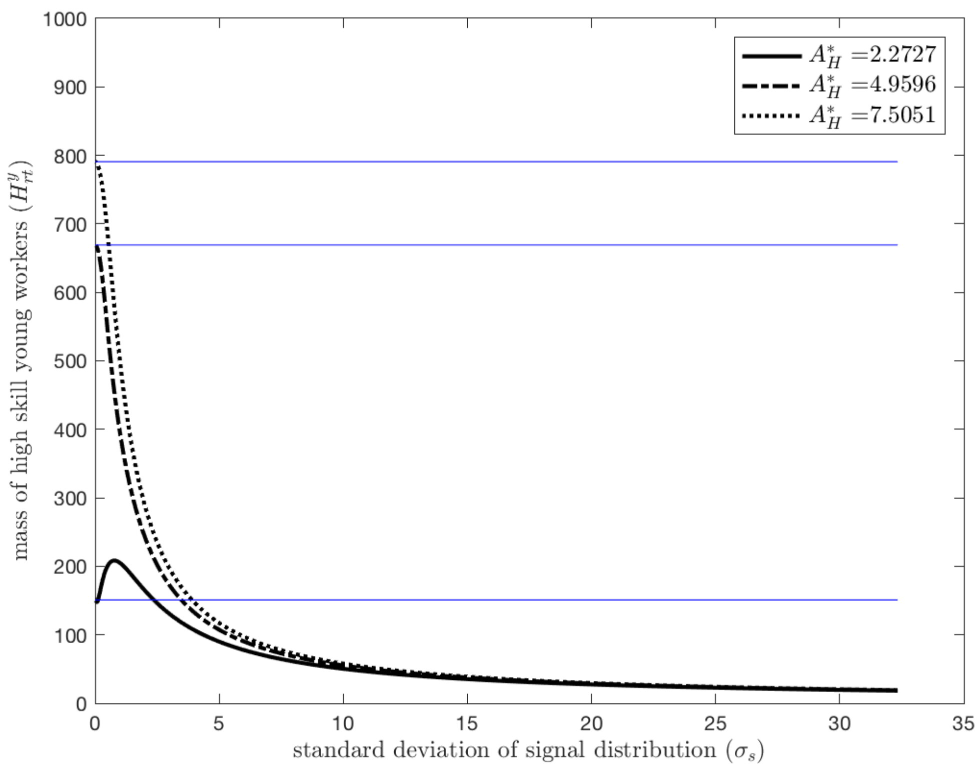
Parameter	**Parameter Desc**	**Value**
N	# of regions	1000
$w_{Lr} = A_{Lr}$	low skill wage	2
μ_H	mean of high skill wage distn	log(3)
σ_H^2	variance of high skill wage distn	1
h_{r0}^o	initial share of high skill old workers in a region	grid of N points from [0,1]
	Cost and Ability Parameters	
ξ	scale of ability distribution	1.45
ψ	shape of ability distribution	1.05

1.4.1 Results of the numerical exercise

In the figures below, I show how the aggregate mass of young workers who choose to become high skilled and the aggregate welfare of a region vary with the signal variance for three different realizations of high skill labor productivity. The solid line in each figure is the low A_H^* realization ($A_H^* \approx 2.27$), the dashed line is the medium A_H^* realization ($A_H^* \approx 4.96$) and the dotted line is the high A_H^* realization ($A_H^* \approx 7.51$). The thin horizontal lines in both figures are the aggregate mass of high skilled young workers and the welfare in a region when there is no uncertainty about the high skill wage in a region. Given the realization of high skill wage A_H^*, under full information, the mass of young workers who choose to become high skilled and the aggregate welfare in a region does not vary with the variance of the signal distribution.

Figure 1.4 shows how the aggregate mass of high skilled young workers changes with the variance of the signal distribution for low, medium and high realizations of high skill productivity A_H^*.

Figure 1.4: Mass of high skill young workers

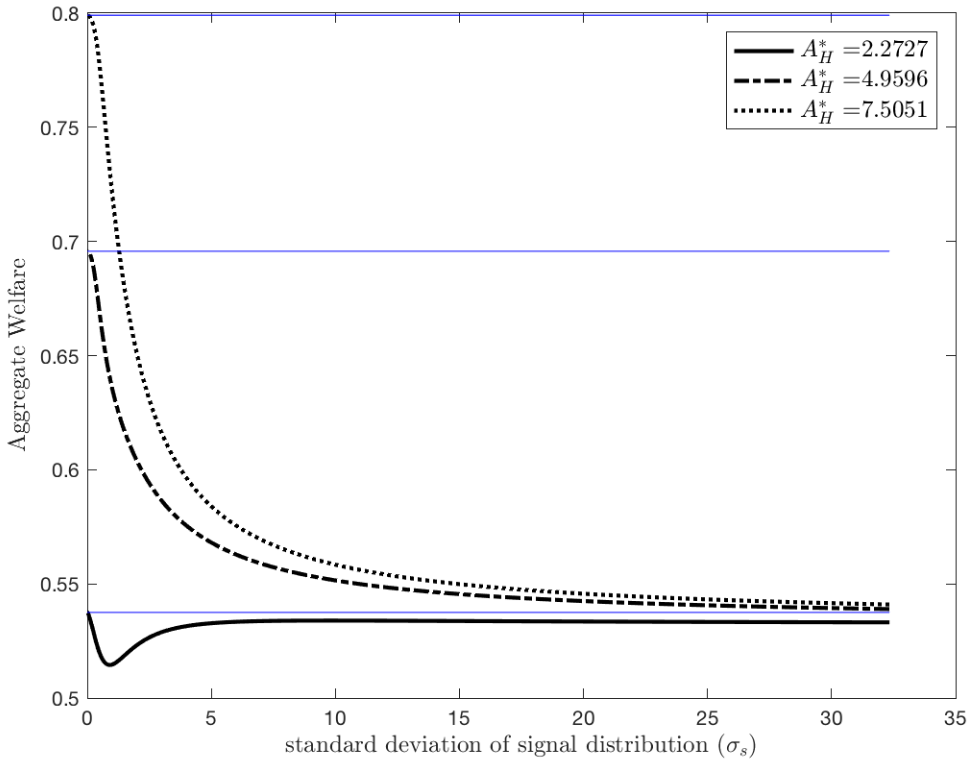


There are two main effects that act upon the skill acquisition decision as the variance of the signal increases. As signal variance increases, workers put a relatively higher weight on their prior. In the case of the high and medium realizations of A_H^* this reduces the expected returns to skill for each worker as compared to the full information equilibrium. In the case of low A_H^*, a higher weight on the initial beliefs or prior implies an increase in the expected returns to skill for the worker (as compared to the full information equilibrium). Thus, in the case of low A_H^* realization, the aggregate mass of young workers who choose to become high skilled increases with an increase in the signal variance. The second effect on skill acquisition decision from an increase in the signal variance comes from the fact that workers are risk averse. All else equal, an increase in signal variance reduces workers' expected utility from becoming high skilled. In the case of low A_H^*, this implies that for large enough values of signal variance, risk aversion dominates the effect of the higher weight on the prior and results in a reduction in expected returns to skill. In the case of high and medium A_H^*, for an increase in signal variance, the higher weight on the prior and risk aversion, both decrease the expected returns to skill for a young worker. This results in an unambiguous decrease in the aggregate mass of high skilled young workers as the variance of the signal distribution increases. Further, when the signal variance is large enough, for any realization of high skill productivity A^*H, the aggregate mass of high skill workers is equalized across regions. This is because when the signal variance is large, i.e. when signal is uninformative enough, a young worker in each region puts a very high weight on her initial beliefs (which are the same across regions). Given worker ability, the expected returns to skill is equalized across regions when the signal is uninformative enough (i.e. the variance of the signal distribution is large enough). This causes the aggregate supply of high skilled young workers to also converge across regions.

Figure 1.5 shows how aggregate welfare changes with the variance of the signal distribution for low, medium and high realizations of A_H^*. For each realization of A_H^*, welfare remains unambiguously below the full information level. For medium and high realizations of A_H^*, welfare is unambiguously decreasing in signal variance. This is because as signal variance increases, young workers place a higher weight on their (relatively lower) prior and the higher signal variance also reduces the expected returns to skill for risk averse workers. Both effects cause an undersupply of aggregate high skill labor and as a result, aggregate welfare unambiguously decreases (relative to the full information level) with an increase in signal variance.

However, in the case of low A_H^* realization we see that welfare is first decreasing in σ_s and then increasing. The initial decrease in welfare observed in the figure below for low A_H^* realization is because at low levels of signal variance, young workers are placing too much weight on their initial (higher) prior, paying the cost $c(\gamma)$ and choosing to become high skilled. As seen in Figure (1.5), this results in an oversupply of the mass of high skill labor , relative to the full information level. However, as signal variance increases further, risk aversion dominates and reduces the expected returns to skill for young workers. This actually has the effect of raising welfare since

Figure 1.5: Welfare under partial information

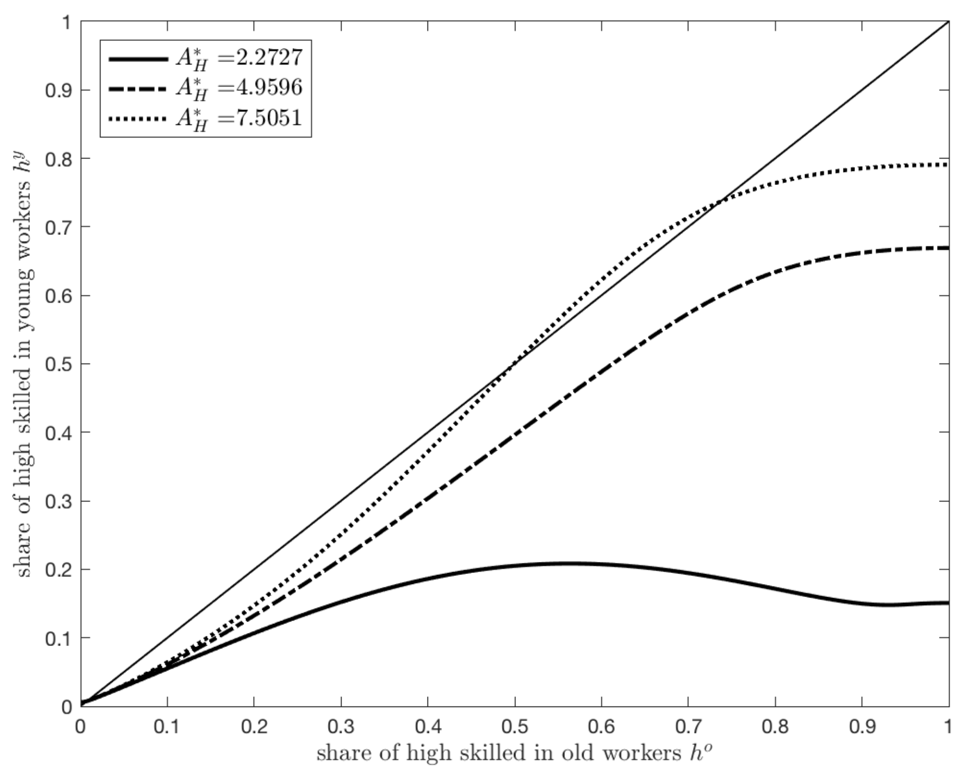


workers are no longer oversupplying high skill labor and paying the cost $c(\gamma)$.

The numerical exercise shows how, in the presence of a local learning effect, the aggregate supply of high skilled young workers in a region depends on the variance of the signal distribution, i.e. the informativeness of the signal received about high skill wage realization. The results above hold for any assumption about how the signal variance in a region depends on the share of high skilled in the mass of old workers in a region r in period t (h^o_{rt}). However, what does this local learning channel imply for the aggregate supply of high skilled workers in a region over time? To answer this, I need to impose a functional form on signal variance that specifies how the share of high skilled in the mass of old workers in a region r in period t affects the variance of the signal distribution from which young workers learn about the high skill wage realization. I assume that signal variance is a decreasing function of the share of high skilled in the mass of old workers in a region (h^o_{rt}). The specific functional form is given in equation (1.12) above. The assumed functional form implies that the signal variance goes to infinity when h^o_{rt} is zero and the signal variance goes to zero as h^o_{rt} goes to one.

The implications of the local learning effect over time can be seen in Figure 1.6 below. The figure shows the law of motion for the share of high skilled workers in a region for different realizations of high skill productivity A^*_H. On the x-axis is the share of high skilled old workers in period t, i.e. h^o_t and on the y-axis is the share of high skilled young workers in period t, $h^y_t = h^o_{t+1}$. As before the solid line represents the low realization of A^*_H, the dashed line represents the medium realization and the dotted line represents the high realization of A^*_H.

Figure 1.6: Law of Motion of Labor Supply



The intersections of the curves with the 45 degree line are the fixed points of the law of motion of high skilled labor supply. For low and medium realizations of A_H^*, regions with different initial values of h^o end up at the same stable point. For high realization of A_H^*, there are multiple fixed points for the law of motion. In this case, the initial share of high skilled in old workers determines the future stable point reached.

For the low realization of A_H^*, the share of young workers that choose to become high skilled is non-monotonic in the share of high skilled old workers. The reason for this is the same as above. For the low realization, consider the full information point, that is where $h^o = 1$. At this point young workers choose to become high skilled as if under full information. As the share of high skilled old workers increases, uncertainty about the high skill wage realization increases. Thus young workers would believe their (higher) prior more, raising the expected returns to skill. As uncertainty increases, expected returns to skill decreases due to risk aversion. Thus when uncertainty is low, the first effect dominates and when uncertainty is high the risk aversion effect dominates. This results in the observed non monotonicity in share of high skilled young workers for low realization of A_H^*.

For medium and high realization of A_H^*, the above two effects work in the same direction. An increase in signal variance results in an increase in how much young workers believe their (lower) prior, thus reducing the expected returns to skill. Further, risk aversion also results in a decrease in the expected returns to skill as signal variance increases. Consider the full information point, when signal variance is equal to zero i.e. $h^o = 1$. As the share of high skilled old workers decreases, the signal variance increases at an increasing rate. When the signal variance increases from the full information point, the expected returns to skill decreases slowly initially. As the signal variance increases further, the rate of decrease in expected returns to skill increases. This pattern holds for both medium and high realizations of A_H^*, since the increasing weight on the prior and risk aversion work in the same direction. However, in the case of the high realization of A_H^*, the gap between the initial beliefs of young workers and the actual realization is larger than in the case of the medium realization. This is key to why there arise multiple fixed points in the law of motion. Consider when the true realization of high skill wage is large enough relative to the initial beliefs of young workers, i.e. high A_H^*. In that case, when young workers are born into a low information region, their expected returns to skill will be very close to their initial beliefs. The share of young workers who choose to become high skilled will be low. Following the law of motion, this would perpetuate the low information cycle, resulting in the region getting stuck in the low skill fixed point. If young workers are born into a high information region, even with the presence of some uncertainty, the large realization of high skill wage would keep expected returns to skill high enough that a sufficiently large share of young workers would choose to become high skilled. This would perpetuate the high information cycle, resulting the region arriving at the high skill supply fixed point. The law of motion described is to show how the local learning channel itself can result in regions getting stuck in low information traps. It is to illustrate how, even for regions with the same skill premium, small differences in initial information levels can lead to persistent dispersion in regional educational attainment.

1.5 Conclusion

In this paper, I provide evidence of one way in which the existing skill composition in a local labor market affects the future production of skill in that labor market. I draw on insights of a growing body of experimental work that shows that information about the returns to skill is an important determinant of the educational investment decision. Using detailed individual level panel data, I show that the responsiveness of education attainment to the skill premium in a local labor market additionally varies with the existing share of high skilled in that labor market. I show that this effect persists even when controlling for important individual level determinants of the education attainment and also when accounting for other widely studied channels such as school quality.

I then provide a simple framework that allows us to think about the broader implications of this local learning channel and its role in generating persistent spatial variation in educational attainment. When the gap between beliefs and the actual skill premium is large enough, regions can get "stuck" in low skill traps. The model is able to rationalize the patterns observed in the data.

Understanding better the different mechanisms through which local skill share affects education outcomes is important since each mechanism has different implications for welfare and policy analysis. If local skill composition contributes to spatial variation in college attainment by generating spatial variation in information about college returns, then policies that provide students with information about the returns to a college degree would reduce this spatial variation and also be welfare improving. Existing work has shown that such policies can be undertaken at relatively low cost (Hoxby and Turner (2013)). In future work it would be useful to show how much of the social channel of human capital spillovers studied in the literature could be attributed to information spillovers.

Chapter 2

Rules of Origin and Export Quality: The case of Bangladesh

2.1 Introduction

Trade preferences to Least Developed Countries (LDCs) have been a part of international trade policy for a very long time. However, simply granting tariff preferences or duty-free market access to all exports from LDCs does not necessarily ensure that the benefits provided are confined to products *originating* in those countries. Rules of Origin (ROOs) were established to ensure that goods produced in other countries and trans-shipped or given minimal processing in a beneficiary country did not benefit from trade preferences (Inama (2009)). On the other hand, stringent Rules of Origin might prevent trade preferences from being effectively utilized by beneficiary countries. The focus of this paper is the impact of a relaxation in the ROO requirement of the EU on the apparel sector in Bangladesh and what this might say about the inadvertent effects of stringent Rules of Origin.

The apparel sector accounts for a substantial part of exports for several Least Developed Countries. For instance, as of 2013, the share of apparel exports in total mechandise exports was about 54% for Cambodia, 49% for Lesotho and 88% for Haiti. Apparel exports account for 80% of Bangladesh's total merchandise exports in 2013.

Further, the EU is the world's largest importer of apparel[1]. Thus it is important to understand the implications of EU's Rules of Origin policy on the apparel sector of Least Developed Countries.

The implications of Rules of Origin policies on the apparel sector in Bangladesh has been studied previously. Demidova et al. (2012) provide a theoretical framework in which firms sort themselves across export markets in response to differences in trade policy, preferences and the associated costs in a heterogenous firm setting with firm-market specific demand shocks. Cherkashin et al. (2015) develop and estimate a model of firms with heterogenous productivity and firm-market specific demand shocks that shows how trade preferences given by one country can have positive spillovers on exports to other countries in the presence of free entry. Further, they also show how firms decide whether or not to utilize EU ROO preferences on the basis of their productivity draw and EU market-firm specific demand shock.

The focus of this paper is a specific change in 2011 in the European Union's Rules of Origin policy vis-á-vis Least Developed Countries. In 2001, the European Union initiated the Everything But Arms (EBA) agreement under which almost all exports from Least Developed Countries are eligible for duty-free and quota-free treatment subject to compliance with product specific Rules of Origin[2]. Between 2004 and 2010 under the EBA, the Rules of Origin for apparel exports from LDCs specified a two stage conversion requirement : from yarn to textile to apparel. In other words, before 2010 apparel exports from Bangladesh could get duty-quota-free access to the EU only if domestic cloth/ textile was used in production. If apparel was produced using imported textiles, then a tariff of 12.1% would be imposed on exports from Bangladesh to the EU. In Bangladesh, this regulation was particularly binding for the woven apparel sector. The woven textile industry in Bangladesh meets only about quarter of the domestic exporters' demand for woven fabric (Rahman et al. (2014)). Due to the limited supply, domestic woven fabric commands a premium price in Bangladesh. Therefore, before 2010, to meet the Rules of Origin under the EBA, firms would have to use domestic cloth in apparel production instead of the relatively cheaper imported cloth. Since domestic supply of woven textiles was not

[1] 37.9% of total world apparel imports in 2013. Source: WTO International Trade Statistics 2014
[2] Rahman et al. (2014) and Inama (2009)

able to meet exporters' demand, it was difficult for the woven apparel sector to utilize the preferences offered under the EBA between 2004 and 2010. Only about 28% of Bangladeshi woven exports were given duty free entry to the EU (Rahman et al. (2014)).

However, effective January 1st 2011, there was a major shift in the Rules of Origin policy under the EBA with regard to LDCs. In the apparel sector, exports from LDCs would now be eligible for duty-free access to the EU as long as they satisfied a one stage conversion requirement : from fabric to apparel. That is, unlike before, apparel exports are now eligible for duty-free access to the EU even if imported cloth is used in production. This means that firms exporting to the EU are no longer constrained to use relatively more expensive domestic cloth in order to meet the ROOs. They can use imported cloth in production and still get duty free access. Since there is no longer any advantage in using the relatively more expensive domestic cloth, it was expected that the relaxation of the ROO requirement under the EBA would lead to a sharp fall in the average price of exports from Bangladesh to EU[3]. However, in the data we observe that the average price of apparel exports from Bangladesh to the EU increased between 2010 and 2011. This observation contradicts the expected impact of the 2011 ROO policy change on the price of apparel exports from Bangladesh to the EU. This paper provides an explanation for this counter intuitive observation by taking into account *quality* of output produced by firms. In the explanation, the quality of output in the apparel sector depends heavily on the quality of the intermediate input - cloth. After the policy change in 2011, firms can meet the EU ROOs and get duty free access to the EU even by using relatively less expensive imported fabric. Thus profit maximizing firms will switch to using imported fabric in production instead of relatively more expensive domestic fabric. However, the contention is that instead of switching to imported fabric of the same quality, post policy change, firms choose import fabric of *higher* quality. Taking into account this quality upgrading effect helps to explain the observed increase in average price of exports. Section 2.2 describes in more detail the trade policy environment faced by Bangladeshi exporters and the patterns observed in the data.

[3]Cherkashin et al. (2015) conduct a similar counter factual exercise that predicts a fall in the price index in the EU

Section 2.3 develops a partial equilibrium model with monopolistic competition based on Melitz (2003) and Cherkashin et al. (2015) in which firms are allowed to make a choice about the quality of output. To emphasize the impact of a change in trade policy on the quality of output exported, the model includes features of the trade policy environment faced by Bangladeshi exporters. Section 2.3 sets up the model and solves for equilibrium pre and post Rules of Origin policy change. Section 2.4 presents the results of an illustrative numerical exercise. Section 2.5 concludes.

2.2 Trade Policy Environment and Evidence in the Data

I have transactions level customs data for Bangladesh exports from 2008 to 2012[4]. For each transaction, the data has information on exporter id, port code, bill of entry date and number, the value of the transaction and the quantity exported per transaction (weight and number of units). In addition to the impact on exports from Bangladesh to the EU, I also consider the effect of the policy change on Bangladesh's exports to other destinations. As of 2010, apparel exports from Bangladesh to the EU and the US together account for 85% of total apparel exports from Bangladesh. The following analysis is restricted to the effect of the 2011 EU ROO policy change on Bangladesh apparel exports to the EU and the US.

The transactions level customs data is for the period 2008 to 2012. Since exports to the US are also considered, it is important to note that there were no major changes in US trade policy vis-á-vis apparel exports from Bangladesh during this period. After the phase out of the MFA, effective January 1st 2005, quotas on apparel exports from Bangladesh to the US were eliminated. Between 2008 and 2012, Bangladeshi apparel exports have quota free access to the US market. However, tariffs are imposed on apparel exports from Bangladesh to the US. The tariffs applied vary by product. Rahman et al. (2014) estimates that average US MFN tariff rates on Bangladesh apparel exports is about 16.3%.

[4]The data was obtained from Prof. Rocco Macchiavello and Prof. Chris Woodruff of the Department of Economics, Warwick University through Filippo Sebastio at the International Growth Center, Bangladesh. I thank all of them for providing access to this data set.

On the basis of the manufacturing process, apparel products can be divided into two broad subsectors - knits and wovens. Knits and wovens are distinguished by the manufacturing process involved in converting yarn to fabric. The machines used for the two are very different. For simplicity, one can think of a sweater as being representative of knit apparel and a pair of cotton trousers as an example of woven apparel. Due to the specific characteristics of the industry, the 2011 change in the EU Rules of Origin requirements affected these two sub-sectors quite differently.

2.2.1 Knit Apparel Exports

Before the policy change in 2011, apparel exports would meet the EU's Rules of Origin and be eligible for duty free access to the EU only if they were produced using **domestic fabric**. Compared to woven textile production, knit textile production is less capital intensive and can be sustained using lower levels of technology (Rahman et al. (2014)). Domestic production of knit textiles in Bangladesh are adequate to meet the exporters' demand. Further, in the case of knit apparel, the manufacturing process is such that in most cases conversion of yarn to fabric and fabric to apparel is undertaken within the same production unit. Thus knit apparel exports from such units were ROO compliant even when the ROOs required the use of domestic fabric. Before 2011, about 95% of knit apparel exports from Bangladesh to the EU were meeting the ROOs and obtaining duty free access to the EU market. It was expected that a change in the Rules of Origin in 2011 would not significantly affect the input decision of such units. Since knit exports to the EU were almost five times larger than knit exports to the US, it was expected that the aggregate impact of the 2011 ROO policy change on knit exports to the EU and US would not be drastic.

Despite the decline in trade during the global recession of 2008-09, Bangladesh's knit apparel exports to the EU registered a growth rate of 4.6% per year to the EU and 1.3% per year to the US between 2005-2010. The growth in knit exports to the US could be due to the phase out of the MFA in 2005. The growth in knit exports to the EU could be due to a change in the EU ROO policy in 2004. In 2004, under the EBA, the Rules of Origin requirement for duty free access to the EU was relaxed - from a three stage requirement (domestic conversion of cotton $\rightarrow$ yarn $\rightarrow$ fabric $\rightarrow$

apparel) to a two stage requirement. This two stage requirement made it easier for the knit apparel sector to be ROO compliant and possibly led to the observed growth in exports between 2005 and 2010.

Table 2.1: Annual Growth Rate of Bangladesh Apparel Exports

	Annual Growth Rate Knit Exports		
Year	**to the EU**	**to the US**	**Overall EU & US**
2005-2010	4.6	1.3	4
2010-2013	3.3	-4.2	2.1

Between 2010 and 2013, while exports to the EU grew at $\sim 3\%$ per year, knit exports to the US **fell** by $\sim 4\%$ annually during the same period. The fall in knit exports to the US could indicate that the 2011 change in EU ROO policy might have resulted in a diversion of exports from the US to the EU. Note that knit exports to the US account for only about 17% of total Bangladesh knit exports to the EU and US combined. Thus despite the fall in knit exports to the US, there is approximately a 2% annual growth in the exports to the EU and US combined between 2010 and 2013.

Therefore, consistent with expectations, the 2011 change in EU Rules of Origin policy did not seem to have a significant impact on knit apparel exports from Bangladesh. There is no clear out-of-trend increase in the Bangladesh's knit apparel exports after the EU ROO policy change in 2011. The fall in knit exports to the US indicate that the change in EU ROO policy might have resulted in a slight short term diversion of exports from the US to the EU. Further, between 2010 and 2012, the average unit values of knit exports **fell** by $\sim 4.8\%$ per year for the European Union and by $\sim 8.3\%$ for the United States. This fall in unit values is still consistent with expectations of the 2011 ROO policy change. Even prior to the ROO policy change in 2011, there is a general downward pressure on unit values across apparel products possibly due to competition from other exporters like China. The impact on knit apparel exports of the 2011 change in EU Rules of Origin requirements are consistent with a priori expectations.

2.2.2 Woven Apparel Exports

While the production process for knit apparel is such that firms undertake the manufacture of apparel from yarn itself, this is not the case with woven apparel. Firms producing woven apparel usually assemble cut fabric into garments (Demidova et al. (2012)). Firms can choose to procure fabric domestically or import it. Under the European Union's "Everything But Arms" agreement, apparel products exported from LDCs are given duty free access to the EU market only if they satisfy the Rules of Origin requirements. Before 2011, the Rules of Origin specified that only apparel produced using **domestic fabric** would be given duty free access to the EU market. If woven apparel firms chose to use domestic fabric in production, then they would be granted duty free access to the EU. If instead, they chose to use imported fabric in production, a tariff of 12.1% would be imposed on their exports to the EU.

However, the domestic supply of woven fabric is limited in Bangladesh. According Rahman et al. (2014), the domestic woven textile sector is only able to meet about 25% of exporters' demand for woven fabric. In the case of **high quality fabric**, domestic supply is virtually non existent. Firms that choose to produce apparel using high quality fabric *have* to use imported fabric. Given the limited domestic supply of woven fabric in Bangladesh, it commands a premium price. Before 2011, woven apparel firms could only meet the ROOs by using the relatively more expensive domestic fabric. Before the ROO change in 2011, only about 28% of Bangladeshi woven exports were given duty free entry to the EU.

Effective January 1st 2011, there was a major shift in the EU-GSP Rules of Origin with respect to Least Developed Countries. Under the new ROOs, apparel exports are eligible for duty free entry to the EU even if imported fabric is used in production. Almost all apparel exports from Bangladesh are now eligible for duty free access to the EU. For the woven apparel sector in particular, this means that firms exporting to the EU are no longer constrained to use relatively more expensive domestic fabric to meet the ROOs. They can use imported fabric in production and still get duty free access. The elimination of the domestic fabric requirement means that the tariffs on all apparel exports to the EU have now effectively fallen to zero. This is particularly significant for the woven sector, since before 2011, approximately 75% of Bangladesh's woven exports to the EU paid an average tariff of 12.1%.

Table 2.2: Annual Growth Rate of Bangladesh Apparel Exports

Year	Annual Growth Rate of Woven Exports[5] to the EU	to the US	Overall EU & US
2005-2010	-2.3	0.8	-0.7
2010-2013	23.2	-0.5	10

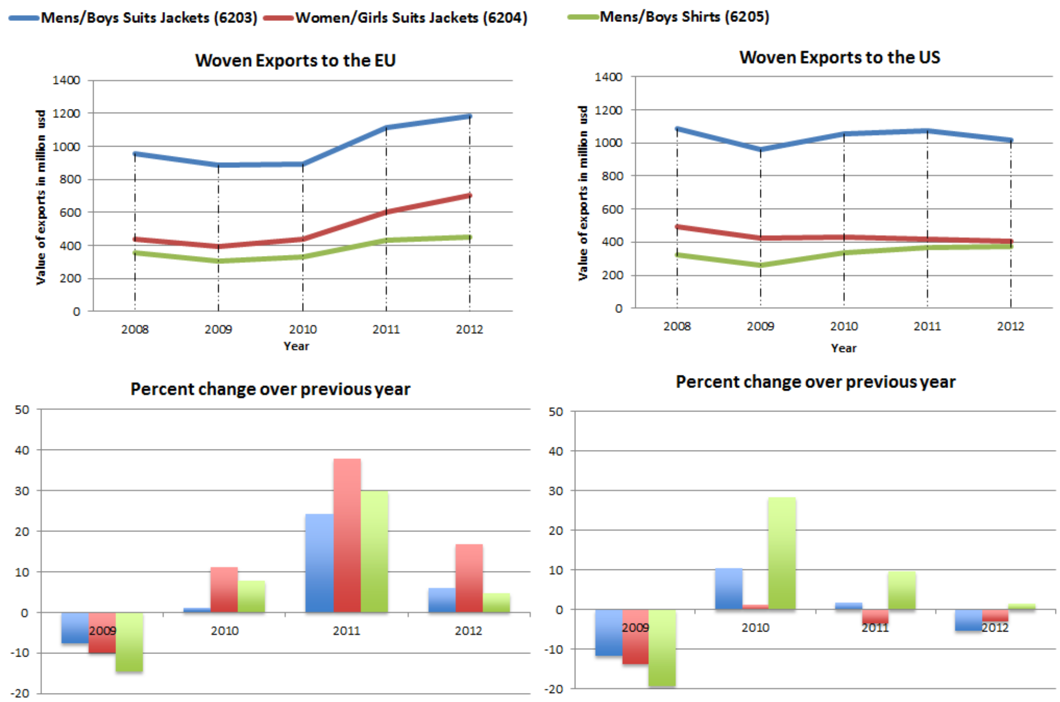
Woven exports to the EU grew at an annual rate of 23% between 2010 and 2013. Woven exports to the US on the other hand, *fell* at the rate of 0.5% per year during the same period. In the case of woven apparel, the magnitude of Bangladeshi exports to the US and the EU are quite similar. Thus, woven exports to the EU and US combined increase about $\sim$ 10% per year between 2010 and 2013. The 0.7% per year *decline* in aggregate woven exports between 2005 and 2010 is consistent with the global decline in trade during the global recession of 2008-2009. As before, the growth in woven exports to the US between 2005 and 2010 can be explained by the phase out of the MFA in 2005.

Figure 2.1 below shows the change in aggregate exports for the three largest products within woven apparel which on average account for 90% of Bangladesh's woven exports to the EU and the US combined[6]. Trends at this disaggregated level are consistent with those in the table above. For the EU, there is a sharp increase in aggregate woven exports across products between 2010 and 2011 - from a little over 20% for Men's suits (6203) to almost 40% for Women's suits (6204). Similar to the pattern for *aggregate* woven exports, the rise in export value to the EU continues into 2012. In fact, between 2010 and 2012, the value of exports to the EU grew at annual rate of 15%, 30% and 17% per year for Men's suits (6203), Women's suits (6204), Men's Shirts (6205) respectively.

With regard to woven apparel export to the US, for Men's and Women's suits (6203 & 6204) export value has *fallen* between 2010 and 2012 at an annual rate of $\sim$ 1.87% and 3.2% respectively. As mentioned before, this could be indicative of a short term effect of the policy change - a diversion of exports from the US to the EU.

[6]Data used in Figure 2.1 is customs data

Figure 2.1: Woven apparel exports to the EU and the US



On the other hand, for Men's shirts (6205) exports to the US actually grew by 5.6% per year between 2010 and 2012. However, Men's shirts account for only about 16% of total woven exports to the US and the effect of this expansion is outweighed in the aggregate.

The EU Rules of Origin change in 2011 means that firms are able to get duty free access to the EU even if imported fabric is used in production. Thus woven apparel producing firms are no longer constrained to use relatively more expensive domestic fabric in order to meet the ROOs. It was expected that this relaxation of the ROO requirement would lead to a large fall in marginal cost and hence the average price of woven apparel exports from Bangladesh to the EU. Firms that were previously meeting the Rules of Origin by using domestic fabric could now switch to relatively cheaper imported fabric and still meet the ROOs. Firms that previously *did not* meet the ROOs because they used imported fabric, are now considered ROO compliant and do not have to pay tariffs on their exports to the EU. Both these effects exert a downward pressure on the prices charged by firms.

Table 2.3: Average Price of Bangladesh's Woven Exports : Annual Rate of Change

	Annual Rate of Change of Unit Values	
Year	**Exports to the EU**	**Exports to the US**
2008-2010	-9.78 %	-9.83 %
2010-2012	**3.3** %	**0.3** %

However, contrary to expectations, after the 2011 policy change, we see an *increase* in the average price of woven exports[7]. Between 2010 and 2012, average price of woven exports to the EU actually *grows* at the rate of 3.3% per year. Unit values also increase for woven exports to the US. To ensure that the results on prices are not driven by outliers, observations in the top and bottom 1 percentile have been removed.

The increase in prices is even starker at the disaggregated product level. Figure 2.2 shows the percent change over the previous year of the average price of three woven products exports to the EU. The three products represented together account for about 90% of Bangladesh's woven apparel exports to the EU and the US. For all three of these products, the average price of exports fall every year *except* between 2010 and 2011. In fact, for Men's/Boys shirt exports to the EU, the average price increases by as much as 4.6% per year between 2010 and 2012. The fall in export prices in other years seen in Figure 2.2 is not surprising. There is a general downward pressure on prices in other years due to competition from other low cost exporters.

Figure 2.3 below provides a comparison of price distributions between 2010 and 2011 for each of the largest HS4 level woven products. Only firm-product combinations that exported to the EU both in 2010 and 2011 are considered. Each figure compares the price distribution of woven exports from Bangladesh to the EU between 2010 & 2011 for a different HS4 woven product. Figure 2.3(a) gives the price distributions for Men's/Boys Suits Jackets (6203), Figure 2.3(b) for Women's/Girls Suits/Jackets

[7]The products included in the calculation of prices in Table 2.3 are the three largest woven products exported by Bangladesh to the EU and US - Mens/Boys suits jackets (6203), Womens/Girls suits jackets (6204) and Mens/Boys shirts (6205). These three products together account for 90% of woven exports from Bangladesh to the EU and US

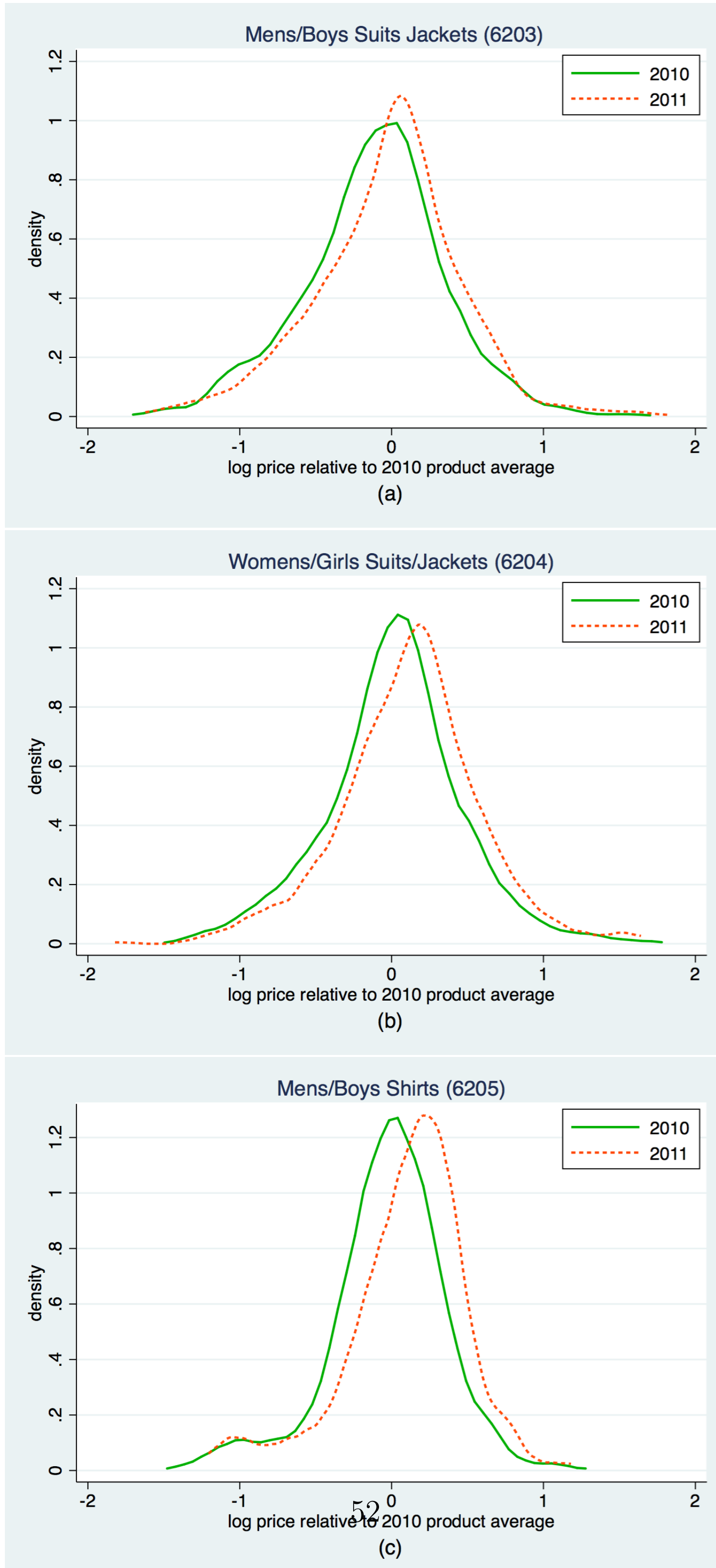
Figure 2.2: Percent change in weighted average price of woven exports to the EU

(6204) and Figure 2.3(c) for Mens/Boys Shirts (6205). Prices are computed log relative to the 2010 HS6 product average weighted price of woven exports. For each of the three products, between 2010 and 2011 the distribution of prices shifts to the right, consistent with the increase in average prices seen in Figure 2.2 above. The increase in prices between 2010 and 2011 is driven by an increase across firm-product combinations.

There is a clear increase in the average price of Bangladesh woven exports to the US and EU after 2010. Between 2010 and 2012, price of exports to the EU increase by 2.9% per year for Mens/Boys Suits Jackets and by as much as 4.6% per year for Mens/Boys Shirts. What is particularly striking about the data on average prices is that the 2011 elimination of the domestic fabric requirement for duty free access was expected to significantly lower marginal costs for exporters and cause a *sharp, out-of-trend fall* in the price of Bangladeshi woven exports to the EU. Instead, we see the price of exports of some woven products increase by more than 18% between 2010 and 2011.

What could be driving this increase in average prices? It is possible that the observed increase in output prices are driven by an increase in the price of inputs. In 2011, there was a sharp spike in worldwide cotton prices. This in turn drove up the price of textiles. However, I account for the increase in input price when converting the data from nominal to real values. The nominal data is deflated using

Figure 2.3: Price Distribution of Woven Exports to the EU : 2010 and 2011



a weighted average of the wholesale price of textiles and the Nominal Wage Index for Manufacturing in Bangladesh[8]. The price increase in woven exports to the EU after the policy change is observed even when the index is constructed with a higher weight on the price of textiles. Therefore, the increase in average price of woven exports is observed even after taking into account possible increases in input prices.

Alternatively, it is also possible that in 2011 there was some aggregate negative shock to productivity that drove up prices across the board between 2010 and 2011 as seen in Figure 2.3. However, if it was indeed a negative shock to productivity that was driving prices up, then one would also expect it to have a negative impact on Bangladesh's market share in the EU. If an aggregate negative productivity shock did coincide with the relaxation of ROO requirements under the EBA, then at the very least, this would partially offset the positive effect of the ROO policy change on the Bangladesh exports' share in the EU market.

Table 2.4: Market Share of Bangladesh Apparel Exports in the EU

Year	**Share of Woven Exports**	**Share of Knit Exports**
2008	1.32 %	2.54 %
2009	1.48 %	2.72 %
2010	1.57 %	3.06 %
2011	2.14 %	3.81 %
2012	2.78 %	4.08 %

Table 2.4 shows the share of Bangladesh woven and knit exports in the total apparel market of the European Union. The share of Bangladesh's woven exports in the EU apparel market becomes larger after 2010. Not only does Bangladesh woven exports' share in the EU apparel market continue to grow after 2010, but the annual *rate of growth* also increases. Between 2010 and 2012, market share of Bangladesh woven exports in the EU grows at the rate of $\sim 38\%$ per year. This is especially large, compared to the average growth rate of 9.6 % between 2008 and 2010. The data on the share of Bangladesh exports in the EU apparel market also shows the differential

[8]Data is from of Statistics (2016) and of Statistics (2013) In constructing the index, the weight given to the price of textiles is 0.6. This is consistent with the findings of Kabeer and Mahmud (2004)

impact of the Rules of Origin policy change on the woven and knit export sectors in Bangladesh. While the share of Bangladesh knit exports in the EU apparel market also grows after 2010, the rate of growth before and after 2010 is not too different ($\sim$ 10% per year between 2008 and 2010, compared to $\sim$ 16% per year between 2010 and 2012). This is consistent with the previous observation that knit exports from Bangladesh to the EU do not show any clear out-of-trend growth after the Rules of Origin policy change in 2011.

For Men's/Boys suits and jacket (6203) and Mens/Boys shirts (6205), the two woven products that together account for about 70 % of Bangladesh's total woven exports, between 2010 and 2012, share in the EU apparel market grows at an annual rate of 32 % and 34 % respectively. Thus, in the context of the *accelerated* growth of Bangladesh's share in the EU apparel market after 2010 and considering the *magnitude* of this acceleration, it is unlikely that the rise in average price of exports after 2010 was due to an aggregate negative productivity shock of some kind.

Our explanation for the observed rise in average prices is that the relaxation of the ROO requirement in 2011 led to a change in the *quality* composition of Bangladesh's woven apparel exports. Recall that prior to 2011, to get duty free access to the EU, firms in Bangladesh *had* to use relatively more expensive domestic fabric. In 2011, this policy changed. Firms could now get duty free access to the EU even if cheaper imported fabric was used in production. The hypothesis is that, after the policy change, firms that were previously meeting the ROOs using domestic fabrics switched to using imported fabric. However, instead of switching to relatively cheaper imported fabric of the same quality, they chose to import fabric of *higher quality.*

As noted before, in Bangladesh the domestic supply of woven fabric is limited. Moreover, apart from a few composite units that produce high quality cloth to make apparel, domestic supply of *high quality* woven fabric is nearly non-existent[9]. Thus before 2011, firms that chose to produce high quality output would necessarily need to import fabric and could thus not meet the ROOs. Firms that were not productive enough to profit from high quality output despite the tariff on exports, chose instead to use low quality domestic fabric that was available and get duty free access to the EU. In fact, there is a positive correlation between export prices and export revenues

[9]Rahman et al. (2014) and personal correspondence with the author

in the woven sector across Bangladeshi firms selling a given HS-6 product to a given destination. For a given product and destination, a doubling of revenue is associated with the 4% higher export price.

Once the ROO policy changed in 2011, there was no longer a "tariff penalty" to producing high quality apparel. After the policy change, firms that were previously meeting the ROOs using domestic (low quality) fabric, chose instead to export using imported fabric of **higher** quality. In the data on woven exports from Bangladesh to the EU, there is a significant negative correlation between sales to the EU of a firm-HS-6 product combination in 2010 and the percentage increase in prices between 2010 and 2011. For a particular firm-product combination, the lower the sales to the EU in 2010, the higher the percentage increase in prices between 2010 and 2011. A doubling of sales to the EU in 2010 is associated with a 1.37% *lower* price change between 2010 and 2011. The negative correlation is even stronger between 2010 firm-HS6 product sales to all destinations and price change between 2010 and 2011 of exports to the EU. While no strong conclusion can be drawn from this, if productivity is positively correlated with sales, the the above information does not contradict the hypothesis that firms which were not productive enough to export high quality apparel to the EU before the policy change and were instead exporting low quality apparel while meeting the ROOs, were the ones that undertook the largest relative quality upgradation after the EU ROO policy change in 2011. Further, in the data on woven exports from Bangladesh to the EU, there is a strong negative correlation between price charged in the EU in 2010 and the percentage *increase* in price to EU between 2010 and 2011. For a given product, the lower the price charged by the firm in 2010, the higher the percentage increase in price between 2010 and 2011. This finding again is consistent with the hypothesis that firms that were meeting the ROOs before 2011 by using domestic (low quality) fabric, after the policy change, choose to export to the EU using *higher* quality imported fabric.

The hypothesis is that it is the upgradation in quality by firms after the policy change that outweighs the effect of falling marginal costs and drives the observed price increase between 2010 and 2011. To illustrate this point, a model of the Bangladeshi woven apparel market with heterogenous firms and quality choice is developed in the next section.

2.3 Model

This section describes a partial equilibrium model of a small open economy based on Melitz (2003). As in Melitz (2003), there are monopolistically competitive firms that are heterogenous in terms of their productivity. In addition to price, firms optimally choose the quality of output. In Baldwin and Harrigan (2011) quality of output depends solely on an individual firm's productivity. However this model allows firms to optimally choose the quality of their output. This is done to emphasize that quality choice by firms depends not only on the firm's productivity but also on the specific trade policy environment in the destination market.

Production uses two inputs - labour and an intermediate input. The quality of output in this model is entirely determined by the quality of the intermediate input. This model only allows for two quality levels - high and low. The model is first set up by incorporating features of both the EU and US trade policy environment before 2011. The equilibrium for this environment is solved. Then, the environment is altered to represent the change in EU trade policy. US trade policy vis-á-vis Bangladesh does not change. The equilibrium is solved in this post 2011 policy environment.

Following Cherkashin et al. (2015), the domestic Bangladeshi market is not modeled at all. As in Cherkashin et al. (2015), it is assumed that the EU and US make up the entire world market for Bangladesh apparel exports. In fact, in 2008, about $\sim 89\%$ of Bangladesh's apparel exports were to the EU and US markets. It is further assumed that firms are constrained to sell only one variety in each market but can vary the quality of their variety across markets.

2.3.1 Demand Side

This model closely follows Cherkashin et al. (2015) with regard to the system of preferences. The preferences in country $j \in \{EU, US\}$ are given as follows:

$$U_j = (N_j)^{1-\beta} (C_j)^{\beta} \qquad 0 < \beta < 1 \qquad \text{where} \qquad C_j = \left(\sum_{i \in \Omega_j} [X_{ij}]^{\frac{(\sigma_j - 1)}{\sigma_j}} \right)^{\frac{\sigma_j}{(\sigma_j - 1)}}$$

where N_j is a competitively produced numeraire good that is freely traded and takes a unit of effective labour to produce. As in Cherkashin et al. (2015), C_j can be interpreted as the aggregated consumption of the apparel exports of all the trading partners of country j. β is the share of income spent on C_j by a representative consumer in country j and Ω_j is the set of trading partners of country j.

$$X_{ij} = \left(\int_{\omega \in \Omega_{ij}} q_{ij}(\omega)^{\frac{1}{\sigma_j}} x_{ij}(\omega)^{\frac{\sigma_j - 1}{\sigma_j}} d\omega \right)^{\frac{\sigma_j}{\sigma_j - 1}}$$

X_{ij} can be thought of as the services produced by the apparel exports of a trading partner i of country j that produces and sells a continuum of varieties indexed by ω. Ω_{ij} is the set of varieties of country i available to consumers in country j. X_{ij} is in turn determined by the quantity of each variety consumed $x_{ij}(\omega)$ as well as the corresponding quality of the variety $q_{ij}(\omega)$ of all $\omega \in \Omega_{ij}$. $\sigma_j > 1$ is the elasticity of substitution between these varieties in country $j \in \{EU, US\}$. Since the share of income spent on aggregated apparel consumption C_j is fixed at β, an increase in the X_{ij} for an i comes at the expense of all other $i' \in \Omega_j,\ i \neq i'$.

Solving the optimization problem of the consumer in country j gives the following demand for variety $\omega \in \Omega_{ij}$ produced in country i and exported to country j:

$$x_{ij}(\omega) = E_{ij} P_{ij}^{\sigma_j - 1} q_{ij}(\omega) p_{ij}(\omega)^{-\sigma}$$

Note that the demand $x_{ij}(\omega)$ depends on the quality $(q_{ij}(\omega))$ of variety ω, the price $p_{ij}(\omega)$, E_{ij} and P_{ij}, where $E_{ij} = \int_{\omega \in \Omega_{ij}} p_{ij}(\omega) x(\omega) dw$ is the expenditure by a representative consumer in country j on the exports of country i and

$$P_{ij} = \left[\int_{\omega \in \Omega_{ij}} q_{ij}(\omega) p_{ij}(\omega)^{1-\sigma_j} dw \right]^{\frac{1}{1-\sigma_j}}$$

is the aggregate quality adjusted price index of exports from country i to country j.

2.3.2 Supply Side and Equilibrium : Before the ROO Policy Change

In this model, there is a continuum of firms, each choosing to produce a different variety ω. Firms are ex-ante identical and must pay a fixed cost of entry f_e to get their productivity draw ϕ from the Weibull distribution $G(\phi) = 1 - e^{-\left(\frac{x}{\lambda}\right)^{\gamma}}$.

Upon realizing their productivity firms must decide whether to exit or to export to the EU, US or both. It is assumed that if a firm decides to enter both the EU and the US markets, then it does so by producing on different production lines for each market. Thus a firm's decision in each market is considered separately.

Once a firm decides to export to destination $j \in \{EU, US\}$, then it also needs to decide the quality of exports to destination j. With regard to quality choice, a firm can only choose between two quality levels- low (q_L) and high quality (q_H). There is a fixed cost of producing and exporting to a market and it depends on the quality of output exported. f_j is the fixed cost that a firm must pay to export low quality output to market j. There is a fixed cost of quality upgrading - $f_{HQ} > 0$. Since production for different markets is undertaken on different production lines, f_{HQ} can be thought of as the fixed costs associated with investment in more sophisticated machinery and equipment. Thus $(f_j + f_{HQ})$ is the fixed cost that a firm must pay to export high quality output to market $j \in \{US, EU\}$.

For exports to the EU market, firms additionally have to decide whether or not to meet the Rules of Origin (ROOs). Recall that to meet the ROOs and thus obtain duty free access to EU, output must be produced using domestic intermediate input. Meeting the ROOs on exports to the EU before 2011 meant proving that domestic cloth was used in production. The process associated with proving this is modeled as a fixed documentation cost d_{EU} that the firms must pay in order to gain duty free access to the EU.

In this model, the quality of the output is determined by the quality of the intermediate input. Production requires two inputs, labour (L) and an intermediate input (M) which in the case of the apparel industry should be interpreted as cloth/fabric.

Output is determined by following production function:

$$Y = \chi\phi L^{1-\mu}(M^{ks})^{\mu} \qquad \text{where} \quad \chi = ((1-\mu)^{1-\mu}\mu^{\mu})^{-1}$$

and $k = l, h$ indicates whether the intermediate is of low or high quality and $s = D, I$ indicates whether the intermediate input is domestic or imported.

Wage can be normalized to 1 since N_j is a competitively produced numeraire good that is freely traded and requires one unit of effective labour to produce. The relative cost of one unit of the intermediate input M^{ks} of quality k and source s is c^{ks}. Thus, for a firm with productivity ϕ, the marginal cost of output of quality k and input source s is $\frac{(c^{ks})^{\mu}}{\phi}$.

Due to limited supply, domestic cloth is priced at a premium in Bangladesh. The domestic price premium is modeled as $c^{kD} > c^{kI}$ - the per unit cost of domestic intermediate input of quality k is higher than that of the imported intermediate input of the same quality. Specifically it is assumed $c^{kD} = \frac{c^{kI}}{\alpha_k}$ where $\alpha_k < 1$.

2.3.2.1 Firm's Problem in the US Market

This section describes the firm's problem of exporting to the US market taking to account the US trade policy environment for Bangladesh apparel exports. After the phase-out of the Multi Fibre Agreement (MFA), effective January 1st 2005, quotas on apparel exports from Bangladesh to the US were eliminated. Between 2008 and 2012, Bangladeshi apparel exports have quota free access to the US market. However, tariffs are imposed on apparel exports from Bangladesh to the US. This is represented as an ad valorem tariff t^{US} that is levied on the price and the firm receives $(1 - t^{US})p$ for every unit sold at price p. Tariffs are applied on exports regardless of the source of the intermediate input (cloth) used in production. Thus apparel exports to the US are not *penalized* for using relatively cheaper imported fabric in production. Given the lower price, firms exporting to the US strictly prefer to use imported intermediate input in production. In exporting to the US, firms only need to make a decision on the quality of output. That is, on the basis of their productivity draw, firms need to decide whether to exit or export low or high quality output to the US.

Due to the existence of the fixed costs of quality upgradation (f_{HQ}), the total fixed cost of producing high quality output is larger than the fixed cost of producing low quality output. Production of high quality output involves higher marginal costs than low quality output. It is assumed that the positive effect of high quality output on demand and revenues outweighs the negative effect of higher prices. Specifically for $j \in \{EU, US\}$,

$$\frac{q_H(c^{HI})^{\mu(1-\sigma_j)}}{q_L(c^{LI})^{\mu(1-\sigma_j)}} > 1 \qquad \text{[Assum 1]}$$

Further it is assumed that the fixed cost of producing high quality output is large enough such that the additional profits from producing high quality output outweigh the additional fixed costs only for firms with sufficiently high productivity ϕ. Specifically, I assume:

$$\frac{f_{US} + f_{HQ}}{f_{US}} > \frac{q_H(c^{HI})^{\mu(1-\sigma_{US})}}{q_L(c^{LI})^{\mu(1-\sigma_{US})}} \qquad \text{[Assum 2]}$$

The profits for a firm with productivity ϕ from exporting low quality output to the US market is given below.

$$\pi_{BD,US}(L,\phi) = \max_p \left\{ (1-t^{US}) \left[p - \frac{\tau_{BD,US}\left(c^{LI}\right)^{\mu}}{\phi(1-t^{US})} \right] x_{BD,US}(L,\phi) - f_{US} \right\}$$

where $\tau_{BD,j}$ is the iceberg transport cost for a firm exporting from Bangladesh to country $j \in \{US, EU\}$. The optimal price charged by the firm is given by: $p_{BD,US}(L,\phi) = \frac{\sigma_{US}}{\sigma_{US}-1} \frac{\tau_{BD,US}\left(c^{LI}\right)^{\mu}}{\phi(1-t^{US})}$.

$$\Rightarrow \pi_{BD,US}(L,\phi) = \frac{(1-t^{US})E_{BD,US}\ P_{BD,US}^{\sigma_{US}-1}\ q_L}{\sigma_{US}} \left[\frac{\tau_{BD,US}\,(c^{LI})^{\mu}}{\rho_{US}\phi(1-t^{US})} \right]^{1-\sigma_{US}} - f_{US}$$

where $E_{BD,US}$ is the total expenditure in US on all varieties exported from Bangladesh, $P_{BD,US}$ is the aggregate price index of varieties exported from Bangladesh to the US and σ_{US} is the elasticity of substitution between the varieties in the US and

$\rho_{US} = \frac{\sigma_{US}-1}{\sigma_{US}}$.

The profits for a firm with productivity ϕ from exporting high quality output to the US market is as follows:

$$\pi_{BD,US}(H,\phi) = \max_{p}\left\{(1-t^{US})\left[p - \frac{\tau_{BD,US}\,(c^{HI})^{\mu}}{\phi(1-t^{US})}\right] x_{BD,US}(H,\phi) - f_{US} - f_{HQ}\right\}$$

$$\Rightarrow \pi_{BD,US}(H,\phi) = \frac{(1-t^{US})E_{BD,US}\;P_{BD,US}^{\sigma_{US}-1}\;q_{H}}{\sigma_{US}}\left[\frac{\tau_{BD,US}\,(c^{HI})^{\mu}}{\rho_{US}\phi(1-t^{US})}\right]^{1-\sigma_{US}} - f_{US} - f_{HQ}$$

2.3.2.2 Firm's Problem in the EU Market

Prior to 2011, the EU trade policy environment for Bangladesh apparel exports was very different from that of the US. Before 2011, firms could only meet the Rules of Origin (ROOs) and obtain duty free access to the EU by using domestic cloth in production. As mentioned before, due to limited supply, domestic cloth is priced at a premium in Bangladesh and $c^{kD} = \dfrac{c^{kI}}{\alpha_k}$ where $\alpha_k < 1$ for quality $k = L, H$. Therefore prior to 2011, Bangladeshi exporters faced a trade off when exporting to the European Union. By using domestic cloth, they were able to get duty free access. If instead they chose to use relatively cheaper imported cloth, a tariff of 12.1% would be imposed on exports to the European Union.

If a firm with productivity ϕ chooses to meet the ROOs when exporting to the EU, then it must use domestic intermediate input. In addition to the cost of exporting output of quality k to the EU - $(f_{EU} + f_{kq})$ - the firm must also pay a documentation cost d_{EU} of meeting the ROOs. The profits of a Bangladeshi firm with productivity ϕ exporting output of quality k to the EU and meeting ROOs is given as follows:

$$\pi^{roo}_{BD,EU}(k,\phi) = \max_{p}\left\{\left[p - \frac{\tau_{BD,EU}\left(c^{kD}\right)^{\mu}}{\phi}\right] x_{BD,EU}(k,\phi) - f_{EU} - f_{kq} - d_{EU}\right\}$$

with $f_{LQ} = 0$

$$\Rightarrow \pi^{roo}_{BD,EU}(k,\phi) = \frac{E_{BD,EU}P_{BD,EU}^{\sigma_{EU}-1}q_k}{\sigma_{EU}}\left[\frac{\tau_{BD,EU}}{\rho_{EU}\phi}\left(\frac{c^{kI}}{\alpha_k}\right)^{\mu}\right]^{1-\sigma_{EU}} - f_{EU} - f_{kq} - d_{EU}$$

where $E_{BD,EU}$ is the total expenditure in EU on all varieties exported from Bangladesh,

$P_{BD,EU}$ is the aggregate quality adjusted price index of varieties exported from Bangladesh to the EU and σ_{EU} is the elasticity of substitution between the varieties in the EU.

If on the other hand, a firm with productivity ϕ chooses *not* to meet the ROOs when exporting to the EU, then an ad-valorem tariff t^{EU} is levied on the price. Also, given the relatively higher price of domestic cloth, a firm that produces output of quality k and decides not to meet the ROOs would always make higher profits by using relatively cheaper imported cloth. Thus the profits to a firm with productivity ϕ exporting output of quality k to the EU without meeting the ROOs is given by: M

$$\pi_{BD,\,EU}(k,\phi) = \max_{p} \left\{ (1-t^{EU}) \left[p - \frac{\tau_{BD,\,EU}(c^{kI})^{\mu}}{\phi(1-t^{EU})} \right] x_{BD,\,EU}(k,\phi) - f_{EU} - f_{kq} \right\} \quad \text{with } f_{LQ}=0$$

$$\Rightarrow \pi_{BD,\,EU}(k,\phi) = \frac{(1-t^{EU})E_{BD,\,EU}P_{BD,\,EU}^{\sigma_{EU}-1}q_k}{\sigma_{EU}} \left[\frac{\tau_{BD,\,EU}(c^{kI})^{\mu}}{\rho_{EU}\phi(1-t^{EU})} \right]^{1-\sigma_{EU}} - f_{EU} - f_{kq}$$

The choices of the firm with productivity ϕ exporting to the EU and the associated fixed costs are summarized in the table below.

Table 2.5: Choice of firms in the EU market

Firm's choices in exporting to the EU market		**Associated Fixed Costs**
→ Produce high quality	→ don't meet ROOs	$f_{EU} + f_{HQ}$
	→ meet ROOs	$f_{EU} + f_{HQ} + d_{EU}$
→ Produce low quality	→ meet ROOs	f_{EU}
	→ don't meet ROOs	$f_{EU} + d_{EU}$
→ Exit		

2.3.2.2.1 Model Assumptions

In order to be consistent with the observations in the data and information about the Bangladeshi apparel export sector, some assumptions are made on the parameters of the model.

A firm exporting high quality output to the EU can choose either to meet the

Rules of Origin or not to meet them. If a firm chooses to meet the ROOs it needs to use domestic high quality cloth. However, except for a few composite units that produce high quality cloth to make apparel, domestic supply is nearly non existent in Bangladesh[10]. In Bangladesh, firms that produce high quality apparel *have* to use imported high quality cloth. In the context of the model, the non-existent domestic supply of high quality cloth is represented by assuming the price premium on domestic high quality cloth is so large that it outweighs the benefits of meeting ROOs. Specifically it is assumed that α_H is small enough to satisfy :

$$(1-t^{EU})^{\sigma_{EU}} > (\alpha_H)^{\mu(\sigma_{EU}-1)} \qquad \text{[Assum 3]}$$

Assumption 3 implies that for all $\phi \sim G(\phi)$:

$$\pi^{roo}_{BD,EU}(H,\phi) = \frac{E_{BD,\,EU} P^{\sigma_{EU}-1}_{BD,\,EU} q_H}{\sigma_{EU}} \left[\frac{\tau_{BD,\,EU}}{\rho_{EU}\phi} \left(\frac{c^{HI}}{\alpha_H} \right)^{\mu} \right]^{1-\sigma_{EU}} - (f_{EU} + f_{HQ} + d_{EU})$$

$$< \frac{(1-t^{EU}) E_{BD,\,EU} P^{\sigma_{EU}-1}_{BD,\,EU} q_H}{\sigma_{EU}} \left[\frac{\tau_{BD,\,EU}(c^{HI})^{\mu}}{\rho_{EU}\phi(1-t^{EU})} \right]^{1-\sigma_{EU}} - f_{EU} - f_{HQ} = \pi_{BD,EU}(H,\phi)$$

Due to the extremly high premium on domestic high quality intermediate input, no firm exporting high quality output to the EU will choose to meet ROOs since it can always make larger profits by not meeting ROOs.

However, in the data, it is observed that prior to 2011 only about 28% of Bangladeshi woven exports to the EU meet the Rules Of Origin and are able to enter duty free[11]. In order to be consistent with this observation, it must be profitable for some firms to meet the ROOs when exporting low quality output to the EU. Thus, it is assumed that the price premium of domestic low quality intermediate is not as high as that of high quality domestic intermediate. Specifically, it is assumed that

$$\frac{\alpha_L^{\mu(\sigma_{EU}-1)}}{(1-t^{EU})^{\sigma_{EU}}} > 1 + \frac{d_{EU}}{f_{EU}} \qquad \text{[Assum 4]}$$

[10] Rahman et al. (2014) & personal correspondence with the author.

[11] While the percentage of Bangladeshi exports to the EU that enter duty free varies by product, Rahman et al. (2014) estimates that on average about 28% of Bangladeshi woven exports to the EU have no duty imposed on them

That is, the variable profits from meeting ROOs with low quality output outweigh the additional fixed documentation costs (d_{EU}) of meeting ROOs. The implication of this assumption is evident in the Figure 2.4 below and the explanation that follows.

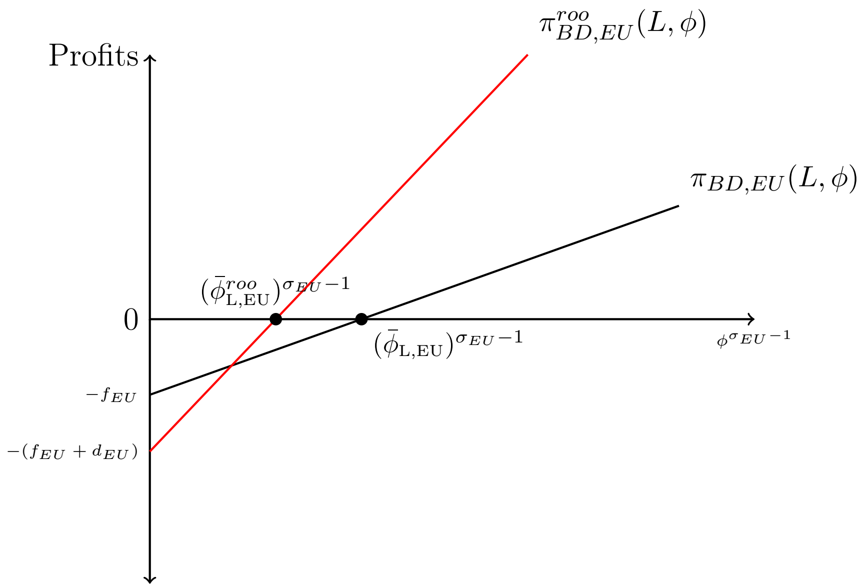


Figure 2.4: Profits from exporting low quality to EU with and without meeting ROOs

Figure 2.4 shows the profits from producing low quality output with and without meeting Rules of Origin. $\bar{\phi}^{roo}_{\text{L,EU}}$ is the productivity of a firm that makes zero profits from exporting low quality output to the EU and meeting ROOs. Correspondingly, $\bar{\phi}_{\text{L,EU}}$ is the productivity of a firm that makes zero profits by exporting low quality output to the EU and *not* meeting ROOs.

That is:

$$\pi^{roo}_{BD,\,EU}(L,\bar{\phi}^{roo}_{\text{L,EU}}) = 0 \Rightarrow \bar{\phi}^{roo}_{\text{L,EU}} = \frac{\tau_{BD,\,EU}(c^{LI})^{\mu}}{\rho_{EU}}\left[\frac{\sigma_{EU}(f_{EU}+d_{EU})}{E_{BD,\,EU}P^{\sigma_{EU}-1}_{BD,\,EU}q_L(\alpha_L)^{\mu(\sigma_{EU}-1)}}\right]^{\frac{1}{\sigma_{EU}-1}}$$

$$\pi_{BD,\,EU}(L,\bar{\phi}_{\text{L,EU}}) = 0 \Rightarrow \bar{\phi}_{\text{L,EU}} = \frac{\tau_{BD,\,EU}(c^{LI})^{\mu}}{\rho_{EU}}\left[\frac{\sigma_{EU}f_{EU}}{E_{BD,\,EU}P^{\sigma_{EU}-1}_{BD,\,EU}q_L(1-t^{EU})^{\sigma_{EU}}}\right]^{\frac{1}{\sigma_{EU}-1}}$$

Assumption 4 implies that $\bar{\phi}^{roo}_{\mathrm{L,EU}} < \bar{\phi}_{\mathrm{L,EU}}$. Further, $\pi^{roo}_{BD,\,EU}(L,\phi) - \pi_{BD,\,EU}(L,\phi) > 0 \;\forall\; \phi \geq \bar{\phi}^{roo}_{\mathrm{L,EU}}$ - since the price premium on domestic low quality intermediate is not too high, all firms with sufficiently high productivity exporting low quality output to the EU will always make higher profits from meeting the ROOs than from not meeting the ROOs.

Thus under the assumptions of the model so far, when exporting low quality output to the EU, firms will prefer to use domestic intermediates and meet the ROOs. And when exporting high quality output to the EU, firms will make higher profits by using imported intermediates and not meeting the ROOs. At this point, it is important to examine the trade off involved for a firm in choosing between high and low quality output export to the EU. If a firm chooses to produce high quality output, it incurs a higher marginal cost of production. However given price, demand for output is also higher (since demand $x(\omega)$ depends positively on quality $q(\omega)$). I assume that the positive effect of higher quality on demand outweighs the negative effect of higher marginal cost. Specifically, I assume that -

$$q_H\left[(1-t^{EU})^{\sigma_{EU}}(c^{HI})^{\mu(1-\sigma_{EU})}\right] > q_L\left[\left(\frac{c^{LI}}{\alpha_L}\right)^{\mu(1-\sigma_{EU})}\right] \qquad \text{[Assum 5]}$$

In addition to f_{EU}, exporting high quality output to a market also requires a firm to incur a fixed cost of quality upgradation f_{HQ}. As mentioned before, this fixed cost of quality upgradation can be thought of as investment in more sophisticated machinery and equipment. On the other hand, documentation costs of meeting ROOs in the EU involves only proving that the intermediate input was domestically obtained. I assume that the fixed cost of quality upgradation is higher than the documentation costs of meeting ROOs (d_{EU}) - $f_{HQ} > d_{EU}$.

By the assumptions of the model, a firm exporting low quality output to the EU will always prefer to meet the ROOs and a firm exporting high quality output to the EU will prefer not to meet ROOs. While the fixed costs of quality upgradation are higher than the fixed costs of meeting ROOs, it is further assumed that f_{HQ} is high enough such that the additional variable profits from exporting high quality output to the EU outweigh the additional fixed costs only for firms with sufficiently high productivity ϕ. Specifically

$$\frac{f_{EU} + f_{HQ}}{f_{EU} + d_{EU}} > \frac{q_H(1 - t^{EU})^{\sigma_{EU}}(c^{HI})^{\mu(1-\sigma_{EU})}}{q_L(\alpha_L)^{\mu(\sigma_{EU}-1)}(c^{LI})^{\mu(1-\sigma_{EU})}} \qquad \text{[Assum 6]}$$

2.3.2.3 Equilibrium : Before the ROO Policy Change

As described in Section 2.3.2.1, the US trade policy environment is such that Bangladeshi firms exporting to the US would always use imported intermediate inputs and on the basis of their productivity level need to only decide whether to export high or low quality output. Further, by assumption 2 of the model, the total fixed costs of exporting high quality output to the US is large enough that the additional profits from exporting high quality output outweigh the additional fixed costs only for firms with sufficiently high productivity. Thus with regard to exporting to the US, firms sort themselves into exporting high quality and low quality output on the basis of their productivity draws. Specifically, all firms with productivity $\phi \in (\phi_L^{US}, \phi_H^{US})$ export low quality output to the US and firms with productivity $\phi \in (\phi_H^{US}, \infty)$ export high quality output to the US. The threshold productivities ϕ_L^{US} and ϕ_H^{US} satisfy the following zero profit conditions:

$$\pi_{BD,US}(L, \phi_L^{US}) = 0 \qquad \text{[US ZPC I]}$$

$$\pi_{BD,US}(H, \phi_H^{US}) - \pi_{BD,US}(L, \phi_H^{US}) = 0 \qquad \text{[US ZPC II]}$$

For the EU market, from the assumptions of the Section 2.3.2.2, firms exporting low quality output to the EU market prefer to meet the ROOs. On the other hand, firms that export high quality output to the EU prefer *not* to meet the Rules of Origin. By assumption 6 of the model, the fixed costs of exporting high quality output to the EU is large enough that the additional profits from exporting high quality output outweigh the additional fixed costs only for firms with sufficiently high productivity. Thus, on the basis of their productivity draw ϕ, firms choose whether to export low quality output to the EU while meeting the ROOs or to export high quality output to the EU without meeting the ROOs.

Specifically, all firms with productivity $\phi \in (\phi_L^{EU}, \phi_H^{EU})$ export low quality output to the EU and meet the Rules of Origin and firms with productivity $\phi \in (\phi_H^{EU}, \infty)$ export high quality output to the EU without meeting the Rules of Origin. The threshold productivities ϕ_L^{EU} and ϕ_H^{EU} satisfy the following zero profit conditions:

$$\pi_{BD,EU}^{roo}(L, \phi_L^{EU}) = 0 \qquad \text{[EU ZPC I]}$$

$$\pi_{BD,EU}(H, \phi_H^{EU}) - \pi_{BD,US}^{roo}(L, \phi_H^{EU}) = 0 \qquad \text{[EU ZPC II]}$$

The equilibrium level of entry is such that the expected profits from entering the industry, obtaining a productivity draw and choosing optimally in each market $j \in \{EU, US\}$ is equal to the fixed cost of entry, f_e. The following free entry condition, together with the four zero profit conditions above determine the pre-policy change equilibrium:

$$\mathbb{E}_\phi \left[\max\left\{\pi_{BD,US}(L,\phi), \pi_{BD,US}(H,\phi), 0\right\} + \max\left\{\pi_{BD,EU}(H,\phi), \pi_{BD,EU}^{roo}(L,\phi), 0\right\}\right] = f_e$$

The free entry condition and the four zero profit conditions can be solved for the equilibrium mass of entrants, the threshold productivities in both the US market $(\phi_L^{US}, \phi_H^{US})$ and the EU market $(\phi_L^{EU}, \phi_H^{EU})$ and the market specific equilibrium distribution over productivity levels.

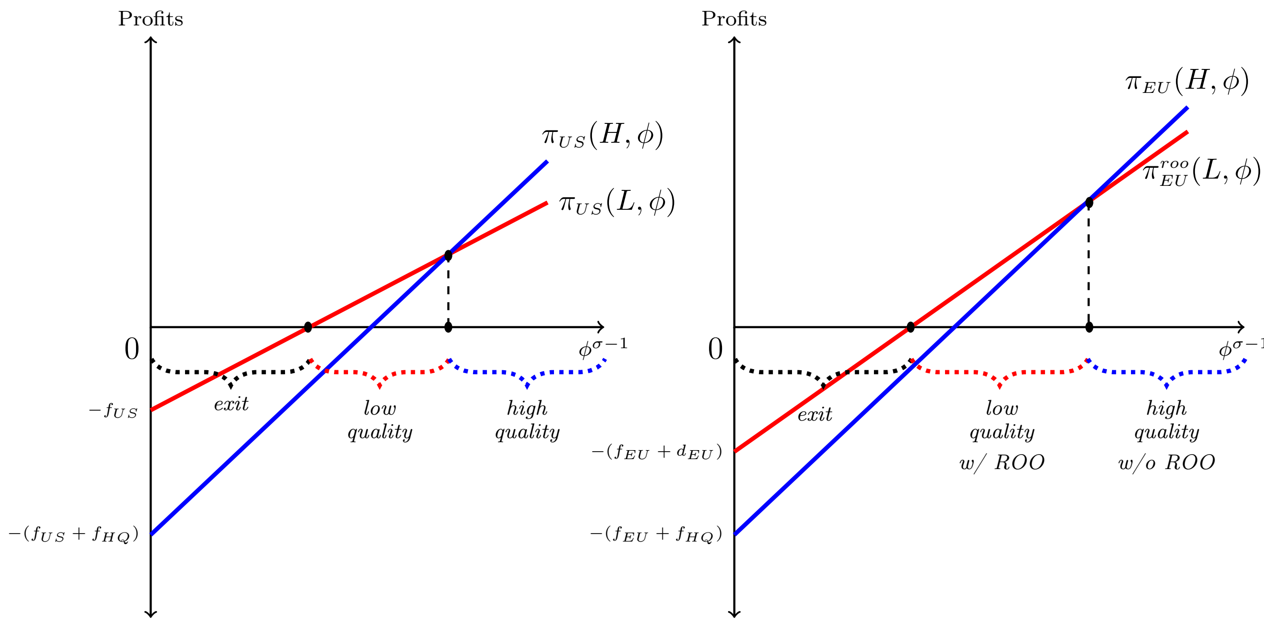
The equilibrium partitioning of firms into different choices in each market (US & EU) on the basis of productivity levels is represented graphically in Figure 2.5 below.

2.3.3 Supply Side and Equilibrium : After ROO Policy Change

2.3.3.1 Firm's Problem in the EU and US Market

To understand the impact on Bangladesh of the trade policy change in the EU in 2011, the following is a description of the firm's problem in both the EU and the US market after the policy change and the resulting equilibrium.

In 2011, the European Union changed the Rules of Origin requirements that allowed exports from LDCs to enter the EU market duty free. In the apparel sector,



(a) US Market

(b) EU Market

Figure 2.5: Equilibrium Before the Policy Change

firms in LDCs like Bangladesh can now export duty free to the European Union even if they use imported cloth in production. Thus firms in Bangladesh are no longer constrained to use relatively more expensive domestic cloth in order to meet the ROOs and obtain duty free access to the EU market. After the policy change, all firms regardless of whether they use imported or domestic cloth, can meet the Rules of Origin and obtain duty free access to the EU. After the policy change, nearly 100% of Bangladeshi exports to the EU met the Rules of Origin and were given duty free access[12].The US trade policy environment for apparel exports from Bangladesh did not change between 2008 and 2012.

In the model, the firms' problem is altered to be consistent with the policy change and the observations from the data. Since meeting the Rules of Origin when exporting to the EU no longer involves proving the use of domestically produced cloth, the post policy change documentation costs of meeting the ROOs is set equal to 0. Further,

[12]Conversation with Zillul Hye Razi, Trade Advisor, Delegation of the European Union to Bangladesh

when exporting to the EU, since firms can meet the ROOs regardless of the source of cloth, they choose to produce output of a given quality using imported cloth rather than the relatively more expensive domestic cloth.

After the policy change, all firms exporting to the EU meet the ROOs. Now, as in the US market, when exporting to the EU, firms only need to decide whether to exit or to export low or high quality output. Due to the existence of the fixed costs of quality upgradation, the total fixed costs of producing high quality output are larger than the fixed cost of producing low quality output. In fact, it is assumed that in both the EU and the US market, the fixed costs of exporting high quality output is large enough such that the additional profits from producing high quality output outweigh the additional fixed costs only for firms with sufficiently high productivity ϕ. Specifically for $j \in \{EU, US\}$:

$$\frac{f_j + f_{HQ}}{f_j} > \frac{q_H (c^{HI})^{\mu(1-\sigma_j)}}{q_L (c^{LI})^{\mu(1-\sigma_j)}} \qquad \text{[Assum 7]}$$

For a firm with productivity ϕ, the profits from exporting low and high quality output to market $j \in \{EU, US\}$ are given by:

$$\pi^{new}_{BD,j}(L,\phi) = \frac{(1-t^j)E_{BD,j}P^{\sigma_j-1}_{BD,j}q_L}{\sigma_j}\left[\frac{(c^{LI})^{\mu}}{\rho_j(1-t^j)\phi}\right]^{1-\sigma_j} - f_j$$

$$\pi^{new}_{BD,j}(H,\phi) = \frac{(1-t^j)E_{BD,j}P^{\sigma_j-1}_{BD,j}q_H}{\sigma_j}\left[\frac{(c^{HI})^{\mu}}{\rho_j(1-t^j)\phi}\right]^{1-\sigma_j} - f_j - f_{HQ}$$

where now $t^{EU} = 0$ and t^{US} is the same as before the policy change. Given the quality adjusted price index $P_{BD,EU}$ and expenditure $E_{BD,EU}$, Figure 2.6 shows that for a firm with productivity ϕ, the profits from exporting both low and high quality output to the EU are higher after the policy change than before. Note that Figure 2.6 is only to illustrate the mechanism that would have a positive effect on the prices charged by firms after the policy change. $P_{BD,EU}$ is a quality adjusted price index which is lower in the equilibrium after policy change than in the equilibrium before. The expenditure on exports, $E_{BD,EU}$ also adjusts and the net effect on "pure price index" (defined in Section 2.4) depends on the parameters of the model.

After the change in the EU Rules of Origin requirement in 2011, Bangladeshi

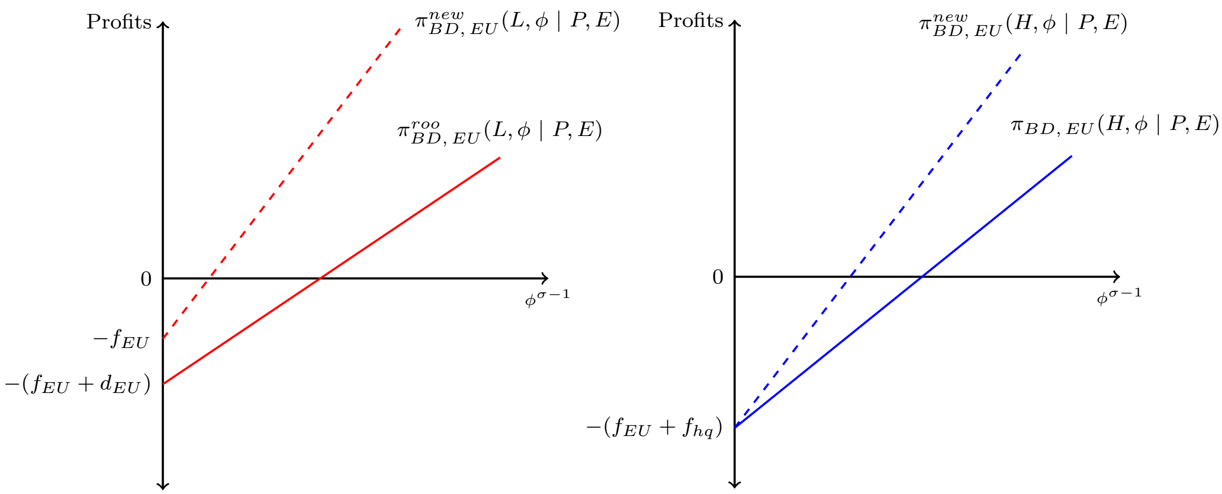


Figure 2.6: Profits Before and After Policy Change

firms are no longer constrained to use domestic cloth in order to receive duty free access to the EU. Since there is no *tariff penalty* to using relatively cheaper imported intermediate, a *fall* in the average unit values of exports to the EU is expected as firms can now get duty free access to the EU even when using relatively cheaper imported cloth. However, in the data there is an increase in the quantity weighted average price. Figure 2.6 above illustrates the key mechanism that might be driving this increase in prices. While the policy change would lead to a fall in prices for any given quality choice, the increase in prices could be driven by a post policy change increase in the quality of output exported to the EU by firms. Firms exporting to the EU that were previously indifferent between exporting low quality output while meeting the ROOs and exporting high quality output without meeting the ROOs, make strictly higher profits by exporting high quality output to the EU than from low quality output under the new ROO policy. The effect of this resulting quality upgrading could, in equilibrium, outweigh the effect of falling costs on the pure (non quality adjusted) aggregate price index.

2.3.3.2 Equilibrium : After the ROO Policy Change

After the EU Rules of Origin Policy Change in 2011, when exporting to market $j \in \{EU, US\}$, Bangladeshi firms only need to decide whether to exit or to export low or high quality output to market j. It is assumed that in both the EU and US markets, the benefits of producing high quality output outweigh the costs only for firms with sufficiently high productivity. In equilibrium, in each market, firms sort themselves into high and low quality production on the basis of their productivity.

Specifically, all firms with productivity $\phi \in (\hat{\phi}_L^j, \hat{\phi}_H^j)$ export low quality output to market j and firms with productivity $\phi \in (\hat{\phi}_H^j, \infty)$ export high quality output to market $j \in \{EU, US\}$. The threshold productivities $\hat{\phi}_L^j$ and $\hat{\phi}_H^j$ satisfy the following zero profit conditions:

$$\pi^{new}_{BD,j}(L, \hat{\phi}_L^j) = 0 \qquad \text{[ZPC I in market } j\text{]}$$

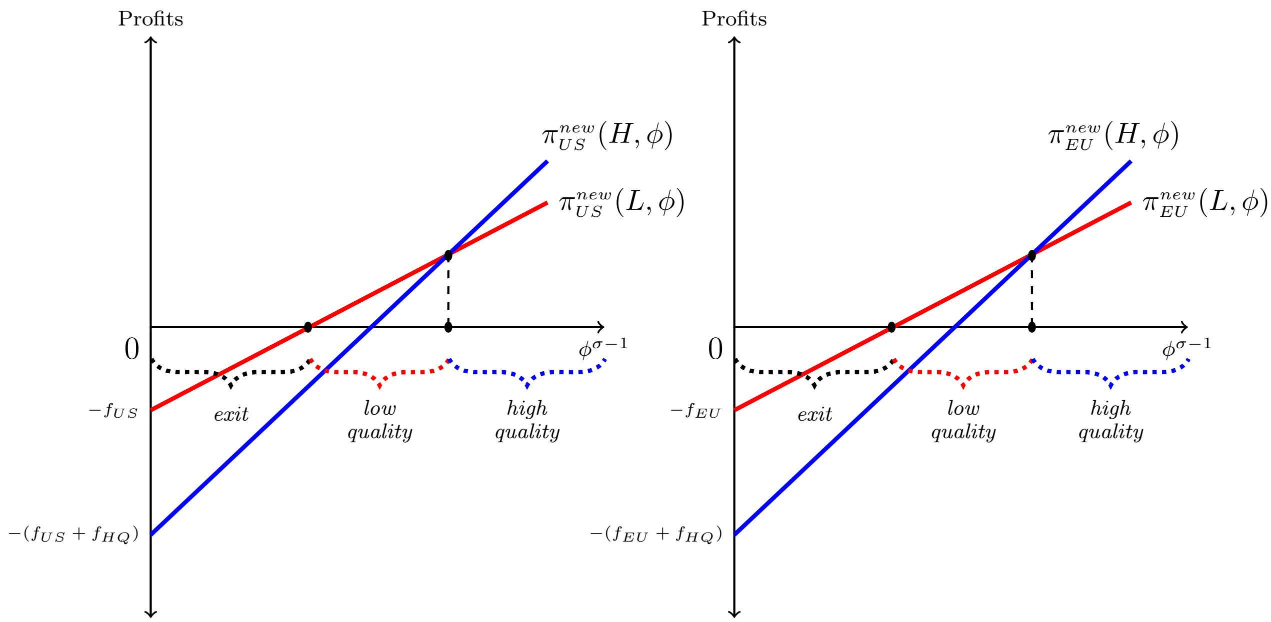
$$\pi^{new}_{BD,j}(H, \hat{\phi}_H^j) - \pi^{new}_{BD,j}(L, \hat{\phi}_H^j) = 0 \qquad \text{[ZPC II in market } j\text{]}$$

The equilibrium mass of entrants in the new trade policy environment is determined by the free entry condition where expected profits from entering the industry and choosing optimally in each market $j \in \{EU, US\}$ is equal to the fixed cost of entry f_e.

$$\mathbb{E}_\phi \left[\max\left\{\pi^{new}_{BD,US}(L,\phi), \pi^{new}_{BD,US}(H,\phi), 0\right\} + \max\left\{\pi^{new}_{BD,EU}(H,\phi), \pi^{new}_{BD,EU}(L,\phi), 0\right\}\right] = f_e$$

The four zero profit conditions and the free entry condition together pin down the equilibrium mass of entrants, the threshold productivities for each market and the market wise equilibrium distribution over productivity levels in the new trade policy environment.

The aggregate price index for each market $P_{BD,j}$ is a quality adjusted price index. Therefore, the falling costs implied by the policy change would lead to a fall in the aggregate quality adjusted price index for the EU ($P_{BD,EU}$). Given the fall in marginal costs, the mass of entering firms would increase. However, the effect on the



(a) US Market

(b) EU Market

Figure 2.7: Equilibrium After the Policy Change

productivity threshold above which firms would export (or below which firms would exit) is ambiguous. The point of interest is the impact of the policy change on a non-quality adjusted "pure price index". A measure of this "pure price index" is defined in the next section. If the effect of an increase in quality of output produced by firms outweighs the effect of falling costs in the new equilibrium, then the equilibrium pure price index will be higher after the policy change and will thus be consistent with the observed data. The next section describes the numerical solution of the model and shows that for a reasonable set of parameters, the effect of quality upgrading by firms is strong enough to generate the increase in price of exports to the EU that is observed in the data.

2.4 Numerical Exercise

This section describes the results of the numerical solution of the model in the previous section. Both the equilibria before and after the policy change are solved for a given set of parameters. The parameters are chosen to match two observations in the data - the increase in the weighted average price of exports to the EU between 2010 and 2012 and the share of exports meeting the EU Rules of Origin in 2010[13]. Data on Bangladesh exports of Men's/Boys' Cotton Shirts (HS 620520) is used.

Table 2.6: Observations from the data to match in the numerical exercise

Product Code	**Share of Exports meeting ROOs**	**Percent change in average price of exports to EU**
620520	29.1 %	3.98%

The price index of exports from Bangladesh to the EU in the model of Section 2.3 ($P_{BD,\,EU}$) is a quality adjusted price index. Thus even if firms upgrade quality after the policy change, the relaxation of the domestic cloth requirement for exports to the EU and the associated elimination of the tariff (t^{EU}) in the environment after the policy change will necessarily imply that the *quality-adjusted* price index $P_{BD,EU}$ is lower in the equilibrium after the policy change than in the equilibrium before the policy change.

To match the data on price change, a measure analogous to weighted average price is constructed as follows:

$$\bar{P}_{BD,\,EU} = \frac{E_{BD,\,EU}}{\displaystyle\int_{\omega \in \Omega_{BD,EU}} x(\omega)\, d\omega}$$

where $\displaystyle\int_{\omega \in \Omega_{BD,EU}} x(\omega)\, d\omega$ is the aggregate quantity of exports from Bangladesh to EU that is demanded and consumed in equilibrium and $E_{BD,\,EU}$ is the aggregate expenditure on exports from Bangladesh to the EU. The percentage change in $\bar{P}_{BD,\,EU}$ between the equilibrium prior to and post the EU ROO policy change is matched to the percentage change in quantity weighted average price given in Table 2.9.

[13]Data on the share of exports meeting the Rules of Origin and availing preferences under the EBA in 2010 was provided by Zillul Hye Razi, Delegation of the European Union to Bangladesh.

2.4.1 Value of Parameters

According to Rahman et al. (2014) before the change in the Rules of Origin policy of the EU in 2011, the average tariff imposed on apparel exports from Bangladesh that did not meet the ROOs was 12.1%. Between 2008 and 2012, the average tariff imposed by the US on apparel exports from Bangladesh is 16.3%. In the numerical exercise t^{EU} is set equal to 0.12 and t^{US} is set at 0.16.

Table 2.7: Parameter Values

Tariffs		**Elasticity of Substitution**		**Productivity Distribution Parameters**	
t^{EU} t^{US}	0.12 0.16	σ_{EU} σ_{US}	1.34 1.45	λ (scale) γ (shape)	0.42 0.81

The values of the elasticity of substitution between varieties in the EU and the US (σ_{EU}, σ_{US}) and the shape and scale parameters of the productivity distribution (γ and λ) are the estimated values in Cherkashin et al. (2015).

τ	1.14
μ	0.75
α_L	0.85

Iceberg transport costs for the apparel industry are estimated to range from 8% to 14%[14]. Following **??**, τ is set equal to 1.14. Following the estimates in **??**, values of the share of intermediate input in production (μ) is set equal to 0.75 and the measure of the domestic price premium of low quality intermediate (α_L) is set to 0.85.

From Bhattacharya et al. (2000), the average cost of fabric per shirt (when wages are normalized to 1) is \$2.56. This is assumed to be the cost of medium quality fabric. It is assumed that high quality fabric costs twice as much as this and low quality fabric costs about half. The values of q_H and q_L are chosen to satisfy the assumptions of the model.

[14]**??** from **??**

Table 2.8: Cost and Quality Parameters

c^H	2.56×2
c^L	2.56×0.5
q_H	7
q_L	4

f_j/f_e for $j \in \{US, EU\}$	0.155
f_e	82000
f_{HQ}	5500
d_{EU}	966.7

The parameter f_j is the fixed cost of exporting low quality output to market j. As an approximation, the ratio f_j/f_e is set at 0.155 following the ratio of the value of fixed cost of entry and fixed cost of exporting to market $j \in \{US, EU\}$ estimated in **??**. The values of the fixed cost of entry f_e, the fixed cost of upgrading output quality f_{HQ} and the documentation costs of meeting the Rules of Origin before the policy change d_{EU} are chosen such that the results of the model match the data as close as possible.

2.4.2 Results of the Numerical Exercise

The two main observations in the data that this numerical exercise tries to match is the share of exports from Bangladesh given duty free access to the EU in 2010 (before the policy change) and the percent change in weighted average price of exports of Mens/Boys' Shirts (HS 620520) from Bangladesh to the EU between 2010 and 2012.

The assumptions of the model in Section 2.3 imply that in the environment before the policy change, the Rules of Origin are met only by low quality exports from Bangladesh to the EU. Further, in the equilibrium, *all* low quality output exported from Bangladesh to the EU meet the Rules of Origin. Therefore, the share of exports meeting the ROOs before the policy change is calculated as the share of low quality exports from Bangladesh to the European Union in the equilibrium before the policy change.

As mentioned before, in the numerical exercise, a measure analogous to weighted average price is constructed - $\bar{P}_{BD,\,EU}$. The percent change in weighted average price of exports between 2010 and 2012 observed in the data is matched to the percent change in $\bar{P}_{BD,\,EU}$ between the equilibrium before the policy change and the equilibrium after the policy change. The results of the numerical exercise and the corresponding observations in the data are given in the table below.

Table 2.9: Results of the Numerical Exercise

	Share of Exports to EU meeting ROOs	**Percent change in Average Price of exports b/w 2010 and 2012**
Data	29.1 %	4.06 %
Model Results	34.7 %	3.93 %

For the parameter values given in the previous section, the model generates that before the ROO policy change, 34.7% of exports from Bangladesh to the EU were meeting the Rules of Origin and given duty free access. The model also generates that in the equilibrium after the policy change, $\bar{P}_{BD,\,EU}$ is 3.93 % higher than in the equilibrium before the policy change. After the policy change, the tariff previously imposed on the export of high quality output from Bangladesh to the EU is effectively eliminated. Firms that were previously indifferent between exporting high or low quality output to the EU, after the policy change would strictly prefer to export high quality output to the EU. After the policy change, there is a fall in equilibrium threshold productivity above which firms export high quality output to the EU. In the numerical exercise, the positive effect of quality upgrading outweighs the negative effect of falling costs leading to an increase in the average price of exports to the EU after the ROO policy change.

While the values given to some parameters of the model (especially to the variable cost of intermediate input - c^H & c^L and the quality levels -q_H & q_L) are quite ad-hoc, the main purpose of the numerical exercise is to illustrate that the quality of exports can depend on the trade policy environment faced by exporters and specifically that quality upgrading by firms after the EU-ROO policy change can explain the observed increase in prices to the EU.

However, it is important to note that the results generated on the change in average price of exports to the US are opposite to the observations in the data. The data shows that between 2010 and 2012, there is an increase in the price of exports to the US. Even though, as mentioned in Section 2.2, the percentage increase in average price of woven exports to the US is *less* than that of woven exports to the EU, the evidence does suggest that the change in the EU ROO policy in 2011 might have resulted in an upgrading of the quality of exports to the US as well. This indicates that Bangladeshi firms producing for both export markets (US & EU), do so on a single production line. However, the model in Section 2.3 assumes that firm produce for different markets on different production lines. Thus in the numerical exercise, the model generates a *decrease* in prices to the US. Specifically in the equilibrium after the policy change $\bar{P}_{BD,US}$ is 6.18 % *lower* than in the equilibrium before the policy change. In the environment of the model, before and after the EU ROO policy change, trade policy of the US with respect to Bangladesh exports is not altered. The relaxation of the EU's Rules of Origin policy leads to a greater mass of entrants into the industry and lowers the quality adjusted price index in the US ($P_{BD,US}$). The threshold productivity in the US market below which firms exit, increases after the EU-ROO policy change. Thus, both the quality adjusted price index ($P_{BD,US}$) and the constructed measure of weighted average price ($\bar{P}_{BD,US}$) are lower in the new equilibrium after the policy change than before.

In the model, even though firms are constrained to export only one variety to each market, they can vary the quality of their variety across markets. Thus the decision of quality of exports is considered separately in each market. Firms exporting high quality output to the EU and the US markets, must pay a fixed cost of ($f_j + f_{HQ}$) in each market. The change in the export and quality decisions made by firms exporting to the US and consequent fall in weighted average price measure $\bar{P}_{BD,US}$ is thus driven by the increase in the mass of entrants to the industry after the EU ROO policy change.

However the increase in the price of exports to the EU *and* the US observed in the data suggest that the relaxation of the EU Rules of Origin Policy resulted in an upgrade in the quality of exports to both the EU and the US markets. If this is the case, then it would be useful not to consider the export decision in each market separately. It would be more appropriate to assume that each firm has a single production line. That is, it would be useful to see the implications of the relaxation of EU Rules of Origin requirements on the measure of average price of exports to the EU and the US ($\bar{P}_{BD,EU}$, $\bar{P}_{BD,US}$), if firms were constrained to offer the same quality of their variety across markets.

2.5 Conclusion

Rules of Origin were established to ensure that trade preferences given to countries were confined only to products sufficiently "produced" in those countries. However, the specific requirements of the Rules of Origin might have unexpected implications on the composition of exports from the beneficiary countries. This paper uses the specific example of the impact of a relaxation in the Rules of Origin requirements by the EU on apparel exports from Bangladesh.

The relaxation of EU's Rules of Origin requirements in 2011 allowed Bangladeshi apparel firms to obtain duty free access to the EU even when imported fabric is used in production. Due to limited domestic supply, woven fabric is priced at a premium in Bangladesh. The change in the Rules of Origin allows Bangladeshi firms to get duty free access to the EU even when relatively cheaper imported fabric is used in production. Thus it was expected that this relaxation in the Rules of Origin and effective elimination of import tariffs in the EU would cause firms to switch to using relatively cheaper imported fabric and lead to a sharp fall in the unit values of exports from Bangladesh to the EU. Instead, in the data, an increase in the unit values of Bangladeshi apparel exports to the EU is observed along with an accelerated growth in the share of Bangladesh apparel exports in the EU market. The explanation provided in this paper for the observed increase in unit values is that the relaxation in EU ROOs allowed Bangladeshi firms to upgrade the quality of the output they exported and it was this quality upgrading effect that outweighed the effect of falling costs resulting in the increase in unit values observed in the data. A model emphasizing the dependence of export quality choice by a firm on the trade policy environment in the export market is developed to illustrate this point.

Chapter 3

Regional exposure to trade shocks: Reconciling theory and evidence

with Marisol Rodríguez Chatruc

3.1 Introduction

A growing literature shows that international trade does not affect all regions in a country in the same manner. This literature has taken two broad approaches to estimate or quantify the effect of trade shocks, such as a change in tariffs or an increase in foreign productivity, on regional economies. One approach, which we call reduced-form, consists in regressing changes in regional outcomes such as wages, employment, and poverty rates on measures of regional exposure to trade. Although exposure measures can vary across the different research designs, the common feature is that they are calculated as a weighted sum of sectoral country-level shocks, where the weights reflect the relative importance of each sector in regional employment. This implies that the only initial characteristic of regions that drives its sensitivity to a trade shock is its pattern of sectoral specialization. This is the approach pioneered by Topalova (2010) and followed by others, such as Autor et al. (2013b) and Kovak (2013). The other approach, which we call quantitative, consists in using general equilibrium trade models to simulate changes in regional outcomes such as welfare or employment after an international trade shock. This is the approach taken by

Caliendo et al. (2017) , Galle et al. (2017).

The two approaches differ not only in the methodology they use - one employs reduced-form regressions and the other simulations - but also in the underlying theory. Quantitative approaches are based on standard trade models such as Armington, Krugman (1980), and Eaton and Kortum (2002). In these models, regional economies trade with each other and trade flows follow gravity forces. The impact of a trade shock on regional welfare and incomes is determined in equilibrium and does not have a closed-form representation. In contrast, reduced-form approaches are generally not grounded in trade models. An exception is Kovak (2013) who derives his measure of regional exposure from the specific factors model in Jones (1975). However, the model is not general equilibrium and gravity forces are absent.

In general, the results from the reduced form literature are robust. However, lack of a model from which the relationship between the exposure measure and change in regional outcomes is derived makes it difficult to interpret the results within the context of structural general equilibrium models of international trade.

In this paper, we ask first, if reduced form measures of trade exposure can be derived from the standard general equilibrium trade models under reasonable assumptions. We start with a simple model where the home country consists of many regions and the foreign economy consists of many countries. There are many tradable sectors and a non-traded sector and workers are perfectly mobile across sectors but not allowed to migrate across regions or countries. We focus on changes in regional wages – which in the model are equivalent to changes in regional incomes – as an outcome variable and show that they can be decomposed into a direct effect of an international trade shock and an indirect effect. The direct effect is a partial equilibrium effect, holding constant the endogenous variables in the model. The direct effect depends both on the shock itself but also the initial pattern of trade linkages between a region i, the other regions within the Home country, and foreign countries. The indirect effect is the effect of the international trade shock that operates through endogenous wage changes in all regions. We argue that, by construction, the reduced-form measures of exposure ignore the impact of wage changes in other regions on the wage changes in region i and hence ignore the indirect effect. Thus, empirical measures of exposure can be thought of as trying to capture a partial equilibrium effect of an international trade shock on regional wage changes.

Further, we also find analytical differences between the reduced-form exposure measures and the partial equilibrium effect derived from the model (Direct Effect - DE). The regional variation in the reduced-form measures is driven primarily by variation in sectoral employment shares across regions. In contrast, the variation in the Direct Effect measure is driven by the initial pattern of trade linkages that vary not only across regions but also across the source country of the international trade shock.

Our second question is, do these analytical differences between the Direct Effect measure and reduced-form measures result in quantitatively significant differences in how the reduced-form measures perform in predicting equilibrium wage changes relative to the Direct Effect measure? For this purpose, we take the model to Brazilian data in 1999, treating Brazil as the home country and Brazilian states as regions within the home country. We solve for equilibrium wage changes after an international trade shock using the hat algebra method of Dekle et al. (2008). Then, we compare the coefficients of correlation between the model-based equilibrium wage changes and different measures of regional exposure. We distinguish between two popular types of reduced-form measures. The first one, employment weighted trade cost change (ETC) is based on the measures by Topalova (2010) and Kovak (2013) and uses the actual sectoral shock (for example a trade cost change) and weights it with sectoral employment shares in a region. The second one, based on the measure by Autor et al. (2013b), uses the change in sector-wise imports into the home country (Brazil) per worker employed in the sector in the Home country and weights it by the region's sectoral employment share. We refer to this as the employment weighted trade flow change or ETF.

In the quantitative exercises we first consider an increase in the iceberg trade cost of importing from a foreign country into Brazil for all manufacturing sectors. We do this exercise for USA, China and Mexico separately. We find that the correlation between the model-based regional wage changes and the Direct Effect vary with the source country of the import cost shock. We also find that the coefficients of correlation between the wage changes and the empirical exposure measures are not monotonically related to the correlation coefficient of the Direct Effect. That is, it is not the case that empirical measures of exposure exhibit a higher correlation with the counterfactual wage changes when the partial equilibrium effect is relatively larger.

In the second set of exercises we increase the iceberg cost of importing from a specific foreign country into Brazil for each manufacturing sector at a time and solve for the resulting counterfactual equilibrium wage changes. We find that the coefficient of correlation between the equilibrium wage changes and the different measures of regional exposure vary not only across source countries of the import cost shock but also across sector and source country combinations. We also find that reduced-form measures of exposure perform less consistently in predicting the model based wage changes even when compared to the theoretically derived partial equilibrium effect (Direct Effect - DE).

The reduced-form measures (ETC and ETF) and the Direct Effect are different measures of a region's partial equilibrium exposure to an international trade shock. An iceberg import cost shock to only one sector at a time simplifies the Direct Effect measure and the employment weighted trade cost change measure ETC. The ranking over regions provided by these two measures for different source countries of the import cost shock can be compared without having to solve for the counterfactual equilibrium for each sector-source country combination. We calculate the Direct Effect and the ETC measures of exposure for each manufacturing sector specific shock and for each different source country in our data and investigate whether these two measures rank regions in a similar manner. For certain sectors, the rank correlation between the two exposure measures differs widely depending on the source country of the import cost shock and ranges from 0.31 to 0.72. Thus we find that, in certain sectors, by not taking into account the initial pattern of trade linkages as in the Direct Effect, rankings of regional exposure driven solely by sectoral employment shares can be significantly different from those of model-based partial equilibrium effect.

Finally we simulate a reversal of the Brazilian trade liberalization event of the 1990s. Our model is calibrated to Brazilian data in 1999. We take the economy backwards to the tariff levels in 1990 - modeling it as a proportional change in sector-specific iceberg trade costs. We find that the ETC measure exhibits the highest correlation with the model-based wage changes. However, when the shocks are applied to one sector at a time, we find that the correlation between the exposure measures and wage changes varies depending on the specific sector shocked, with the Direct Effect once again performing the most consistently.

We study Brazil for several reasons. First, it provides a suitable environment to study regional responses to trade shocks given that it is a large developing economy, with regions that are heterogeneous in their sectoral activity and their degree of involvement in trade. Second, it has the advantage of having international trade data at the state and product level and, for the year 1999, it also has data on interstate trade, which together with production data it allows us to reconstruct the full trade matrix of Brazilian states with each other and with the rest of the world. Finally, 1999 is an ideal year to study the type of shocks we analyze in this paper given that it is right after the liberalization period of the 1990s which allows to conduct a trade liberalization reversal counterfactual and it is before China's accession to the WTO, which allows us to conduct a China-shock counterfactual.

This paper relates to several strands of the literature. As mentioned above, it speaks to the empirical literature that studies the regional effects of trade using reduced-form designs. A group of studies pioneered by Topalova (2010) use regionally-weighted tariff changes to study the impact of trade on different outcomes such as poverty (Topalova (2010) in India) and wages (Kovak (2013) in Brazil and Hakobyan and McLaren (2016) in the U.S.). In parallel, a related series of studies started by Autor et al. (2013b) use regionally-weighted measure of imports per worker to study, for example, the impact of the increase in Chinese import competition outcomes such as employment and wages (Autor et al. (2013b) in the U.S., Balsvik et al. (2015) in Norway, Mendez (2015) in Mexico), health (McManus and Schaur (2016) in the U.S.), and crime (Dell et al. (2018) in Mexico), among others.

This paper also speaks to the relatively smaller but growing literature that brings general equilibrium trade models to the data, to quantify the regional effects of trade shocks. Monte (2016) studies the response of local real wages to trade shocks in a model with commuting, Galle et al. (2017) quantifies the distributive effects of the China shock across educational groups and U.S. commuting zones, and Caliendo et al. (2015) quantifies the local employment effects of the China shock in the U.S.

The most closely related papers to ours are Monte (2016) and Adao et al. (2019). Monte (2016) compares predictions from reduced-form approaches to the predictions of general equilibrium models with regional linkages and does so in a model where workers are allowed to commute across regions but where trade costs are uniform across regions in the country, so – unlike in our setting – there is no role for gravity forces driving trade across regions. Adao et al. (2019) develop a model with multiple local labor markets and a methodology to estimate aggregate elasticities that control cross market linkages in labor supply, productivity and trade flows. Using the estimated parameters they compute reduced form elasticities of wages and employment to measures of local exposure. However, the measures of local exposure they use depend on initial trade linkages and are not solely driven by variation in sectoral employment shares across regions.

The rest of the paper is structured as follows. Section 3.2 describes a general model of inter and intra national trade based on Eaton and Kortum (2002), provides the decomposition of model-based regional wage changes into direct and indirect effects and a detailed description of the partial equilibrium measure of regional exposure, i.e. the direct effect. Section 3.3 describes the reduced-form measures of regional exposure. Section 3.4 presents the outline of the quantitative exercises and describes the data used. Section 3.5 presents the results of our quantitative exercises and Section 3.6 concludes.

3.2 Deriving exposure from existing trade models

We assume a world with two countries, Home (H) and Foreign (F).[1] Home is comprised of N local labor markets or regions. Thus the set of total $N+1$ regions is given by $\mathcal{R} = \{1, 2, ...N, F\}$. Labor is the only factor of production and each region $i \in \mathcal{R}$ has a fixed supply of labor L_i. There are K sectors in the economy $k = \{1, 2, ...K\}$ and labor is perfectly mobile between sectors of a region. Consumer preferences are homogeneous of degree one and μ_k is the share of income spent on sector k goods.

Under the above assumptions the goods market clearing condition in a region i in

[1]For simplicity, in this section we treat the Rest of the World as a single region but the conclusions we reach are not altered by treating it as a group of countries. When taking the model to the data, we work with multiple countries.

each sector k is given by

$$w_i L_i^k = \sum_{n \in \mathcal{R}} \pi_{in}^k \mu_k w_n L_n, \quad k = 1 \dots K \tag{3.1}$$

Trade balance further implies that

$$w_i L_i = \sum_{k \in K} \sum_{n \in \mathcal{R}} \pi_{in}^k \mu_k w_n L_n \tag{3.2}$$

where w_i are wages in region i, L_i^k is total employment in region i and sector k, μ_k is the expenditure share in sector k and π_{in}^k is the bilateral trade share, that is, the share of expenditure that region n allocates on goods from region i and sector k. The left hand side is equal to total revenue (which also equals the wage bill) in region i and sector k and the right hand side is equal to the sum of expenditure on goods from region i across all destination markets (including itself).

The conditions above hold for the standard models of international trade mentioned in the Introduction. However, the micro-foundations of the different models give rise to different expressions of the bilateral trade share. In turn, this implies different expressions for the changes in wages in response to trade cost and productivity shocks. We describe below the expressions for the trade shares in three standard models: Armington, Krugman (1980), and Eaton and Kortum (2002).

Armington

Adapting the Armington model to the above setup, each region produces a distinct variety and consumers would like to consume at least some of each variety. Varieties within a sector can be indexed by region. The market for each variety is perfectly competitive and each worker in region i can produce A_i^k units of region i variety in sector k. Consumer preferences are given by an upper level Cobb-Douglas and a lower level CES with elasticity of substitution σ_k. The bilateral trade shares for sector k goods exported from i to n are given by:

$$\pi_{in}^{k,Arm} = \frac{(w_i \tau_{in}^k / A_i^k)^{1-\sigma_k}}{\sum_{r \in \mathcal{R}} (w_r \tau_{rn}^k / A_r^k)^{1-\sigma_k}} \tag{3.3}$$

where σ_k is the elasticity of substitution between sector k varieties and τ_{in}^k are the iceberg trade costs of shipping a good from i to n.

Krugman (1980)

Krugman (1980) is a monopolistic competition setup with homogeneous firms. Firms in region i sector k have productivity z_i. There is free-entry of firms subject to a fixed cost f_e, which implies a linear relationship between the number of firms and sectoral employment, L_i^k. Consumer preferences are given by an upper level Cobb-Douglas and a lower level CES with elasticity of substitution σ_k. The bilateral trade shares for sector k goods exported from i to n are given by:

$$\pi_{in}^{k,Krug} = \frac{L_i^k \left(w_i \tau_{in}^k / z_i^k\right)^{1-\sigma_k}}{\sum_{r\in\mathcal{R}} L_r^k \left(w_r \tau_{rn}^k / z_r^k\right)^{1-\sigma_k}} \tag{3.4}$$

Eaton and Kortum (2002)

In each sector, there are a continuum of goods $\Omega_k = [0,1]$. Markets are perfectly competitive. Regions vary in their productivity of each good within a sector $z_i^k(\omega)$, for $\omega \in \Omega_k$. $z_i^k(\omega)$ is drawn independently across countries and goods from a Fréchet distribution with sector specific location parameter A_i^k and sector specific dispersion parameter $\theta_k > 1$.

$$\pi_{in}^{k,\mathrm{EK}} = \frac{A_i^k (w_i \tau_{in}^k)^{-\theta_k}}{\sum_{r\in\mathcal{R}} A_r^k (w_r \tau_{rn}^k)^{-\theta_k}} \tag{3.5}$$

After showing that the expressions for bilateral trade shares do vary with the micro-foundations of different trade models, we now proceed with the rest of the analysis using the Eaton and Kortum (2002) setup. The analysis for the Armington and Krugman setups can be undertaken analogously.

3.2.1 Deriving exposure in an Eaton-Kortum model

We are interested in the response of wages to international trade shocks. We focus on two types of shocks: a shock to iceberg trade costs of exporting goods from Foreign to Home ($\hat{\tau}_{FH}^k$) and a Foreign productivity shock ($\hat{A}_F^k$). These are the shocks most frequently analyzed in the empirical literature (Kovak (2013); Autor et al. (2013b)).

To simplify notation, we denote with $\hat{x} = d\ln(x)$ the logarithm change of x. Starting from the equilibrium condition in equation (3.2), and totally differentiating yields:

$$\hat{w}_i = \sum_k \sum_n \xi^k_{in} \left(\hat{\pi}^k_{in} + \hat{w}_n\right) \tag{3.6}$$

where $\xi^k_{in} = \frac{\pi^k_{in}\mu_k w_n L_n}{w_i L_i}$ is the share of total revenue in region i earned from exports to region n in sector k. Further substituting the value of $\hat{\pi}^k_{in}$ into equation (3.6) we get:

$$\begin{aligned}
\hat{w}_i \quad = \quad & \underbrace{\sum_k \theta_k \left(\sum_{n \neq R} \xi^k_{in}\pi^k_{Fn}\right)\hat{\tau}^k_{FH}}_{\text{direct effect of } \hat{\tau}^k_{FH}} - \underbrace{\sum_k \sum_n \xi^k_{in}\pi^k_{Fn}\hat{A}^k_F}_{\text{direct effect of } \hat{A}^k_F} \\
& \underbrace{-\sum_k \theta_k \left(\sum_n \xi^k_{in}\left(1-\pi^k_{in}\right)\right)\hat{w}_i + \sum_k \xi^k_{ii}\hat{w}_i}_{\text{own-region indirect effect}} \\
& \underbrace{+\sum_k \theta_k \sum_{h \neq i}\left(\sum_n \xi^k_{in}\pi^k_{hn}\right)\hat{w}_h + \sum_k \sum_{h \neq i} \xi^k_{ih}\hat{w}_h}_{\text{other-region indirect effects}}
\end{aligned} \tag{3.7}$$

The above equation shows that the wage change in a region i as a result of a country level import cost shock or foreign productivity shock can be decomposed into the direct effect of the shock and the indirect effect. The direct effect is the partial equilibrium effect of an international trade shock on a region's wage changes, holding constant the endogenous variables, i.e. wages in all other regions and economies. The indirect effect is the effect of the international trade shock that operate through endogenous wage changes in all regions. The direct effect is a function of the shock itself and the initial pattern of trade linkages between a region i, the other regions of Home (H) and Foreign (F). The indirect effect depends on the wage changes in all the regions which are endogenous and have to be solved for using the full system of equations.

The empirical measures of exposure commonly used in the literature do not take into account the indirect effects of an international trade shock that arise from endogenous wage changes in all regions. Thus the empirical exposure measures can be interpreted as partial equilibrium measures of a region's sensitivity to an international trade shock. Within the environment of the model, the Direct Effect (DE) is the partial equilibrium effect of the international trade shock. In the next section we further examine the components of the Direct Effect and provide economic interpretations for the same.

3.2.2 The Direct Effect: A theoretical exposure measure

Equation (3.7) gives us both the direct and indirect effects of a shock to trade costs or productivity on the equilibrium wages in a region i at $Home$. The Direct Effect in region i (DE_i) can be written as follows:

$$\begin{aligned} DE_i &= \sum_k \theta_k \left(\sum_{n \neq F} \xi_{in}^k \pi_{Fn}^k \right) \hat{\tau}_{FH}^k - \sum_k \left(\sum_n \xi_{in}^k \pi_{Fn}^k \right) \hat{A}_F^k \\ &= \underbrace{\sum_k \theta_k \frac{L_i^k}{L_i} \left(\sum_{n \neq F} \tilde{\xi}_{in}^k \pi_{Fn}^k \right) \hat{\tau}_{FH}^k}_{DE_i^{\tau_{FH}}} - \underbrace{\sum_k \frac{L_i^k}{L_i} \left(\sum_n \tilde{\xi}_{in}^k \pi_{Fn}^k \right) \hat{A}_F^k}_{DE_i^{A_F}} \end{aligned} \tag{3.8}$$

We focus on the direct effect of a shock to the iceberg trade cost of importing goods from Foreign to Home on the wage changes in region $i \in Home$.

$$DE_i^{\tau_{FH}} = \sum_k \theta_k \frac{L_i^k}{L_i} \left(\sum_{n \neq F} \tilde{\xi}_{in}^k \pi_{Fn}^k \right) \hat{\tau}_{FH}^k \tag{3.9}$$

The Direct Effect ($DE_i^{\tau_{FH}}$) has three main components. The sector specific trade elasticity (θ_k), the sectoral employment share (L_i^k/L_i) and $\left(\sum_{n \neq F} \tilde{\xi}_{in}^k \pi_{Fn}^k\right)$ which we interpret in greater detail below.

The magnitude of the direct effect is increasing in sector specific trade elasticity θ_k. However, a larger sectoral trade elasticity also implies that for a given change in trade costs, the bilateral trade shares change more. This further implies that the overall general equilibrium effects of a change in trade costs are larger. Thus, even though a higher sectoral trade elasticity makes the absolute magnitude of the direct effect larger, it does not imply that it makes its relative magnitude larger.

The second component of the direct effect is the sectoral employment share in region i. Given all else, the larger the share of workers employed in sector k, the greater the effect of a sector k shock to trade costs on the total counter-factual wage change - both through the direct and indirect effects. The absolute magnitude of the Direct Effect of a sector k shock is increasing in the sector k employment share. However, whether the magnitude of the Direct Effect relative to the indirect effect increases with the sectoral employment share is unclear. As will be described below, the sectoral employment shares in a region are also an important component of empirical measures of a region's exposure to trade shocks.

The third component of the Direct Effect ($DE_i^{\tau_{FH}}$) is the following expression:

$$\left(\sum_{n \neq F} \tilde{\xi}_{in}^k \pi_{Fn}^k\right) \qquad \text{where} \qquad \tilde{\xi}_{in}^k = \frac{\pi_{in}^k \mu_k w_n L_n}{w_i L_i^k}$$

where $\tilde{\xi}_{in}^k$ is the share of revenue for region i sector k from exports to region n and π_{Fn}^k is the share of sector k expenditure in region n on exports from Foreign F.The term $\tilde{\xi}_{in}^k \pi_{Fn}^k$ is the product of the sector k revenue share of region i earned from market n times the penetration of Foreign F in market n. This is summed over all relevant destination markets n. This can be thought of as the *effective competition* from F faced by region i sector k in all relevant destination markets n.

Note that the set of relevant destination markets depends on the nature of the shock. In the case of a shock to iceberg trade costs of exporting from Foreign F to Home H ($\hat{\tau}_{FH}^k$), the set of relevant destination markets for region $i \in H$ are all the other domestic markets $n \in H$.

In the rest of the paper we refer to this term as the *effective competition* faced by region i from Foreign country F. The larger the effective competition faced by domestic region i from Foreign country F, the larger the absolute magnitude of the direct effect. Thus within the model, even when we ignore the changes in overall trade flows as a result of an exogenous shock and focus only on the Direct Effect

- the initial intra- and inter-country trade linkages are a component of the Direct Effect ($DE_i^{\tau_{FH}}$). In addition to fundamental sectoral productivities ($A_i^k\ \forall\ i \in \mathcal{R}$), these linkages are in turn crucially governed by gravity forces.

Using the Direct Effect measure of exposure requires sector level inter-country and intra-country trade flows and international trade data at the sub-country level. Data on inter-country trade flows can be obtained quite easily for most countries. However, data on intra-country trade flows and international trade data at the sub-country level is not usually available. In the absence of this, existing literature employs different formulations to construct measures of regional exposure to international trade shocks. The following section describes the most commonly used empirical measures of exposure.

3.3 Reduced-form measures of exposure

In the following section we describe two measures of regional exposure to international trade shocks from the existing reduced-form literature. Both measures use variation in regional employment composition to estimate the impact of international trade shocks on regional economic outcomes.

The first measure, denoted by ETF, is an employment-weighted trade flow change similar to the one used in Autor et al. (2013b)[2]:

$$ETF_i^F = \sum_{k=1}^{K} \frac{L_i^k}{L_i} \left(\frac{\Delta M_{FH}^k}{L_H^k} \right) \tag{3.10}$$

where (L_i^k/L_i) is the share of labor in region i employed in sector k, ΔM_{FH}^k is the change in total sector k imports from foreign country F to home country H and L_H^k is the total sector k employment in Home country (H).

Similar to the Direct Effect ($DE_i^{\tau_{FH}}$) measure in equation (3.8), the employment weighted trade flow measure (ETF_i^F) uses sectoral employment shares in a region as

[2]This measure is derived from an underlying model of international trade that yields a gravity equation. The theoretical expression for counter-factual wage changes is very similar to equation (3.7) above. However, the paper makes a set of simplifying assumptions to arrive at the final empirical measure used.

weights. However, the $DE_i^{\tau_{FH}}$ measure is additionally composed of the sector specific trade elasticity (θ_k), the size of the trade cost shock $\hat{\tau}^k_{FH}$ and the *effective competition* from foreign country F faced by region i in all relevant destination markets. On the other hand, the ETF_i^F measure considers sector-wise change in imports from Foreign R into Home country (H) as a whole per worker employed in sector k in Home (H).

The variation in the Direct Effect measure across regions is driven both by the pattern of sectoral specialization and the initial set of trade linkages (given by the *effective competition*). On the other hand, the variation in intra-country sensitivity to a trade shock as measured by ETF_i^F is driven primarily by the variation in sectoral employment share across regions. Thus, while using the actual change in imports might help to capture the sector specific trade elasticity and the size of the trade cost shock, the measure does ignore the *effective competition* from foreign country F faced by region i.

In the exercises below we also use an alternative specification of the employment-weighted trade flow change measure:

$$ETF_i^W = \sum_{k=1}^{K} \frac{L_i^k}{L_i} \left(\frac{\Delta M^k_{WH}}{L^k_H} \right) = \sum_{k=1}^{K} \frac{L_i^k}{L_i} \left(\frac{\sum_{F \in \mathcal{W}} \Delta M^k_{FH}}{L^k_H} \right) \tag{3.11}$$

where ΔM^k_{WH} is the change in the sector k imports from all countries of the World into the country Home (H). Similar to the ETF_i^F measure, the variation in ETF_i^W measure across regions within a country is primarily driven by the variation in sectoral employment shares.

The second reduced-form measure we focus on, denoted as ETC_i (Rodríguez Chatruc (2016)), is an employment-weighted trade cost change, based on Kovak (2013) and Topalova (2010).

$$ETC_i = \sum_{k=1}^{K} \frac{L_i^k}{L_i} \hat{\tau}^k_{FH} \tag{3.12}$$

In contrast to the previous empirical measure, the employment-weighted trade cost change (ETC_i) can be derived from a specific factors model that gives rise to wage changes as a weighted average of goods price changes where the weights are the fraction of a region's labor allocated to each sector. Within the context of the specific factors model, this is reduced to a weighted average of the sectoral trade cost changes ($\hat{\tau}^k_{FH}$). Thus, even though this second empirical measure has a direct theoretical foundation, intra-country variation in this measure is once again driven by variation in sectoral employment specialization across regions. This specification arises because all regions face the same world prices that are exogenously given. Since goods' prices are not endogenously determined in the model, a trade liberalization event or a fall in import costs is treated as a proportional change in the world prices faced by all regions within a country.

However, within a general equilibrium model of trade such as Eaton and Kortum (2002), a shock to trade costs results in wage changes that also depend on initial bilateral trade flows (*effective competition*) that follow a gravity structure. While Kovak (2013) does provide a direct theoretical foundation to the exposure measure, the model is not general equilibrium and gravity forces are absent.

3.4 Empirical Exercise: Outline and Data

3.4.1 Outline

In the previous section we described two measures of regional exposure to international trade shocks that are widely used in the reduced-form literature. We also compared the measures to the Direct Effect (DE^{τ}_i) that is derived from a model of international trade based on Eaton and Kortum (2002). We observe that intra-country variation in the reduced-form measures of regional exposure is driven purely by intra-country variation in sectoral employment shares. While the Direct Effect (DE) also has sectoral employment shares, variation across regions is additionally driven by variation across regions in the *effective competition* that they face from the source country of the international trade shock.

However, computing the *effective competition* requires data on intra-country trade flows and trade between domestic regions with Foreign countries which is not usually available. On the other hand, the reduced-form measures described in the previous section require only employment data at the region and sector level and data on tariff changes or international trade flows. The question follows - do these analytical differences between the theoretical measure of exposure (Direct Effect - DE) and the reduced-form measures of exposure result in quantitatively significant differences in each measure's predictions of regions' sensitivity to international trade shocks?

To answer this question, we undertake the following exercise. First, we take the model described in Section 3.2 to Brazilian data in 1999, treating Brazil as the Home economy with 27 Brazilian states as regions within Home, and 24 countries and a constructed rest of the world as Foreign. Second, we apply different shocks to international trade costs and solve for counterfactual wage changes for the states of Brazil and the Foreign countries in our sample.

We then use the model-generated data to assess the strength of the Direct Effect (DE_i^{τ}) in predicting the equilibrium wage changes. In other words, we are interested in how much of the variation in the total counterfactual equilibrium wage changes across regions can be explained by variation in the Direct Effect. To understand the importance of the Direct Effect, we calculate beta weights[3] and undertake relative weights analysis.

Recall from equation (3.7) that the total counterfactual wage changes can be decomposed into the Direct Effect (DE_i^{τ}) and Indirect Effect (IE_i), which is the sum of the own-region indirect effect and other-regions indirect effect.

$$\hat{w}_i = DE_i^{\tau} + IE_i$$

We construct the variables DE_i^{τ} and IE_i from data on the initial equilibrium trade flows and the size of the trade cost shock, and solve for counterfactual wage changes ($\hat{w}_i$). We then convert all the variables into z scores and run the following regression:

$$(\hat{w}_i)^z = \beta_1 (DE_i^{\tau})^z + \beta_2 (IE_i)^z$$

the coefficients β_1 and β_2 are the beta weights. They provide an initial rank ordering of the predictor variable's importance in predicting the dependent variable (Nathans et al. (2012)). However, beta weights can be solely relied upon to provide an accurate

[3]Beta weights are the regression coefficients when both the dependent and independent variables are standardized (converted to z-scores). Therefore, both the dependent and independent variables are measured in standard deviation units. They provide an initial rank ordering of the predictor variable's importance in predicting the dependent variable

ordering of the contributions of the independent variables only when they are perfectly uncorrelated with each other (Nathans et al. (2012)). Thus we supplement these calculations with relative weights.

Relative weights is a method of partitioning the R^2 in a multiple regression between the independent variables in the model based on a procedure that addresses the problem of correlations between the independent variables. Our results present both the raw and rescaled relative weights. The raw relative weights sum to the R^2 of the regression and the rescaled relative weights sum to 100. Thus the rescaled relative weights can be interpreted as the percentage of the explained variance of the dependent variable that can be attributed to each independent variable.

We also examine the predictive power of the reduced-form measures of regional exposure with respect to the counter-factual wage changes. We compare the coefficient of correlation between the equilibrium wage changes and the empirical exposure measures with the coefficient of correlation between the equilibrium wage changes and theoretically derived partial equilibrium effect (Direct Effect - DE). Recall that in addition to employment weights, the Direct Effect (DET) also contain the *effective competition* term that takes into account the initial configuration of trade linkages. These exercises allow us to assess whether not taking into account the initial configuration of trade linkages results in quantitatively significant differences in each measure's predictions of regions' sensitivity to international trade shocks.

3.4.2 Data sources and measurement

In taking the model to the data, 1999 is the initial year for our counterfactual exercises. The Home country is Brazil, which consists of 27 states and the Foreign country consists of 24 countries and a "Rest of the World" aggregate. The set of countries used are the same as those in Caliendo and Parro (2015), listed in Table B.1 of Appendix B.2[4].

We combine different data sources to obtain the full matrix of trade flows between Brazilian states and foreign countries for each of the 15 traded industries in our analysis. Data on international (i.e. country-to-country) trade flows is obtained from

[4]More details about the data sources and its processing can be found in Appendix B.2

the World Input-Output database (WIOD) (Timmer et al. (2015)). Data on trade flows between Brazilian states and foreign countries is obtained from ComexStat (MDIC (2018)). Data on within-country trade flows (i.e. state-to-state) is taken from Vasconcelos and Oliveira (2006). Both Comexstat and WIOD data are available for several years. However, the interstate trade data is only available for 1999. Therefore, all our counterfactual exercises take 1999 as the initial year. Finally, we use data from the Brazilian Institute of Geography and Statistics (IBGE) on total output by sector to calculate trade with self for each state as a residual. We concatenate data from all three sources to ensure consistency in inter-country, inter-state and country-state bilateral trade flows.[5]

The industrial classifications are not uniform across different data sources, so we use different crosswalks to arrive at a final classification of 15 tradable sectors (that include agriculture, mining, and 13 manufacturing sectors) and a non-tradable sector. We use sector specific trade elasticities from Costinot and Rodriguez-Clare (2014). Table B.2 in Appendix B.2 contains the final list of 15 sectors and the sector specific trade elasticities.

Average ad-valorem tariffs applied by Brazil at the sectoral level for 1990 and 1998 are taken from Kume et al. (2000). Since we do not have reliable tariff data for 1999–the base year for counterfactual exercises–we assume tariffs in 1999 remained at the same level as in 1998. Finally, we eliminate trade deficits from our data before conducting the counterfactual analysis.

3.5 Results

The following subsections describe the results of our quantitative exercises. In section 3.5.1 we increase the iceberg cost of importing from a Foreign country into Brazil for all manufacturing sectors by 1%. We do this for USA, China and Mexico separately. In section 3.5.2 we increase the iceberg cost of importing from a Foreign country into Brazil by 1% for each manufacturing sector at a time. This exercise is once again

[5]Throughout the paper we only consider trade in goods and assume services are entirely consumed in the region or country where they are produced. Although the WIOD an interstate trade data provide information on services trade, the state-to-couNtry data does not. Therefore, we assign all exports of services to other countries in the WIOD as exports to self.

undertaken for USA, China and Mexico, treating each one separately as the source country of the import cost shock.

3.5.1 All manufacturing sectors shock to iceberg import costs

We have calibrated the initial equilibrium of the model using Brazilian data in 1999. In the following section we first increase the iceberg trade costs of importing from a specific Foreign country into Brazil by 1% for all manufacturing sectors. The sectors for which trade costs change are: Food, Textile, Wood, Paper, Petroleum, Chemicals, Plastic, Minerals, Metal, Machinery, Electrical, Auto and Other (miscellaneous). We solve for the counterfactual equilibrium wage changes in every region of Brazil ($\hat{w}_i$) following the hat-algebra method of Dekle et al. (2008).

We examine the strength of the Direct Effect in predicting the equilibrium wage changes. We also compare the coefficient of correlation between the Direct Effect and the wage changes with the coefficient of correlation between the wage changes and the reduced-form measures of regional exposure. We do this exercise for USA, China and Mexico. We undertake the exercise for three different countries because we want to investigate whether the performance of the different measures of regional exposure varies with the source country of the import cost shock.

3.5.1.1 One percent increase in import cost from USA: All Sectors

In this section we increase the iceberg trade costs of importing from USA into Brazil by 1% for all manufacturing sectors. To begin, we are interested in how much of the variation in the model-based equilibrium wage changes across regions can be explained by the Direct Effect. The results in Table 3.1 below present the beta weights and the raw and rescaled relative weights of the Direct Effect and Indirect Effect.

The beta weights indicate that in the case of a 1% increase in import cost from USA to Brazil, the Direct Effect contributes more to predicting the total counterfactual wage changes than the indirect effect. This conclusion holds even when looking at the relative weights. The variation in Direct Effect across regions accounts for 71% of the explained variation in the total counterfactual wage changes. We now compare each exposure measure's predictions of a region's sensitivity to the iceberg import

Table 3.1: Relative Importance of Direct Effect (USA)

Beta Weights

	Direct Effect	**Indirect Effect**
Beta Weight	1.7940^{***}	1.3426^{***}
Std. Error	(0.0348)	(0.0348)

Relative Weights Analysis

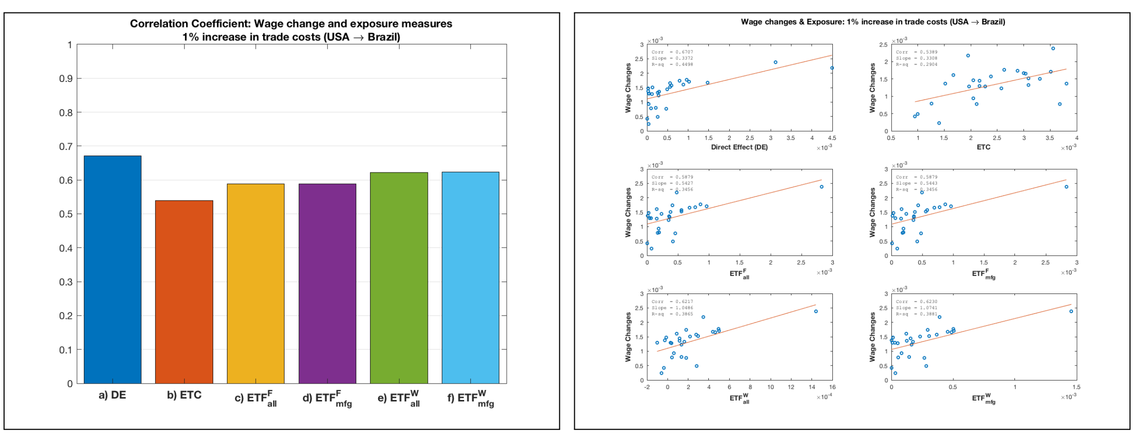
	Direct Effect	**Indirect Effect**
Raw relative weights	0.7082	0.2831
Rescaled Relative Weights	71.441	28.559

This is for a 1% increase in import cost from USA into Brazil

cost shock from USA.

Figure 3.1 below presents a comparison of the correlation coefficients between the equilibrium wage change and the different measures of regional exposure - the model derived Direct Effect, the employment weighted trade cost change (ETC), the employment weighted trade flow change (ETF^F and ETF^W). There are two versions of each measure of the employment weighted trade flow change, one where we sum over all sectors (ETF^F_{all} and ETF^W_{all}) and the other where we sum over only the manufacturing sectors (ETF^F_{mfg} and ETF^W_{mfg}).

Figure 3.1: Wage changes and exposure measures: Import cost shock from USA



Note that, since the magnitude of the trade cost shock is the same across all manufacturing sectors, the employment weighted trade cost change measure (ETC) for a region i reduces to the share of employment in manufacturing multiplied by the magnitude of the shock. Hence, in this case, the variation in ETC across regions is purely driven by the variation in the manufacturing employment share and doesn't depend on the source of the shock (i.e. the origin country).

Consistent with the results of the beta weights and relative weights analysis, the Direct Effect measure has a correlation of ~ 0.67 with the wage change, higher than that of the other measures. The coefficients of correlation between the empirical exposure measures and the wage changes, while lower than that of the Direct Effect, are all above 0.5.

3.5.1.2 One percent increase in import cost from China: All Sectors

We are interested in whether the coefficient of correlation between the wage changes and different measures of regional exposure vary with the source country of the import cost shock. In this section we simulate a 1% increase in the iceberg trade costs of importing from China into Brazil for all manufacturing sectors. The results in Table 3.2 below present the beta weights and the raw and rescaled relative weights of the Direct Effect and Indirect Effect.

Table 3.2: Relative Importance of Direct Effect (CHN)

Beta Weights

	Direct Effect	**Indirect Effect**
Beta Weight	1.1155^{***}	1.0196^{***}
Std. Error	(0.0032)	(0.0032)

Relative Weights Analysis

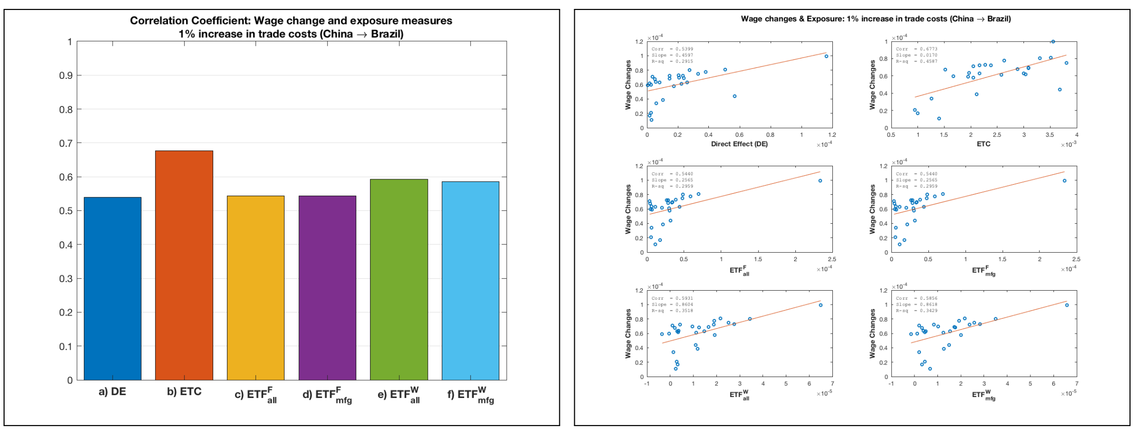
	Direct Effect	**Indirect Effect**
Raw relative weights	0.5696	0.4303
Rescaled Relative Weights	56.9676	43.0324

This is for a 1% increase in import cost from China into Brazil

The beta weights indicate that in the case of a 1% increase in import costs from

China to Brazil, the Direct Effect contributes more to predicting the counterfactual wage changes than the Indirect Effect. However, the relative weights analysis results indicate that the marginal importance of the Direct Effect is lower in the case of an import cost shock from China than it was in the case of an import cost shock from USA. The variation in the Direct Effect across regions accounts for only about $\sim 57\%$ of the total explained variation in counterfactual wage changes in the case of a import cost shock from China compared to the case of an import cost shock from USA ($\sim 70\%$). Both measures - the beta weights and relative weights - imply that the importance of the Direct Effect in driving variation in the counterfactual wage changes is higher in the case of an import cost shock from USA as compared to an import cost shock from China.

Figure 3.2: Wage changes and exposure measures: Import cost shock from China



Results in Figure 3.2 show that the correlation between the Direct Effect and the wage changes is ~ 0.54, lower than in the case of USA as the source country of the import shock (~ 0.67). Thus the correlation seems to be sensitive to the source country of the import cost shock. Note, on the other hand, that the employment weighted trade cost change (ETC) performs much better in the case of China with a correlation of ~ 0.67 with the counterfactual wage change, compared to ~ 0.54 in the case of USA. However, in the case of a uniform import cost shock in all manufacturing sectors, we should be careful about interpreting the employment weighted trade cost change (ETC) measure of exposure. The ETC measure for each region is identical in the two cases of USA and China - the share of employment in manufacturing multiplied by the magnitude of the shock.

In contrast to the ETC measure, the employment weighted trade flow change (ETF) measures do in fact depend on the source country of the import cost shock. ETF^F_{all} and ETF^F_{mfg} are the employment weighted change in trade flows from the source country of the import cost shock into Brazil. ETF^W_{all} and ETF^W_{mfg} are the employment weighted change in trade flows from the all countries of the world into Brazil. Changes in trade flows from the World into Brazil also depend on the source country of the import cost shock within the multi-country Eaton Kortum structure. Like the Direct Effect, the coefficients of correlation between the employment weighted trade flow change measures and the equilibrium wage changes are lower in the case of an import cost shock from China as compared to the import cost shock from USA.

3.5.1.3 One percent increase in import cost from Mexico: All Sectors

In this section we increase the iceberg trade costs of importing from Mexico into Brazil by 1% for all manufacturing sectors. The results in Table 3.3 present the beta weights and the raw and rescaled relative weights of the Direct Effect and Indirect Effect. The beta weights indicate that in the case of a 1% increase in import costs from

Table 3.3: Relative Importance of Direct Effect (MEX)

Beta Weights

	Direct Effect	**Indirect Effect**
Beta Weight	1.4331^{***}	0.8529^{***}
Std. Error	(0.0378)	(0.0378)

Relative Weights Analysis

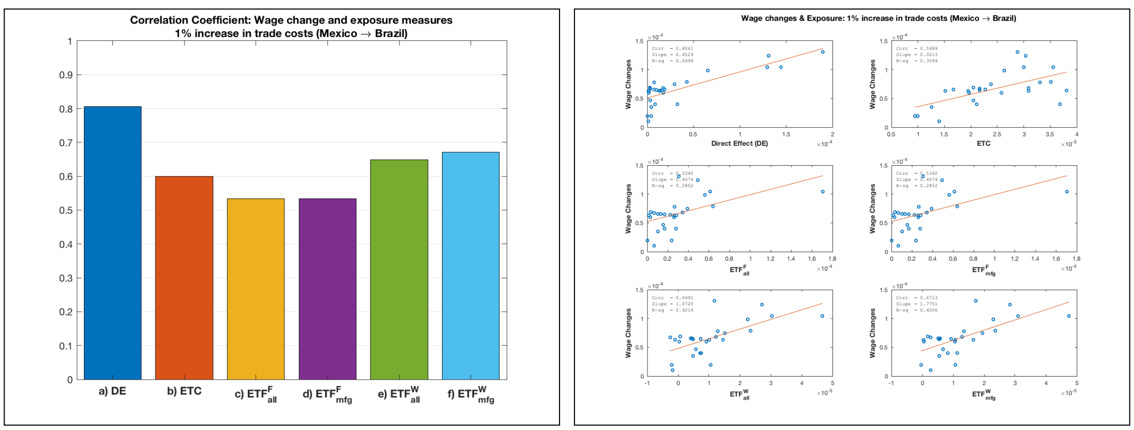
	Direct Effect	**Indirect Effect**
Raw relative weights	0.7969	0.1873
Rescaled Relative Weights	80.9696	19.0303

This is for a 1% increase in import cost from Mexico into Brazil

Mexico to Brazil, the Direct Effect contributes more to predicting the counterfactual wage changes than the Indirect Effect. The difference in magnitude of the two effects is much larger than in the case of import cost shocks from China or USA. The results of the relative weights analysis show that the Direct Effect accounts for $\sim 81\%$ of the explained variation in counterfactual wage changes. This is higher than the re-scaled relative weight of the Direct Effect in the cases of import cost shocks from USA and China ($\sim 71\%$ for USA and $\sim 57\%$ for China).

Further, as can be seen in Figure 3.3, the correlation coefficient between the wage change and Direct Effect is very high, at 0.80. The correlation coefficients of the empirical measures of exposure with the wage changes are all above 0.5, but lower than the correlation coefficient for the Direct Effect.

Figure 3.3: Wage changes and exposure measures: Import cost shock from Mexico



Comparing across the three different source countries of the import cost shock, the coefficient of correlation between the employment weighted trade flow changes from the World into Brazil (ETF^W_{all} and ETF^W_{mfg}) and wage changes are monotonically related to the coefficient of correlation between the wage changes and the Direct Effect. The correlation coefficients are highest for Mexico, followed by USA and then China. While the employment weighted trade flow changes from the World into Brazil (ETF^W_{all} and ETF^W_{mfg}) do move with the Direct Effect (in terms of correlation coefficients), it is important to further understand what these two measures (ETF^W_{all} and ETF^W_{mfg}) capture and their practical applicability. ETF^W_{all} and ETF^W_{mfg} are the trade flow changes from the World into Brazil. They are calculated using trade flow changes from the initial to the new equilibrium (after the import cost shock). Since they take into account the changes from the World as a whole and not just the source country of the import cost shock, they also capture general equilibrium effects. In fact, they might even have greater predictive power than the Direct Effect, which is a partial equilibrium effect. In practice however, it would be challenging to control for confounding factors when using employment weighted trade flow changes from the World into a particular country as a measure of regional exposure.

Considering all three source countries of the import cost shock, the predictive power of the Direct Effect and the employment weighted trade flows from the source country of the import cost shock (ETF^F) are no longer monotonically related. The coefficients of correlation between employment weighted trade flow changes from the Foreign country (ETF^F_{all} and ETF^F_{mfg}) measures and the counterfactual wage changes are higher in the case of the import cost shock from USA (0.59 for both) than in the case of the import cost shock from Mexico (0.53 for both). For the Direct Effect measure, the correlation coefficient with wage changes is lower in the USA case (0.67) than in the case of Mexico (0.8). This non monotonic relation between the correlation coefficients of the Direct Effect and the ETF^F measures across USA, China and Mexico is nowhere near conclusive evidence of poor performance of reduced-form measures within an Eaton-Kortum structure. Further, the model does not give rise to a closed form solution for equilibrium wage changes so it is not possible to isolate under what conditions we would expect to see the reduced form measures exhibit a high correlation with the counterfactual wage changes. However, it is worth noting that the effects on equilibrium wage changes of an import cost shock from a particular Foreign country depend on the trade linkages between the Foreign country and regions of the Home country. From the maps in Figures B.1,B.2,B.3and B.4, we see that the trade linkages of Brazil with USA, China and Mexico are different not only in magnitude but also in their spatial heterogeneity across Brazilian regions. Thus in the model, this would give rise to different equilibrium effects of a 1% increase in iceberg import costs depending on the source country of the import cost shock. This variation would not necessarily be captured by reduced-form measures since their variation is driven by variation in sectoral employment shares across regions. To investigate whether the predictive power of the measures of regional exposure vary not only with the source country of the import cost shock but additionally with the specific industry shocked, in the next subsection we increase the iceberg trade costs of importing from a specific Foreign county into Brazil by 1% for each manufacturing industry at a time and examine the results.

3.5.2 Sector-wise shock to iceberg import costs

In this subsection we increase the iceberg trade costs of importing from a specific Foreign country into Brazil by 1% for each manufacturing sector at a time and solve for the resulting counterfactual wage changes. We undertake this exercise because we are interested in whether different exposure measures' predictions of a region's sensitivity to an import cost shock additionally vary with the specific sector shocked. Also, an import cost shock to only one sector at a time simplifies the Direct Effect (DE) and the employment weighted trade cost change (ETC) measures of exposure to the cost shock and allows for easier comparisons between the different measures. To illustrate, when there is a change in the iceberg trade cost of importing from foreign country F into Home H only in one sector k, the regional exposure measures are given below:

$$DE_i^{\tau_{FH}} = \theta_k \frac{L_i^k}{L_i} \left(\sum_{n \neq F} \tilde{\xi}_{in}^k \pi_{FH}^k \right) \hat{\tau}_{FH}^k \qquad \forall i \in H$$

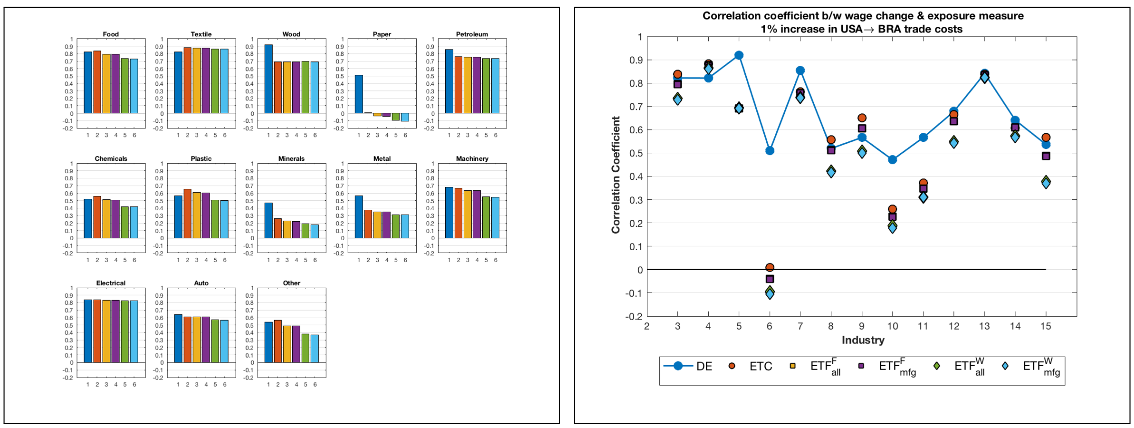
$$ETC_i = \frac{L_i^k}{L_i} \hat{\tau}_{FH}^k \qquad \forall i \in H$$

We undertake this exercise again for three different source countries - USA, China and Mexico because we are interested in whether the coefficients of correlation vary not only with the sector shocked but also depend on the source country of the sector specific import cost shock.

3.5.2.1 Sector-wise one percent increase in import cost from USA

In this section we increase the iceberg trade costs of importing from USA into Brazil by 1% for each manufacturing sector at a time and solve for the resulting counterfactual wage changes. Figure 3.4 presents the coefficient of correlation between the model-based equilibrium wage changes and the different exposure measures for each industry specific import cost shock. Each bar chart in subfigure ?? presents the coefficient of correlation between the wage changes and different measures of exposure for a given industry specific shock. In subfigure ??, we have industry codes on the x-axis to indicate the industry that experienced the import cost shock and correlation coefficients on the y-axis. The blue line with markers in subfigure ?? presents the coefficient of correlation between the wage changes and the Direct Effect for each sector specific shock.

Figure 3.4: Wage changes and exposure measures: Sector-wise import cost shock from USA



The predictive power of all the measures of regional exposure vary depending on the industry that experienced the increase in iceberg trade cost of importing from USA into Brazil. The Direct Effect performs the most consistently across industries in terms of correlation with regions' sensitivity to sector specific import cost shocks. The coefficient of correlation between the Direct Effect and the counterfactual wage changes range from 0.47 in Non-Metallic Minerals to 0.92 in Wood, products of wood and cork. The correlation coefficient with respect to the Direct Effect is above 0.5 in the case of all industry specific shocks except for Minerals (0.47). A lower coefficient of correlation between the Direct Effect and the counterfactual wage changes indicates that the Indirect Effect has a relatively larger impact on counterfactual wage changes than the Direct Effect.

Since only one sector k is shocked at a time, the employment weighted trade cost change measure (ETC) is now the sector k employment share in region i multiplied by the magnitude of the trade cost shock. Thus the variation in the ETC measure across regions is driven by variation in sector k employment share across regions. The employment weighted trade flow measures ETF is specified as before and takes into account the changes in trade flows in all sectors as a result of the changes in iceberg import cost in a specific sector k.

The coefficient of correlation between Direct Effect and wage changes is higher than the coefficients of correlation between the empirical measures of exposure and the wage changes for eight out of thirteen manufacturing sectors shocked. However, the correlation coefficients for all measures of regional exposure do seem to be monotonically related across industries. The rank-rank correlation between the coefficient of the Direct Effect measure and the coefficients of the reduced-form exposure measures over the sector shocks are at least 0.86.

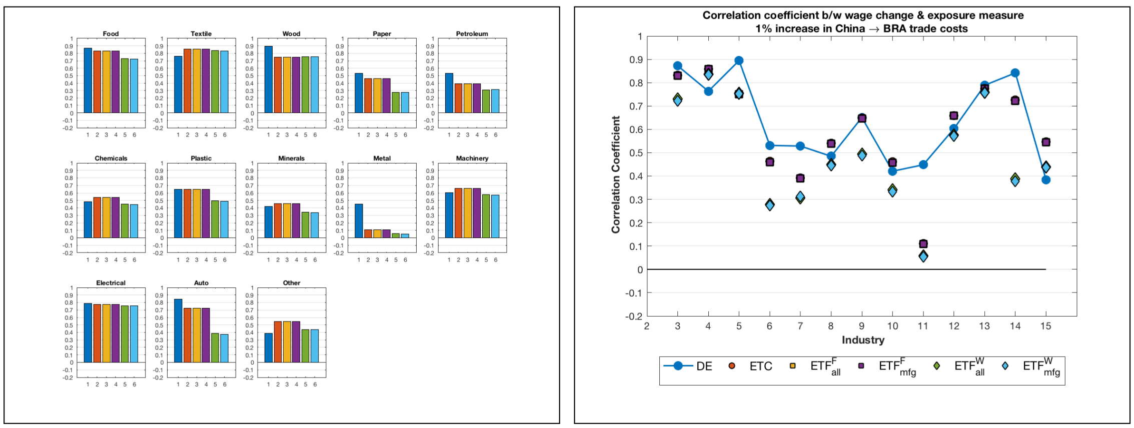
Despite having a similar ordering as the Direct Effect measure over the sector specific shocks as mentioned above, the magnitude of the coefficients of the empirical measures of exposure vary more across industries than that of the Direct Effect measure. The coefficient of correlation between the Direct Effect and the wage changes ranges from 0.47 to 0.92. The coefficient of correlation between wage changes and the employment weighted trade flow changes from USA to Brazil (ETF^F_{all} and ETF^F_{mfg}) ranges from -0.0949 to 0.8648 and -0.1047 to 0.8608 respectively. The reduced-form measures of exposure exhibit particularly low correlation with the model-based wage changes in the case of an import cost shock from USA in Paper, Minerals and Metal, with the lowest coefficient of correlation for Paper.

We are interested in whether the co-movement in the correlation of the wage changes with the Direct Effect measure and the reduced-form measures of exposure across sectors shocked is a general phenomenon or due to the particulars of the source country of the import cost shock. We are also interested in whether the reduced-form measures exhibit low correlation with the counterfactual wage changes in the same sectors (i.e. Paper, Minerals, Metal) irrespective of the source country shocked.

3.5.2.2 Sector-wise one percent increase in import cost from China

In this section we increase the iceberg trade costs of importing from China into Brazil by 1% for each manufacturing sector at a time and solve for the equilibrium counterfactual wage changes. Figure 3.5 presents the coefficient of correlation between the equilibrium wage changes and the different measures of regional exposure for each sector specific import cost shock.

Figure 3.5: Wage Changes and exposure measures: Sector-wise import cost shock from China



The predictive power of all measures of regional exposure with respect to the wage changes vary with the sector that experienced the increase in iceberg cost of importing from China. The Direct Effect does not perform across all sectors as well as it did in the case of sector wise shocks from USA. The coefficients of correlation between the Direct Effect and the wage changes range between 0.3843 for Other (Manufacturing nec; Recycling) to 0.8948 for Wood and products of wood and cork, with the coefficients of correlation being less than 0.5 in four out of thirteen sectors - Chemicals and chemical products (0.4846), Minerals (0.4206) and Metal (0.4481) being the other three sectors.

The coefficient of correlation between the Direct Effect and the wage changes is higher than the coefficient of correlation between the reduced-form measures of exposure and the wage changes for eight out of the thirteen manufacturing sectors shocked. Overall, the predictive power of the Direct Effect and the reduced-form measures of regional exposure are monotonically related across sectors. The correlation coefficients of the Direct Effect and the reduced-form measures of exposure with the wage changes exhibit a rank-rank correlation that ranges between 0.6429 (for DE and ETF^W_{all}) and 0.7912 (for DE and ETC). The monotonic relationship between the correlation coefficients of the Direct Effect and the reduced-form measures of exposure with the wage changes is weaker in the case of an sector wise import cost shock from China than in the case of an sector wise import cost shock from USA.

However, similar to the case of USA, we see that the magnitude of the coefficients of the reduced-form measures of exposure are not as consistent across sectors. For instance in the case of the employment weighted trade cost change measure (ETC), the coefficient of correlation ranges from as low as 0.1109 in Metal to 0.8576 in Textiles and Leather. The employment weighted trade flow changes from the World into Brazil in all manufacturing sectors (ETF^{W}_{mfg}) ranges from 0.1093 in Metal to 0.8574 in Textiles and Leather. All the reduced-form measures of exposure perform very poorly in the case of an import cost shock in Metal from China. The coefficient of correlation between the wage changes and all the reduced-form measures of exposure is below 0.11. The coefficient of correlation between the wage changes and the Direct Effect however is approximately 0.44.

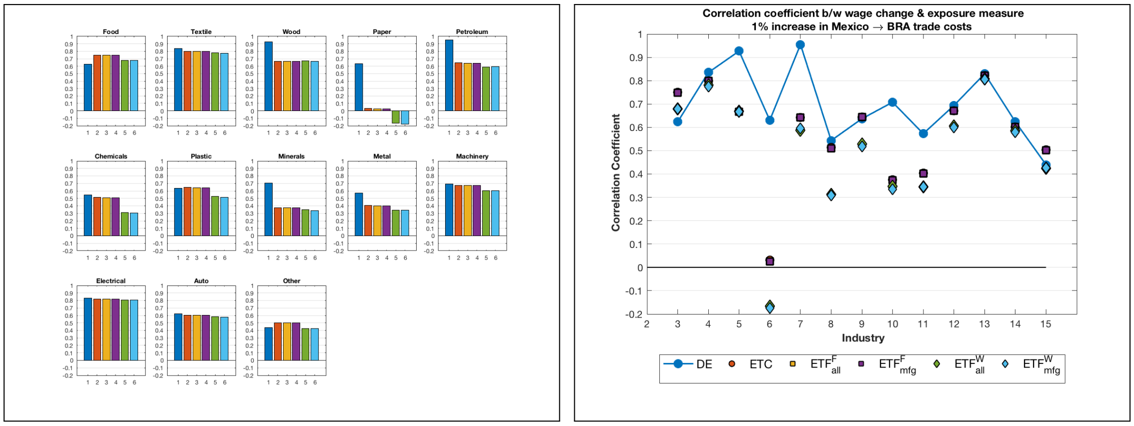
On the other hand, in the case of an import cost shock in the same sector, Metal from the USA, the coefficient of correlation between the model based wage changes and the reduced-form measures of exposure are all above 0.3 and the coefficient of correlation between wage changes and the Direct Effect is ~ 0.57. Thus, even for a shock in a specific sector k, the correlation of the measures of exposure with the model based wage changes continue to depend on the source country of the industry shocked.

3.5.2.3 Sector-wise one percent increase in import cost from Mexico

In this section we increase the iceberg trade costs of importing from Mexico into Brazil by 1% for each manufacturing sector at a time and solve for the resulting counterfactual wage changes. Figure 3.6 presents the coefficient of correlation between the counterfactual wage changes and the different measures of regional exposure for each sector specific import cost shock.

The correlation of the different measures of regional exposure with respect to the wage changes vary with the sector that experienced the increase in iceberg trade cost of importing from Mexico into Brazil. The Direct Effect performs the most consistently across sectors in terms of correlation with regions' sensitivity to sector specific import

Figure 3.6: Wage changes and exposure measures: Sector-wise import cost shock from Mexico



cost shocks, with coefficient of correlation above 0.5 in the case of all sector specific shocks, except for Other (~ 0.44). However, the coefficient of correlation between the Direct Effect and the counterfactual wage changes does vary with the sector shocked and ranges from 0.44 in Other to 0.96 in Coke, refined petroleum and nuclear fuel (Petroleum).

The coefficients of correlation between the Direct Effect and the wage changes is higher than the coefficients of correlation between the reduced-form measures exposure and the wage changes for ten out of the thirteen manufacturing sectors shocked in this exercise. However, the predictive power of the different reduced-form measures of regional exposure have a weaker relationship with that of the Direct Effect in the case of Mexico than in the case of USA or China. The coefficient of correlation with the wage changes for all reduced-form measures of regional exposure are weakly monotonically related with that of the Direct Effect measure across sectors exhibiting a rank correlation ranging between 0.45 (between the DE and ETC coefficients) and 0.56 (between DE and ETF^{W}_{all} coefficients).

The magnitude of the coefficients of correlation between the reduced-form measures of exposure and counterfactual wage changes are not as consistent across sectors as those for the Direct Effect. For instance, in the case of employment weighted trade cost change measure (ETC), the coefficient of correlation with the model-based wage changes ranges from as low as 0.0313 in Paper to 0.8213 in Electrical and optical equipment. It is interesting to note that the ordering of the sectors in which empirical measures perform the worst is same as when the sector specific import cost shocks are from USA - Paper, Minerals and Metal.

3.5.2.4 Regional exposure rankings across source countries of import cost changes

In the above three subsections we see that the coefficient of correlation between the model-based wage changes and the Direct Effect (DE) measure vary both with the specific industry that experiences an increase in the iceberg import cost and also with the source country of the import cost shock. As stated before, the Direct Effect (DE) measure is the theoretical partial equilibrium effect of a change in iceberg import costs derived from the model. The Direct Effect by definition ignores the indirect effect, that is, the effect on a region's wages that operates through the equilibrium wage changes in all regions. Thus a low coefficient of correlation between the Direct Effect and the equilibrium wage changes implies a greater role for the indirect effect on equilibrium regional wage changes.

The reduced-form exposure measure, employment weighted trade cost change (ETC) by construction also ignores the indirect effect described above. However, from the exercises in sections 3.5.2.1, 3.5.2.2 and 3.5.2.3 we see that the correlation of the Direct Effect (DE) with model-based wage changes and the correlation of ETC exposure measure with model-based wage changes do not always exhibit a strong monotonic relationship. In other words, a large coefficient of correlation between the Direct Effect and the equilibrium wage changes is not necessarily likely associated with a large coefficient of correlation between ETC and the equilibrium wage changes. This is particularly stark in the case of an increase in the cost of importing Metal from China and in the case of an increase in the cost of importing Paper from USA or Mexico.

Considering an increase in the iceberg import cost in only one sector at a time, the Direct Effect (DE) and the employment weighted trade cost change (ETC) measures of exposure are simpler than in the case of an iceberg import cost shock in all manufacturing sectors together. The employment weighted trade flow measures remain the same as they are the weighted sum of the actual change in trade flows across all sectors as a result of the shock to iceberg import costs in even one sector. When there is a change in the iceberg trade cost of importing from Foreign country F into Home H in only sector k ($\hat{\tau}_{FH}^{k}$), the Direct Effect and employment weighted trade cost shock are reduced to:

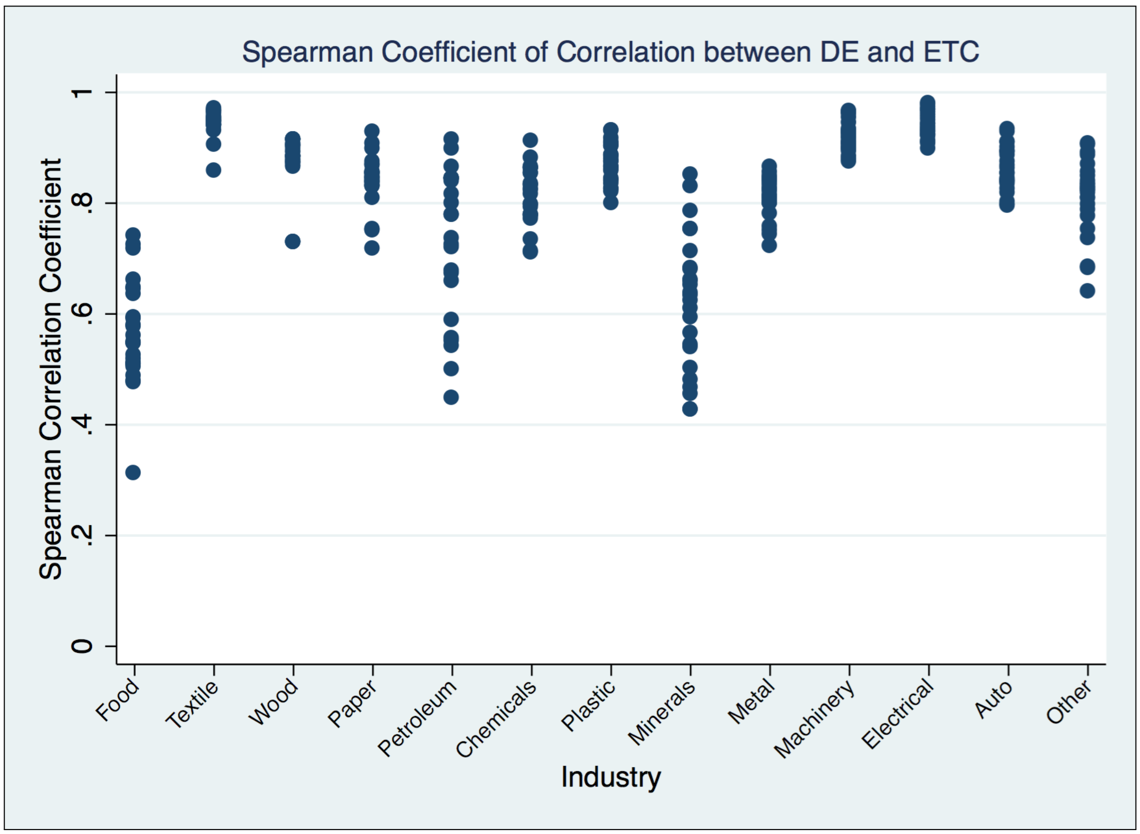
$$DE_i^{\tau_{FH}} = \theta_k \frac{L_i^k}{L_i} \underbrace{\left(\sum_{n \neq F} \tilde{\xi}_{in}^k \pi_{Fn}^k \right)}_{Effective\ Competition} \hat{\tau}_{FH}^k \tag{3.13}$$

$$ETC_i = \frac{L_i^k}{L_i} \hat{\tau}_{FH}^k \tag{3.14}$$

The variation in the ETC measure across regions is driven solely by variation in employment shares. In fact, when there is an import cost shock to only one sector k, the ETC measure of regional exposure to the import cost shock is larger, the larger the industry k employment share in a region. On the other hand, the Direct Effect measure of a region's sensitivity to an import cost shock in only one sector k is not solely determined by the sector k employment share in a region. As seen from equation (3.13), the Direct Effect measure includes an additional component, the *effective competition* from F faced by region i sector k in all relevant destination markets n.

While the analytic differences in the two measures can be seen from equations (3.13) and (3.14) above, it is unclear whether this translates to quantitatively significant differences in how the two measures order regions in terms of their exposure to a change in iceberg import costs. The Direct Effect measure orders regions according to their partial equilibrium exposure to an iceberg import cost change. The question now is whether the ETC measure, even without taking into account the variation across regions in the *effective competition* faced from a Foreign country F, gives rise to an ordering of regions similar to that provided by the Direct Effect measure. The advantage of comparing the rankings over regions provided by these two measures is that, unlike the employment weighted trade flow change measures (ETF), the DE and ETC measures can be constructed without having to solve for the counterfactual equilibrium for each sector-source country combination. We calculate the Direct Effect (DE) and ETC measures of exposure for each sector specific shock and for each different source country in our data. We have a total of 24 Foreign countries and one constructed rest of the world in our data. The complete list is given in Table B.1 in Appendix B.2. For each industry-source country combination, we calculate the rank correlation (Spearman Correlation Coefficient) between the Direct Effect (DE) and the employment weighted trade cost (ETC) measures of regional exposure. The results are in Figure 3.7 below. The x-axis indicates the industry that experienced a shock to iceberg import cost. Each point on the scatter corresponds to a different source country of the import cost shock. For some industries, such as Plastic and

Figure 3.7: Rank Correlation of DE and ETC exposure measures by industry and source country



Electrical, the rank correlation between the exposure measures is similar across source countries of the import cost shock. For instance, in Plastic, the rank correlation between the two exposure measures ranges from ~ 0.80 in the case of an import cost shock from South Korea to ~ 0.92 in the case of China. In Electrical the rank correlation between the two exposure measures ranges from ~ 0.90 in the case of an import cost shock from Turkey to ~ 0.98 in the case of France.

However, the ordering over regions' exposure given by the DE and ETC measures do not consistently exhibit similar correlation across the source countries of the import cost shock. In Food, Beverages and Tobacco (Food) the rank correlation between the two exposure measures differs a lot across source countries of the import cost shock. The rank correlation is quite low, at ~ 0.31, when the source country of the import cost shock is India and is approximately ~ 0.72 when the source country is the USA. In the case of non metallic minerals, the rank correlation between the two measures ranges from 0.43 when the source country of the import cost shock is Indonesia to 0.85 when the cost shock is in products imported from Spain.

Thus, the analytical differences in the DE and ETC measures of exposure as seen in equations (3.13) and (3.14), when taken to the data in the case of some sector specific shocks translate into significant differences in how the two measures order regions' exposure to an iceberg import cost shock. When examining the Pearson Correlation Coefficient between the two measures of regional exposure (DE and ETC), there is an even larger variation in the correlation coefficients across the source countries of the import cost shock (See Figure B.5 in Appendix **??**). We see that in some cases, by not taking into account the *effective competition* that a region i faces from a Foreign country in the relevant destination markets, rankings of regional exposure driven solely by the industry employment shares do not always capture the partial equilibrium exposure of a region to a trade cost shock as determined within a structure based on the model described in Section **??**.

3.5.3 Brazilian Trade Liberalization Event

Until now the results have focused on comparing the correlation between different exposure measures and counterfactual equilibrium wage changes in response to a simulated one percent increase in the iceberg cost of importing from a particular Foreign country into Brazil. However, empirical measures of exposure have been used to study regional sensitivity not only to bilateral trade shocks, but also to multilateral trade shocks, like trade liberalization events. In the 1990s Brazil underwent a massive trade liberalization process. Between 1990 and 1998, import tariffs fell by 52% on average across all manufacturing industries[6]. As mentioned before, we calibrate the initial equilibrium of our model using Brazilian trade data in 1999. We can thus use our model to simulate a reversal of the trade liberalization event and calculate the counterfactual equilibrium wage changes. This exercise has two advantages. This is the first step to future work that compares the wage changes in different regions of Brazil as predicted by the model to the actual wage changes in Brazil between 1990 and 1998. Secondly, this exercise allows us to compare the predictive power of different measures of exposure and how different measures order regions according to their exposure to a trade shock in the case where the Direct Effect (DE) captures the effective competition that a region i faces in all destination markets n, not only from one particular Foreign country F but from all foreign countries that trade with Brazil.

3.5.3.1 Brazilian trade liberalization (reversed): All Industries

In this section we undertake the reversal of the Brazilian trade liberalization. As before, we have calibrated the initial equilibrium to Brazilian data in 1999. We do not have reliable tariff data for 1999, the base year of the initial equilibrium. We assume tariffs in 1999 remained at the same level as in 1998. We then simulate the reversal of the trade liberalization event - taking the economy backwards from the tariff levels in 1998 to the tariff levels in 1990. However, we do not incorporate this as a tariff change. We instead model it as a proportional change in sector specific iceberg trade costs.

The results in Table 3.4 present the beta weights and the raw and rescaled relative weights of the Direct Effect and Indirect Effect in this trade liberalization exercise. The beta weights indicate that in this case, the Direct Effect contributes more to predicting the counterfactual wage changes than the Indirect Effect. Consistent with the beta weight ranking, the Direct Effect accounts for $\sim 69\%$ of the explained variation in counterfactual wage changes.

[6] See Kovak (2013) and Kume et al. (2000) for details of the trade liberalization process. The tariffs in 1990 and 1998 for each of the 15 industries are given in Table B.3.

Table 3.4: Relative Importance of Direct Effect: Trade liberalization (reversed)

Beta Weights

	Direct Effect	**Indirect Effect**
Beta Weight	0.9723^{***}	0.7390^{***}
Std. Error	(0.0941)	(0.0941)

Relative Weights Analysis

	Direct Effect	**Indirect Effect**
Raw relative weights	0.5738	0.2585
Rescaled Relative Weights	68.9369	31.0631

This is for a reversed trade liberalization even

Figure 3.8: Wage changes and exposure measures: Trade liberalization event (reversed)

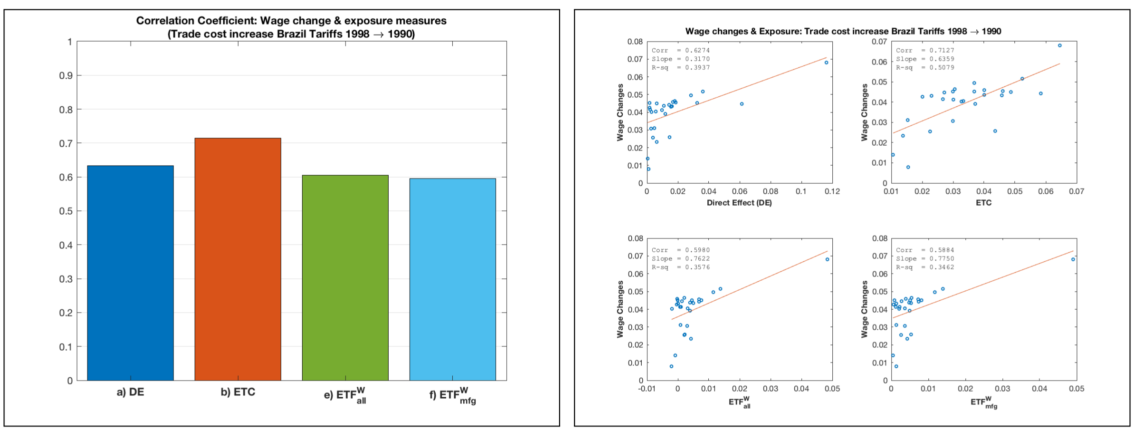


Figure 3.8 presents the coefficient of correlation between the counterfactual wages and the different measures of regional exposure. Since there is a change in the iceberg cost of importing from all countries into the world, the set of source countries when constructing the ETF^F_{all} and ETF^F_{mfg} measures are all the countries of the world. Thus we have that, for this case, ETF^F_{all} and ETF^F_{mfg} are the same as ETF^W_{all} and ETF^W_{mfg} respectively. We only present the results for ETC^W_{all} and ETF^W_{mfg} measures.

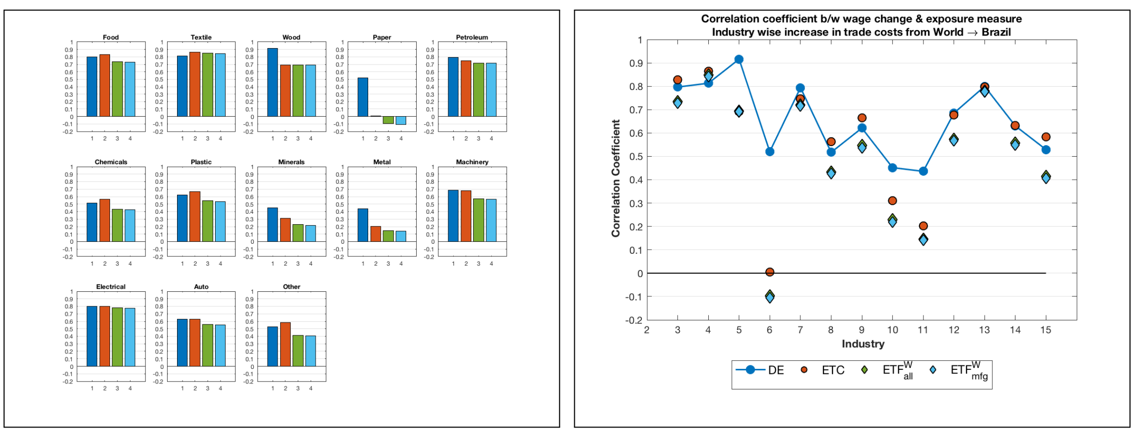
The correlation coefficient is above 0.5 for all measures of regional exposure. The employment weighted trade cost change measure (ETC) exhibits the highest correlation with the counterfactual wage changes with a correlation coefficient of 0.72.

In the trade liberalization exercise the variation in ETC across regions of Brazil is no longer purely driven by the share of employment in manufacturing as a whole. Since the trade cost changes vary across sectors, variation in the ETC measure is driven by variation in sectoral employment shares.

3.5.3.2 Sector-wise trade liberalization (Reversed)

In this section we undertake the reversal of the Brazilian trade liberalization except that that we apply the trade cost shock to one sector at a time. Figure 3.9 presents the coefficient of correlation between the counterfactual wages and the different measures of regional exposure for each sector-specific import cost shock.

Figure 3.9: Wage Changes and exposure measures: Sector-wise trade liberalization event (reversed)



The primary difference between this and the exercises in section 3.5.2 is that here there is an increase in the iceberg cost of importing from all foreign countries of the world instead of just one specific Foreign country. Thus the Direct Effect measure now takes into account the effective competition that a region i faces from all Foreign countries.

The predictive power of all the measures of regional exposure once again vary depending on the industry that experienced the increase in the iceberg trade cost of importing into Brazil. The coefficient of correlation between the counterfactual wage changes and the Direct Effect range from ~ 0.44 in Basic and fabricated metals (Metal) to ~ 0.92 in Wood and products of wood and cork. The correlation between the Direct Effect and equilibrium wage changes is less that 0.5 in only two out of the thirteen manufacturing industries.

However, for each industry specific shock the ordinal rankings over regions in terms of exposure to the shock provided by the DE and ETC measures are similar. The rank correlation between the Direct Effect (DE) and the employment weighted trade cost change (ETC) measures vary from ~ 0.70 in industry Food, beverages and tobacco to 0.97 in industry Electrical and optical equipment.

3.6 Conclusion

This paper focuses on the growing literature that studies how shocks to international trade can have heterogeneous effects across regions within a country. In particular, we seek to understand whether results from the two broad approaches taken by the literature are compatible with each other.

In the reduced form approach, variation in regional exposure to a trade shock is driven primarily by variation in sectoral employment shares across regions. On the other hand, a partial equilibrium measure of regional exposure grounded in a general equilibrium model of trade not only depends on the sectoral employment shares but also on the initial pattern of trade linkages between regions - i.e. the *effective competition* that a region faces from the source country of the trade shock. We show that these analytical differences in the two types of exposure measures translate into quantitative differences in the measures' correlation with model-based equilibrium wage changes in response to a trade cost shock. Even when we undertake a comparison of the ordinal rankings regional exposure to a trade shock provided by the two measures, we find that the correlation between the rankings is sensitive to the source country of the import cost shock. We interpret our results as indicative of a disconnect between the two approaches in the literature, and not an indictment of either. The results presented caution against indiscriminately relying on reduced-form exposure measures to recover partial elasticities of regional wages to a shock to international trade.

Our analysis has some limitations. First, we focus on Brazil but our results may not hold in other countries, where regional variation in sectoral composition and in trade linkages is different. Second, we only consider linkages in final goods' trade but we do not consider that regional economies are linked also by trade in intermediates and by internal migration. Although it is likely that adding these other linkages would generate an even higher disconnect between reduced form-measures of exposure and model-derived ones, we do not formally prove this. Finally, we focus on a single outcome, wages, whereas the literature has also focused on employment. We do this to keep the analysis as parsimonious as possible, to show that even in a simple environment this disconnect between measures emerges. We therefore leave for future research the analysis of other types of linkages between regions and of other labor market outcomes.

Appendix A

Appendix to Chapter 1

A.1 Empirical Evidence

A.1.1 Descriptive Statistics: Region level variables

Table A.1: Descriptive Statistics (Aggregate/Region level variables)

Variable	**All Commuting Zones**			
	Mean	**Std. Dev.**	**25th percentile**	**75th percentile**
Commuting Zone level variables				
skill premium (associate's)	1.330	0.101	1.258	1.393
skill premium (bachelor's)	1.385	0.110	1.304	1.464
skill share (associate's)	0.310	0.070	0.258	0.356
skill share (bachelor's)	0.224	0.061	0.180	0.256
County level variables				
school expenditure per student	6.092	2.102	5.027	6.735
number of colleges per capita	0.014	0.034	0	0.019

A.1.2 Logit Specification: Commuting Zone Level

Table A.2: Probability of degree attainment: Logit specification I

Dependent Variable: Indicator for degree attainment by age 23				
	$\mathbb{1}(\geq$ associate's degree)		$\mathbb{1}(\geq$ bachelors degree)	
	(1)	(2)	(3)	(4)
Panel A: Baseline controls				
log(skill premium)$_c$	4.356**	4020.298***	11.519*	426827.100***
	(3.135)	(99926.316)	(9.373)	(1338846.000)
log(skill share)$_c$	1.344	0.126**	1.156	0.0484***
	(0.372)	(0.104)	(0.275)	(0.043)
log(skill premium)$_c\times$ log(skill share)$_c$		1175.095***		4034.039***
		(2916.084)		(9783.985)
# of observations	8353	8353	8353	8353
Panel B: Baseline and school quality controls				
log(skill premium)$_c$	4.058*	4633.591***	12.097***	221493.200***
	(3.029)	(11615.010)	(9.067)	(653113.8)
log(skill share)$_c$	1.195	0.113***	0.893	0.050***
	(0.249)	(0.093)	(0.175)	(0.042)
log(skill premium)$_{c_y}\times$ log(skill share)$_{c_y}$		1356.928***		2178.516***
		(3236.531)		(4955.503)
# of observations	7439	7439	7439	7439

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;
Standard errors are clustered at the state level

Table A.3: Probability of degree attainment: Logit specification II

Dependent Variable: Indicator for degree attainment by age 23				
	$\mathbb{1}(\geq$ associate's degree)		$\mathbb{1}(\geq$ bachelors degree)	
	(1)	(2)	(3)	(4)
Panel A: Baseline, school quality and college access				
log(skill premium$_{c_o}$)	4.841^{**}	4023.543^{***}	12.765^{***}	222063.900^{***}
	(3.743)	(10960.500)	(9.543)	(701480.7)
log(skill share$_{c_o}$)	1.423	0.149^{**}	1.025	0.058^{***}
	(0.355)	(0.138)	(0.231)	(0.055)
log(skill premium$_{c_o}$)× log(skill share$_{c_o}$)		947.319^{***}		2004.596^{***}
		(2454.593)		(4876.468)
# of observations	7439	7439	7439	7439
Panel B: Baseline, school quality, college access, parent income and peer effects				
log(skill premium$_{c_o}$)	5.172^{**}	4525.374^{***}	14.159^{***}	254846.800^{***}
	(3.924)	(12887.430)	(11.015)	(842240.700)
log(skill share$_{c_o}$)	1.442	0.148^{**}	1.033	0.058^{***}
	(0.370)	(0.143)	(0.241)	(0.058)
log(skill premium$_{c_o}$)× log(skill share$_{c_o}$)		994.233^{**}		2039.119^{***}
		(2719.062)		(5171.019)
# of observations	7439	7439	7439	7439

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;
Standard errors are clustered at the state level

A.1.3 Analysis at MSA Level

Table A.4: Probability of Degree Attainment: MSA - OLS specification I

Dependent Variable: Indicator for degree attainment by age 23				
	$\mathbb{1}(\geq$ associate's degree)		$\mathbb{1}(\geq$ bachelors degree)	
	(1)	(2)	(3)	(4)
Panel A: Baseline controls				
log(skill premium$_{m_o}$)	0.227*	1.014***	0.184	1.104***
	(0.115)	(0.308)	(0.110)	(0.362)
log(skill share$_{m_o}$)	0.046	-0.248^{**}	0.025	-0.266^{**}
	(0.030)	(0.101)	(0.022)	(0.107)
log(skill premium$_{m_o}$)× log(skill share$_{m_o}$)		0.826**		0.743**
		(0.322)		(0.285)
Panel B: Baseline and school quality controls				
log(skill premium$_{m_o}$)	0.189	1.124***	0.170	1.165***
	(0.117)	(0.343)	(0.103)	(0.373)
log(skill share$_{m_o}$)	0.040	-0.302^{**}	0.005	-0.302^{**}
	(0.025)	(0.124)	(0.019)	(0.110)
log(skill premium$_{m_o}$)× log(skill share$_{m_o}$)		0.972***		0.795***
		(0.351)		(0.283)

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;
Standard errors are clustered at state level

Table A.5: Probability of Degree Attainment: MSA - OLS specification II

Dependent Variable: Indicator for degree attainment by age 23				
	$\mathbb{1}(\geq$ associate's degree)		$\mathbb{1}(\geq$ bachelors degree)	
	(1)	(2)	(3)	(4)
Panel A: Baseline, school quality and college access				
log(skill premium$_{m_o}$)	0.183	0.963**	0.166	1.103**
	(0.122)	(0.394)	(0.103)	(0.413)
log(skill share$_{m_o}$)	0.059*	−0.233	0.008	−0.289**
	(0.031)	(0.149)	(0.022)	(0.127)
log(skill premium$_{m_o}$)× log(skill share$_{m_o}$)		0.810**		0.751**
		(0.398)		(0.316)
Panel B: Baseline, school quality, college access, parent income and peer effects				
log(skill premium$_{m_o}$)	0.176	0.910**	0.163	1.043**
	(0.117)	(0.410)	(0.097)	(0.421)
log(skill share$_{m_o}$)	0.068**	−0.207	0.013	−0.266**
	(0.033)	(0.151)	(0.022)	(0.128)
log(skill premium$_{m_o}$)× log(skill share$_{m_o}$)		0.762*		0.706***
		(0.410)		(0.323)

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;
Standard errors are clustered at state level

A.1.4 Origin Commuting Zone: Alternative definition

Table A.6: Probability of Degree Attainment: Alternative Origin CZ (OLS specification)

	Dependent Variable: Indicator for degree attainment by age 23			
	$\mathbb{1}(\geq$ associate's degree)		$\mathbb{1}(\geq$ bachelors degree)	
	(1)	(2)	(3)	(4)
Panel A: Baseline controls				
log(skill premium$_{c_o}$)	0.214^{**}	1.208^{***}	0.292^{***}	1.331^{***}
	(0.105)	(0.325)	(0.106)	(0.337)
log(skill share$_{c_o}$)	0.049	-0.287^{**}	0.026	-0.277^{***}
	(0.035)	(0.106)	(0.024)	(0.091)
log(skill premium$_{c_o}$)× log(skill share$_{c_o}$)		1.012^{***}		0.804^{***}
		(0.312)		(0.239)
Panel B: Baseline and school quality controls				
log(skill premium$_{c_o}$)	0.212^{*}	1.269^{***}	0.292^{***}	1.291^{***}
	(0.106)	(0.361)	(0.098)	(0.339)
log(skill share$_{c_o}$)	0.030	-0.312^{***}	-0.001	-0.284^{***}
	(0.031)	(0.113)	(0.023)	(0.090)
log(skill premium$_{c_o}$)× log(skill share$_{c_o}$)		1.063^{***}		0.766^{***}
		(0.330)		(0.238)

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$;
Standard errors are clustered at state level

A.2 Model Characterization

Expected utility from being high skilled: Derivation

After receiving a signal s_{Hr} about the realized high skill wage w^*_{Hr}, the expected utility from being high skilled for a worker with ability γ in region r in period t is given by:

$$\begin{aligned}
\mathbb{E}_{\hat{w}_{Hr}}\left[V^H\left(\gamma, \hat{w}_{Hr}, p\right) \middle| s_{Hr}, \theta^y_{rt}\right] &= \mathbb{E}_{\hat{w}_{Hr}}\left[\frac{1}{1-\eta}\left(\left(\frac{\hat{w}_{Hr}}{c(\gamma)p}\right)^{1-\eta} - 1\right)\middle| s_{Hr}, \theta^y_{rt}\right] \\
&= \frac{1}{1-\eta}\left[\frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}|s_{Hr}, \theta^y_{rt}\right]}{\left[c(\gamma)p\right]^{1-\eta}} - 1\right]
\end{aligned}$$

where $\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}|s_{Hr}, \theta^y_{rt}\right] = \exp\left((1-\eta)\hat{\mu}_{Hr}(s_{Hr}, \theta_{rt}) + \frac{(1-\eta)^2\left(\hat{\sigma}_{Hr}(s_{Hr}, \theta_{rt})\right)^2}{2}\right)$.

After receiving a signal s_{Hr} about the high skill wage realization w^*_{Hr}, a young worker in region r with known characteristics θ^y_{rt} updates his beliefs about high skill wage to $\hat{\omega}_{Hr} \sim N(\hat{\mu}_{Hr}, \hat{\sigma}^2_{Hr})$.

$$\begin{aligned}
\hat{\omega}_{Hr} \sim N(\hat{\mu}_{Hr}, \hat{\sigma}^2_{Hr}) \quad &\Rightarrow \hat{w}_{Hr} && \sim \log N(\hat{\mu}_{Hr}, \hat{\sigma}^2_{Hr}) \\
&\Rightarrow \left(\hat{w}_{Hr}\right)^{1-\eta} && \sim \log N\left((1-\eta)\hat{\mu}_{Hr}, (1-\eta)^2\hat{\sigma}^2_{Hr}\right) \\
&\Rightarrow \mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}\right] && = \exp\left((1-\eta)\hat{\mu}_{Hr} + (1-\eta)^2\tfrac{\hat{\sigma}^2_{Hr}}{2}\right)
\end{aligned}$$

Prediction 1: Given known region characteristics θ^y_{rt}, signal s_{Hr} and cost function $c(\gamma)$ where $c'(\gamma) < 0$ (i.e. cost is decreasing in ability), expected returns to skill is increasing in ability.

Proof. From equation (1.7) we have that the expected returns to skill is given by:

$$
\begin{aligned}
R^{skill}(\gamma, s_{Hr}|\theta^y_{rt}) &= \mathbb{E}_{\hat{w}_{Hr}}\left[V^H(\gamma, \hat{w}_{Hr}, p)|s_{Hr}, \theta^y_{rt}\right] - V^L(\gamma, w_{Lr}, p) \\
&= \frac{1}{1-\eta}\left[\frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}|s_{Hr}, \theta^y_{rt}\right]}{c(\gamma)^{1-\eta}} - w^{1-\eta}_{Lr}\right]
\end{aligned}
$$

Taking the derivative with respect to ability γ,

$$
\frac{\partial R^{skill}(\gamma, s_{Hr}|\theta_{rt})}{\partial \gamma} = -\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}|s_{Hr}, \theta^y_{rt}\right] \times c(\gamma)^{\eta-2} \times c'(\gamma) > 0
$$

This only requires that the cost of skill acquisition is decreasing in ability, $c'(\gamma) < 0$. Thus, given signal s_{Hr} and regional characteristics θ_{rt}, the higher the worker's ability, the greater the (expected) returns to skill. □

Prediction 2: Given known region characteristics θ^y_{rt} and worker ability γ, expected returns to skill is increasing in signal (s_{Hr}) received about the high skill wage realization.

Proof. From equation (1.7) we have that the expected returns to skill is given by:

$$
R^{skill}(\gamma, s_{Hr}|\theta^y_{rt}) = \frac{1}{1-\eta}\left[\frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}|s_{Hr}, \theta^y_{rt}\right]}{c(\gamma)^{1-\eta}} - w^{1-\eta}_{Lr}\right]
$$

where $\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}\right] = \exp\left((1-\eta)\hat{\mu}_{Hr} + (1-\eta)^2\frac{\hat{\sigma}^2_{Hr}}{2}\right)$.

$$
\begin{aligned}
\frac{\partial R^{skill}(\gamma, s_{Hr}|\theta^y_{rt})}{\partial s_{Hr}} &= \frac{1}{(1-\eta)c(\gamma)^{1-\eta}}\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}\right] \times (1-\eta) \times \frac{\sigma^2_H}{\sigma^2_s + \sigma^2_H} \\
&= \frac{1}{c(\gamma)^{1-\eta}}\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}\right] \times \frac{\sigma^2_H}{\sigma^2_s + \sigma^2_H} \geq 0
\end{aligned}
$$

□

Prediction 3: Given signal s_{Hr} and worker ability γ, expected returns to skill is decreasing in signal variance if the signal received s_{Hr} is "high enough", that is if

$s_{Hr} > \log\left[\mathbb{E}\left(w_{Hr}^{1-\eta}\right)\right]^{\frac{1}{1-\eta}}$ and is increasing otherwise.

Proof. From equation (1.7) we have that the expected returns to skill is given by:

$$R^{skill}(\gamma, s_{Hr}|\theta_{rt}^{y}) \quad = \frac{1}{1-\eta}\left[\frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}_{Hr}^{1-\eta}|s_{Hr},\theta_{rt}^{y}\right]}{c(\gamma)^{1-\eta}} - w_{Lr}^{1-\eta}\right]$$

Taking the derivative with respect to standard deviation of signal distribution σ_s,

$$\begin{aligned}
\frac{\partial R^{skill}(\gamma, s_{Hr}|\theta_{rt})}{\partial \sigma_s} &= \frac{1}{(1-\eta)c(\gamma)^{1-\eta}}\frac{\partial}{\partial \sigma_s}\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}_{Hr}^{1-\eta}|s_{Hr},\theta_{rt}^{y}\right] \\
&= \frac{1}{(1-\eta)c(\gamma)^{1-\eta}}\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}_{Hr}^{1-\eta}|s_{Hr},\theta_{rt}^{y}\right] \times \ldots \\
&\qquad \ldots\left((1-\eta)\frac{\partial \hat{\mu}_{Hr}}{\partial \sigma_s} + \frac{(1-\eta)^2}{2}\frac{\partial \hat{\sigma}_{Hr}^2}{\partial \sigma_s}\right)
\end{aligned}$$

We have that:

$$\begin{aligned}
\hat{\mu}_{Hr} &= \frac{\sigma_s^2}{\sigma_s^2+\sigma_H^2}\mu_H + \frac{\sigma_H^2}{\sigma_H^2+\sigma_s^2}s_{Hr} \\
\Rightarrow \quad \frac{\partial \hat{\mu}_{Hr}}{\partial \sigma_s} &= \frac{\left(\sigma_s^2+\sigma_H^2\right)2\sigma_s\mu_H - 2\sigma_s\left(\sigma_s^2\mu_H+\sigma_H^2 s_{Hr}\right)}{\left(\sigma_s^2+\sigma_H^2\right)^2} \\
\Rightarrow \quad \frac{\partial \hat{\mu}_{Hr}}{\partial \sigma_s} &= \frac{2\sigma_s\sigma_H^2\left(\mu_H - s_{Hr}\right)}{\left(\sigma_s^2+\sigma_H^2\right)^2}
\end{aligned}$$

$$\begin{aligned}
\hat{\sigma}_{Hr}^2 &= \left[\sigma_H^{-2}+\sigma_s^{-2}\right]^{-1} = \frac{\sigma_s^2\sigma_H^2}{\left(\sigma_s^2+\sigma_H^2\right)} \\
\Rightarrow \quad \frac{\partial \hat{\sigma}_{Hr}^2}{\partial \sigma_s} &= \frac{\left(\sigma_s^2+\sigma_H^2\right)2\sigma_s\sigma_H^2 - \left(\sigma_s^2\sigma_H^2 \times 2\sigma_s\right)}{\left(\sigma_s^2+\sigma_H^2\right)^2} \\
\Rightarrow \quad \frac{\partial \hat{\sigma}_{Hr}^2}{\partial \sigma_s} &= \frac{2\sigma_s\sigma_H^4}{\left(\sigma_s^2+\sigma_H^2\right)^2}
\end{aligned}$$

Therefore substituting this above we have

$$\begin{aligned}
\frac{\partial R^{skill}(\gamma, s_{Hr}|\theta_{rt})}{\partial \sigma_s} &= \frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}_{Hr}^{1-\eta}|s_{Hr}, \theta_{rt}^{y}\right]}{(1-\eta)c(\gamma)^{1-\eta}} \times \left((1-\eta)\frac{\partial \hat{\mu}_{Hr}}{\partial \sigma_s} + \frac{(1-\eta)^2}{2}\frac{\partial \hat{\sigma}_{Hr}^2}{\partial \sigma_s}\right) \\
&= \frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}_{Hr}^{1-\eta}|s_{Hr}, \theta_{rt}^{y}\right]}{(1-\eta)c(\gamma)^{1-\eta}} \times \frac{2\sigma_s\sigma_H^2}{\left(\sigma_s^2+\sigma_H^2\right)^2} \times \dots \\
&\qquad \dots \times \left((1-\eta)\mu_H - (1-\eta)s_{Hr} + \frac{(1-\eta)^2\sigma_H^2}{2}\right)
\end{aligned}$$

The term $\left((1-\eta)\mu_H - (1-\eta)s_{Hr} + \frac{(1-\eta)^2\sigma_H^2}{2}\right)$ can be further re-written as:

$$\begin{aligned}
\left((1-\eta)\mu_H - (1-\eta)s_{Hr} + \frac{(1-\eta)^2\sigma_H^2}{2}\right) &= \left(\log\left(\mathbb{E}\left[w_h^{1-\eta}\right]\right) - (1-\eta)s_{Hr}\right) \\
&= \frac{1}{1-\eta}\left(\log\left(\mathbb{E}\left[w_h^{1-\eta}\right]\right)^{\frac{1}{1-\eta}} - s_{Hr}\right)
\end{aligned}$$

Therefore,

$$\begin{aligned}
\frac{\partial R^{skill}(\gamma, s_{Hr}|\theta_{rt})}{\partial \sigma_s} &= \underbrace{\frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}_{Hr}^{1-\eta}|s_{Hr}, \theta_{rt}^{y}\right]}{(1-\eta)^2c(\gamma)^{1-\eta}} \times \frac{2\sigma_s\sigma_H^2}{\left(\sigma_s^2+\sigma_H^2\right)^2}}_{\geq 0} \times \dots \\
&\qquad \dots \times \left(\log\left(\mathbb{E}\left[w_h^{1-\eta}\right]\right)^{\frac{1}{1-\eta}} - s_{Hr}\right)
\end{aligned}$$

From the expression above it is evident that the whether expected returns to skill is increasing or decreasing in signal variance only depends on the relationship between the signal s_{Hr} received about the high skill wage and the apriori expectation about the high skill wages. This can be seen very clearly by assuming $\eta = 0$. Then the condition above just becomes $(\log(\mathbb{E}[w_h]) - s_{Hr})$. Thus the expected returns to skill is decreasing in signal variance if the signal received about log high skill wage realization is greater than log of ex-ante expected high skill wage. $\square$

Prediction 4: For each worker with ability γ in region r with known characteristics θ_{rt}^{y}, there exists a threshold signal $s^*(\gamma, \theta_{rt}^{y})$ such that worker will choose to become high skilled for all signals $s_{Hr} \geq s^*(\gamma, \theta_{rt})$ where $s^*(\gamma, \theta_{rt})$ solves:

$$R^{skill}(\gamma, s^*(\gamma, \theta^y_{rt})|\theta^y_{rt}) = \ 0$$

and is given by

$$s^*(\gamma, \theta^y_{rt}) = \frac{\sigma^2_s(h^o_{rt}) + \sigma^2_H}{\sigma^2_H} \ \left[\log(c(\gamma)) + \log(A_{Lr}) - \frac{(1-\eta)\hat{\sigma}^2_{Hr}}{2}\right] - \frac{\sigma^2_s(h^o_{rt})}{\sigma^2_H}\mu_H$$

Proof. Given worker ability γ and known regional characteristics θ^y_{rt}, we have expected returns to skill given by:

$$R^{skill}(\gamma, s_{Hr}|\theta^y_{rt}) \ \ = \frac{1}{1-\eta}\left[\frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}|s_{Hr}, \theta^y_{rt}\right]}{c(\gamma)^{1-\eta}} - w^{1-\eta}_{Lr}\right]$$

where $\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}\right] = \exp\left((1-\eta)\hat{\mu}_{Hr} + (1-\eta)^2\frac{\hat{\sigma}^2_{Hr}}{2}\right)$, when $\hat{w}_{Hr} \sim \log N(\hat{\mu}_{Hr}, \hat{\sigma}_{Hr})$ and $\hat{\mu}_{Hr} = \frac{\sigma^2_s}{\sigma^2_{Hr}+\sigma^2_s}\mu_{Hr} + \frac{\sigma^2_{Hr}}{\sigma^2_{Hr}+\sigma^2_s}s_{Hr}$ and s_{Hr} has support $(-\infty, +\infty)$.

For $\eta > 1$

$$\lim_{s_{Hr}\to-\infty}\hat{\mu}_{Hr} = -\infty \quad \Rightarrow \lim_{s_{Hr}\to-\infty}\exp\left((1-\eta)\hat{\mu}_{Hr}\right) = \infty$$

$$\Rightarrow \lim_{s_{Hr}\to-\infty}\frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}|s_{Hr}, \theta^y_{rt}\right]}{c(\gamma)^{1-\eta}} \to -\infty$$

$$\Rightarrow \lim_{s_{Hr}\to-\infty}R^{skill}(\gamma, s_{Hr}|\theta^y_{rt}) < 0$$

$$\lim_{s_{Hr}\to\infty}\hat{\mu}_{Hr} = \infty \qquad \Rightarrow \lim_{s_{Hr}\to-\infty}\exp\left((1-\eta)\hat{\mu}_{Hr}\right) = 0$$

$$\Rightarrow \lim_{s_{Hr}\to-\infty}\frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}^{1-\eta}_{Hr}|s_{Hr}, \theta^y_{rt}\right]}{c(\gamma)^{1-\eta}} = 0$$

$$\Rightarrow \lim_{s_{Hr}\to-\infty}R^{skill}(\gamma, s_{Hr}|\theta^y_{rt}) = \frac{-w^{1-\eta}_{Lr}}{1-\eta} > 0$$

For $\mathbf{0 \leq \eta < 1}$

$$\begin{aligned}
\lim_{s_{Hr}\to-\infty} \hat{\mu}_{Hr} = -\infty \quad &\Rightarrow \lim_{s_{Hr}\to-\infty} \exp\left((1-\eta)\hat{\mu}_{Hr}\right) = 0 \\
&\Rightarrow \lim_{s_{Hr}\to-\infty} \frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}_{Hr}^{1-\eta}|s_{Hr},\theta_{rt}^{y}\right]}{c(\gamma)^{1-\eta}} = 0 \\
&\Rightarrow \lim_{s_{Hr}\to-\infty} R^{skill}(\gamma, s_{Hr}|\theta_{rt}^{y}) = \frac{-w_{Lr}^{1-\eta}}{1-\eta} < 0
\end{aligned}$$

$$\begin{aligned}
\lim_{s_{Hr}\to\infty} \hat{\mu}_{Hr} = \infty \quad &\Rightarrow \lim_{s_{Hr}\to-\infty} \exp\left((1-\eta)\hat{\mu}_{Hr}\right) = +\infty \\
&\Rightarrow \lim_{s_{Hr}\to-\infty} \frac{\mathbb{E}_{\hat{w}_{Hr}}\left[\hat{w}_{Hr}^{1-\eta}|s_{Hr},\theta_{rt}^{y}\right]}{c(\gamma)^{1-\eta}} \to +\infty \\
&\Rightarrow \lim_{s_{Hr}\to-\infty} R^{skill}(\gamma, s_{Hr}|\theta_{rt}^{y}) > 0
\end{aligned}$$

Thus we have that $\forall\ \eta \geq 0$ and $\eta \neq 1$,

$$\lim_{s_{Hr}\to-\infty} R^{skill}(\gamma, s_{Hr}|\theta_{rt}^{y}) < 0 \quad \text{and} \quad \lim_{s_{Hr}\to\infty} R^{skill}(\gamma, s_{Hr}|\theta_{rt}^{y}) > 0$$

Further, since $R^{skill}(\gamma, s_{Hr}|\theta_{rt}^{y})$ is increasing in signal s_{Hr}, by the intermediate value theorem there exists a threshold signal $s^{*}(\gamma, \theta_{rt}^{y})$ that solves:

$$\begin{aligned}
R^{skill}(\gamma, s^{*}(\gamma,\theta_{rt}^{y})|\theta_{rt}^{y}) = \quad & 0 \\
\Rightarrow \quad \frac{\mathbb{E}\left[\hat{w}_{Hr}^{1-\eta}\right]}{(1-\eta)(c(\gamma))^{1-\eta}} \quad & = \tfrac{w_{Lr}^{1-\eta}}{(1-\eta)} \\
\Rightarrow \quad \log(w_{Lr}c(\gamma)) \quad & = \log\left(\exp\left(\tfrac{(1-\eta)^2\hat{\sigma}_{Hr}}{2} + (1-\eta)\hat{\mu}_{Hr}\right)\right) \\
\Rightarrow \quad \frac{(1-\eta)\hat{\sigma}_{Hr}^{2}}{2} + \hat{\mu}_{Hr} \quad & = \log(c(\gamma)) + \log(w_{Lr}) \\
\Rightarrow \quad \hat{\mu}_{Hr}(s^{*}(\gamma,\theta_{rt}),\theta_{rt}) \quad & = \log(c(\gamma)) + \log(w_{Lr}) - \tfrac{(1-\eta)\hat{\sigma}_{Hr}^{2}}{2}
\end{aligned}$$

$$\Rightarrow s^*(\gamma, \theta^y_{rt}) = \frac{\sigma^2_s(h^o_{rt}) + \sigma^2_H}{\sigma^2_H} \left[\log(c(\gamma)) + \log(A_{Lr}) - \frac{(1-\eta)\hat{\sigma}^2_{Hr}}{2}\right] - \frac{\sigma^2_s(h^o_{rt})}{\sigma^2_H}\mu_H$$

□

Aggregate Effective Supply of Labor

If a young worker chooses to remain low skilled, then she supplies one unit of effective labor inelastically. The aggregate supply of effective units of low skilled labor in region r at time t is given by:

$$E^L(\theta_{rt}) = L^y(\theta_{rt})$$

However, if a young worker chooses to become high skilled, then she must pay a cost in terms of effective units of labor. Specifically, a young worker with ability γ can supply $1/c(\gamma)$ effective units of high skill labor. Thus the aggregate supply of effective units of low skilled labor in region r at time t is given by:

$$E^H(\theta_{rt}) = \left[\int_{\xi}^{\infty} \Pr\left(s_H \geq s^*_{Hr}(\gamma, \theta^y_{rt}) \mid \theta_{rt}\right) \frac{1}{c(\gamma)} dG(\gamma)\right] M_{rt}$$

Appendix B

Appendix to Chapter 3

B.1 Theory Appendix

B.1.1 Deriving Wage Changes

Goods market clearing and trade balance implies

$$w_i L_i = \sum_{k \in K} \sum_{n \in \mathcal{R}} \pi_{in}^k \mu_k w_n L_n \tag{B.1}$$

Totally differentiating equation (B.1) and dividing both sides by $w_i L_i$ we get:

$$\begin{aligned}
& \tfrac{w_i dL_i + L_i dw_i}{w_i L_i} &&= \frac{1}{w_i L_i} \sum_k \sum_n \left(\mu_k \pi_{in}^k w_n L_n \frac{d\pi_{in}^k}{\pi_{in}^k} + \mu_k \pi_{in}^k w_n L_n \frac{dw_n}{w_n} \right) \\
\Rightarrow \quad & \hat{w}_i &&= \frac{1}{w_i L_i} \sum_k \sum_n \left(\mu_k \pi_{in}^k w_n L_n \hat{\pi}_{in}^k + \mu_k \pi_{in}^k w_n L_n \hat{w}_n \right) \\
\Rightarrow \quad & \hat{w}_i &&= \sum_{k \in K} \sum_{n \in \mathcal{R}} \xi_{in}^k \left(\hat{\pi}_{in}^k + \hat{w}_n \right) \text{ where } \xi_{in}^k = \frac{\pi_{in}^k \mu_k w_n L_n}{w_i L_i}
\end{aligned}$$

We now differentiate π_{in}^k:

$$
\begin{aligned}
\pi_{in}^k = &\ \underbrace{\frac{A_i^k (w_i \tau_{in}^k)^{-\theta_k}}{\sum_{l\in\mathcal{R}} A_l^k (w_l \tau_{ln}^k)^{-\theta_k}}}_{D} \\
\hat{\pi}_{in}^k = &\ \frac{1}{\pi_{in}^k}\frac{1}{D}\left[(w_i \tau_{in})^{-\theta_k} dA_i^k + A_i^k (\tau_{in}^k)^{-\theta_k}(-\theta_k) w_i^{-\theta_k - 1} dw_i \ldots\right. \\
&\left. \cdots - \theta_k A_i^k (w_i)^{-\theta_k} (\tau_{in}^k)^{-\theta_k - 1} d\tau_{in}^k\right] - \frac{1}{\pi_{in}^k}\frac{1}{D^2}\left[A_i^k (w_i \tau_{in}^k)^{-\theta_k} dD\right] \\
dD = &\ \left[\sum_l A_l^k (w_l \tau_{ln}^k)^{-\theta_k}\right] \\
= &\ \sum_l \left\{(w_l \tau_{ln}^k)^{-\theta_k} dA_l^k + A_l^k (\tau_{ln}^k)^{-\theta_k}(-\theta_k) w_l^{-\theta_k - 1} dw_l \ldots\right. \\
&\qquad\qquad\qquad \left. \cdots + A_l^k w_l^{-\theta_k}(-\theta_k)(\tau_{ln}^k)^{-\theta_k - 1} d\tau_{ln}^k\right\}
\end{aligned}
$$

We need a line here to tell us what the margins are. what should that line be? I don't know. Perhaps something that can also be seen while not being heard too much. Substituting dD into expression for $\hat{\pi}_{in}^k$ we get for all $i \in \mathcal{R}$

$$
\begin{aligned}
\hat{\pi}_{in}^k &= \frac{1}{\pi_{in}^k}\left\{\pi_{in}^k \hat{A}_i^k - \theta_k \pi_{in}^k \hat{w}_i - \theta_k \pi_{in}^k \hat{\tau}_{in}^k - \pi_{in}^k \frac{dD}{D}\right\} \\
\hat{\pi}_{in}^k &= \frac{1}{\pi_{in}^k}\left[\pi_{in}^k \hat{A}_i^k - \theta_k \pi_{in}^k \hat{w}_i - \theta_k \pi_{in}^k \hat{\tau}_{in}^k - \sum_{l\in\mathcal{R}}\left\{\pi_{in}^k \pi_{ln}^k \hat{A}_l^k - \theta_k \pi_{in}^k \pi_{ln}^k \hat{w}_l - \theta_k \pi_{in}^k \pi_{ln}^k \hat{\tau}_{ln}^k\right\}\right] \\
\Rightarrow \quad \hat{w}_i &= \sum_k \sum_n \xi_{in}^k \left\{\hat{w}_n + \hat{A}_i - \theta_k \hat{w}_i - \theta_k \hat{\tau}_{in}^k + \sum_{l\in\mathcal{R}}\left(\theta_k \pi_{ln}^k (\hat{w}_l + \hat{\tau}_{ln}^k) - \pi_{ln}^k \hat{A}_l^k\right)\right\}
\end{aligned}
$$

Consider only domestic wage changes, that is $i \in$ Home and $\forall\ n \in R$, and set $\hat{\tau}_{il}^k = 0\ \forall\ i, l \in$ Home:

$$
\hat{w}_i = \sum_{k\in K}\sum_{n\in\mathcal{R}} \xi_{in}^k \hat{w}_n + \underbrace{\sum_{k\in K}\sum_{n\in\mathcal{R}} \xi_{in}^k \hat{A}_i^k}_{=0\ \forall\ i\in\text{Home}} - \sum_{k\in K}\sum_{n\in\mathcal{R}} \theta_k \xi_{in}^k \hat{w}_i - \sum_{k\in K} \theta_k \xi_{iR}^k \hat{\tau}_{iR}^k + \sum_{k\in K}\sum_{n\in\mathcal{R}} \xi_{in}^k \ldots
$$

$$\dots\left[\sum_{l\in\mathcal{R}}\theta_k\pi^k_{ln}\hat{w}_l\right]+\sum_{k\in K}\sum_{n\in\mathcal{R}}\xi^k_{in}\left\{\sum_{l\neq R}\theta_k\pi^k_{ln}\hat{\tau}^k_{ln}+\theta_k\pi^k_{Rn}\hat{\tau}^k_{Rn}\right\}-\underbrace{\sum_{k\in K}\sum_{n\in\mathcal{R}}\xi^k_{in}\left[\sum_{l\in\mathcal{R}}\pi^k_{ln}\hat{A}^k_l\right]}_{\text{Recall }\hat{A}^k_l=0\ \forall\ l\in\text{Home}}$$

Imposing $\hat{A}^k_i=0\ \forall\ k\in K$ and $i\in$ Home and $\hat{\tau}^k_{ln}=0\ \forall\ l,n\in$ Home:

$$\begin{aligned}\hat{w}_i\ &=\sum_{k\in K}\sum_{n\in\mathcal{R}}\xi^k_{in}\hat{w}_n-\sum_{k\in K}\sum_{n\in\mathcal{R}}\theta_k\xi^k_{in}\hat{w}_i-\sum_{k\in K}\theta_k\xi^k_{iR}\hat{\tau}^k_{iR}+\sum_{k\in K}\sum_{n\in\mathcal{R}}\xi^k_{in}\left[\sum_{l\in\mathcal{R}}\theta_k\pi^k_{ln}\hat{w}_l\right]\dots\\&+\sum_{k\in K}\xi^k_{iR}\left[\sum_{l\neq R}\theta_k\pi^k_{lR}\hat{\tau}^k_{lR}\right]+\sum_{k\in K}\sum_{n\neq R}\xi^k_{in}\theta_k\pi^k_{Rn}\hat{\tau}_{Rn}+\sum_{k\in K}\xi^k_{iR}\theta_k\pi^k_{RR}\hat{\tau}^k_{RR}-\sum_{k\in K}\sum_{n\in\mathcal{R}}\xi^k_{in}\pi^k_{in}\hat{A}^k_R\end{aligned}$$

Rearranging terms and imposing $\hat{\tau}^k_{iR}=\hat{\tau}_{HR}\ \forall\ i\in$ Home we get:

$$\begin{aligned}\hat{w}_i\ &=\sum_{k\in K}\sum_{n\in\mathcal{R}}\xi^k_{in}\hat{w}_n-\sum_{k\in K}\sum_{n\in\mathcal{R}}\theta_k\xi^k_{in}\hat{w}_i-\sum_{k\in K}\theta_k\xi^k_{iR}\hat{\tau}_{HR}+\sum_{k\in K}\sum_{n\in\mathcal{R}}\theta_k\xi^k_{in}\left[\sum_{l\in\mathcal{R}}\pi^k_{ln}\hat{w}_l\right]\dots\\&+\sum_{k\in K}\theta_k\xi^k_{iR}\left[\sum_{l\neq R}\pi^k_{lR}\right]\hat{\tau}_{HR}+\sum_{k\in K}\sum_{n\neq R}\theta_k\xi^k_{in}\pi^k_{Rn}\hat{\tau}_{RH}+\sum_{k\in K}\theta_k\xi^k_{iR}\pi^k_{RR}\hat{\tau}^k_{RR}-\sum_{k\in K}\sum_{n\in\mathcal{R}}\xi^k_{in}\pi^k_{Rn}\hat{A}^k_R\end{aligned}$$

Rearranging all terms to put the direct effect first we have:

$$\begin{aligned}\Rightarrow\quad\hat{w}_i\ &=\sum_{k\in K}\sum_{n\neq R}\theta_k\xi^k_{in}\pi^k_{Rn}\hat{\tau}_{RH}-\sum_{k\in K}\sum_{n\in\mathcal{R}}\xi^k_{in}\pi^k_{Rn}\hat{A}^k_R+\sum_{k\in K}\theta_k\xi^k_{iR}\pi^k_{RR}\hat{\tau}^k_{RR}\dots\\&\dots-\sum_{k\in K}\theta_k\xi^k_{iR}\left(1-\sum_{l\neq R}\pi^k_{lR}\right)\hat{\tau}_{HR}+\sum_{k\in K}\sum_{n\neq i}\xi^k_{in}\hat{w}_n+\sum_{k\in K}\xi^k_{ii}\hat{w}_i-\sum_{k\in K}\sum_{n\in\mathcal{R}}\theta_k\xi^k_{in}\hat{w}_i\dots\\&\dots+\sum_{k\in K}\sum_{n\in\mathcal{R}}\theta_k\xi^k_{in}\left[\sum_{l\neq i}\pi^k_{ln}\hat{w}_l+\pi^k_{in}\hat{w}_i\right]\end{aligned}$$

$$\Rightarrow\quad\hat{w}_i\ =\sum_{k\in K}\sum_{n\neq R}\theta_k\xi^k_{in}\pi^k_{Rn}\hat{\tau}_{RH}-\sum_{k\in K}\sum_{n\in\mathcal{R}}\xi^k_{in}\pi^k_{Rn}\hat{A}^k_R+\sum_{k\in K}\theta_k\xi^k_{iR}\pi^k_{RR}\hat{\tau}^k_{RR}\dots$$

$$\cdots - \sum_{k\in K}\theta_k\xi^k_{iR}\left(1-\sum_{l\neq R}\pi^k_{lR}\right)\hat{\tau}_{HR} + \sum_{k\in K}\xi^k_{ii}\hat{w}_i - \sum_{k\in K}\sum_{n\in\mathcal{R}}\theta_k\xi^k_{in}\hat{w}_i + \sum_{k\in K}\sum_{n\in\mathcal{R}}\theta_k\xi^k_{in}\pi^k_{in}\hat{w}_i \ldots$$

$$\cdots + \sum_{k\in K}\sum_{h\neq i}\xi^k_{ih}\hat{w}_h + \sum_{k\in K}\theta_k\sum_{n\in\mathcal{R}}\xi^k_{in}\left[\sum_{l\neq i}\pi^k_{ln}\hat{w}_l\right]$$

Thus equilibrium wage changes in a region can be decomposed as follows:

$$\begin{aligned}\hat{w}_i \;&= \sum_{k\in K}\sum_{n\neq R}\theta_k\xi^k_{in}\pi^k_{Rn}\hat{\tau}_{RH} - \sum_{k\in K}\sum_{n\in\mathcal{R}}\xi^k_{in}\pi^k_{Rn}\hat{A}^k_R + \sum_{k\in K}\theta_k\xi^k_{iR}\pi^k_{RR}\hat{\tau}^k_{RR}\cdots\\ &\cdots - \sum_{k\in K}\theta_k\xi^k_{iR}\left(1-\sum_{l\neq R}\pi^k_{lR}\right)\hat{\tau}_{HR} + \underbrace{\sum_{k\in K}\xi^k_{ii}\hat{w}_i - \sum_{k\in K}\sum_{n\in\mathcal{R}}\theta_k\xi^k_{in}(1-\pi^k_{in})\hat{w}_i}_{\text{own region indirect effect}}\cdots\\ &\cdots + \underbrace{\sum_{k\in K}\sum_{h\neq i}\xi^k_{ih}\hat{w}_h + \sum_{k\in K}\sum_{h\neq i}\theta_k\left[\sum_{n\in\mathcal{R}}\xi^k_{in}\pi^k_{hn}\right]\hat{w}_h}_{\text{other region indirect effect}}\end{aligned} \tag{B.2}$$

B.2 Data Appendix

B.2.1 Trade flows

B.2.1.1 Country-to-country trade data

Data on international (i.e. country-to-country) trade flows is obtained from the World Input-Output database (WIOD) (Timmer et al. (2015)). The advantage of this dataset is that it allows to obtain trade of each country with itself.

B.2.1.2 State-to-country trade data

Data on trade flows between Brazilian states and foreign countries is obtained from ComexStat (MDIC (2018)).This dataset reports the f.o.b. value of exports and imports in current US dollars at the 8-digit Mercosur's Common Nomenclature (NCM96, Nomenclatura Comum do Mercosul).

Table B.1: List of Countries used in Counterfactual Exercises

No.	**Country Name**	**Country Code**
1	Australia	AUS
2	Austria	AUT
3	Brazil	BRA
4	Canada	CAN
5	China	CHN
6	Germany	DEU
7	Spain	ESP
8	Finland	FIN
9	France	FRA
10	United Kingdom	GBR
11	Greece	GRC
12	Hungary	HUN
13	Indonesia	IDN
14	India	IND
15	Ireland	IRL
16	Italy	ITA
17	Japan	JPN
18	South Korea	KOR
19	Mexico	MEX
20	Netherlands	NLD
21	Portugal	PRT
22	Sweden	SWE
23	Turkey	TUR
24	United States	USA
25	Rest of the World	ROW

B.2.1.3 State-to-state trade data

Trade flows between Brazilian states at the sector level are from Vasconcelos and Oliveira (2006). This data corresponds to the year 1999 and is reported using the 2-digit Brazilian National Classification of Economic Activities (CNAE), which has a total of 59 industry codes. The original data corresponds to exports by Brazilian states to other states. However, six states (Acre, Amapá, Ceará, Maranhão, Rio Grande do Norte, and Roraima) did not report exports. Since the other 21 states report exports to the 6 missing states, this allows us to recover import flows for all 27 states. We run PPML gravity regressions - i.e. trade flows on origin output, origin area, distance between origin and destination and destination fixed effects separately for each sector and dropping Amazonas. We then predict flows for each sector-origin-destination combination, and use these predicted flows for the 6 states for which flows we missing.

B.2.1.4 Trade with self

We use data on output from the Brazilian Institute of Geography and Statistics (IBGE) to calculate trade with self for each state as a residual. The first step is to calculate output for each of the 16 sectors an each state. We use IBGE's regional accounts to obtain the value of output at the state level for agriculture, mining, manufacturing, and services. This data presents manufacturing as an aggregate. Therefore, we complement this data with the IBGE's Annual Industrial Survey (Pesquisa Industrial Anual, PIA) of the year 1999 to obtain the value of output for the 13 manufacturing industries at the state level. We calculate for each state the share of each of the 13 industries in total manufacturing output, and we apply this share to the regional accounts data. In this way we can obtain output for the 13 manufacturing industries and the 3 other sectors (agriculture, mining, and services). All values are in current Reais and converted to US dollars using exchange rates from the World Development Indicators Database. Once we have output for each sector and state we substract exports to other states and exports to other countries to obtain exports to self. Since the data come from different sources, it is possible to obtain negative values. In addition, it is possible that output for a given state and manufacturing sector is missing or zero. We use the following imputation rules in these cases: (i) If output is zero and exports to other states and to the world are greater than zero, then we set output equal to total exports; (ii) If trade with self is negative but output is greater than zero, then we set exports to Brazilian states equal to: $X_{BRA}^{new} = \frac{X_{BRA}}{X_{BRA}+X_{WLD}} Output$.

B.2.2 Trade elasticities

We use sector specific trade elasticities from Caliendo and Parro (2015), using the sectoral aggregation in Costinot and Rodriguez-Clare (2014). Table **??** contains the final list of 16 sectors, and their corresponding elasticities.

Table B.2: Industries and Trade Elasticities

No.	**Industry Description**	**ISIC Rev. 3**	**Trade Elasticity**
1.	Agriculture, hunting, forestry and fishing	1-5	8.11
2.	Mining and quarrying	10-14	15.72
3.	Food, beverages and tobacco	15-16	2.55
4.	Textile and textile products; Leather and footwear	17-19	5.56
5.	Wood and products of wood and cork	20	10.83
6.	Pulp, paper, printing and publishing	21-22	9.07
7.	Coke, refined petroleum and nuclear fuel	23	51.08
8.	Chemicals and chemical products	24	4.75
9.	Rubber and plastics	25	1.66
10.	Other non-metallic mineral	26	2.76
11.	Basic metals and fabricated metal	27-28	7.99
12.	Machinery, nec	29	1.52
13.	Electrical and optical equipment	30-33	10.60
14.	Transport equipment (Auto)	34-35	0.37
15.	Manufacturing nec; Recycling (Other)	36-37	5.00
16.	Services	40-95	5.00

B.2.3 Tariffs

Average ad-valorem tariffs applied by Brazil at the sectoral level for 1990 and 1998 are taken from Kume et al. (2000). Since we do not have reliable tariff data for 1999–the base year for counterfactual exercises–we assume tariffs in 1999 remained at the same level as in 1998. The authors start from data at the tariff-line level and aggregate it using simple averages up to SCN (Sistema de Contas Nacionais), the Brazilian National Accounts sector classification, at the 4-digit level (also called “Nivel 80” or

Level 80). Then, they aggregate the data to the 2-digit level (also called SCN 43) using industry value added weights. We aggregate their data from SCN 43 to our industry classification using value added weights in 1990, obtained from IBGE. The tariff levels in 1990 and 1998 for each of the fifteen industries are given in the Table **??**.

Table B.3: Tariffs in 1990 and 1998

No.	**Industry Description**	**Tariffs 1990**	**Tariffs 1998**
1.	Agriculture, hunting, forestry and fishing	5.9	9.9
2.	Mining and quarrying	5.46	2.19
3.	Food, beverages and tobacco	33.04	16.07
4.	Textile and textile products; Leather and footwear	38.22	20.27
5.	Wood and products of wood and cork	25.4	14
6.	Pulp, paper, printing and publishing	23.6	14.2
7.	Coke, refined petroleum and nuclear fuel	19.4	5.4
8.	Chemicals and chemical products	25.22	13.81
9.	Rubber and plastics	41.60	17.04
10.	Other non-metallic mineral	31.50	13.6
11.	Basic metals and fabricated metal	25.00	14.73
12.	Machinery, nec	37.20	17.7
13.	Electrical and optical equipment	42.15	18.33
14.	Transport equipment (Auto)	51.50	25.19
15.	Manufacturing nec; Recycling (Other)	41.60	16.4

B.2.4 Industry crosswalks

The industrial classifications are not uniform across different data sources, so we use different crosswalks to arrive at a final classification of 15 tradable sectors (that include agriculture, mining, and 13 manufacturing sectors) and a non-tradable sector. Our final classification combines sectors at the 2-digit level of the ISIC Rev. 3 classification, which is the classification of the WIOD data. We follow the 16-sector aggregation of Costinot and Rodriguez-Clare (2014) (see **??**), which is also based on

WIOD and that allows to use the trade elasticities estimated by Caliendo and Parro (2015).

Brazilian imports and exports are expressed in the 8-digit Common Nomenclature of Mercosur (NCM) in its 1996 version. At the six-digit, this nomenclature is equivalent to HS 1996. We then use the mapping provided by UN to convert from 6-digit HS 1996 to ISIC Rev. 3. Aggregating from ISIC-3 to our 16-sector classification is straightforward.

Interstate trade and state's output are reported using the 2-digit CNAE classification, which is equivalent to 2-digit ISIC Rev.3, so the mapping to our final classification is straightforward.

Finally, tariffs are converted from SCN43 to CNAE using a mapping provided by IBGE.[1] The mapping has many-to-many matches at the 2-digit level, so we created our own one-to-one mapping, available upon request.

[1] See http://concla.ibge.gov.br/classificacoes/correspondencias/atividades-economicas

B.3 Results Appendix

B.3.1 Gravity and inter-state trade

Table B.4: Inter-state trade gravity estimation. PPML estimates.

Sector	Distance	s.e.	Origin GDP	s.e.	Dest. GDP	s.e.	Obs.	R-sq
Agriculture	-1.374***	0.217	0.429***	0.146	0.523***	0.136	520	0.160
Mining	-1.854***	0.377	0.592**	0.296	0.872***	0.267	520	0.216
Food	-0.947***	0.132	0.645***	0.056	0.768***	0.059	520	0.814
Textile	-0.699***	0.139	0.806***	0.072	0.742***	0.081	520	0.807
Wood	-0.844***	0.191	0.288***	0.087	0.876***	0.091	520	0.403
Paper	-1.129***	0.147	1.112***	0.093	0.766***	0.091	520	0.947
Petroleum	-0.965***	0.202	0.994***	0.118	0.755***	0.125	520	0.740
Chemicals	-0.629***	0.190	1.150***	0.111	0.800***	0.124	520	0.885
Plastic	-0.711***	0.136	1.150***	0.080	0.859***	0.078	520	0.957
Minerals	-1.203***	0.158	0.723***	0.081	0.655***	0.086	520	0.733
Metal	-0.623***	0.235	0.937***	0.113	0.956***	0.153	520	0.738
Machinery	-0.371**	0.181	1.266***	0.090	0.776***	0.094	520	0.906
Electrical	-0.374**	0.169	1.600***	0.093	1.087***	0.098	520	0.982
Auto	-0.131	0.143	1.503***	0.092	1.009***	0.126	520	0.854
Other	-0.774***	0.156	0.941***	0.068	0.786***	0.082	520	0.840

The estimates in each row correspond to a regression at the sectoral level where the dependent variable is exports from an origin state to a destination state in a sector. The regressors are the logarithm of: the geographic distance between the centroids of the states, the sectoral GDP of the origin state, and the sectoral GDP of the destination state. The number of observations is equal to 26×20, where 26 is the number of origin states (excluding Amazonas since it contains a free-trade zone) and 20 is the number of destination states, also excluding Amazonas and six other states for which there is no data on exports (see Data Appendix for more details).
Robust standard errors. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

B.3.2 Intra-country dispersion in manufacturing import shares

Figure B.1: Share of total imports in manufacturing expenditure

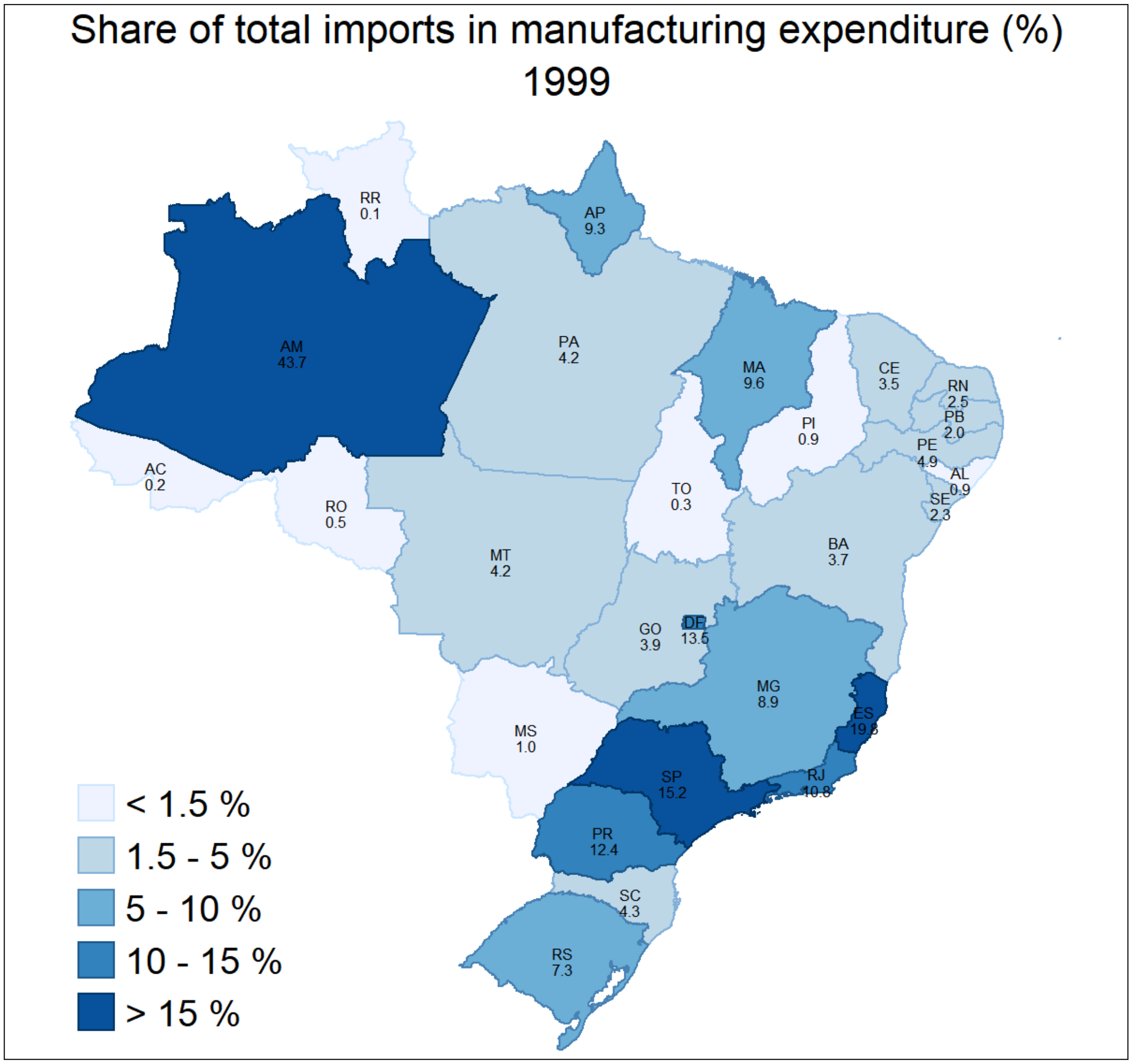


Figure B.2: Share of USA in total manufacturing imports

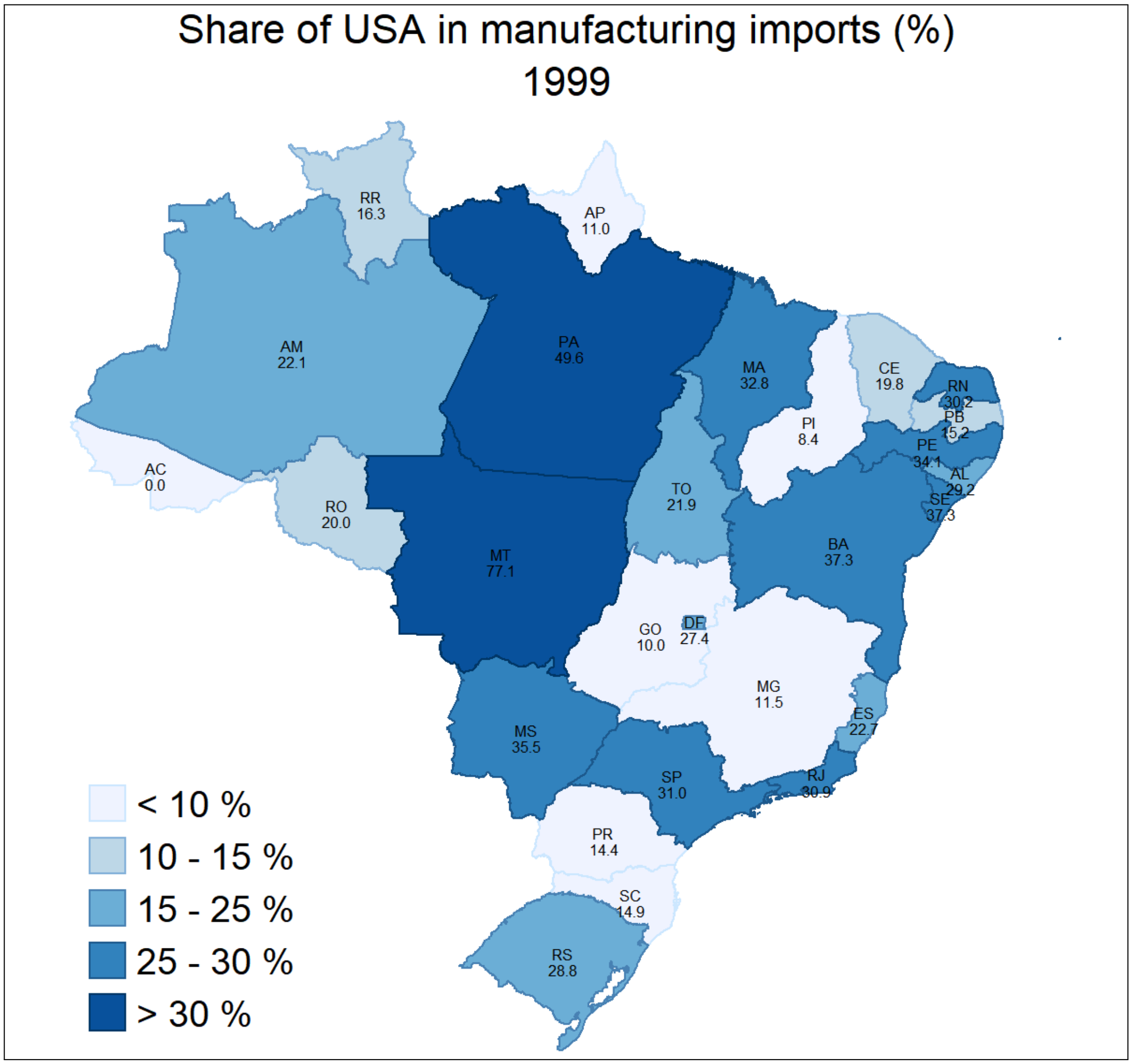


Figure B.3: Share of China in total manufacturing imports

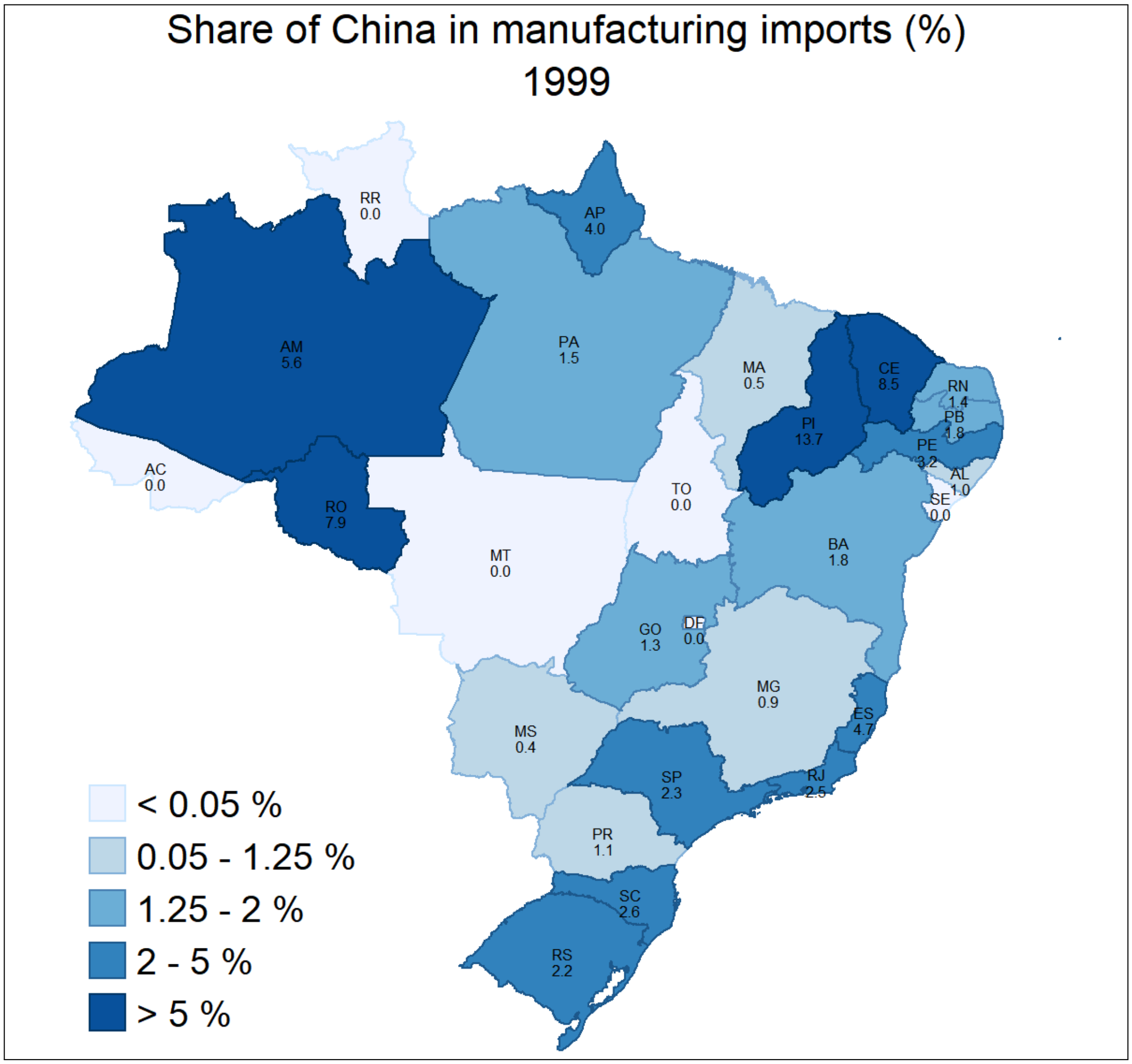
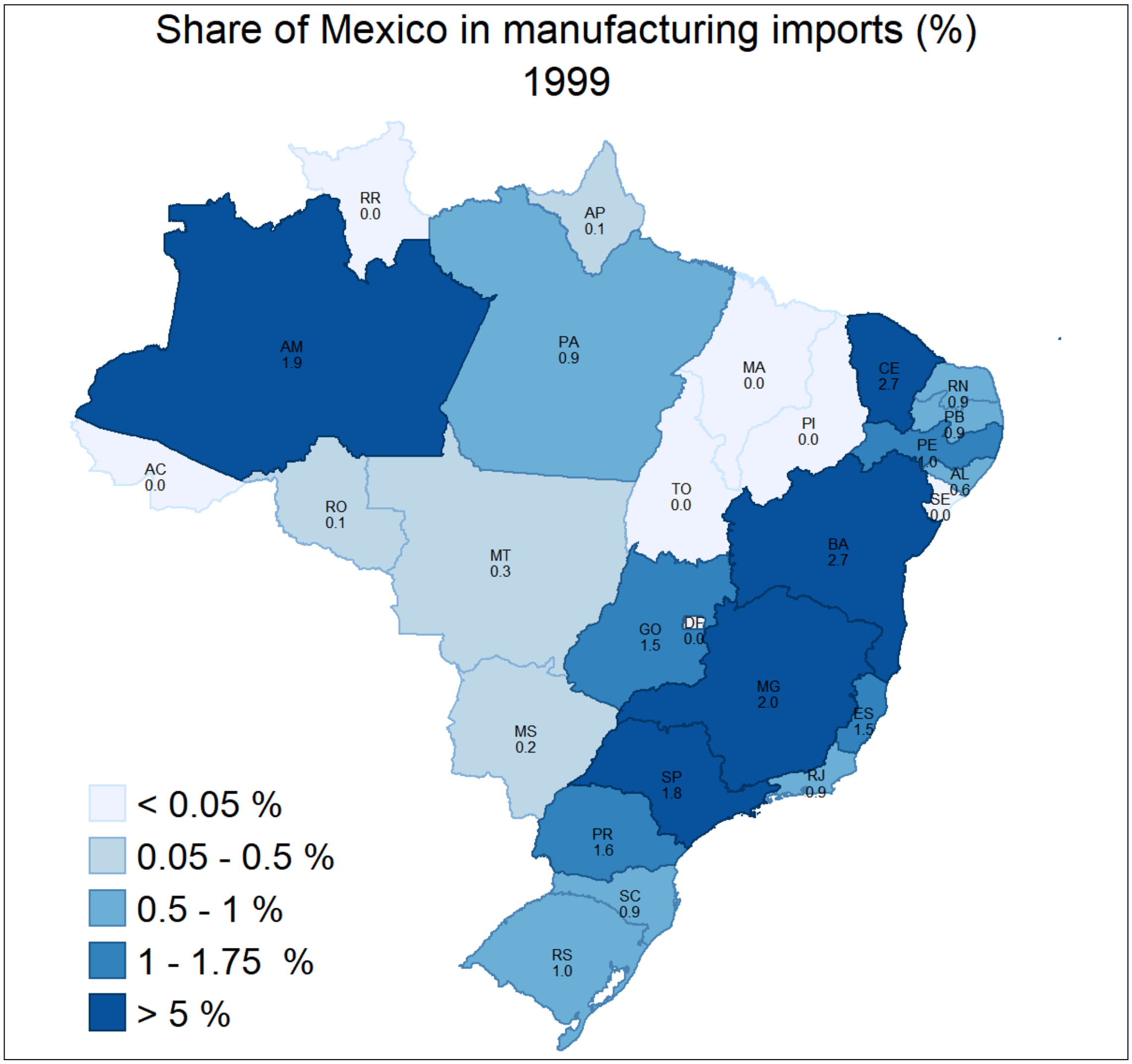
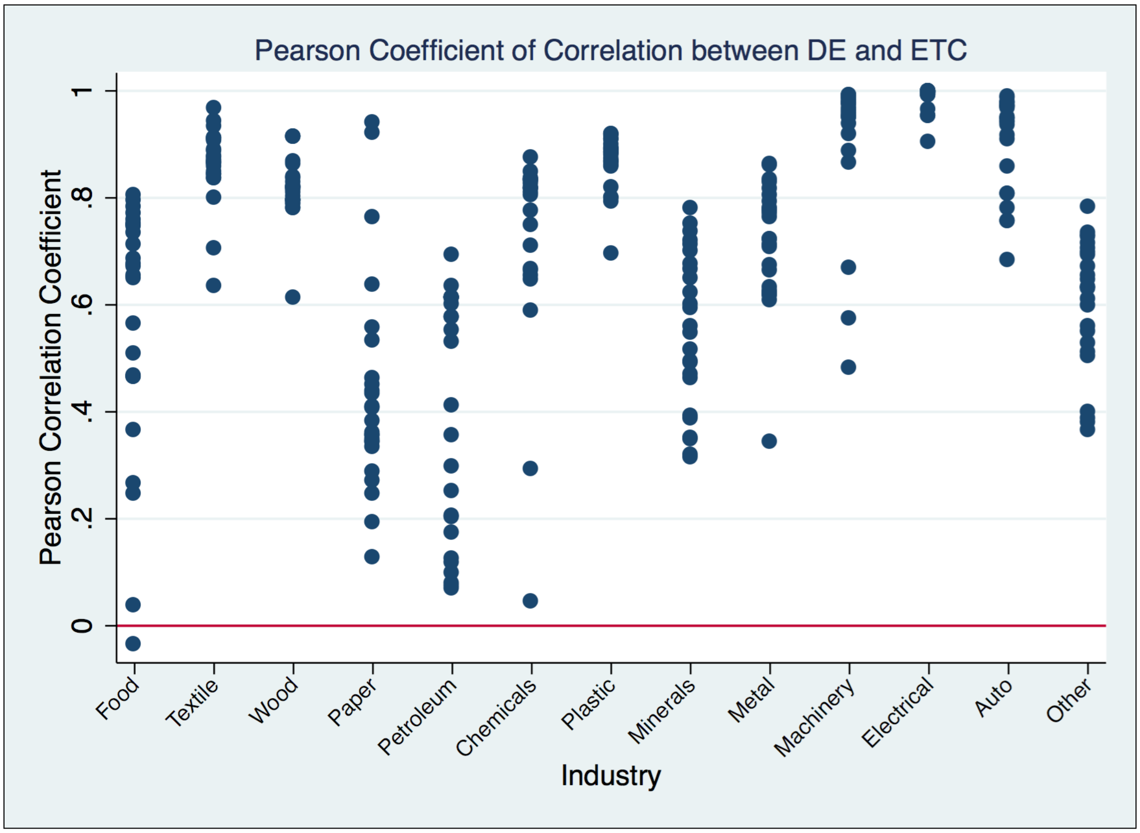


Figure B.4: Share of Mexico in total manufacturing imports



B.3.3 Pearson Correlation of exposure measures by industry and source country

Figure B.5: Pearson Correlation of *DE* and *ETC* exposure measures by industry and source country



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