The London School of Economics and Political Science

Essays on Chinese Economy

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A thesis submitted to the Department of Economics
of the London School of Economics and Political Science
for the degree of Doctor of Philosophy

November 2013

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Wenya Cheng

Abstract

This thesis consists of three independent chapters on Chinese economy. The first chapter examines the impact of import tariff reduction and its interaction with market-oriented policies on regional manufacturing employment in China between 1998 and 2006. I address the concerns of tariff endogeneity by exploiting the fact that tariffs of WTO members are bound by common exogenous WTO regulations. The IV estimates suggest that a reduction in tariffs on final goods increases employment while decline in input tariffs reduces employment in economic zones. Yet, opposite effects are found in non-economic zones. The differential impact is mainly driven by reallocation of labour to economic zones and, in particular, to foreign-invested enterprises and exporting firms. The second chapter models firm hiring across local labour markets and estimates the role of distinct regional labour markets in firm input use, productivity and location using firm and population census data. Considering modern China as a country with substantial regional variation, the results suggest that labour costs vary by 30-80%, leading to 3-17% differences in total factor productivity once non-labour inputs are considered. Favourably endowed regions attract more value added per capita, providing new insights into within-country comparative advantage and specialization. The last chapter investigates the effects of schooling on occupational status and children's educational attainment using trend deviations in graduation rates during the Chinese Cultural Revolution as instruments of schooling. The results show that education increases the likelihood of obtaining an off-farm and white-collar job. Also, there is evidence of causal relationship between parent's and children's education.

Acknowledgements

Foremost, I want to thank my supervisor Alan Manning for his help and guidance. Alan has given me the maximum freedom to pursuit various projects. His enduring enthusiasm for research is contagious and inspiring. I have learnt a great deal from him.

I am grateful to Guy Michaels, Barbara Petrongolo, Steve Pischke and the participants of the LSE labour work-in-progress seminars and labour market workshops for their insightful comments and feedbacks. In the last few years, I have been fortunate enough to meet some amazing colleagues and work with them. I thank John Morrow, Sorawoot Srisuma, Kitjawat Tacharoen, and in particular, Yanhui Wu who encouraged me to work on Chinese Economy. I also thank my officemates Abhinmanyu Gupta and Attakrit Leckcivilize for the friendly atmosphere and many joyful moments.

Finally, I wish to express my deepest gratitude to my parents, who have given me endless support, love and guidance throughout my life and education. I wouldn't have come this far without their encouragement. I warmly thank my sister for her loving support and sympathy during my studies.

To my parents, Xiuyi and Hanlu

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Preface

It is widely believed that institutions affect the efficiency of resource allocation and outcomes of economic policies. The central theme of my research is to study the interactions between market reforms and local institutions, and their relationship to labour market outcomes in China.

A common and much debated policy prescription for economic growth is trade liberalisation. While the existing theoretical literature suggests that there are always gains in trade, the empirical evidence on employment is rather mixed. There is an increasing realisation that institutional factors, such as initial market openness and market frictions play an important role in determining the outcomes of trade reform. The first chapter examines the differential impact of tariff reduction on manufacturing employment across regions with different market regimes. By utilising a 9-year panel data of Chinese prefectural industries, I obtain within-industry variation in local institutions to show that decline in import tariffs have considerable heterogeneous effects. In contrast to previous studies which use initial tariffs or industrial characteristics as instruments, I exploit the fact that after joining the WTO, a country's bound rates not only depends on its domestic industrial policies but also constrained by the WTO rules which are exogenous. Using tariffs of WTO members with little trade link with China, I find that fall in tariffs on final goods reduces employment in non-economic zones but increases employment in economics zones. I argue that the seemingly counter-intuitive results in economic zones are mainly driven by the expansion of foreign enterprises and exporting firms when tariffs were lowered. These results highlight the importance of foreign investment and other pro-trade policies during the process of trade liberalisation.

The presence of regional market segregation not only affects the outcomes of economic policies but also has potentially large consequences on firms' behaviour and efficiency. The second chapter, which is a collaborative work with John Morrow and Kitjawat Tacharoen, develops a multi-region, multi-industry general equilibrium model to explain how regional wage and skill dispersion affects firm's location and productivity. The model has two main implications. First, within sectors, some regions have comparative advantage of lower effective labour cost than others, and these regions attract more firms per capita. Second, regional variation in labour costs help explain productivity dispersion across firms. Based on the model framework, we develop a 2 stage OLS estimation strategy to obtain the effective labour costs which link regional characteristics to firm's productivity. Applying our methodology to Chinese manufacturing and census data, we find that favourable labour market conditions explain substantial differences in firm productivity. Regional differences in labour costs explain 3 to 17 percent of the productivity differences across firm. Also, labour costs are negatively related to the value-added per capita across regions, which indicate that firms are more concentrated in regions where labour costs are lower. This work suggests that increasing labour mobility or reducing factor price inequality have potentially large gains in the economy.

In additional to market liberalisation, investment in human capital is widely agreed to be an important element in development process. The last chapter exploits the exogenous shock to basic education during the Cultural Revolution to estimate the impact of schooling on occupational status and children's educational attainment. Using trend deviations in graduation rates as instruments of schooling, the results show that education has positive and significant effects on an individual's first occupation. Each additional year of schooling increases the probability of obtaining an off-farm job and white-collar occupation. Moreover, there is a significant causal relationship between parent's and children's education. This suggests that the effects of increased schooling are persistent across generations.

Chapter 1

Tariffs and Employment: Evidence from Chinese Manufacturing Industry

1.1 Introduction

In the past few decades, many developing countries have liberalised their trade regime with the hope that globalisation would lead to economic growth and welfare improvement. By removing trade barriers, countries would gain from cheaper imported inputs and access to export markets, and therefore increase employment. However, empirical evidence on the employment effects of trade liberalisation is rather mixed.[1] Recent work suggests that domestic institutions affect the outcomes of market liberalisation (Aghion et al., 2008). Successful market reforms are often complemented with other supporting policies which facilitate the reallocation of resource towards more productive uses. On the

[1]For instance, Ghana's industrial sector was devastated by the increased import competition after opening its country to foreign trade in 1987. In early 1990s, growth in manufacturing was barely over 1% per year and employment in manufacturing fell from 78,700 in 1987 to 28,000 in 1993. Zambia reduced its maximum tariff from 100% to 25% and eliminated most non-tariff barriers between 1992 and 1997. During this period, formal sector employment in manufacturing fell by 40% and manufactures fell as a proportion of GDP.

contrary, market liberalisation can be detrimental to growth with the presence of unfavourable institutions.

The aim of this paper is to explore the impact of trade liberalisation on regional manufacturing employment and, in particular, how the effects vary across regions under different market regimes. I focus on China, which reduced import tariffs significantly after its accession to the WTO in December 2001. Between 1998 and 2006, average tariffs on agricultural and industrial products fell from 22% to 17.5% and 24.6% to 9.4% respectively. During the same period, import values grew at an average annual rate of 25%, from USD 140 billion in 1998 to USD 791 billion in 2006. I investigate the role of market-oriented policies on the effects of tariff decline by exploiting the fact that institutions vary considerably across regions in China due to its earlier reform policy. Since 1980, China has established more than a hundred economic zones of various types throughout the country.[2] Economic zones have more liberalized economies and offer a number of preferential policies which encourage foreign investment and export activities. With greater autonomy and integration with international markets, industries in economic zones lead the country in technology and productivity growth.

Tariff protection is endogenous as it is correlated with unobservable time-varying industrial characteristics which affect tariffs and employment simultaneously (Trefler 1994; 2004). I am particularly concerned about the endogeneity of tariff reduction after China's WTO accession since China's bound rates were negotiated between China and other WTO members, and special exemptions were granted to certain industries.[3] I depart from the previous studies which use pre-reform tariff levels and industry characteristics as instruments for future tariff changes (Trefler 1993; 2004; Goldberg and Pavcnik 2005; Amiti and

[2]In China, economic zones include special economic zones, coastal open cities, coastal economic zones, national and provincial economic and technological development zones, export-processing zones, high-tech zones and industrial parks. Many economic zones locate in same prefectures.

[3]Bound rates are maximum tariff rates allowed by the WTO to charge on imports from other WTO member states. They are negotiated between the new member and other WTO states before accession.

Konings 2007; Amiti and Davis 2012). Instead, I adopt an instrumental variable strategy which takes advantage of the fact that after joining the WTO, a country's bound rates not only depends on its domestic industrial policies but also constrained by the WTO rules on tariffs which are exogenous. I show that tariffs of other WTO members are strong instruments for China's post-WTO tariffs if two conditions are satisfied. First, China and other members' tariffs are bound by common WTO rules. Second, they have different industrial characteristics from China. Countries which joined the WTO between 2000 and 2003 have similar average bound rates but different economic structure and limited trade links with China. Therefore, I construct the instruments for China's tariffs by combining the bound rates of these countries.[4] The main advantage of my instrumental variable strategy over the conventional approaches is the exogeneity assumption still holds even if there is serial correlation in industry characteristics.

Using the Annual Surveys of Industrial Firms, I construct an unbalanced panel of prefecture-industries spanning the period from 1998 to 2006. The regional industry data includes 109 4-digit ISIC industries across 336 prefectures, among which 49 have established at least one economic zone before 2000. The data is then matched with 4-digit industry tariffs. The impact of tariff reduction is decomposed into two effects: reduction in output tariff (tariffs on imported final goods) and reduction in input tariffs (tariffs on imported intermediate inputs) (Amiti and Konings, 2007). A fall in output tariffs increases the degree of import competition while a fall in input tariffs reduces production costs and increases the variety of intermediate input available.

My IV estimates suggest that tariff reduction has insignificant impact on

[4]Between 2000 and 2003, eleven countries joined the WTO. They include Jordan, Georgia, Albania, Oman, Croatia, Lithuania, Moldova, China, Taiwan, Armenia and Macedonia.

employment on average; however, the effects vary considerably across economic and non-economic zones.[5] A 1% fall in output tariffs increases employment in economic zones by 0.43% but reduces employment in non-economic zones by 0.57%. Similarly, a 1% fall in input tariffs reduces employment in economic zones by 0.93% but increases employment in non-economic zones by 0.75%. This suggests that tariff reduction has strong reallocation effects. Employment adjustments in economic zones are mainly driven by the expansion of foreign and exporting firms in industries which faced larger output tariff cuts but smaller input tariff changes. By restricting the sample to coastal economic zones and their nearby prefectures, I show that my results are not entirely driven by the geographical factors. Yet, the results do suggest that among non-economic zones, the impact of tariff reduction is larger in inland prefectures which have less favourable regulatory and economic conditions compared to its eastern counterparts. Our estimates are robust to controlling non-tariff barriers and changes in tariffs on Chinese exports.

This study is relevant to the recent empirical literature on the heterogeneous effects of market liberalisation. Amiti and Konings (2007) find that reductions in output and input tariffs increase firm's productivity and the size of effects vary with firm's export and import orientation. Another paper by Amiti and Davis (2012) studies the relationship between tariffs and firm wages suggests that firm's initial trade status could explain the heterogeneous effects of tariff reduction on firm's wages. Aghion et al. (2008) analyse how the delicensing of manufacturing industry interacts with local labour market regulations in India. They find that the delicensing reform increased industrial output of states with pro-employer regulations but reduced output of states with pro-labour regulations.

The rest of the paper is organised as follows. In Section 2, I describe the

[5] Since my unit of analysis is a prefecture-industry, I identify prefectures which have established economic zones and use the terms 'economic zones' and 'prefectures with economic zones' interchangeably in this paper.

background of the two reforms which are relevant to this study. Section 3 explains my empirical strategy and Section 4 describes the data. In Section 5, I discuss the mechanism and in Section 6, I present the empirical results. Section 7 interprets the results and Section 8 concludes.

1.2 Background

1.2.1 Tariffs and WTO Accession

When China joined the WTO in December 2001, it committed to reduce tariffs significantly within five years of accession.[6] 60% of the products' tariffs were reduced below their final bound tariff rates within 1 year of accession; and by 2005, 98% of the products' tariffs were bound.[7] The degree of trade liberalisation varied significantly across industries. To satisfy the WTO general rules on tariffs, industries with higher tariff protection were required to make larger concessions. Since China is a developing country, exemptions were granted for certain key products.

Table 1.1 reports the changes in China's average import tariffs for 2-digit ISIC manufacturing industry.[8] It shows that China's pre-WTO tariffs were higher for industries with large state interests, such as tobacco, beverages and motor vehicles (more than 30%), and lower for raw materials which are abundant in China, such as petroleum, chemicals and basic materials (less than 15%). Major tariff cuts occurred in 2002 where industries with higher pre-WTO tariffs experienced larger fall in tariffs. Between 1998 and 2006, average tariffs on tobacco products and motor vehicles fell by more than 20% while tariffs on petroleum and basic materials reduced by 1 to 3% only. Although tariffs converge over time, there

[6] China is required to reduce tariffs across ten years but major tariff cuts occured between 2002 and 2005.

[7] Figures are based on author's calculations using 8-digit HS tariff data from WITS and China's Schedule of Concessions.

[8] Industry tariffs is the simple average of 8-digit HS product tariffs. Concordance table for HS and ISIC Rev. 3 codes is obtained from UNSTAT.

TABLE 1.1: Changes in China's Average Import Tariffs

Code	Industry	1998	2001	2002	2006	Total Change
15	Food & Beverages	30.86	29.25	21.81	17.01	-13.84
16	Tobacco	65.00	57.00	48.00	38.17	-26.83
17	Textiles	25.01	20.50	16.56	10.23	-14.78
18	Apparel	32.65	24.03	21.70	16.36	-16.29
19	Leather & fur	21.43	19.63	17.38	15.77	-5.67
20	Wood	12.12	11.46	7.37	5.24	-6.88
21	Paper	15.99	14.82	9.90	5.84	-10.16
22	Printing	10.82	9.71	6.64	4.15	-6.67
23	Petroleum	6.99	6.54	6.14	6.14	-0.85
24	Chemicals	11.27	10.28	7.72	6.54	-4.73
25	Rubber & plastic	16.31	15.49	11.90	9.87	-6.44
26	Other non-metallic products	17.07	16.49	13.78	12.19	-4.89
27	Basic metals	8.27	7.34	5.56	5.12	-3.15
28	Fabricated metal	13.71	12.87	11.36	10.99	-2.71
29	Machinery & equipment	15.32	14.75	10.96	9.49	-5.82
30	Office machinery	17.29	14.38	7.81	4.03	-13.26
31	Electical machinery	15.04	14.51	10.38	8.93	-6.12
32	Radio, tv, pc & comm equip	18.17	17.12	10.73	8.84	-9.32
33	Medical, prec equip & clocks	14.58	13.55	10.29	9.32	-5.27
34	Motor vehicles & trailers	36.98	33.16	23.55	14.62	-22.36
35	Other transport equip	12.47	11.47	9.68	8.43	-4.04
36	Furniture	21.93	20.60	16.99	13.75	-8.18

Note: Each row is a 2-digit ISIC industry. Tariffs are simple average of 8-digit HS product tariffs. Tariff data is from the database of World Integrated Trade System (WITS) and industry concordance is provided from UN Statistics Division.

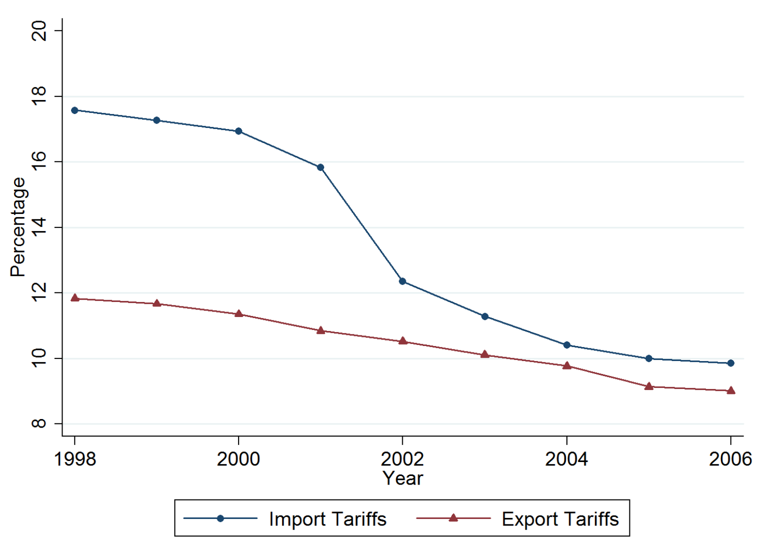
is still considerable variation in tariff protection across sectors. This suggests that China's post-WTO tariff concessions are endogenous. The issue of tariff endogeneity is discussed in Section 3.1 in details.

Compared to China's import tariffs, tariffs on Chinese exports decline very slowly over time. China was granted permanent most-favoured nation (MFN) status upon its accession, which guarantees that other WTO members cannot increase their tariffs against Chinese exports above the MFN rates applied to non-Chinese exports. However, the US has granted China MFN Status on an annually-renewable basis since 1980. Other major trading partners such as Canada, EU and Japan have also granted China preferential tariffs through the Generalized System of Preferences (GSP) before China's accession.[9] Therefore,

[9]GSP exempts WTO member countries from the MFN for the purpose of lowering tariffs for the least developed countries. The preferential rates are lower than the MFN rates for some products.

there is little changes in China's export tariffs. Figure 1.1 plots the average tariffs on Chinese imports and exports.[10] Between 1998 and 2006, import tariffs fell by an average of 8% while export tariffs reduced by less than 3%.

FIGURE 1.1: China's Average Import and Export Tariffs



1.2.2 Economic Zones

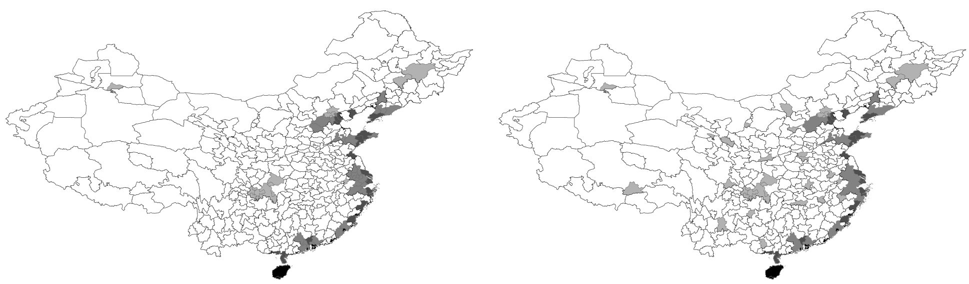
China began to liberalise its trade regime well before its accession to the WTO. One of the most notable and successful reforms is the establishment of economic zones. The primary objective of economic zones is to attract foreign investment and increase exports, thereby stimulate regional economic and employment growth. The legal and regulatory frameworks of economic zones have two important features. First, a more free-market oriented system is adopted. Firms have more autonomy in management, operations, employment and engagement in trade activities. Government regulations are more flexible and administrative procedures are simplified. Second, preferential policies are offered to foreign-invested and exporting firms in economic zones. The statutory corporate income tax rate for foreign enterprises in economic zones is 15 or 24%

[10]Import tariffs are simple averages of 8-digit HS product tariffs. Export tariffs are weighted average of 6-digit HS product tariffs of 149 countries. Export tariff weights are China's country-export shares in 1998.

while the national average is 33%.[11] Also, tariffs on imported materials and machinery are exempted for exported products in economic zones.

The earliest economic zones in China can be traced back to 1980 when four Special Economic Zones were established in Guangdong and Fujian Province. In 1984, fourteen coastal cities were opened to foreign investment, and in 1988, the entire Hainan Province was designated as a Special Economic Zone. Between 1984 and 1994, thirty four National Economic and Technological Development Zones and two Coastal Economic Zones were set up in China. After 2000, there was a rapid expansion of economic zones in inland China to take advantage of the increased export opportunities after China's accession to the WTO. By 2010, almost every provincial capital has an economic zone. Figure 1.2 depicts the prefectures which have established one of the four types of economic zones in China. It shows that economic zones were initially more concentrated in the coastal regions and later expanded to inland cities.

FIGURE 1.2: Locations of China's Economic Zones



(a) Before 2000 (b) After 2000

[11] Before 2007, domestic and foreign firms were subject to separate enterprise income tax regulations. Various tax incentives and tax holidays are granted to foreign enterprises and export-oriented firms in China. However, only foreign-invested firms in Special Economic Zones, Coastal Development Zones and Economic and Technological Development Zones were entitled to a lower statutory enterprise income tax rate of 15% or 24% before 2007.

Rapid economic growth was witnessed in economic zones. Table 1.2 compares the pre-WTO economic performance of manufacturing sector across regions. Prefectures with economic zones had larger manufacturing employment and higher average wages in 1998. They also had higher export-to-sales ratio and foreign investment.

TABLE 1.2: Mean Characteristics of Manufacturing Industries in 1998

	Prefectures with Economic Zone	Prefectures without Economic Zone
Employment	417,194	87,513
Annual Wages	9,361	6,377
Capital-Labour Ratio	67,957	58,486
Value-Added per Worker	35,450	25,082
Number of Firms	1,386	237
Export-Sales Ratio	0.231	0.064
Foreign Share of Employment	0.387	0.032
Foreign Share of Firms	0.203	0.034
Foreign Share of Equity	0.323	0.066
Number of Prefectures	49	287

Source: 1998 Annual Survey of Industrial Firms and author's calculations.

1.3 Empirical Strategy

The average effects of tariff reduction on employment are estimated by exploiting the within industry variation in tariff levels over time:

$$Y_{jst} = \alpha_1 + \delta_1 \tau^O_{jt} + \delta_2 \tau^I_{jt} + \eta_{js} + \omega_{st} + \upsilon_{jst} \tag{1.3.1}$$

where Y_{jst} is the log of total employment of industry j in prefecture s at time t, τ^O_{jt} and τ^I_{jt} are the industry output and input tariff rates, η_{js} is the industry-prefecture interaction effect, ω_{st} is prefecture-time fixed effect, and υ_{jst} is the stochastic error term[12]. The industry-prefecture fixed effects capture the variation in regional industry policies such as local industrial subsidies, and the prefecture-time fixed effects controls for other time-varying regional characteristics such improvement in infrastructure, proximity to markets, and migration trends. Standard errors are clustered by industry and year.

The differential impact of tariff reduction in economic and non-economic zones is estimated by the following specification:

$$Y_{jst} = \alpha_2 + \beta_1 \tau_{jt}^O + \beta_2 \tau_{jt}^I + \beta_3 \tau_{jt}^O \times EZ_s + \beta_4 \tau_{jt}^I \times EZ_s + \eta_{js} + \omega_{st} + \upsilon_{jst}$$

where EZ_s is a dummy which equals to one if prefecture s has created an economic zone before 2000. I focus on the four types of economic zones: Special Economic Zones, Coastal Open Cities, Coastal Economic Zones and National Economic and Technological Development Zones. Economic zones established after 2000 are classified as non-economic zones in this analysis since their creation are likely to be endogenous to China's tariff reduction. Some of these economic zones are at prefecture level while others are at more disaggregated county level. Since my unit of analysis is a prefecture-industry, the estimates of equation (1.3.2) would provide the lower bound of the true effects of economic zones. For simplification, the terms 'economic zones' and 'prefectures with economic zones' are used interchangeably in this paper.

In equation (1.3.2), β_1 and β_2 measure the percentage change in total employment in non-economic zones when tariffs fall by 1%, while $\beta_1 + \beta_3$ and $\beta_2 + \beta_4$ measure the percentage change in employment in economic zones. Therefore, the relative signs of βs capture the heterogeneous effects of tariff reduction in economic and non-economic zones. If β_1 and β_2 have the same signs as β_3 and

[12] A number of studies estimate the impact of tariffs in differences instead of levels (Trefler, 2004; Goldberg and Pavcnik, 2005; Yu, 2011; Amiti and Davis, 2012). The advantage of estimating in long differences is it allows firms to have longer time to adjust wages and employment. If there are serial correlations in employment and wages, taking long differences would generate unbiased estimates. However, estimating in differences is not suitable in this context. In China, tariffs fell at unequal rates across time. Tariff changes were minimal in 1998 to 2001 and 2002 to 2006, yet tariff levels were much lower in 2002-2006. If we take less than three-year differences, we would wrongly assume that the treatment effects in 1998 to 2001 and 2002 to 2006 are the same.

β_4 respectively, then reduction in tariffs have larger effects in economic zones. If the signs are reversed, then tariff cuts have smaller or opposite effects in economic zones.

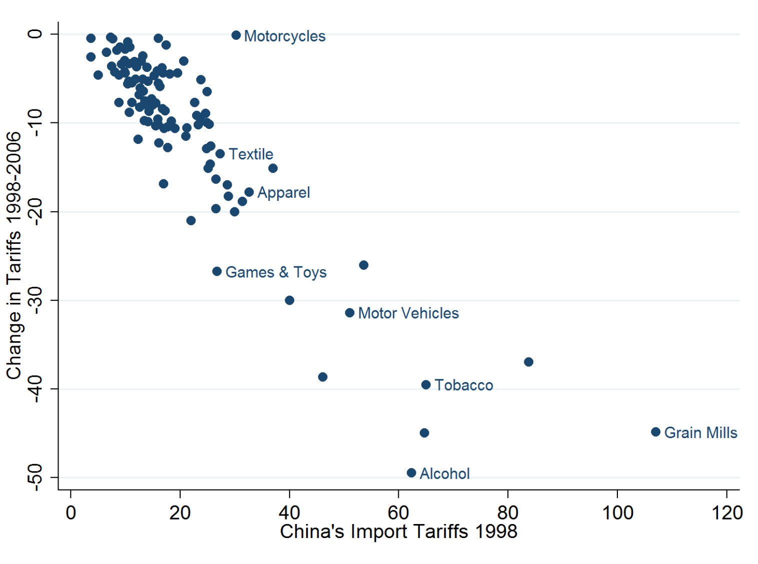
1.3.1 Tariff Endogeneity

Our OLS estimates for equations (1.3.1) and (1.3.2) would be biased with the presence of time-varying industry characteristics which are correlated with employment and tariffs. The endogeneity of trade protection is well documented in the existing trade literature. Trefler (1993; 1994) argues that trade protection are determined by two broad factors: the cost of coordinating lobbying and the interests of politicians. Industries with lower opportunity cost of lobbying and larger gains from protection would have greater trade protection.
In China, industries are more protected either because they are important sources of government revenue or crucial to national interest. As shown in Table 1.1 previously, industry tariffs varied considerably even after China's accession to the WTO. Figure 1.3 plots the percentage change in China's import tariffs against the initial tariff levels for 4-digit ISIC. It shows that the extent of tariff reduction was unequal across sectors with similar initial tariff levels. For instance, tariffs on games and toys and motorcycles were about 35% in 1998. However, tariffs on games and toys fell by 20% in 2006 while tariffs on motorcycles reduced by only 0.5%.

The direction of bias is uncertain. Fast growing industries might have lower tariffs because they can compete with foreign competition. Industries might also experience higher growth rate because they were more protected. The former would lead to an upward bias of the OLS estimates while the latter would lead to a downward bias of the OLS estimates.

Since tariffs depend on political and economic factors, Trefler (1993) uses industry characteristics such as market concentration ratio and degree of import penetration as instruments for non-tariff barriers and finds that the impact of

FIGURE 1.3: Changes in Tariffs Relative to Initial Levels



non-tariff barriers on wages is large and significant. In contrast, the impact is minimal if non-tariff barriers are assumed exogenous. A number of studies have adopted Trefler's instrumental variable strategy to estimate the impact of tariff reduction on industry and firm outcomes (Trefler, 2004; Amiti and Konings, 2007; Amiti and Davis, 2012). The problem of this approach is industry characteristics are correlated with tariffs and the outcomes of interest, therefore fail the exogeneity assumption. For instance, many studies find that tariffs are higher for industries with larger share of unskilled workers. However, these industries tend to be more labour intensive and have lower average wages and larger employment.

Another instrument commonly used in the literature is pre-reform tariff levels. This strategy was first adopted by Goldberg and Pavcnik (2005) who study the impact of tariff reduction on industry wage premium in Colombia. Columbia entered the WTO in 1995 and reduced its tariff rates to a uniform rate of 13%. Goldberg and Pavcnik argue that initial tariffs are strong instruments for future tariff changes since industries with higher pre-WTO tariffs face larger tariff cuts and post-WTO tariffs are exogenous. Goldberg and Pavcnik's approach is subject to the same problem as Trefler's. Initial tariffs are strongly correlated with industry characteristics, and therefore are endogenous.[13]

1.3.2 Instrumental Variable Strategy

I adopt a new approach to tackle the problem of tariff endogeneity. According to the WTO principles of trading system, tariffs should be reduced and bound against future increase. Tariff commitments made by countries are reached through multilateral negotiations among WTO member states. Each country is obliged not to increase tariffs above the bound rates listed in its schedule of concessions. Special exemptions and longer transition period are granted to developing countries taking into account their level of economic development and specific trade needs. Since the terms of accession are unique for each country, I find considerable cross-country variation in bound rates within industries. For example, the average bound rate for motorcycles is 30% in China but only 9% and 13.4% in Macedonia and Croatia respectively. Since bound rates tend to be higher for industries with larger state interests, tariffs of countries which are required to make larger tariff concessions would better reflect the WTO general rules on tariffs.

By 2010, the WTO has 157 member states, so the question is which country's tariffs are suitable instruments for China's tariffs. Our choice of instruments is guided by a simple econometric model. Suppose a country's tariff policy can be summarized by the following specification:

$$\tau_{jkt} = \alpha_k + \pi_k' \theta_{jkt} + \delta_k' (D_{kt} * WTO_{jkt}) + u_{jkt} \tag{1.3.2}$$

where τ_{jkt} is the tariff rate of industry j in country k at time t, θ_{jkt} captures the industry-time effect, D_{kt} is a dummy which equals to 1 if country k is a member of the WTO, and WTO_{jkt} is the WTO rule on the country k's industry tariffs.

[13] Suppose θ_{jt} are unobservable time-varying political-economic factors that are correlated with tariffs and I use intital tariffs τ_{j0} as instruments for future tariff changes. Then τ_{j0} is a good instrument if the relevance and exogeneity assumptions are satisfied i.e. $Cov(\tau_{j0}, \Delta\tau_{jt}) \neq 0$ and $Cov(\tau_{j0}, \Delta\theta_{jt}) = 0$. It can be immediately shown that two conditions cannot be satisfied simultaneously if $\tau_{jt} = f(\theta_{jt})$.

Equation (1.3.2) suggests that a country's bound rates depends on its industry characteristics and the WTO rules after its accession. Our identification strategy requires the following two conditions to be satisfied:

$$Cov(\tau_{kjt}, \tau_{jt}) \neq 0 \tag{1.3.3}$$

$$Cov(\tau_{kjt}, \theta_{jt}) = 0 \tag{1.3.4}$$

where τ_{jt} and θ_{jt} are the industry tariffs and time-varying industry characteristics of China respectively. Substituting equation (1.3.2) into the equations (1.3.3) and (1.3.4) suggest that

$$Cov(WTO_{jt}, WTO_{kjt}) \neq 0 \tag{1.3.5}$$

$$Cov(\theta_{jt}, \theta_{kjt}) = 0 \tag{1.3.6}$$

Condition (1.3.5) requires China and country k to be subject to common exogenous WTO rules while condition (1.3.6) suggests that country k's industry should not affect China's employment via its impact on China's industry development.

Table 1.3 compares the China and other WTO members' final bound rates. Countries are divided into two groups based on their comparability with China and date of WTO accession. The first group consists of large developing countries and Southeast Asian countries such as Brazil, India and the Philippines. By coincidence, all of them joined the WTO in 1995. The second group includes all countries which joined the WTO between 2000 and 2003. The average bound rates of new WTO members decline with their year of accession as the WTO regulations become more stringent over time. Hence, although the first group of countries are more comparable to China in terms of economic size or level of economic development, their average bound rates are much higher than China's as they joined the WTO earlier than China (above 25%). In contrast, the

TABLE 1.3: Comparison of Tariff Bound Rates

Country	Date of Entry	Trade to GDP Ratio 2010	Average Final Bound Rates		
			All	Agriculture	Non-Agriculture
China	Dec 2001	55.2	10	15.7	9.2
Group 1					
Argentina	Jan 1995	41.3	31.9	32.4	31.8
Brazil	Jan 1995	23.8	31.4	35.4	30.7
Chile	Jan 1995	74.8	25.1	26.0	25.0
India	Jan 1995	47.7	48.7	113.1	34.6
Indonesia	Jan 1995	49.5	37.1	47.1	35.5
Mexico	Jan 1995	59.2	36.1	44.2	34.9
Philippines	Jan 1995	68.2	25.7	35.0	23.4
Colombia	Apr 1995	33.2	42.8	91.4	35.4
Group 2					
Jordan	Apr 2000	116.6	16.3	23.6	15.2
Georgia	Jun 2000	83.3	7.4	13.0	6.5
Albania	Sep 2000	84.3	7.0	9.5	6.6
Oman	Nov 2000	109.0	13.7	27.6	11.6
Croatia	Nov 2000	75.8	6.1	10.4	5.5
Lithuania	May 2001	126.5	5.0	12.3	3.9
Moldova	Jul 2001	120.5	7.0	14.0	5.9
Taiwan	Jan 2002	132.2	6.3	16.9	4.7
Armenia	Feb 2003	59.3	8.5	14.7	7.6
Macedonia	Apr 2003	112.9	7.1	12.9	6.3

Source: WTO Trade Profile.

average bound rates of the second group are similar to China's. This suggests that the 1995 WTO regulations were obsolete during China's accession.

In the remaining section, I focus on the second group of countries and examine if they have different industry characteristics from China. I use a country's pre-WTO industry tariffs as a proxy for its domestic industry policy and calculate their correlations with China's tariffs. Since data on pre-WTO tariffs is not available for every year and country, I compute the country's industry tariffs by taking simple average of 8-digit HS product tariffs to 4-digit ISIC for any tariff year where data is available.[14] Table 1.4 shows that the tariff correlations between China and the second group of countries range from 0.20 to 0.59, which are quite low.

[14]Pre-WTO tariff data is downloaded from WITS. Data is available for the following country-year pairs: Albania 1997; Armenia 2001; Georgia 1999; Lithuania 1997; Macedonia 2001; Moldova 1996, 2000; Taiwan 1996, 1999-2001.

TABLE 1.4: Correlations of Pre-WTO Industry Tariffs

Year	China 1998	Albania 1997	Armenia 2001	Georgia 1999	Lithuania 1997	Macedonia 2001	Moldova 1996	Taiwan 1999
China	1.000							
Albania	0.203	1.000						
Armenia	0.526	0.509	1.000					
Georgia	0.334	0.687	0.557	1.000				
Lithuania	0.487	0.355	0.672	0.461	1.000			
Macedonia	0.491	0.554	0.601	0.440	0.579	1.000		
Moldova	0.283	0.566	0.546	0.561	0.517	0.560	1.000	
Taiwan	0.594	0.184	0.664	0.399	0.580	0.636	0.317	1.000

Source: WITS and author's calculations.

Tables 1.3 and 1.4 together suggest that the tariffs of the second group of countries' are strong instruments for China's post-WTO tariffs. Since these countries joined the WTO around the same time as China, their bound rates better reflect the WTO's regulations on tariffs during that period. Also, most of these countries have different industry features from China, therefore their tariffs are unlikely to be correlated with the time-varying industry characteristics of China.

1.4 Data and Measurement

This paper uses data from the 1998 to 2006 Annual Surveys of Industrial Firms, the World Integrated Trade Solution (WITS) and the WTO Tariff database. The firm surveys include all state-owned enterprises and non-state owned enterprises with sales over 5 million RMB. Firms report their zip codes, 4-digit CIC codes, ownership, export status and more than 60 financial variables from their balance sheets and profit statements.[15] I exclude firms not in the manufacturing sector and industries that report no tariff or import data (e.g. finishing of textiles).[16] The firm data is aggregated to create a panel of prefecture-industries for 9 years. Our aggregate sample consists of 109 4-digit ISIC industries in 330

[15]Firms report 4-digit industry code based on the 1996 and 2002 Chinese Industrial Classification (410 industries). I employ the industry concordance provided by Brandt et al. (2012) to match firm's CIC code cross time.

[16]Surveys include firms in mining, manufacturing, construction and public utilities.

prefectures. Among the 330 prefectures, 49 have established an economic zone before 2000. A complete list of prefectures is in the Appendix. The number of prefectures per industry-year ranges from 15 to 330. Table 1.5 summaries the data.

TABLE 1.5: Mean Characteristics of Sample

	Prefectures with Economic Zones	Prefectures without Economic Zones
1998		
Total Employment	4,411	1,788
Average Annual Wages	9,444	5,760
Total Equity	243,747	59,444
Value-Added Per Worker	42,478	23,707
State Share of Employment	0.39	0.63
Foreign Share of Employment	0.21	0.04
State Share of Equity	0.36	0.61
Foreign Share of Equity	0.29	0.06
Observations	4,415	14,621
2006		
Total Employment	7,236	1,761
Average Annual Wages	20,372	15,093
Total Equity	625,338	147,183
Value-Added Per Worker	186,243	145,478
State Share of Employment	0.15	0.23
Foreign Share of Employment	0.33	0.10
State Share of Equity	0.16	0.23
Foreign Share of Equity	0.41	0.12
Observations	4,517	14,176

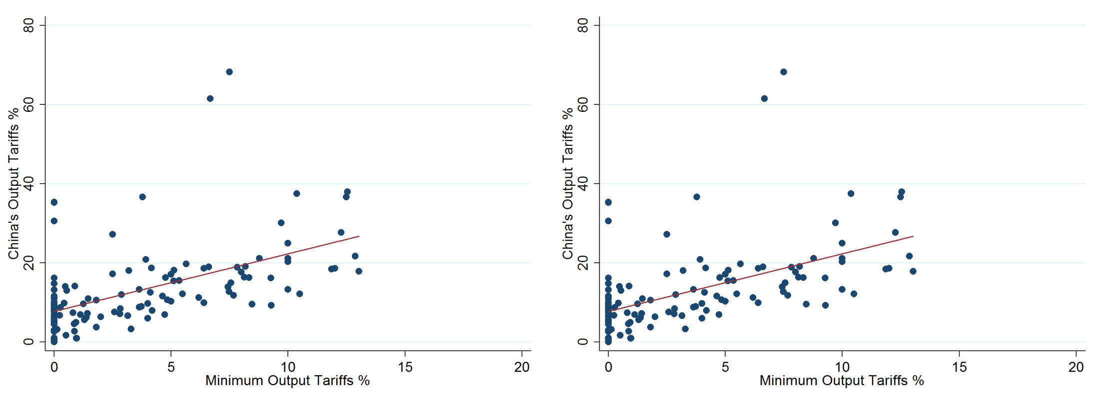
Notes: Each observation is a 4-digit ISIC industry-prefecture pair.

To construct China's output tariffs, I take simple average of 8-digit HS to 6-digit HS then weight the 6-digit HS product tariffs using China's 1998 import shares. Input tariffs are weighted average of output tariffs where weights are the industry input-shares obtained from the 2002 Chinese Input-Output Table. Output tariffs are constructed at 4-digit ISIC (109 industries) and input tariffs are computed at 3 to 4-digit ISIC level (69 industries). Input tariffs are more aggregate due to higher level of aggregation in the Chinese Input-Output Table.[17]

[17]Further details on calculations of output and input tariffs are in the Appendix.

The instruments for China's post-WTO tariffs are constructed by combining the tariffs of the second group of countries in Table 1.3. I exclude Taiwan in my calculations due to its close economic relationship with China. Since countries joined the WTO at different time, I use 5 years of bound rates upon accession. Each country's output tariffs are the simple average of 8-digit HS bound rates within 4-digit ISIC industry. Input tariffs are calculated in the same way as China's input tariffs, using the country's output tariffs and China's input-cost shares in 2002. For each industry-year, the instruments for China's tariffs are the minimum output and input tariffs among the nine countries. Figure 1.4 illustrates the IV strategy. It shows that the instruments are lower but positively correlated with China's tariffs. At last, I matched the tariff measures with the prefecture-industry data.

FIGURE 1.4: Instruments For China's Tariffs (2002)



(a) Output Tariffs (b) Input Tariffs

1.5 Mechanism

While previous studies find that reductions in output and input tariffs increase firm's productivity, their impact on employment is ambiguous.[18] This section

[18]Existing trade models mainly focus on the effects of increased export opportunities on firms and workers' outcomes (Melitz, 2003; Melitz and Ottaviano, 2008; Helpman et al., 2010b). To the best of my knowledge, the only paper that models the impact of tariff reductions is by Amiti and Davis (2012) which looks at

discusses the possible mechanisms that explain the employment outcomes of tariff concessions.

1.5.1 Direction of Adjustment

Changes in tariff affect the direction of employment adjustment via two channels. The first one is firm's profits. Decline in output tariffs reduces the price of imported final goods, hence increases exposure to foreign competition and reduces firms' domestic market share. As firms' profits are lower, their demand for labour decreases. Aggregate industrial employment decreases in the intensive and extensive margins, as surviving firms reduce employment and loss-making firms exit the market.

A fall in input tariffs has opposite effects on firms' profits. Lower input tariffs reduce the price of imported inputs, therefore reduce firms' cost of production and increases firms' profits. Aggregate employment increases since existing firms increase their demand of labour and higher industry profits encourage new firm entry.

The second channel is related to firms' product scope and production technology. Previous studies suggest that access to export markets or external shocks induce firms to change their product variety (Bernard et al., 2010; Ma et al., 2012; Bilbiie et al., 2012). Industries subject to larger output tariff cuts face tougher import competition. Since China has comparative advantage of low labour cost, firms may produce more labour intensive goods and increase their demand for labour. Some may choose to produce more capital-intensive or high quality products that require less unskilled labour to increase their competitiveness and reduce their demand for labour.

the relationship between output and input tariffs and firm wages. Empirical work by Amiti and Konings (2007) and Yu (2011) find that reduction in output and input tariffs increase firm's productivity; Trefler (2004) shows that reduction in import tariffs reduce manufacturing employment.

Decline in input tariffs increases the variety and quality of inputs available to firms, hence allow firms to expand their product scope (Goldberg et al., 2010). Yet, the effects on employment also depend on the degree of complementarity between labour and intermediate inputs. If firms increase the share of intermediate inputs in production, and labour and intermediate inputs are complements, labour demand would increase. In contrast, if the two factor inputs are substitutes, labour demand and employment would decrease. Therefore, the net effect on aggregate employment depends on the relative magnitude of these opposing effects.

1.5.2 Heterogeneous Effects

The effects of tariff reduction are likely to vary across regions for two reasons. First, local institutions affect the extent of resource reallocation, hence the outcomes of trade reform. Economic zones have relatively free economy than the rest of the country, therefore would respond to tariff reduction differently. Regions with stronger local protectionism may impose other trade barriers to offset the undesirable effects of import competition. Labour markets rigidities such as trade unions or unemployment benefits increase the cost of employment adjustment, thus affect the process of labour reallocation. Credit market imperfections reduce firms' ability to offset negative shocks through lending and borrowing, hence amplify the effects of tariff reduction. Since the reform outcomes depend on the nature and degree of market frictions, the estimates capture the joint effects of various institutions and policies on employment.

Apart from market frictions, local institutions and policy measures also affect the regional composition of firms and therefore the size of adjustment. To take advantage of the business-friendly environment and preferential policies, foreign enterprises and exporting firms are more concentrated in economic zones. Compared with domestic non-exporting firms, foreign enterprises and exporting firms are more productive and larger in size on average. Also, the product scope and technological level vary across firm types within a sector. Therefore, employment adjustment would differ across regions.

Third, some regions have more advantageous geographical position than others. As shown in Figure 1.2 previously, economic zones established before 2000 are mainly located along the coastal regions which have close proximity to foreign markets and port terminals. With larger market size and lower transport cost, industries in economic zones may have higher profit margins than those in inland prefectures which allow them to maintain more internal capital to smooth employment.

1.6 Empirical Results

Table 1.6 displays the estimation results for equations (1.3.1) and (1.3.2). The OLS estimates in column 1 suggest that a 1% fall in output tariffs reduces prefectural employment by an average of 0.28%. A 1% drop in input tariffs increases employment by 0.14% on average but the estimate is insignificant. In column 2, I instrument China's post-WTO tariffs with the bound rates of other countries. The F-statistics reported in the last line of the table are well above 10. The IV estimates are similar to the OLS estimates but very imprecise, which suggest that tariff reduction has insignificant impact on employment.

Columns 3 and 4 show that there are considerable regional heterogeneity in the effects of tariff cuts. The OLS results imply that tariff cuts have opposite impact in economic zone and non-economic zones. A fall in output tariffs reduces employment in non-economic zones (0.44) and increases employment in economic zones (-0.17). Similarly, a fall in input tariffs increases employment in non-economic zones (-0.48) and reduces employment in economic zones (0.83).

The IV estimates suggest larger heterogeneous effects than the OLS estimates. This implies that output tariffs of fast-growing industries and input tariffs of slow-growth industries fell to a greater extent in non-economic zones.

TABLE 1.6: The Impact of Tariffs on Employment: Baseline Results

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Output Tariff	0.281*	0.298	0.440**	0.561**
	(0.144)	(0.226)	(0.171)	(0.255)
Input Tariff	-0.141	-0.250	-0.483**	-0.685***
	(0.186)	(0.193)	(0.211)	(0.207)
Output Tariff × Economic Zone			-0.608***	-0.953***
			(0.192)	(0.232)
Input Tariff × Economic Zone			1.316***	1.621***
			(0.181)	(0.188)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Observations	161,668	161,668	161,668	161,668
F-statistic		141.591		65.327

Notes: Dependant variable is the log of employment in a prefecture-industry between 1998 and 2006. Post-WTO tariffs are instrumented with the minimum bound rates of countries which entered the WTO between 2000 and 2003 for each industry. Constant not reported. Standard errors clustered by industry and year. F-statistic is the Kleibergen-Paap rk Wald F statistic for non i.i.d. errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

The bias of OLS estimates goes in the opposite direction in economic zones. A possible reason is China's WTO tariff concessions is endogenous to the industrial performance of domestic firms, yet the results in economic zones are driven by foreign or exporting firms which are more concentrated in economic zones. In Section 7, I discuss the possible mechanism driving the results in details.

China's WTO accession involves a wide range of trade reforms, therefore the results might be driven by other liberalisation policies included in China's accession package. According to its schedules of concessions, China has to remove quotas, licensing and other quantitative restrictions on its imports within two years of accession. Presence of non-tariff barriers shields firms from foreign competition. Also, some industries may use non-tariff barriers instead of tariffs to reduce import penetration. To control for non-tariff barriers, I include a dummy which equals to 1 if the industry has imposed any non-tariff barriers for at least one 8-digit HS product in the regressions.

Another concern is the change in tariffs imposed on Chinese exports. Since China's MFN status guarantees that other WTO members cannot increase their tariffs against China's imports above the MFN rates for non-Chinese imports, industries may benefit from a fall in export tariffs and increase employment. To control for export tariffs, I compute a weighted average of tariffs on Chinese exports using trade data from 149 countries. Export tariffs are computed from 6-digit HS applied rates and weighted by country-import shares in 1998.[19] I allow for the impact of non-tariff barriers and export tariffs to differ in economic and non-economic zones by interacting the two measures with an economic zone dummy. Table 1.7 shows that the results persist controlling for other trade policies. Removal of non-tariff barriers has insignificant effects on employment. A 1% decline in export tariffs increases employment by 0.31% and the effects do not vary across economic and non-economic zones.

TABLE 1.7: The Impact of Tariffs on Employment: Other Controls

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Output Tariff	0.305**	0.295	0.468***	0.568**
	(0.147)	(0.234)	(0.176)	(0.268)
Input Tariff	-0.198	-0.299	-0.546**	-0.749***
	(0.187)	(0.196)	(0.213)	(0.214)
Output Tariff × Economic Zone			-0.626***	-0.996***
			(0.197)	(0.250)
Input Tariff × Economic Zone			1.342***	1.679***
			(0.187)	(0.208)
Non-Tariff Barrier	0.0248	0.0244	0.0278	0.0250
	(0.0253)	(0.0260)	(0.0302)	(0.0312)
Export Tariff	-0.265***	-0.278***	-0.286***	-0.313***
	(0.0848)	(0.0888)	(0.0976)	(0.104)
Non-Tariff Barrier × Economic Zone			-0.00672	0.000758
			(0.0298)	(0.0307)
Export Tariff × Economic Zone			0.0931	0.141
			(0.0862)	(0.0936)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Observations	161,668	161,668	161,668	161,668
F-statistic		127.024		57.41

Notes: Dependant variable is the log of employment in a prefecture-industry between 1998 and 2006. Post-WTO tariffs are instrumented with the minimum bound rates of countries which entered the WTO between 2000 and 2003 for each industry. Constant not reported. Standard errors clustered by industry and year. F-statistic is the Kleibergen-Paap rk Wald F statistic for non i.i.d. errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

[19]Further details on calculations of export tariffs are in the Appendix.

1.6.1 Robustness Checks

So far I have allowed for entry and exit of industries within a prefecture. However, a number of studies have found a significant increase in regional specialization of industries in China since the mid-1980s (Naughton 1999; Bai et al. 2004). In Table 1.8, I restrict my analysis to a balanced panel of prefecture-industries. This reduces the sample size to 116,602 observations. Our main results are robust to this specification.

TABLE 1.8: Robustness Checks: Balanced Panel

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Output Tariff	0.206**	0.176	0.440***	0.479**
	(0.0938)	(0.160)	(0.0990)	(0.203)
Input Tariff	-0.0572	-0.162	-0.501***	-0.678***
	(0.118)	(0.138)	(0.142)	(0.168)
Output Tariff × Economic Zone			-0.741***	-0.936***
			(0.150)	(0.240)
Input Tariff × Economic Zone			1.393***	1.599***
			(0.160)	(0.198)
Non-Tariff Barrier	0.00747	0.00690	0.00136	-0.000789
	(0.0188)	(0.0195)	(0.0221)	(0.0231)
Export Tariff	-0.200***	-0.216***	-0.257***	-0.283***
	(0.0580)	(0.0611)	(0.0665)	(0.0720)
Non-Tariff Barrier × Economic Zone			0.0195	0.0241
			(0.0248)	(0.0255)
Export Tariff × Economic Zone			0.188**	0.218***
			(0.0755)	(0.0819)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Observations	116,602	116,602	116,602	116,602
F-statistic		137.663		61.372

Notes: Dependant variable is the log of employment in a prefecture-industry between 1998 and 2006. Sample is restricted to a balanced panel. Post-WTO tariffs are instrumented with the minimum bound rates of countries which entered the WTO between 2000 and 2003 for each industry. Standard errors clustered by industry and year. F-statistic is the Kleibergen-Paap rk Wald F statistic for non i.i.d. errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Next, I check if the IV estimates are robust to alternative measures of the instruments. In Table 1.9, I instrument China's post-WTO tariffs with the average output and input tariffs of countries which have lower bound rates than China. The IV estimates of the new instruments are very similar to the main results. Tariff reduction has insignificant average effects on employment but the impact varies considerably across economic and non-economic zones.

TABLE 1.9: Robustness Checks: Alternative Instruments

	IV	
	(1) (3)	(2) (4)
Output Tariff	0.261	0.493**
	(0.197)	(0.230)
Input Tariff	-0.255	-0.725***
	(0.180)	(0.196)
Output Tariff × Economic Zone		-0.795***
		(0.212)
Input Tariff × Economic Zone		1.522***
		(0.184)
Non-Tariff Barrier	0.0246	0.0264
	(0.0259)	(0.0311)
Export Tariff	-0.280***	-0.309***
	(0.0882)	(0.102)
Non-Tariff Barrier × Economic Zone		-0.00335
		(0.0304)
Export Tariff × Economic Zone		0.116
		(0.0896)
Prefecture-Industry FE	Yes	Yes
Prefecture-Year FE	Yes	Yes
Observations	161,668	161,668
F-statistic	125.95	56.793

Notes: Dependant variable is the log of employment in a prefecture-industry between 1998 and 2006. Post-WTO tariffs are instrumented with the average bound rates of countries which entered the WTO between 2000 and 2003 and have lower import bound rates than China. Standard errors clustered by industry and year. F-statistic is the Kleibergen-Paap rk Wald F statistic for non i.i.d. errors. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

One might suspect that the heterogeneous effects of tariffs are driven by the increase in export opportunities after China's accession to WTO. Also, China's permanent MFN status reduces uncertainty of future tariff increase against Chinese exports, therefore encourages export activities. I attempt to capture these changes by controlling for industry-time fixed effects. Since tariffs are perfectly correlated with the industry-time dummies, I only include their interactions with the economic zone dummy in the regressions. Table 1.10 shows that the results remain intact.

TABLE 1.10: Robustness Checks: Industry-Time Effects

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Output Tariff × Economic Zone	-1.189***	-1.468***	-1.124**	-1.469***
	(0.417)	(0.471)	(0.436)	(0.513)
Input Tariff × Economic Zone	2.334***	2.724***	2.221***	2.679***
	(0.432)	(0.479)	(0.454)	(0.520)
Non-Tariff Barrier × Economic Zone			-0.0186	0.0281
			(0.0751)	(0.0746)
Export Tariff × Economic Zone			-0.183	-0.168
			(0.198)	(0.246)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	161,668	161,668	161,668	161,668
F-statistic		200.452		200.934

Notes: Dependant variable is the log of employment in a prefecture-industry between 1998 and 2006. Post-WTO tariffs are instrumented with the minimum of tariffs of countries which entered the WTO between 2000 and 2003 for each industry. Constant not reported. Standard errors clustered by industry and year. F-statistic is the Kleibergen-Paap rk Wald F statistic for non i.i.d. errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

1.6.2 Other Outcomes

Apart from employment, I also consider the impact of tariff reduction on two labour market outcomes: average wages and labour productivity.

Average wage of a prefecture-industry depends on the total demand of workers and relative demand of different types of workers. Holding labour supply constant, average wages increase if labour demand increases, and decreases if labour demand decreases. Trade liberalisation also may affect the relative demand of skilled workers. In our firm surveys, about 25% of the firms produce more than one type of product. Each product requires different skill mix. Firms may change their product mix, and therefore worker's composition, in response to tariff cuts. When import competition is higher or imported inputs are cheaper, firms may use labour more intensively and hire relatively more unskilled workers to take advantage of the low labour cost in China. In this case, the relative demand for unskilled workers increases and average wages would decrease. Firms may also improve their product quality and increase the relative demand for skilled labour if product quality is positively correlated with worker's skill level.[20] If the relative demand for skilled workers increases, then average wages would increase. So far our analysis is based on fixed labour supply. If I relax this assumption and allow labour to move across regions and sectors, the direction of adjustment would depend on the relative supply and demand for each type of workers.

Ideally I would want to estimate the impact of tariffs on wage inequality; however I don't have information on firm's skill composition. Therefore, I focus on average wages. Average wage is defined as total wage divided by total employment in a prefecture-industry. Table 1.11 shows that reduction in tariffs has insignificant effects on average wages. Our findings are similar to previous studies which find that tariffs have little impact on wages but large effects on

[20]Verhoogen (2008) finds that during the peso crisis in Mexico, more productive firms upgrade their product quality which increase the relative wage inequality between white-collar and blue-collar workers.

TABLE 1.11: The Impact of Tariffs on Average Wages

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Output Tariff	0.0337	0.0437	0.0265	0.0321
	(0.0344)	(0.0419)	(0.0568)	(0.0626)
Input Tariff	0.0209	0.0161	0.0393	0.0365
	(0.0408)	(0.0472)	(0.0527)	(0.0609)
Output Tariff × Economic Zone		-0.0421		-0.0334
		(0.0640)		(0.0878)
Input Tariff × Economic Zone		0.0170		0.0122
		(0.0672)		(0.0857)
Non-Tariff Barrier	-0.0209***	-0.0130*	-0.0207***	-0.0127*
	(0.00561)	(0.00697)	(0.00571)	(0.00708)
Export Tariff	-0.0228	-0.0116	-0.0202	-0.00867
	(0.0148)	(0.0210)	(0.0161)	(0.0219)
Non-Tariff Barrier × Economic Zone		-0.0253***		-0.0254**
		(0.00976)		(0.00988)
Export Tariff × Economic Zone		-0.0379		-0.0385
		(0.0356)		(0.0367)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Observations	161,668	161,668	161,668	161,668
F-statistic		127.024		57.41

Notes: Dependant variable is the log of average wages in a prefecture-industry between 1998 and 2006. Post-WTO tariffs are instrumented with the minimum of tariffs of countries which entered the WTO between 2000 and 2003 for each industry. Constant not reported. Standard errors clustered by industry and year. F-statistic is the Kleibergen-Paap rk Wald F statistic for non i.i.d. errors. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

employment (Trefler, 2004). In the past two decades, China has experienced massive rural-urban migration which increases the supply of labour in manufacturing industries. Therefore, firms can adjust employment easily without changing wages.

Increase in import competition and imported inputs may affect the average productivity of labour in an industry. I use value-added per worker as a measure for labour productivity and compute the real industrial value-added for each prefecture by deflating value-added by 4-digit CIC industry deflators before aggregating to 4-digit ISIC industry level.[21] Table 1.12 suggest that tariff changes have little impact on labour productivity.

TABLE 1.12: The Impact of Tariffs on Value-Added Per Worker

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Output Tariff	-0.0715	-0.0748	-0.259	-0.210
	(0.131)	(0.119)	(0.186)	(0.183)
Input Tariff	-0.104	-0.118	-0.00895	-0.0640
	(0.104)	(0.102)	(0.127)	(0.128)
Output Tariff × Economic Zone		0.0117		-0.176
		(0.114)		(0.191)
Input Tariff × Economic Zone		0.0534		0.193
		(0.134)		(0.167)
Non-Tariff Barrier	-0.150***	-0.145***	-0.146***	-0.142***
	(0.0296)	(0.0293)	(0.0305)	(0.0303)
Export Tariff	-0.0537	-0.0666	-0.0385	-0.0573
	(0.0471)	(0.0440)	(0.0500)	(0.0469)
Non-Tariff Barrier × Economic Zone		-0.0144		-0.0118
		(0.0189)		(0.0192)
Export Tariff × Economic Zone		0.0462		0.0659
		(0.0533)		(0.0578)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Observations	161,668	161,668	161,668	161,668
F-statistic		127.024		57.41

Notes: Dependant variable is the log of value-added per worker in a prefecture-industry between 1998 and 2006. Post-WTO tariffs are instrumented with the minimum of tariffs of countries which entered the WTO between 2000 and 2003 for each industry. Constant not reported. Standard errors clustered by industry and year. F-statistic is the Kleibergen-Paap rk Wald F statistic for non i.i.d. errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

1.7 Interpretation

The OLS and IV estimates suggest that there are considerable heterogeneous effects of tariff reduction. In Section 5, I discussed the roles of market policies

[21] Industry deflators are obtained by Brandt et al. (2010).

and geographical factors in explaining the differential impact of tariffs. I test these hypotheses by re-estimating equations (1.3.1) and (1.3.2) by firm type and region and compare the estimates with the main results.

1.7.1 Firm Type

A notable difference between economic and non-economic zones is the composition of firms. The share of foreign enterprises and exporting firms are higher in economic zones, therefore the results might be driven by the growth of foreign enterprises and exporting firms in economic zones.

To examine the role of firm ownership, I estimate equations (1.3.1) and (1.3.2) for domestic and foreign firms separately. Foreign firms include foreign-owned enterprises, Sino-foreign joint ventures and hybrid firms with more than 50% foreign share in equity. I allow for changes in foreign ownership, therefore the estimates capture the employment adjustments along the intensive and extensive margins. In Table 1.13, both OLS and IV estimates suggest that reduction in tariffs have opposite impact on domestic and foreign firms, and the size of effect varies across economic and non-economic zones. Aggregate employment of domestic firms reduces when output tariffs are lower and input tariffs are higher, and the effects are larger in non-economic zones. In contrast, employment of foreign firms reduces when output tariffs are higher and input tariffs are lower, and the impact is larger in economic zones. I applied the same strategy to examine the role of export status. Table 1.14 shows that tariff reduction has similar impact on non-exporting firms and domestic firms but little effects on exporting firms.

Tables 1.13 and 1.14 together suggest that there are substantial reallocation effects. Industries in economic zones respond to import competition by increasing foreign investment and exports. One of the aims of establishing economic zones is to increase domestic firms' productivity and competitiveness with the help of foreign capital and technology. When import competition is greater,

TABLE 1.13: Mechanism: Ownership

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Domestic Firms				
Output Tariff	0.486***	0.577**	0.562***	0.675**
	(0.156)	(0.263)	(0.184)	(0.292)
Input Tariff	-0.482**	-0.670***	-0.658***	-0.875***
	(0.203)	(0.208)	(0.224)	(0.228)
Output Tariff × Economic Zone			-0.378**	-0.383*
			(0.189)	(0.210)
Input Tariff × Economic Zone			0.711***	0.797***
			(0.176)	(0.197)
Non-Tariff Barrier	0.0198	0.0173	0.0152	0.0124
	(0.0267)	(0.0275)	(0.0313)	(0.0323)
Export Tariff	-0.300***	-0.326***	-0.288***	-0.317***
	(0.0911)	(0.0968)	(0.0979)	(0.105)
Non-Tariff Barrier × Economic Zone			0.0183	0.0192
			(0.0297)	(0.0303)
Export Tariff × Economic Zone			-0.0627	-0.0536
			(0.0757)	(0.0788)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Observations	157,046	157,046	157,046	157,046
F-statistic		124.7		57.183
Foreign-Invested Firms				
Output Tariff	-0.345**	-0.417**	-0.186	-0.0967
	(0.172)	(0.201)	(0.169)	(0.201)
Input Tariff	1.354***	1.372***	0.761***	0.648***
	(0.180)	(0.198)	(0.185)	(0.189)
Output Tariff × Economic Zone			-0.388*	-0.809**
			(0.225)	(0.317)
Input Tariff × Economic Zone			1.164***	1.468***
			(0.217)	(0.253)
Non-Tariff Barrier	0.0874***	0.0889***	0.151***	0.147***
	(0.0327)	(0.0328)	(0.0367)	(0.0372)
Export Tariff	-0.0781	-0.0725	0.0280	0.0150
	(0.0846)	(0.0866)	(0.120)	(0.122)
Non-Tariff Barrier × Economic Zone			-0.102***	-0.0900**
			(0.0354)	(0.0360)
Export Tariff × Economic Zone			-0.115	-0.0687
			(0.186)	(0.188)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Observations	47,083	47,083	47,083	47,083
F-statistic		210.933		92.459

Notes: Dependant variables in the top and bottom panels are the logs of total employment among domestic and foreign-invested firms in a prefecture-industry. Foreign-invested firms include foreign-owned enterprises and Sino-foreign joint ventures. Each observation is a prefecture-industry pair across 9 years. Post-WTO tariffs are instrumented with the minimum of tariffs of countries which entered the WTO between 2000 and 2003 for each industry. Constant not reported. Standard errors clustered by industry and year. F-statistic is the Kleibergen-Paap rk Wald F statistic for non i.i.d. errors. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 1.14: Mechanism: Export Status

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Non-Exporting Firms				
Output Tariff	0.369**	0.430*	0.508***	0.565**
	(0.150)	(0.232)	(0.179)	(0.255)
Input Tariff	-0.322*	-0.479**	-0.632***	-0.795***
	(0.187)	(0.193)	(0.203)	(0.207)
Output Tariff × Economic Zone			-0.533**	-0.493**
			(0.213)	(0.231)
Input Tariff × Economic Zone			1.208***	1.196***
			(0.178)	(0.202)
Non-Tariff Barrier	0.0447*	0.0428	0.0525*	0.0507
	(0.0259)	(0.0268)	(0.0303)	(0.0314)
Export Tariff	-0.290***	-0.311***	-0.323***	-0.344***
	(0.0914)	(0.0966)	(0.101)	(0.107)
Non-Tariff Barrier × Economic Zone			-0.0219	-0.0229
			(0.0302)	(0.0304)
Export Tariff × Economic Zone			0.153**	0.147**
			(0.0701)	(0.0715)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Observations	154,517	154,517	154,517	154,517
F-statistic		122.348		55.656
Exporting Firms				
Output Tariff	-0.125	0.214	0.0693	0.845
	(0.273)	(0.379)	(0.428)	(0.689)
Input Tariff	0.403	0.137	-0.486	-1.274***
	(0.298)	(0.344)	(0.448)	(0.467)
Output Tariff × Economic Zone			-0.354	-1.060
			(0.469)	(0.736)
Input Tariff × Economic Zone			1.715***	2.537***
			(0.462)	(0.465)
Non-Tariff Barrier	0.0800***	0.0752**	0.101**	0.0855*
	(0.0302)	(0.0305)	(0.0432)	(0.0458)
Export Tariff	-0.225*	-0.260**	-0.321*	-0.413**
	(0.118)	(0.122)	(0.176)	(0.180)
Non-Tariff Barrier × Economic Zone			-0.0426	-0.0263
			(0.0466)	(0.0494)
Export Tariff × Economic Zone			0.267	0.366*
			(0.193)	(0.194)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Observations	62,010	62,010	62,010	62,010
F-statistic		165.866		61.21

Notes: Dependant variables in the top and bottom panels are the logs of total employment among non-exporting and exporting firms in a prefecture-industry. Each observation is a prefecture-industry pair across 9 years. Post-WTO tariffs are instrumented with the minimum of tariffs of countries which entered the WTO between 2000 and 2003 for each industry. Constant not reported. Standard errors clustered by industry and year. F-statistic is the Kleibergen-Paap rk Wald F statistic for non i.i.d. errors. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

employment is reallocated to more productive firms in economic zones and, in particular, to foreign enterprises. Firms also start exporting or increase export intensity, thereby increase employment. This finding is consistent with a recent work by Ma et al. (2012) which finds that Chinese manufacturing firms become more labour-intensive when they export.

The employment effects of input tariffs in economic zones seem puzzling. In Section 5, I argue that firm's product type and technology determine the degree of complementarity between labour and intermediate inputs, hence the outcomes of input tariff reduction. Another reason is employment growth of foreign enterprises and exporting firms is larger for industries which had lower pre-WTO input tariffs, and these industries experienced little changes in input tariffs after China's accession to WTO.

1.7.2 Geographical Location

Our main results capture the joint effects of institutions and geographical factors on the outcomes of tariff reductions. To examine the role of geographical factors, I run separate regressions for prefectures in the eastern and central-western provinces. If the results are driven by geographical advantages, I should not find significant differential impact across economic and non-economic zones for each specification.

While 54% of the eastern prefecture-industries is located in economic zones, only 4% of the central-western prefecture-industries is in economic zones. Therefore, I expect insignificant heterogeneous effects in the central-western provinces. In Table 1.15, I find that the tariff reduction have large effects in the eastern economic zones and central-western non-economic zones. Two conclusions can be drawn from the results. First, the differential impact of tariff cuts is not entirely driven by geographical factors, although they do play an important role. Second, compared to their eastern competitors, the effects of tariff reduction are larger in the central- western non-economic zones which are more geographically disadvantaged.

1.8 Conclusion

This paper studies the impact of trade liberalisation on regional manufacturing employment in China and how this impact varies across regions with different market policies. After joining the WTO in 2001, China was required to reduce tariffs significantly. While industries benefit from cheaper imported inputs, those which faced larger tariff cuts are subject to tougher import competition. I argue that the instrument variable strategies adopted in previous studies to tackle the problem of tariff endogeneity are likely to fail the exogeneity assumption if there are serial correlations in industry characteristics. I address this concern by exploiting the exogeneity of WTO rules which are applied to all member states. Our main results suggest that reduction in output and input tariffs have insignificant impact on regional employment on average, and this is due to the offsetting effects in economic and non-economic zones. Foreign investment and export activities play an important role in the employment adjustments in economic zones while geographical location partly explains the results in non-economic zones. Our findings suggest that free-market system and pro-trade policies affects the outcomes of market reforms. Countries which didn't gain from trade liberalisation might lack of the policies to protect local companies during the initial period of opening or have insufficient incentives to encourage the development of new capacity. How various economic policies affect the outcomes of trade reforms are left for future research.

TABLE 1.15: Mechanism: Geographical Location

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Eastern Provinces				
Output Tariff	-0.0718	-0.249	0.111	0.164
	(0.159)	(0.264)	(0.218)	(0.356)
Input Tariff	0.538***	0.572**	0.110	-0.0770
	(0.199)	(0.233)	(0.264)	(0.281)
Output Tariff × Economic Zone			-0.362*	-0.807***
			(0.210)	(0.304)
Input Tariff × Economic Zone			0.842***	1.272***
			(0.217)	(0.234)
Non-Tariff Barrier	0.0203	0.0228	0.0124	0.00950
	(0.0253)	(0.0255)	(0.0332)	(0.0338)
Export Tariff	-0.253***	-0.248***	-0.244***	-0.270***
	(0.0671)	(0.0700)	(0.0703)	(0.0751)
Non-Tariff Barrier × Economic Zone			0.0139	0.0237
			(0.0303)	(0.0312)
Export Tariff × Economic Zone			-0.0289	0.0347
			(0.0732)	(0.0730)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Observations	68,209	68,209	68,209	68,209
F-statistic		150.322		67.564
Central and Western Provinces				
Output Tariff	0.629***	0.812***	0.625***	0.763***
	(0.169)	(0.256)	(0.174)	(0.256)
Input Tariff	-0.831***	-1.049***	-0.838***	-1.066***
	(0.209)	(0.201)	(0.210)	(0.213)
Output Tariff × Economic Zone			0.0854	0.855
			(0.328)	(0.575)
Input Tariff × Economic Zone			0.210	-0.583
			(0.373)	(0.516)
Non-Tariff Barrier	0.0344	0.0302	0.0384	0.0354
	(0.0315)	(0.0328)	(0.0320)	(0.0333)
Export Tariff	-0.263**	-0.299**	-0.298**	-0.328**
	(0.114)	(0.121)	(0.121)	(0.128)
Non-Tariff Barrier × Economic Zone			-0.0744	-0.103*
			(0.0553)	(0.0576)
Export Tariff × Economic Zone			1.097***	0.934***
			(0.281)	(0.280)
Prefecture-Industry FE	Yes	Yes	Yes	Yes
Prefecture-Year FE	Yes	Yes	Yes	Yes
Observations	93,459	93,459	93,459	93,459
F-statistic		106.93		52.761

Notes: Dependant variables in the two panels are the logs of total employment in a prefecture-industry. Separate regressions are run for eastern and non-eastern provinces. Eastern provinces include Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. Central and Western Provinces include the remaining provinces in China. Each observation is a prefecture-industry pair across 9 years. Post-WTO tariffs are instrumented with the minimum of tariffs of countries which entered the WTO between 2000 and 2003 for each industry. Constant not reported. Standard errors clustered by industry and year. F-statistic is the Kleibergen-Paap rk Wald F statistic for non i.i.d. errors. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

1.A Appendix

1.A.1 Import Tariffs

China's tariff and import data are obtained at 8-digit and 6-digit HS product level respectively. The major challenge in computing the industry-level tariffs is the revision of HS classification in 2002. Only 76% of the 8-digit HS product codes can be matched 1 to 1 between the 1996 and 2002 HS classifications, and the HS concordance table published by the United Nations Statistics Division (UNSD) is only available at 6-digit level. For products that cannot be matched 1 to 1, some of them are divided into multiple products under the 2002 HS classification. Hence, if I take simple average of the 2002 8-digit HS to 6-digit HS, we will incorrectly attribute more weights to those products after 2002.

I tackle this problem by exploiting the fact that China's WTO bound rates were set before China's accession to the WTO; hence, they are reported at 1996 8-digit HS codes. Since China's tariff rates (applied rates) follow its bound rates very closely, I replace the post-2001 tariff rates with the WTO bound rates for products that cannot be matched 1 to 1. The correlation between China's WTO bound rates and applied rates for the 76% products that can be matched one-to-one is 0.998, which implies that the WTO bound rates is a good proxy of the China's applied rates after 2001.

1.A.2 Export Tariffs

I obtain import tariff data for 149 countries which import goods from China from the World Integrated Trade Solution (WITS) database. Each country's tariffs are obtained at 6-digit HS level and converted to HS 1996 6-digit classification using the concordance table created by the United Nations Statistics Division (UNSD). Since tariffs are at 6-digit HS, I cannot correct for the division of products as mentioned in the previous section.

I am able to obtain complete tariff data from China's major trading partners such as EU, US, Japan and South Korea. However, less than 10% of the remaining countries report tariffs every year between 1998 and 2006. To construct China's export tariffs, I replace missing observations with the following assumptions: First, if the first year for which data is available is after 1998, then the tariff rates before are the same as the rates in the first year of reporting. Second, if the last data year is before 2006, then the tariff rates afterwards are the same as the last year of reporting. Third, tariffs missing between 2 years are assumed to change in equal installments. After replacing the missing values, I aggregate the tariff data up to 4-digit ISIC level using the country-import shares of China in 1998. The problem of this approach is it tends to smooth tariff changes across years and won't capture the possible sharp drop in China's export tariffs in 2002. However, this shouldn't introduce a large bias to my estimates since the total change in tariff rates between 1998 and 2006 is quite small. Any drop in export tariffs in 2002 has to be offset by a large increase afterwards, which is unlikely to happen.

1.A.3 Economic Zones in China

TABLE 1.16: List of Prefectures with Economic Zones Before 2000

Province	Prefecture	Special Economic Zone	Coastal Open City	Coastal Economic Zone	National Economic and Technological Development Zone
Anhui	Wuhu				1993
Beijing	Beijing				1994
Chongqing	Chongqing				1993
Fujian	Fuzhou		1984		1985
Fujian	Shantou	1980			
Fujian	Xiamen	1980			1989
Fujian	Zhangzhou				1993
Guangdong	Dongguan			1994	
Guangdong	Foshan			1994	
Guangdong	Guangzhou		1984	1994	1984
Guangdong	Huizhou				1993
Guangdong	Jiangmen			1994	
Guangdong	Shenzhen	1980		1994	
Guangdong	Zhanjiang		1984		1984
Guangdong	Zhongshan			1994	
Guangdong	Zhuhai	1980		1994	
Guangxi	Beihai		1984		
Hainan	All Prefectures	1988			
Hebei	Qinhuangdao		1984		1984
Heilongjiang	Harbin				1993
Jiangsu	Changzhou			1992	
Jiangsu	Lianyungang		1984		1984
Jiangsu	Nanjing			1992	
Jiangsu	Nantong		1984		1984
Jiangsu	Suzhou			1992	1992
Jiangsu	Taizhou			1992	
Jiangsu	Wuxi			1992	
Jiangsu	Zhenjiang			1992	
Jilin	Changchun				1993
Liaoning	Dalian		1984		1984
Liaoning	Shengyang				1993
Liaoning	Yingkou				1992
Shandong	Qingdao		1984		1984
Shandong	Weihai				1992
Shandong	Yantai		1984		1984
Shanghai	Shanghai		1984	1992	1986
Tianjin	Tianjin		1984		1984
Xinjiang	Urumqi				1994
Zhejiang	Hangzhou			1992	1993
Zhejiang	Huzhou			1992	
Zhejiang	Jiaxing			1992	
Zhejiang	Ningbo		1984	1992	1984
Zhejiang	Shaoxing			1992	
Zhejiang	Wenzhou		1984		1992
Zhejiang	Zhoushan			1992	

Notes: Numbers in the table are the years of establishment of economic zones. Source: Ministry of Commerce

Chapter 2

Productivity As If Space Mattered: An Application to Factor Markets Across China

2.1 Introduction

A number of studies document large and persistent differences in productivity across both countries and firms.[1] However, these differences remain largely 'some sort of measure of our ignorance' (Abramovitz, 1956). This paper inquires to what extent the supply characteristics of regional input markets might help explain such systematic productivity dispersion across firms. It would be surprising if disparate factor markets result in similar outcomes, when clearly the prices and quality of inputs available vary considerably. Modelling firm adaptation to different factor markets provides insights and testable predictions about how firms produce and where they choose to locate.

Differences between factor markets, especially for labour, are likely to be especially stark in developing economies undergoing urbanisation (Lewis, 1954), or when government policies increase relocation costs beyond those normally

[1] See Syverson (2011) for a review.

present.[2] Even the US labour market, which is considered relatively fluid, exhibits high migration costs as measured by the wage differential required to drive relocation (Kennan and Walker, 2011). Thus, free movement of factors does not mean frictionless movement, and recent work has indicated imperfect factor mobility has sizable economic effects (Topalova, 2010). Rather than considering the forces which cause workers to locate across space, this paper instead takes a different turn to inquire what existing differences in regional input markets imply for firm input use, productivity and location.

Although there might be many complementary ways to address our question, we take an approach rooted in the general equilibrium trade literature to understand how local endowments impact firms which enter endogenously, as typified by Bernard et al. (2007). We extend their model to incorporate entry across regional markets and richer employment structures. Each region is endowed with a different distribution of skill types and wages across workers. Industries vary in team technology, which is their ability to substitute between different types of labour (e.g. Bowles, 1970). Firms hire teams of workers by choosing the optimal combination of workers given local conditions. Since each firm's optimal labour force varies by industry technology and region, the comparative suitability of regions varies by industry. Firms thus locate in proportion to the cost advantages available.

In the model, finding new employees entails fixed costs and the ease of finding any type of worker increases with their regional supply. Therefore firm hiring depends on the joint distribution of worker types and wages. Since labour demand depends on technology and regional labour markets, this implies effective labour costs vary by region and industry. These labour costs help explain differences in productivity.[3] But are these differences economically important?

[2] Institutional mobility constraints, such as the *hukou* system in China, likely further exacerbate differences.

[3] Effective labour costs are driven by the complementarity of regional endowments with industry technology, and the paper refers to these additional real production possibilities as 'productivity'.

To quantify real world supply conditions, we use the model to derive estimating equations which fix: 1) hiring by wage and worker type distributions, 2) substitution into non-labour inputs, and 3) firm location in response to local factor markets.

The estimation strategy combines manufacturing and population census data for China in the mid-2000s, a setting which exhibits substantial variation in labour market conditions. By revealing how firm demand for skills varies with local conditions, the model allows recovery of the unit costs for labour across China. Our estimates imply an interquartile difference in effective labour costs of 30 to 80 percent. A second stage estimates production functions, explicitly accounting for regional cost differences. Since firms are capable of substituting into non-labour inputs, productivity differences are smaller than labour cost differences. Once substitution is accounted for, labour costs result in firm productivity differences of 3 to 17 percent, and explain 4 to 43 percent of the variance of productivity.[4] Furthermore, we show that economic activity locates where regional costs are lowest, as implied by the model.

We conclude this section by relating the paper to existing work. The paper then continues by laying out a model that incorporates a rich view of the labour hiring process. The model explains how firms internalize local labour market conditions to maximize profits, resulting in an industry specific unit cost of labour by region. Section 3 places these firms in a general equilibrium, monopolistic competition framework, in particular addressing the determination of factor prices and firm location. Section 4 explains how the model can be estimated with a simple nested OLS approach. Section 5 discusses details of the data, while Section 6 presents our model estimates and uses them to explain the effect of different regional input markets on firm behaviour. Section 7 concludes.

[4]These substantial differences underscore Kugler and Verhoogen (2011): since TFP is often the 'primary measure of [...] performance', accounting for local factor markets might substantially alter estimates of policy effects.

Our consideration of firms as dependent on local factor markets is based on models typified by the Heckscher-Ohlin-Vanek theory of international trade (e.g. Vanek, 1968). The departures from H-O-V in our model relax assumptions about perfect labour substitutability and homogeneous factor markets, which quantifies the role of local labour markets. On the product market side, we consider many goods as indicated by Bernstein and Weinstein (2002) as appropriate when considering the locational role of factor endowments. We follow a multi-sector approach similar to Melitz (2003), but add free entry by firms across regions. A firm's optimal location depends on local costs which arise from the regional distribution of worker types and wages, but competition from firms which enter the same region prevent complete specialisation. The model quantifies the intensity of firm entry and shows that within country, advantageous local factor markets are important for understanding specialisation patterns.[5]

Recently, both Borjas (2009) and Ottaviano and Peri (2010) have emphasized the importance of more complete model frameworks to estimate substitution between worker types. In distinction to the labour literature, our interest is firm substitution across factor markets. Dovetailing with this are theories proposing that different industries perform optimally under different degrees of skill diversity. Grossman and Maggi (2000) build a theoretical model explaining how differences in skill dispersion across countries could determine comparative advantage and global trade patterns. Building on this work, Morrow (2010) models multiple industries and general skill distributions, and finds that skill diversity is explains productivity and export differences in developing countries.

The importance of local market characteristics, especially in developing countries, has recently been emphasized by Karadi and Koren (2012). These authors calibrate a spatial firm model to sector level data in developing countries to better account for the role of firm location in measured productivity. Moretti

[5]In spirit, this result is akin to Fitzgerald and Hallak (2004) who study the role of cross country productivity differences in specialisation. In our case, differences in unit labour costs predict specialisation across regions.

(2011) reviews work on local labour markets and agglomeration economies, explicitly modelling spatial equilibrium across labour markets. Distinct from this literature, we take the outcome of spatial labour markets as given and focus on the trade-offs firms face and the consequences of regional markets on effective labour costs and firm location.[6,7]

Although we are unaware of other studies estimating model primitives as a function of local market characteristics, reduced form empirical work is consonant with the theoretical implications. Iranzo et al. (2008) find that higher skill dispersion is associated with higher TFP in Italy. Similarly, Parrotta et al. (2011) find that diversity in education leads to higher productivity in Denmark. Martins (2008) finds that firm wage dispersion affects firm performance in Portugal. Bombardini et al. (2012) use literacy scores to show that countries with more dispersed skills specialize in industries characterized by lower skill complementarity. In contrast, this paper combines firm and population census data to explicitly model regional differences, leading to micro founded identification and estimates. The method used is novel, and results of this paper highlight the degree to which firm behaviour are influenced through the availability of inputs at the micro level.[8]

Clearly this study also contributes to the empirical literature on Chinese productivity. Ma et al. (2012) show that exporting is positively correlated with TFP and that firms self select into exporting which, ex post, further increases TFP. Brandt et al. (2012) estimate Chinese firm TFP, showing that new entry accounts for two thirds of TFP growth and that TFP growth dominates input accumulation as a source of output growth. Hsieh and Klenow (2009) posit that India and

[6]Several papers have explored how different aspects of labour affect firm-level productivity. There is substantial work on the effect of worker skills on productivity (Abowd Kramarz and Margolis (1999, 2005), Fox and Smeets (2011)). Other labour characteristics that drive productivity include managerial talent and practices (Bloom and van Reenen, 2007), social connections among workers (Bandiera et al., 2009), organisational form (Garicano and Heaton, 2010) and incentive pay (Lazear, 2000).

[7]Determinants of productivity include market structure (Syverson (2004)), product market rivalry and technology spillovers (Bloom et al. (2007)) and vertical integration (Horta and Syverson (2007), Atalay et al. (2012)).

[8]The importance of backward linkages for firm behaviour are a recurring theme in both the development and economic geography literature, see Hirschman (1958) and recently Overman and Puga (2010).

China have lower productivity relative to the US due to resource misallocation and compute how manufacturing TFP in India and China would increase if resource allocation was similar to that of the US. This paper uncovers local factors that determine productivity. How this interacts with the above mechanisms is a potential area for further work.[9]

2.2 The Role of Skill Mix in Production

This section develops a model of hiring in which firms respond to both the wages and quantities of locally available worker types. Firms combine homogeneous inputs (materials, capital) and differentiated inputs (types of labour). While homogeneous inputs are perfectly mobile within industries, we take the distribution of labour endowments as given. Special cases of our model would include perfect factor mobility (equal endowments in all regions) or high migration costs (equalisation up to mobility costs). Industries have different technologies available for combining types of labour into teams. We proceed with a detailed specification of the labour hiring process, solving for firms' optimal responses to local labour market supply conditions. This quantifies the unit cost for labour by region in terms of observable local conditions and model parameters.

2.2.1 Firm Production

Firms within an industry T face a neoclassical production technology $F^T(M, K, L)$ which combines materials M, capital K and labour L to produce output. An industry specific capital stock K^T is mobile within each industry, and in equilibrium is available at rental rate r_K^T. Similarly, an industry specific stock of materials M^T is mobile and available at price r_M^T. While M and K are composed

[9]Such regional differences might help explain the Chinese export facts of Manova and Zhang (2012) and the different impact of liberalisation across trade regimes found by Bas and Strauss-Kahn (2012).

of homogeneous units, effective labour L is produced by combining heterogeneous worker types.

There are $\mathbb{S}$ skill types of workers which are distributed unequally across regions R. The distribution of worker types in region R is denoted $a_R = (a_{R,1}, \ldots, a_{R,\mathbb{S}})$. The regional wages for each type are take as exogenous by workers and firms, and in equilibrium are denote $w_R = (w_{R,1}, \ldots, w_{R,\mathbb{S}})$. Workers do not contribute equally to output. This occurs for two reasons. First, each type provides an industry specific level of human capital $\underline{m}_i^T$. Second, when a worker meets a firm, this match has a random quality $h \geq 1$ which follows a Pareto distribution, $\Psi(h) \equiv 1 - h^{-k}$.

In order to hire workers, a firm must pay a fixed search cost of f effective labour units, at which point they may hire from a distribution of worker types a_R. The firm hires on the basis of match quality, and consequently chooses a minimum threshold of match quality for each type they will retain, $\underline{h} = (\underline{h}_1, \ldots, \underline{h}_{\mathbb{S}})$.[10] Upon keeping a preferred set of workers, the firm may this process N times until achieving their desired workforce. At the end of hiring, the amount of human capital produced by each type i is given by

$$H_i \equiv N \cdot a_{R,i}\underline{m}_i^T \int_{\underline{h}_i}^{\infty} h d\Psi. \tag{2.2.1}$$

From a firm's perspective, the threshold of worker match quality $\underline{h}$ is a means to choose an optimal level of H. However, as a firm lowers its quality threshold, it faces an increasing average cost of each type of human capital H_i . These increasing average costs induce the firm to maintain $\underline{h}_i \geq 1$ and to increase N to search harder for suitable workers.

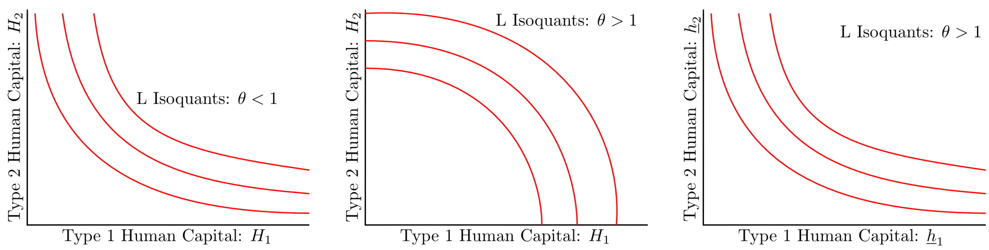
[10]This assumption is familiar from labour search models (see Helpman et al. (2010a)). Unlike Helpman, et al., here differences in hiring patterns are determined by local market conditions.

The amount of L produced by the firm depends on the composition of a team through a technological parameter θ^T in the following way:

$$L \equiv \left(H_1^{\theta^T} + H_2^{\theta^T} + \ldots + H_{\mathbb{S}}^{\theta^T}\right)^{1/\theta^T}. \tag{2.2.2}$$

Notice that in the case of $\theta^T = 1$, this specification collapses to a model where L is the total level of human capital $\sum H_i$. More generally, the Marginal Rate of Technical Substitution of type i for type i' is $(H_i/H_{i'})^{\theta^T-1}$. $\theta^T < 1$ implies worker types are complementary, so that the firm's ideal workforce tends to represent a mix of all types (Figure 2.1). In contrast, for $\theta^T > 1$, firms are more dependent on singular sources of human capital as L becomes convex in the input of each single type (Figure 2.1).[11] Below, we show that despite the convexity inherent in Figure 2.1, once firms choose the quality of their workers through hiring standards $\underline{h}$, the labour isoquants resume their typical shapes as in Figure 2.1. This avoids the possibility that some worker types are never hired, in line with real world data patterns.

FIGURE 2.1: Human Capital Isoquants



(a) Supermodular Production in H (b) Supermodular Production in H (c) Submodular Production in $\underline{h}$

Although the technology θ^T is the same for all firms in an industry, firms do not all face the same regional factor markets. Explicitly modelling these disparate markets emphasizes the role of regional heterogeneity in supplying human capital inputs to the firm in terms of both price and quality. This provides not only differences in productivity across regions by technology, but since industries differ in technology, local market conditions are more or less amenable

[11] See Morrow (2010) for a more detailed interpretation of super- and sub-modularity and implications.

to particular industries. We now detail the hiring process, introducing different markets and deriving firms' optimal hiring to best accommodate these differences.

2.2.2 Unit Labour Costs by Region and Technology

The total costs of hiring labour depend on the regional wage rates w_R, the availability of workers a_R, and the unit cost of labour in region R using technology T, labelled c_R^T. Since the total number of each type i hired is $Na_{R,i}\left(1-\Psi\left(\underline{h}_i\right)\right)$, the total hiring bill is

$$\text{Total Hiring Costs}: \quad N\left[\sum_i w_{R,i}a_{R,i}\left(1-\Psi\left(\underline{h}_i\right)\right)+fc_R^T\right]. \tag{2.2.3}$$

To produce a given vector $(H_1,\ldots,H_{\mathbb{S}})$, the firm faces a trade-off between the quantity and quality of workers hired. For instance, the firm might hire a large number of workers and "cherry pick" the best matches by choosing high values for $\underline{h}$. Alternatively, the firm might save on interviewing costs f by choosing a low number of prospectives N and permissively low values for $\underline{h}$. Local trade offs and the dependence on the regional labour supply characteristics a_R and w_R is made explicit by considering the technology and region specific cost function $C^T\left(H|a_R,w_R\right)$, defined by

$$C^T \equiv \min_{N,\underline{h}} N\left[\sum_i a_{R,i}w_{R,i}\left(1-\Psi\left(\underline{h}_i\right)\right)+fc_R^T\right] \text{ where } H_i = Na_{R,i}\underline{m}_i^T\int_{\underline{h}_i}^{\infty} hd\Psi \quad \forall i. \tag{2.2.4}$$

Letting μ_i denote the Lagrange multiplier for each of the $\mathbb{S}$ cost minimisation constraints, the first order conditions for $\{\underline{h}_i\}$ imply $\mu_i = w_{R,i}/\underline{m}_i^T\underline{h}_i$, while the choice of N implies

$$C^T\left(H|a_R,w_R\right)=\sum_i \mu_i H_i = N\sum w_{R,i}a_{R,i}\int_{\underline{h}_i}^{\infty} h/\underline{h}_i d\Psi. \tag{2.2.5}$$

Equation (2.2.5) shows that the multipliers μ_i are the marginal cost contribution (per skill unit) to H_i of the last type i worker hired. The cost function C^T implies the unit labour cost of L in region R is

$$\text{Unit Labour Cost Problem}: \quad c_R^T \equiv \min_H C^T \left(H|a_R, w_R\right) \text{ subject to } L = 1. \quad (2.2.6)$$

The unit labour cost function may be solved as

$$\text{Unit Labour Costs}: \quad c_R^T = \left[\sum_{i \text{ hired}} \left[a_{R,i} \left(\underline{m}_i^T\right)^k w_{R,i}^{1-k}/f\left(k-1\right)\right]^{\theta^T/\beta^T}\right]^{\left(\beta^T/\theta^T\right)/(1-k)}. \quad (2.2.7)$$

The trade off between being more selective (high $\underline{h}$) and avoiding search costs (fc_R^T) is clearly illustrated by combining Equations (2.2.3) and (2.2.5), which shows:

$$\sum_i a_{R,i} w_{R,i} \int_{\underline{h}_i}^{\infty} \left(h - \underline{h}_i\right)/\underline{h}_i d\Psi = fc_R^T. \quad (2.2.8)$$

The LHS of Equation (2.2.8) decreases in $\underline{h}$, so when a firm faces lower interviewing costs it can afford to be more selective by increasing $\underline{h}$. Conversely, in the presence of high interviewing costs, the firm optimally "lowers their standards" $\underline{h}$ to increase the size of their workforce without interviewing additional workers.[12]

2.2.3 Optimal Hiring Patterns

The above reasoning shows the relationship between technology and the optimal choice of worker types. It is intuitive that if the right tail of the match quality distribution is sufficiently thick, there are a few excellent matches for each

[12]The number of times a firm goes to hire workers, N, can be solved as $N = 1/fk$. Thus, N is decreasing in both hiring costs and k. Increases in k imply lower match quality, so that repeatedly screening workers has lower returns.

type of worker, so all types are hired.[13] Since match quality follows a Pareto distribution with shape parameter k, expected match quality is $\mathrm{E}[h] = k/(k-1)$. As $k \to 1$ match quality increases, so for k sufficiently close to one, all worker types should be hired. To be precise, a sufficient condition for a firm to optimally hire every type of worker, stated as Proposition 1, is that

$$\beta^T \equiv \theta^T + k - k\theta^T > 0.$$

This clearly holds for $\theta^T \leq 1$, and for $\theta^T > 1$, the condition is equivalent to $k < \theta^T / \left(\theta^T - 1\right)$. This induces the isoquants depicted in Figure 2.1, which illustrates a more standard trade off between different types of workers, so long as the coordinates are transformed to the space of hiring standards $\underline{h}$.

Proposition 1. If $\beta^T > 0$ then it is optimal for a firm to hire all types of workers.

Proof. See Appendix. □

Thus, for $\beta^T > 0$, all worker types are hired. The optimal share of workers of type i hired by firm j under technology T in region R, labelled $s^T_{R,ij}$, is fixed by (2.2.6):[14]

$$s^T_{R,ij} = a_{R,i}^{\theta^T/\beta^T} w_{R,i}^{-k/\beta^T} \left(\underline{m}_i^T\right)^{k\theta^T/\beta^T} \left(\widetilde{c}_R^T\right)^{\theta^T k/\beta^T} \left(f\left(k-1\right)\right)^{-\theta^T/\beta^T}. \tag{2.2.9}$$

where $\widetilde{c}_R^T$ denotes the unit labour cost function at wages $\left\{w_{R,i}^{k/(k-1)\theta^T}\right\}$.[15] Notice that in (2.2.6) , unlike most production models, the factor prices w_R are not sufficient to determine the factor shares a firm will buy. The availability of workers a_R is crucial in determining shares hired because costly search makes firms sensitive to the local supply of each worker type.

[13]This is important, not only for the analytical convenience of avoiding complete specialisation in the hiring of worker types, but also because we find that each region-industry combination hires all types of workers in our data.

[14]See Supplemental Appendix.

[15]Formally $\tilde{c}_R^T \equiv \min_H C^T\left(H|a_R, \left\{w_{R,i}^{-k/\theta^T(1-k)}\right\}\right)$ subject to $L = 1$.

2.2.4 Unit Costs: The Role of Substitution

Equation (2.2.7) summarizes the cost of one unit of labour L in terms of the Pareto shape parameter k, the technology θ^T and regional characteristics a_R and w_R. In order to solve for total unit costs (which include non-labour costs), we assume each production function F^T is of a Cobb-Douglas form with constant returns to scale:

$$F^T(M,K,L) = M^{\alpha_M^T} K^{\alpha_K^T} L^{\alpha_L^T}. \tag{2.2.10}$$

It is then straightforward to derive total unit costs from (2.2.7) and (2.2.10) as

$$\text{Total Unit Costs}: \quad u_R^T = \left(r_M^T/\alpha_M^T\right)^{\alpha_M^T} \left(r_K^T/\alpha_K^T\right)^{\alpha_K^T} \left(c_R^T/\alpha_L^T\right)^{\alpha_L^T}, \tag{2.2.11}$$

where u_R^T represents the regional component of unit costs for industry T in region R. Within an industry, productivity then varies across regions as in the following example: if firm 1 in region R and firm 2 in region R' face unit labour costs of c_R^T and $c_{R'}^T$ and have the same wage bill W, they will employ labour of $L^1 = W/c_R^T$ and $L^2 = W/c_{R'}^T$. Thus, if these firms hire the same capital and material inputs (K, M), then the ratio of their output is

$$Y^1/Y^2 = \left(M^{\alpha_M^T} K^{\alpha_K^T} L_1^{\alpha_L^T}\right) / \left(M^{\alpha_M^T} K^{\alpha_K^T} L_2^{\alpha_L^T}\right) = (L_1/L_2)^{\alpha_L^T} = \left(c_{R'}^T/c_R^T\right)^{\alpha_L^T}.$$

Industry differences in productivity therefore depend on 1) the ratio of regional labour costs and 2) the intensity α_L^T of labour in production. Estimating both allows quantification of regional productivity differences. However, we first resolve factor prices and firm location in general equilibrium.

2.3 Firm Production under Monopolistic Competition

This section combines the insights into firm behaviour just developed into a general equilibrium model of monopolistic competition. Firms, who are ex ante identical, choose among regions to locate. Key to a firm's location decision are the expected profits of entry. These profits depend on 1) the distribution of worker types and wages and 2) the competition present from other firms who enter the region. We characterize production and location choices conditional on local labour markets. Most strikingly, lower regional production costs attract more firms for any given technology, which determines the intensity of economic activity. Furthermore, we show an equilibrium wage vector exists which supports these choices by firms for any distribution of labour endowments. Thus, endowment distributions as implied by complete labour mobility or migration models are consistent with our framework.

2.3.1 Firms and Consumers

Each region R is endowed with a population $\mathbb{P}_R$ composed of $\mathbb{S}$ worker types. Firms may enter any region R by paying a sunk entry cost F_e. Firms then receive a random cost draw $\eta_j \sim G$ and face a fixed production cost f_e.[16] Akin to Bernard et al. (2007), firms combine different types of inputs to produce. Each firm j produces a distinct variety, and in equilibrium a mass of firms $\mathbb{M}_R^T$ enter. Entrants with cost draws less than a prohibitively high cost level $\overline{\eta}_R^T$ produce. $\mathbb{M}_R^T$ and $\overline{\eta}_R^T$ together determine the set of varieties available to consumers.
Consumer preferences over varieties j and quantities $\left\{Q_{Rj}^T\right\}$ take the Dixit-Stiglitz form

$$U_R^T \equiv U\left(\mathbb{M}_R^T, \overline{\eta}_R^T, Q_R^T\right) = \mathbb{M}_R^T \int_0^{\overline{\eta}_R^T} \left(Q_{Rj}^T\right)^\rho dG\left(j\right)$$

[16]This follows Melitz (2003). G is assumed to be absolutely continuous with finite mean.

in each region and industry, with total utility $U(\mathbb{M}, \overline{\eta}, Q) \equiv \Pi_T \Pi_R \left(U_R^T\right)^{\sigma_R^T}$, where σ_R^T are relative weights put on final goods normalized so that $\sum_{T,R} \sigma_R^T = 1$. As shown in the Appendix, each σ_R^T has the usual interpretation as the share of income spent on goods from each region and technology pair (R, T).[17]

Firms are the sole sellers of their variety, and thus are monopolists who provide their variety at a price P_{Rj}^T. Consumers, in turn, face a vector of prices $\{P_{Rj}^T\}$, and a particular consumer with income I has the following demand curve for each variety:

$$Q_{Rj}^T = I \cdot \left(P_{Rj}^T U_R^T / \sigma_R^T\right)^{\frac{1}{\rho-1}} / \sum_{t,r} \left(\sigma_r^t\right)^{\frac{1}{\rho-1}} \mathbb{M}_r^t \int_0^{\overline{\eta}_r^t} \left(\left(P_{r,z}^t\right)^\rho U_r^t\right)^{\frac{1}{\rho-1}} dG(z). \quad (2.3.1)$$

Clearly, even if consumers have different incomes, aggregate demand for variety j corresponds to that of a representative consumer with income equal to aggregate income, I_{Agg}. Since labour is supplied inelastically, I_{Agg} is necessarily

$$I_{\text{Agg}} = \sum_R \sum_i \underbrace{w_{R,i} a_{R,i} \mathbb{P}_R}_{\text{Total Wages of Type i in R}} + \sum_T \underbrace{r_M^T M^T + r_K^T K^T}_{\text{Non-labour Income}}. \quad (2.3.2)$$

After paying an entry cost of F_e output units, firms know their cost draw, which paired with regional input markets determine their total unit cost u_R^T. Firms maximize profits

$$\pi_{Rj}^T\left(P_{Rj}^T\right) = \left(P_{Rj}^T - u_R^T \eta_j\right) Q_{Rj}^T - u_R^T f_e$$

by choosing an optimal price $P_{Rj}^T = u_R^T \eta_j / \rho$, resulting in a markup of $1/\rho$ over costs. Firms who cannot make a positive profit do not produce to avoid paying the fixed cost of f_e output units. Since profits decrease in costs, there is a unique cutoff cost draw $\overline{\eta}_R^T$ which implies zero profits, while firms with $\eta_j < \overline{\eta}_R^T$ produce. As there are no barriers to entry besides the entry cost F_e, firms enter

[17]Note that since the demand for goods from each (R, T) pair enter preferences multiplicatively, complete specialisation cannot occur which considerably simplifies the analysis.

in every region until expected profits are zero. This yields the

$$\text{Spatial Zero Profit Condition}: \quad \mathrm{E}\left[\pi_{Rj}^{T}\right] = F_e, \quad \forall R, T.$$

It is shown in the Appendix that the cutoff cost draw $\overline{\eta}_R^T$ depends only on f_e, F_e, and G, so there is a unique cutoff cost that does not vary by region or industry. Having determined firm behaviour in the product market, we now examine input markets.

2.3.2 Regional Factor Market Clearing

The remaining equilibrium conditions are that input prices guarantee firm input demand exhausts materials, capital stocks, and each regional pool of workers. To fix expenditure, we assume each budget share σ_R^T is proportional to $\mathbb{P}_R$, so that $\sigma_R^T = \sigma^T \mathbb{P}_R$ for some σ^T.[18] Since production is Cobb-Douglas, the share of total costs (equal to I_{Agg}) which go to each factor is the factor output elasticity, so full resource utilisation of materials and capital requires

$$M^T = \alpha_M^T \sigma^T I_{\text{Agg}} \mathbb{P}/r_M^T, \qquad K^T = \alpha_K^T \sigma^T I_{\text{Agg}} \mathbb{P}/r_K^T. \tag{2.3.3}$$

where $\mathbb{P} \equiv \sum_R \mathbb{P}_R$ is the total population. These two equations capture the allocation of technology specific resources across regions.

In contrast, effective labour of L_R^T is produced by each technology in each region. Since the wage bill $L_R^T c_R^T$ must receive a share α_L^T of total revenues,

$$\text{Aggregate Labour Demand}: \quad L_R^T = \alpha_L^T \sigma^T I_{\text{Agg}} \mathbb{P}_R / c_R^T. \tag{2.3.4}$$

Embedded in each L_R^T is the set of workers hired by firms attendant to regional market conditions. The total demand for employees of each type in region R

[18] This assumption is justified by the implication that two regions which have identical skill distributions have the same wage schedule.

implied by Equation (2.2.9) must equal the supply of $a_{R,i}\mathbb{P}_R$, yielding the regional resource clearing conditions. Wages are therefore determined by

$$a_{R,i}w_{R,i} = \sum_T \underbrace{\sigma^T}_{\text{Industry Share Per Capita}} \cdot \underbrace{\alpha_L^T}_{\text{Labour Share}} \cdot \underbrace{H_{R,i}^{\theta^T}/\Sigma_j H_{R,j}^{\theta^T}}_{\text{Type Share}} \cdot I_{\text{Agg}} \quad \forall R, i. \tag{2.3.5}$$

Equation (2.3.5) shows that type i's contribution to mean wages, $a_{R,i}w_{R,i}$, is the sum over income spent an industry, times labour's share, times the wages attributable to each type.[19]

Solving Equation (2.3.5) requires finding a wage for each worker type in each region that fully employs all workers. To do so, first note that the resource clearing conditions determine wages, provided an exogenous vector of unit labour costs $\{c_R^T\}$, proved in the Appendix:

Lemma. There is a wage function $\mathbb{W}$ that uniquely solves (2.3.5) given unit labour costs.

Of course, unit labour costs are not exogenous as in the Lemma, but rather depend on endogenous wages $\{w_{R,i}\}$. However, the lemma does show that the following mapping:

$$\{w_{R,i}\} \underset{\text{Equation 2.2.7}}{\mapsto} \{c_R^T(\{w_{R,i}\})\} \underset{\text{Lemma}}{\mapsto} \mathbb{W}\left(\{c_R^T(\{w_{R,i}\})\}\right),$$

which starts at one wage vector $\{w_{R,i}\}$ and ends at another wage vector $\mathbb{W}$ is well defined. This mapping is shown in the Appendix to have a fixed point, which implies

Proposition 2. *An equilibrium wage vector exists which clears each regional labour market.*

[19]In equilibrium, the type share is

$$H_{R,i}^{\theta^T}/\Sigma_j H_{R,j}^{\theta^T} = \left(a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k}\right)^{\theta^T/\beta^T} / \Sigma_j \left(a_{R,j}\left(\underline{m}_j^T\right)^k w_{R,j}^{1-k}\right)^{\theta^T/\beta^T}$$

2.3.3 Limited Factor Price Equalisation

Since workers are imperfectly substitutable, they induce spillovers within firms, and consequently are not paid their marginal product.[20] Mirroring this, the equation for unit labour costs shows that regions with different skill distributions, say region R and R', typically cannot have both $c_R^T = c_{R'}^T$ and $w_R = w_{R'}$. However, factor price equalisation for labour holds in a limited fashion in two ways. First, Equation (2.3.4) shows the industry wage bill *per capita* is equalized, formally

$$c_R^T L_R^T / \mathbb{P}_R = c_{R'}^T L_{R'}^T / \mathbb{P}_{R'} \text{ for all region pairs } (R, R') .$$

Second, summing across types in (2.3.5) implies

$$\text{Average Wages : } \quad \sum_i a_{R,i} w_{R,i} = \sum_T \alpha_L^T \sigma^T I_{\text{Agg}},$$

so average wages are constant across regions. This is summarized as

Proposition 3. Average wages are equalized across regions.

Proposition 3 shows that while our model allows for heterogeneity of wages by worker type, general equilibrium forces still imply that factor price equalisation holds *on average*.

2.3.4 Regional Specialisation of Firms

Of course, differences in input costs will influence the relative concentration of firms across regions. Since regions may vary substantially in population size $\mathbb{P}$, the most relevant metric is the number of firms per capita, $\mathbb{M}_R^T \cdot G\left(\overline{\eta}_R^T\right) / \mathbb{P}_R$. The impact of different regional costs can be clearly seen by fixing an industry T

[20] Such spillovers are internalized by firms in the model. The extent to which spillovers might also occur across industries is beyond the scope of this study, however see Moretti (2004) for evidence in the US context.

and considering the ratio of firms per capita in region R versus R' as in Equation (2.3.6):

$$\text{Firms per Capita, R to R}': \quad \frac{\mathbb{M}_R^T \cdot G\left(\overline{\eta}_R^T\right)/\mathbb{P}_R}{\mathbb{M}_{R'}^T \cdot G\left(\overline{\eta}_{R'}^T\right)/\mathbb{P}_{R'}} = \frac{u_{R'}^T}{u_R^T} = \left(\frac{c_{R'}^T}{c_R^T}\right)^{\alpha_L^T} \tag{2.3.6}$$

Equation (2.3.6) shows that areas with lower unit labour costs have more firms per capita. Additionally, the larger the share of labour in production, α_L^T, the more important are differences between regions. This relationship is summarized as

Proposition 4. Within an industry, regions with lower labour costs have more firms per capita.

The next section lays out a strategy to structurally estimate model parameters.

2.4 Estimation Strategy

This section lays out an estimator for the structural model parameters above. The estimator involves two regressions, with a simple intervening computation. The first stage equation determines firm labour demand, and unlike many approaches, is based on the firm-level shares of workers hired across regions. The second stage equation uses regional unit labour costs from the first stage to estimate the production function. Feasibility is illustrated by simulating a data set consistent with the model above and recovering model primitives accurately with the estimator.

2.4.1 First Stage Estimation

Equation (2.2.9) determines the share of each type of workers hired in each region R and industry T. Taking logs and allowing for errors ϵ_{ij} across firms and types implies

$$\ln s_{R,ij}^{T} = -\frac{k}{\beta^{T}} \ln w_{R,i} + \frac{\theta^{T}}{\beta^{T}} \ln a_{R,i} + \frac{\theta^{T}}{\beta^{T}} k \ln \underline{m}_{i}^{T} + \frac{\theta^{T}}{\beta^{T}} \ln \frac{\left(\widetilde{c}_{R}^{T}\right)^{k}}{f\,(k-1)} + \epsilon_{ij}, \quad (2.4.1)$$

To estimate this equation we use a combination of type and region dummies.[21] To further explain how regional variation identifies the model we discuss equilibrium hiring predicted by Equation (2.4.1) in Appendix 2.A.4.2.

In order to control for firm characteristics which might influence hiring patterns across worker types, $\underline{m}_{i}^{T}$ is allowed to vary with firm observables labelled $\mathrm{Controls}_{j}$:

$$\underline{m}_{ij}^{T} \equiv \underline{m}_{i}^{T} \cdot \exp\left(\mathrm{Controls}_{j} \gamma_{i}^{T}\right), \quad (2.4.2)$$

where γ_{i}^{T} is a type-industry specific estimate which influences the value of each worker type in an industry. The inclusion of $\mathrm{Controls}_{j}$ makes type specific human capital vary by firm, and accordingly we denote unit labour costs as c_{Rj}^{T}. We now discuss how the first stage estimates are used to estimate the production function in a second stage.

2.4.2 Second Stage Estimation

From above we can estimate $\theta^{T}, k, \underline{m}_{i}^{T}/\underline{m}_{\mathbb{S}}^{T}, \gamma_{i}^{T}$ and therefore can estimate regional differences in unit labour cost functions, $\Delta \ln c_{R}^{T} \equiv \mathrm{E}\left[\ln c_{Rj}^{T} | R, T, \mathrm{Controls}_{j}\right] - \mathrm{E}\left[\ln c_{Rj}^{T} | T\right]$. From above, revenues $P_{Rj}^{T} Q_{Rj}^{T}$ for a firm j satisfy

$$\ln P_{Rj}^{T} Q_{Rj}^{T} = \alpha_{M}^{T} \ln M_{j} + \alpha_{K}^{T} \ln K_{j} + \alpha_{L}^{T} \ln L_{j} - \ln \rho \eta_{j}. \quad (2.4.3)$$

As firm expenditure on labour $L \cdot c_{Rj}^{T}$ equals the share α_{L}^{T} of revenues $P_{Rj}^{T} Q_{Rj}^{T}$, we have $L_{j} c_{Rj}^{T} = \alpha_{L}^{T} P_{Rj}^{T} Q_{Rj}^{T}$ and taking differences with the population mean

[21] We suggest the convention of creating of type and region fixed effects, omitting the highest type fixed effect. The remaining type coefficients then correspond to the estimates of $\left(\theta^{T}/\beta^{T}\right) k \ln \underline{m}_{i}^{T}/\underline{m}_{\mathbb{S}}^{T}$.

gives

$$\Delta \ln L_j = \Delta \ln P^T_{Rj} Q^T_{Rj} - \Delta \ln c^T_{Rj}. \tag{2.4.4}$$

Taking differences of Equation (2.4.3) with the population mean and using (2.4.4) yields

$$\Delta \ln P^T_{Rj} Q^T_{Rj} = \alpha^T_M \Delta \ln M_j + \alpha^T_K \Delta \ln K_j + \alpha^T_L \Delta \ln P^T_{Rj} Q^T_{Rj} - \alpha^T_L \Delta \ln c^T_{Rj} - \Delta \ln \eta_j.$$

Rearranging yields the estimating equation

$$\Delta \ln P^T_{Rj} Q^T_{Rj} = \frac{\alpha^T_M}{1-\alpha^T_L} \Delta \ln M_j + \frac{\alpha^T_K}{1-\alpha^T_L} \Delta \ln K_j - \frac{\alpha^T_L}{1-\alpha^T_L} \Delta \ln c^T_{Rj} - \frac{1}{1-\alpha^T_L} \Delta \ln \eta_j. \tag{2.4.5}$$

The entire estimation procedure is now briefly recapped.[22]

2.4.3 Estimation Procedure Summary

1. Using $s^T_{R,ij}$, the share of workers of type i hired in region R and industry T by firm j, estimate Equation (2.4.1) for each industry, using type and region dummies.
2. Recover $\widehat{\theta^T}$, $\widehat{k}$, $\widehat{\underline{m}^T_i / \underline{m}^T_{\mathbb{S}}}$ and $\widehat{\gamma^T_i}$. Bootstrap standard errors or use the delta method.
3. Calculate $\widehat{\Delta \ln c^T_{Rj}}$ from Equation (2.2.7) using regional data and estimates from Step 2.
4. Estimate Equation (2.4.5) using $\widehat{\Delta \ln c^T_{Rj}}$.

[22] This specification is structural, but treats some model parameters as ancillary. In the Appendix, we illustrate the estimator by simulating firms which obey the production model specified above and apply these steps. In the simulation, the two stage estimator explains 97% of the variation in firm output, suggesting that the time savings of this estimator likely outweigh any gain from a completely specified estimator.

Having laid out both a model detailing the interaction of firm technologies with local market conditions and specifying an estimation strategy, we now apply the method to China. The next section discusses these data in detail while the sequel presents our results.

2.5 Data

Firm data come from the 2004 Survey of Industrial Firms conducted by the Chinese National Bureau of Statistics, which includes all state owned enterprises and private enterprises with sales over 5 million RMB. The data include firm ownership, location, industry, employees by education level, profit and cash flow statements. Firm capital stock is reported fixed capital, less reported depreciation while materials are measured by value. For summary statistics, see Appendix 2.A.5.3. From the Survey, a sample was constructed of manufacturing firms who report positive net fixed assets, material inputs, output, value added and wages. The final sample includes 141,464 firms in 284 prefectures and 19 industries at the two digit level.

Regional wage distributions are calculated from the 0.5% sample of the 2005 China Population Census. The census contains the education level by prefecture of residence, occupation, industry code, monthly income and weekly hours of work. We restrict the sample to employees age 15 to 65 who report positive wages and hours of work. The regional wage distribution is recovered from the average annual income of employees by education using census data.[23]

In addition, GIS data from the China Data Center at the University of Michigan locates firms at the county and prefecture level. Port data is provided by GIS data and supplemented by inland port data from the World Port Index.

[23]While firm data is from 2004 and census data is from 2005, firm skill mix is remarkably stable over time: Ilmakunnas and Ilmakunnas (2011) find the standard deviation of plant-level education years is very stable from 1995-2004 in Finland, and Parrotta et al. (2011) find that a firm-level education diversity index was roughly constant over a decade in Denmark.

These data provide controls for urban status, distance to port and Economic Zone status.

Figure 2.2 illustrates the prefectures of China, which we define as regions from the perspective of the model above. Prefectures illustrated by a darker shade in the Figure operate under substantially different government policies and objectives. These regions typically have large minority populations or historically distinct conditions, with the majority declared as autonomous regions, and have idiosyncratic regulations, development, and educational policies.[24] We restrict attention to the lighter shaded regions of Figure 2.2, preserving 284 prefectures displaying distinct labour market conditions.[25]

2.5.1 Regional Variation

Key to our analysis is regional variation in skill distribution and wages. Here we briefly discuss both, with further details in Appendix 2.A.5. Monthly incomes vary substantially across China as illustrated in Figure 2.2. This is due to both the composition of skills (proxied by education) across regions and the rates paid to these skills. Figure 2.3 contrasts educational distributions of the labour force. Figure 2.3(a) shows those with a Junior High School education (the mandated level in China), while Figure 2.3(b) displays those with a Junior College or higher level of attainment.

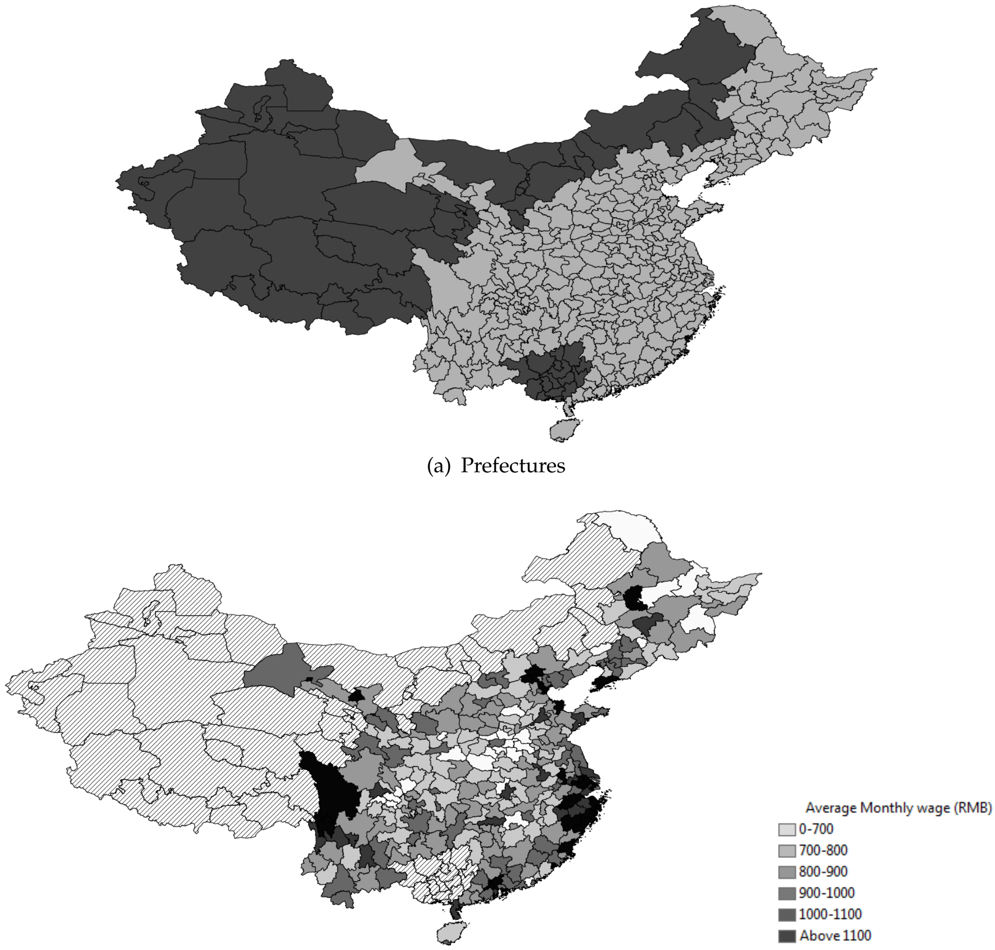
The differing composition of input markets across China in 2004-2005 stem from many factors, including the dynamic nature of China's rapidly growing economy, targeted economic policies and geographic agglomeration of industries across China.[26] Faber (2012) finds that expansion of China's National Trunk Highway System displaced economic activity from counties peripheral

[24]See the Information Office of the State Council of the People's Republic of China document cited.

[25]In 2005, China was composed of thirty three Provinces and we exclude the five Autonomous Provinces and one predominantly minority Non-Autonomous Province.

[26]We consider regional price variation at a fixed point in time. Reallocation certainly occurs and is very important in explaining dynamics (e.g. Borjas (2003)) but are outside the scope of this paper.

FIGURE 2.2: Chinese Prefectures



(a) Prefectures

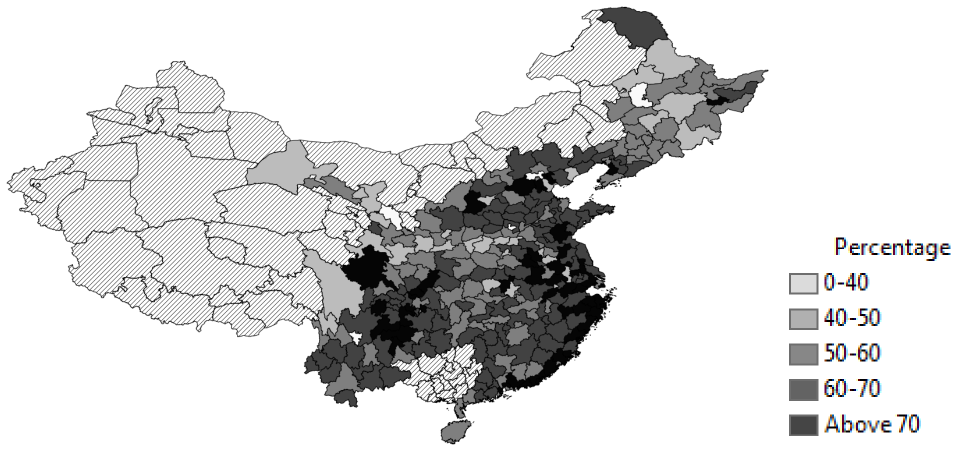
(b) Average Monthly Income of Employees (2005)

to the System. Similarly, Baum-Snow et al. (2012) show that mass transit systems in China have increased the population density in city centers, while radial highways around cities have dispersed population and industrial activity. An overview of Chinese economic policies is provided by Defever and Riano (2012), who quantify their impact on firms.

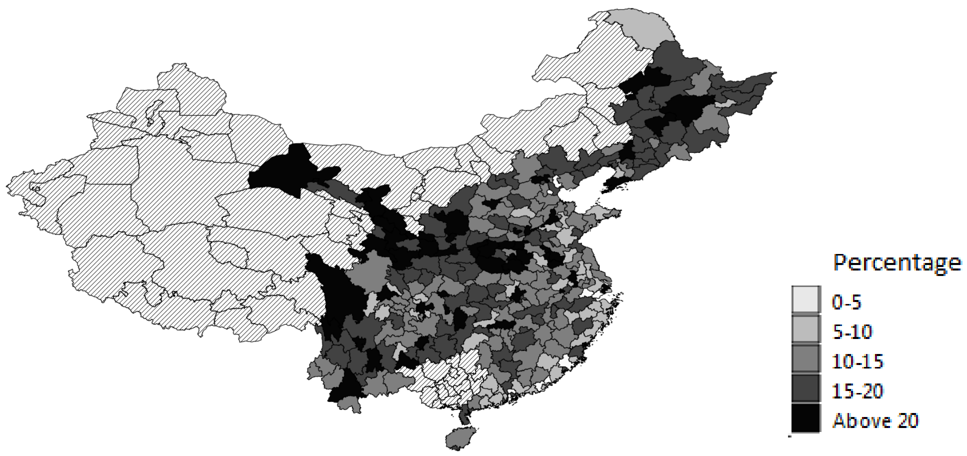
Of particular interest for labour markets are substantial variation in wages and the attendant migration this induces. The quantitative extent to which labour market migration has been stymied by the *hukou* system of internal passports is not well studied, although its impact has likely lessened since 2000.[27]

[27]The Hukou system and its reform in the late 1990s are well explained in Chan and Buckingham (2008). The persistence of such a stratified system has engendered deep set social attitudes which likely affect economic interactions between Hukou groups, see Afridi et al. (2012).

FIGURE 2.3: Low and High Educational Attainment Across China (2005)



(a) % Labour Force with $\leq$ Junior High School



(b) % Labour Force with $\geq$ Junior College

Given that rural to urban migration typifies the pattern of structural transformation underway, we control for rural and urban effects for each type of worker below. Nonetheless, it remains unclear to what degree the hukou system alters labour flows under the present system. In particular, high income and highly educated workers can more easily move among urban regions as local governments are likely to approve their migration applications (Chan et al., 1999). It therefore seems likely that the size of labour markets accessible to workers is extremely heterogeneous. Given what little is known about the actual determinants of migration in China, modelling firm decisions when faced with dynamically changing input markets is an interesting avenue for further work.

2.5.2 Worker Types

Our definition of workers is people between ages 15 and 65 who work outside the agricultural sector and are not employers, self-employed, or in a family business. Our definition of distinct, imperfectly substitutable worker types is based primarily on formal schooling attained. Census data from 2005 shows that the average years of schooling for workers in China ranges from 8.5 to 11.8 years across provinces, with sparse postgraduate education. The most common level of formal education is at the Junior High School level or below. Reflecting substantial wage differences by gender within that group, we define Type 1 workers as Junior High School or Below: Female and Type 2 workers as Junior High School or Below: Male.[28] Completion of Senior High School defines Type 3 and completion of Junior College or higher education defines Type 4.

Having discussed the data, we now apply the estimation procedure developed above.

2.6 Estimation Results

This section reports our estimation results, then turns to a discussion of the quantitative labour cost and productivity differences accounted for by local market conditions in China. The section continues by testing the firm location implications of the model, finding broad support that economic activity locates where estimated unit labour costs are lower. Finally, we compare estimation results of our unit cost based method with one approach common in the literature, which assumes that labour types are perfectly substitutable.

[28]Differentiation of gender for low skill labour is especially important in developing countries as a variety of influences result in imperfect substitutability across gender. Bernhofen and Brown (2011) distinguish between skilled male labour, unskilled male labour and female labour and find that the factor prices across these types differ substantially.

2.6.1 Estimates of Market Conditions and Production Technologies

The full first stage regression results for several manufacturing industries in China are presented in Tables 2.9 and 2.10 of Appendix 2.A.3. A representative set of estimates for the General Machines industry are presented in Table 2.1. The first box in Table 2.1, labelled Primary Variables, are consistent with the model. Though values for the coefficients $\left(\theta^T/\beta^T\right) \ln \underline{m}_i/\underline{m}_4$ are not specified by the model, their estimated values do increase in type in Table 2.1, which is consonant with formal education increasing worker output.

The remaining two boxes include regional controls from the Census and firm level controls from the manufacturing survey. The regional controls are by prefecture, and include the percentage of each type with a non-agricultural Hukou. The firm level controls include the share of foreign equity, the age of the firm, and whether the firm is in an urban area. Inclusion of controls for average worker age, which control for accumulated skill or vintage human capital, do not appreciably alter the results. Other controls which did not appreciably alter the results include State Ownership and the percentage of migrants.

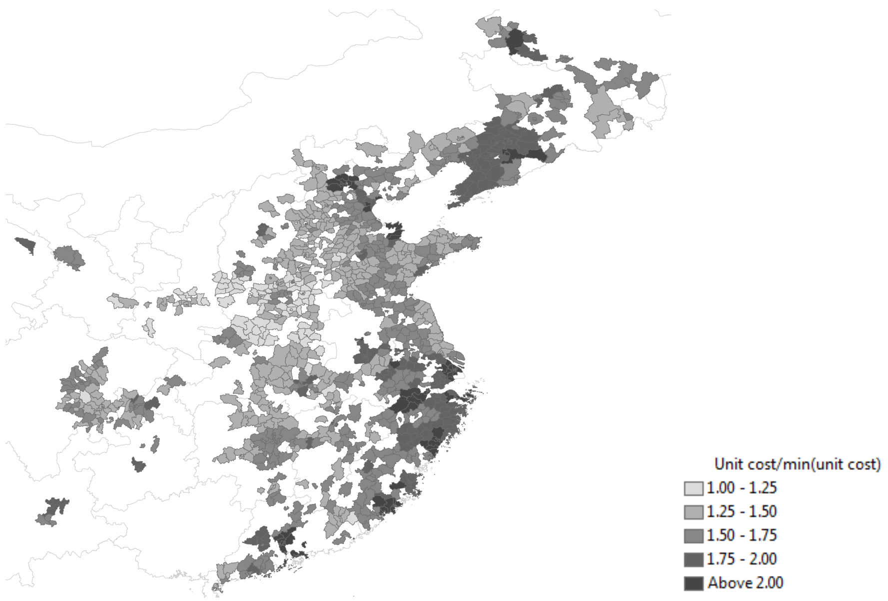
TABLE 2.1: First Stage Results: General Machines

Primary Variables	$\ln(\%\text{ Hired})$	Firm Controls	
$\ln(w_{R,i})$	-2.687***	$\underline{m}_1 *$ Urban Dummy	-1.384***
$\ln(a_{R,i})$	1.794***	$\underline{m}_2 *$ Urban Dummy	-0.980***
$\underline{m}_1$ (≤Junior HS: Female)	-10.170***	$\underline{m}_3 *$ Urban Dummy	0.427***
$\underline{m}_2$ (≤Junior HS: Male)	-6.171***	$\underline{m}_4 *$ Urban Dummy	2.336***
$\underline{m}_3$ (Senior High School)	-3.180***	$\underline{m}_1 *$% Foreign Equity	-2.448***
		$\underline{m}_2 *$% Foreign Equity	-1.864***
		$\underline{m}_3 *$% Foreign Equity	0.311***
Regional Controls		$\underline{m}_4 *$% Foreign Equity	3.847***
$\underline{m}_1 *$% Non-Ag Hukou	-5.957***	$\underline{m}_1 * \ln(\text{Firm Age})$	0.934***
$\underline{m}_2 *$% Non-Ag Hukou	-3.072***	$\underline{m}_2 * \ln(\text{Firm Age})$	0.403***
$\underline{m}_3 *$% Non-Ag Hukou	-3.218***	$\underline{m}_3 * \ln(\text{Firm Age})$	0.143***
$\underline{m}_4 *$% Non-Ag Hukou	-7.026***	$\underline{m}_4 * \ln(\text{Firm Age})$	0.351***
Observations: 62,908. R^2 : 0.139		Includes Regional Fixed Effects	

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

These first stage estimates are interesting in themselves, as the model then implies the unit cost function for labour by region. The dispersion of estimated unit labour costs in the General Purpose Machine industry are depicted in Figure 2.4.

FIGURE 2.4: Geographic Dispersion of Unit Labour Costs: General Machines



(a) Before 2000

The model primitives of our two stage estimation procedure across industries are summarized in Tables 2.2 and 2.3. Standard errors are calculated using a bootstrap procedure stratified on industry and region, presented in the Appendix. Table 2.2 displays the estimated model primitives, showing a range of significantly different technologies θ^T and match quality distributions through k. Table 2.3 shows the second stage estimation results, where the regional unit labour costs are calculated using regional data and the first stage estimates.

TABLE 2.2: Model Primitive Estimates

Industry	k	θ	Industry	k	θ
Beverage	2.12 (.38)	1.24 (.08)	Paper	6.25 (3.8)	0.73 (.11)
Electrical	2.60 (.15)	1.22 (.02)	Plastic	3.51 (.29)	1.08 (.03)
Food	1.59 (.36)	1.28 (.13)	Printing	3.93 (.60)	1.04 (.04)
General Machines	2.50 (.14)	1.22 (.03)	PC & AV	2.21 (.14)	1.41 (.04)
Iron & Steel	3.21 (.56)	1.00 (.06)	Rubber	1.63 (.61)	1.15 (.19)
Leather & Fur	2.15 (.70)	0.76 (.14)	Specific Machines	1.63 (.18)	1.43 (.07)
Precision Tools	2.34 (.18)	1.43 (.05)	Textile	3.73 (.36)	0.95 (.03)
Metal Products	3.20 (.24)	1.10 (.03)	Transport	1.26 (.24)	1.38 (.13)
Non-ferrous Metal	2.89 (.38)	1.15 (.05)	Wood	1.52 (.22)	1.62 (.17)
Non-metal Products	2.02 (.16)	1.25 (.04)	Standard Errors reported in parentheses.		

TABLE 2.3: Second Stage Estimates

Industry	α_L	α_K	α_M	Industry	α_L	α_K	α_M
Beverage	.13 (.05)	.10 (.01)	.70 (.04)	Paper	.18 (.36)	.14 (.03)	.53 (.28)
Electrical	.25 (.01)	.14 (.01)	.47 (.01)	Plastic	.27 (.04)	.14 (.01)	.41 (.02)
Food	.14 (.08)	.09 (.01)	.70 (.06)	Printing	.09 (.06)	.22 (.01)	.55 (.03)
General Machines	.17 (.02)	.12 (.01)	.60 (.01)	PC & AV	.16 (.01)	.21 (.01)	.43 (.01)
Iron & Steel	.40 (.06)	.07 (.01)	.48 (.05)	Rubber	.06 (.15)	.13 (.02)	.63 (.10)
Leather & Fur	.10 (.11)	.13 (.02)	.59 (.07)	Specific Machines	.10 (.03)	.16 (.01)	.55 (.02)
Precision Tools	.20 (.01)	.16 (.01)	.43 (.01)	Textile	.12 (.05)	.11 (.01)	.61 (.03)
Metal Products	.24 (.01)	.14 (.01)	.46 (.01)	Transport	.04 (.03)	.15 (.01)	.65 (.02)
Non-ferrous Metal	.40 (.03)	.08 (.01)	.43 (.02)	Wood	.22 (.11)	.10 (.02)	.56 (.08)
Non-metal Products	.20 (.02)	.07 (.01)	.61 (.02)	Standard Errors reported in parentheses.			

While the capital coefficients may seem low, they are not out of line with other estimates which specifically account for material inputs (e.g. Javorcik (2004)). For the specific case of China, there are few studies estimating production coefficients.[29] The most comparable study is Fleisher and Wang (2004) who find microeconomic estimates for α_K in the range of .40 to .50 (which does not differentiate between capital and materials) and these estimates compare favourably with the combined estimates of $\alpha_K + \alpha_M$ in Table 2.3.

2.6.2 Implied Productivity Differences Across Firms

Table 2.4 quantifies the implied differences in unit labour costs and productivity across regions. The c_R^T column displays the interquartile (75%/25%) unit labour cost ratios by industry, where unit labour costs have been calculated according to the model. The u_R^T column contains the differences in productivity implied by unit labour costs as laid out in Section 2.2.4, taking into account substitution into non-labour inputs. For example, consider two firms in General Machines at the 25th and 75th unit labour cost percentile. If both firms have the same wage bill, the labour (L) available to the lower cost firm is 1.41 times greater than the higher cost firm. From Table 2.3 above, the estimated share of wages in production is $\alpha_L^T = .17$, so the lower cost firm will produce $1.41^{.17} = 1.06$ times

[29] Though not directly comparable, macroeconomic level estimates include Chow (1993) and Ozyurt (2009) who find much higher capital coefficients. These studies do not account for materials.

as much output as the higher cost firm, holding all else constant.

TABLE 2.4: Intraindustry Unit Labour Cost and Productivity Ratios

Industry	c_R^T 75/25	u_R^T 75/25	Industry	c_R^T 75/25	u_R^T 75/25
Beverage	1.51	1.06	Paper	1.66	1.07
Electrical	1.38	1.08	Plastic	1.35	1.09
Food	1.81	1.09	Printing	1.37	1.03
General Machines	1.41	1.06	PC & AV	1.44	1.06
Iron & Steel	1.34	1.13	Rubber	2.16	1.04
Leather & Fur	1.92	1.04	Specific Machines	1.99	1.08
Precision Tools	1.80	1.13	Textile	1.37	1.04
Metal Products	1.33	1.07	Transport	4.01	1.04
Non-ferrous Metal	1.45	1.17	Wood	1.47	1.10
Non-metal Products	1.42	1.08			

Table 2.4 indicates that the range of total unit costs faced by firms within the same industry are indeed substantial, even after explicitly taking into account the technology θ^T and the ability to substitute across several types of local workers. However, the second stage estimates indicate these differences are attenuated by substitution into capital and materials. Thus, while differences in regional markets indicate an interquartile range of 30-80% in unit cost differences, substitution into other factors reduces this range to between 3-17%.[30]

Table 2.5 examines the variance of productivity across industries under our unit cost method and under an approach estimating output by a Cobb-Douglas combination of capital, materials and the number of each worker type. Table 2.5 also shows the average percentage that unexplained productivity is reduced per firm under the unit labour cost method.

Since firms locate freely, the model predicts that these substantial cost differences drive economic activity towards more advantageous locations, which we now examine.

[30]Most models used in production estimation assume perfect labour substitutability. Such models imply that, conditional on wages, the local composition of the workforce is irrelevant for hiring. Our approach is sensitive to local factor supply and an empirical comparison with other models is presented in Appendix 2.A.3.2.

TABLE 2.5: Percentage of Productivity Explained by Unit Cost Method

Industry	Unit Cost σ^2	Four Types σ^2	Avg % Reduced	Industry	Unit Cost σ^2	Four Types σ^2	Avg % Reduced
Beverage	0.41	0.54	0.18	Paper	0.36	0.65	0.30
Electrical	0.40	0.67	0.27	Plastic	0.22	0.64	0.43
Food	0.37	0.61	0.28	Printing	0.49	0.56	0.10
General Machines	0.44	0.59	0.16	PC & AV	0.73	0.94	0.21
Iron & Steel	0.32	0.46	0.19	Rubber	0.55	0.56	0.08
Leather & Fur	0.23	0.66	0.43	Specific Machines	0.51	0.61	0.10
Precision Tools	0.45	0.46	0.07	Textile	0.39	0.45	0.11
Metal Products	0.48	0.69	0.22	Transport	0.58	0.59	0.04
Non-ferrous Metal	0.27	0.43	0.24	Wood	0.26	0.45	0.27
Non-metal products	0.44	0.56	0.15				

2.6.3 Firm Location

Per capita volumes of economic activity across regions are determined by Equation (2.3.6), which states that relatively lower industry labour costs should attract relatively more firms to a region. Table 2.6 summarizes estimates of this relationship, controlling for regional distance to the nearest port (weighted by the share of value added in a region). Whenever the relationship between value added and labour costs is statistically significant, the relationship is negative, in line with the model.[31] While the point estimates vary, the median significant estimates is about -.8, indicating a 10% increase in unit labour costs is associated with an 8% decrease in value added per capita.

2.7 Conclusion

This paper examines the importance of local supply characteristics in determining firm input usage and productivity. To do so, a theory and empirical method are developed to identify firm input demand across industries and heterogeneous labour markets. The model derives labour demand as driven by the local distribution of wages and available skills. Firm behaviour in general equilibrium is derived, and determines firm location as a function of regional

[31] These results are robust if distance is unweighted, and to the inclusion of Economic Zone status.

TABLE 2.6: Determinants of Regional (Log) Value Added per Capita

Industry	$\ln\left(c_R^T\right)$	Std Err	100 km to Port	Std Err	Const	Std Err	Obs	R^2
Beverage	-0.696^b	(.274)	-0.122	(.200)	18.96^a	(3.36)	155	.03
Electrical	-0.057	(.403)	-1.567^a	(.259)	11.98^b	(4.80)	166	.22
Food	-0.553^b	(.229)	-0.397^b	(.179)	15.49^a	(2.15)	171	.04
General Machines	-0.705^c	(.400)	-1.314^a	(.340)	19.68^a	(4.86)	195	.11
Iron & Steel	-1.245^b	(.565)	-0.576^a	(.194)	16.30^a	(2.22)	160	.06
Leather & Fur	-1.255^a	(.249)	-1.028^b	(.421)	25.81^a	(3.05)	89	.27
Precision Tools	-0.267	(.300)	-1.135^b	(.432)	13.13^a	(3.39)	68	.07
Metal Products	-0.236	(.463)	-1.239^a	(.260)	13.24^a	(4.86)	157	.14
Non-ferrous Metal	-1.977^a	(.544)	-0.468^c	(.275)	27.29^a	(4.57)	139	.10
Non-metal Products	-0.827^a	(.290)	-0.910^a	(.155)	20.89^a	(3.38)	259	.11
Paper	-0.911^a	(.197)	-0.320	(.246)	20.04^a	(2.08)	159	.12
Plastic	-0.556	(.352)	-1.406^a	(.221)	16.86^a	(3.99)	159	.22
Printing	0.103	(.655)	-0.123	(.257)	8.54	(7.12)	98	.01
PC & AV	-0.212	(.366)	-0.741^b	(.333)	13.92^a	(4.60)	90	.04
Rubber	-0.424^c	(.219)	-0.470	(.398)	14.06^a	(2.07)	79	.06
Specific Machines	-0.316^c	(.184)	-0.680^a	(.194)	14.74^a	(2.28)	167	.07
Textile	-0.934^a	(.273)	-1.168^a	(.153)	19.70^a	(2.44)	186	.18
Transport	-0.105	(.099)	-1.119^a	(.253)	12.69^a	(1.30)	168	.10
Wood	-2.234^a	(.338)	-1.038^a	(.267)	47.02^a	(5.63)	133	.20

Note: a, b and c denote 1, 5 and 10% significance level respectively.

costs. This results in an estimator which can be easily implemented in two steps. The first step exploits differences in firm hiring patterns across distinct regional factor markets to recover firm labour demand by type. The second step uses the first stage to introduce local labour costs into production function estimation. Both steps characterize the impact of local market conditions on firm behaviour through recovery of model primitives. This is of particular interest when explaining the relative productivity or location of firms, especially in settings where local characteristics are known to be highly dissimilar.

Our empirical strategy combines information from the Chinese manufacturing, population census, and geographic data from the mid-2000s. Our estimates imply an interquartile difference in labour costs of 30 to 80 and productivity differences of 3 to 17 percent. The results suggest that team technologies combined with favourable factor market conditions explain substantial differences in firm input use and productivity. This shows that modelling a firm's local environment yields substantial insights into production patterns that are quantitatively important.

The importance of local factor markets for understanding firm behaviour suggests new dimensions for policy analysis. For instance, regions with labour markets which generate lower unit labour costs tend to attract higher levels of firm activity within an industry. As unit labour costs depend not only on the level of wages, but rather the distribution of wages and worker types that represent substitution options, this yields a more varied view of how educational policy or flows of different worker types could impact firms. Taken as a whole, our results show that policy changes which influence the composition of regional labour markets will have sizable effects on firm behaviour, productivity and location.

Finally, nothing precludes the application of this paper's approach beyond China, and it is suitable for analysing regions which exhibit a high degree of labour market heterogeneity. As the model affords the interpretation of trade between countries which have high barriers to immigration but low barriers to capital and input flows, it is also suitable for analysing firm behaviour across national borders. Further work could leverage or extend the approach of combining firm, census and geographic data to better understand the role of local factor markets on firm behaviour.

2.A Appendix

The organisation of the Appendix is as follows: Section 2.A.1 contains proofs of results discussed in the main text. Section 2.A.2 evaluates the efficacy of the reduced form model estimator. Section 2.A.3 contains more detail regarding model estimates. Three supplemental appendices are provided for online publication: Section 2.A.4 contains additional details on the model solution and properties. Section 2.A.5 contains summary statistics. Section 2.A.6 contains supplemental empirical results.

2.A.1 Further Model Discussion and Proofs

2.A.1.1 Optimality of Hiring All Worker Types

Proposition. If $\beta^T > 0$ then it is optimal for a firm to hire all types of workers.

Proof. Let c_R^T denote a firm's unit labour cost when all worker types are hired, and $\check{c}_R^T$ the unit labour cost if a subset of types $\mathbb{T} \subset \{1, \dots \mathbb{S}\}$ is hired. For the result, we require that $c_R^T \leq \check{c}_R^T$ for all $\mathbb{T}$. Considering a firm's cost minimisation problem when $\mathbb{T}$ are the only types available shows with Equation (2.2.7) that

$$\check{c}_R^T = \left[\sum_{i \in \mathbb{T}} \left[a_{R,i} \left(\underline{m}_i^T \right)^k w_{R,i}^{1-k} / f \left(k - 1 \right) \right]^{\theta^T / \beta^T} \right]^{\left(\beta^T / \theta^T \right) / (1-k)} .$$

Considering then that

$$c_R^T / \check{c}_R^T = \left[1 + \left(\sum_{i \notin \mathbb{T}} \left[a_{R,i} \left(\underline{m}_i^T \right)^k w_{R,i}^{1-k} \right]^{\theta^T / \beta^T} / \sum_{i \in \mathbb{T}} \left[a_{R,i} \left(\underline{m}_i^T \right)^k w_{R,i}^{1-k} \right]^{\theta^T / \beta^T} \right) \right]^{\left(\beta^T / \theta^T \right) / (1-k)} ,$$

clearly $c_R^T \leq \check{c}_R^T$ so long as $\beta^T / \theta^T (1-k) \leq 0$, which holds for $\beta^T > 0$ since $k > 1$. □

2.A.1.2 Existence of Regional Wages to Clear Input Markets

What is required is to exhibit a wage vector $\{w_{R,i}\}$ that ensures Equation (2.3.5) holds. Since all prices are nominal, WLOG we normalize $I_{\text{Agg}} = 1$ in the following.

Lemma. There is a wage function that uniquely solves (2.3.5) given unit labour costs.

Proof. Formally, we need to exhibit $\mathbb{W}$ such that

$$a_{R,i} = \mathbb{W}_{R,i}\left(\left\{c_{R'}^{T'}\right\}\right)^{-1}\sum_t \alpha_L^t\sigma^t\left(c_R^t\right)^{k/\beta^t-1}\left(\frac{\mathbb{W}_{R,i}\left(\left\{c_{R'}^{T'}\right\}\right)^{1-k}a_{R,i}\left(\underline{m}_i^t\right)^k}{f\left(k-1\right)}\right)^{\theta^t/\beta^t}\quad\forall R,i.$$

Fix $\left\{c_{R'}^{T'}\right\}$ and define $h_{R,i}\left(x\right)\equiv\sum_t\alpha_L^t\sigma^t\left(c_R^t\right)^{k/\beta^t-1}\left(x^{1-k}a_{R,i}\left(\underline{m}_i^t\right)^k/f\left(k-1\right)\right)^{\theta^t/\beta^t}$, $g_{R,i}\left(x\right)\equiv a_{R,i}x$. For the result we require a unique x s.t. $g_{R,i}\left(x\right)=h_{R,i}\left(x\right)$. $g_{R,i}$ is strictly increasing and ranges from 0 to ∞, while $h_{R,i}\left(x\right)$ is strictly decreasing, and ranges from ∞ to 0, so x exists and is unique. □

Lemma. The function $\left\{c_R^T\circ\mathbb{W}\left(\left\{c_R^T\right\}\right)\right\}$, *where* c_R^T *is the unit cost function of Equation (2.2.7), has a fixed point* $\left\{\widehat{c}_R^T\right\}$ *and so* $\mathbb{W}\left(\left\{\widehat{c}_R^T\right\}\right)$ *is a solution to* Equation (2.3.5).

Proof. We first show that any equilibrium wage vector must lie in a strictly positive, compact set $\times_{R,i}\left[\underline{w}_{R,i},\overline{w}_{R,i}\right]$. From (2.3.5), $H_{R,i}^{\theta^T}/\Sigma_j H_{R,j}^{\theta^T}\in[0,1]$ so $w_{R,i}\leq\overline{w}_{R,i}\equiv\sum_t\alpha_L^t\sigma^t/a_{R,i}$. Let

$$\underline{b}_R\equiv\min_i\sum_t\alpha_L^t\sigma^t\left(a_{R,i}\left(\underline{m}_i^t\right)^k\right)^{\theta^t/\beta^t}/\sum_i\left[a_{R,i}\left(\underline{m}_i^t\right)^k\right]^{\theta^t/\beta^t}a_{R,i},$$

and we will show that a lower bound for equilibrium wages is $\underline{w}_R\equiv\begin{bmatrix}\underline{b}_R, & \ldots, & \underline{b}_R\end{bmatrix}$ for each R. Consider that for $\mathbb{W}$ evaluated at $\left\{c_R^T\left(\underline{w}_R\right)\right\}$,

$$\mathbb{W}_{R,i}=\sum_t\alpha_L^t\sigma^t\left(a_{R,i}\left(\underline{m}_i^t\right)^k\left(\mathbb{W}_{R,i}/\underline{w}_R\right)^{1-k}\right)^{\theta^t/\beta^t}/\sum_i\left[a_{R,i}\left(\underline{m}_i^t\right)^k\right]^{\theta^t/\beta^t}a_{R,i}. \tag{2.A.1}$$

Evaluating Equation (2.A.1), if $\mathbb{W}_{R,i} \leq \underline{w}_R$ then $\mathbb{W}_{R,i} \geq \underline{w}_R$, and otherwise, $\mathbb{W}_{R,i} \geq \underline{w}_R$ so $\{\underline{w}_R\}$ is a lower bound for $\mathbb{W}\left(\left\{c_R^T\left(\underline{w}_R\right)\right\}\right)$. Since necessarily $\mathbb{W}\left(\left\{c_R^T\left(\hat{w}_R\right)\right\}\right) = \{\hat{w}_R\}$, $\mathbb{W}$ is increasing in $\left\{c_R^T\right\}$, and $c_R^T\left(w_R\right)$ is increasing in w_R, we have $\{\hat{w}_R\} = \mathbb{W}\left(\left\{c_R^T\left(\hat{w}_R\right)\right\}\right) \geq \mathbb{W}\left(\left\{c_R^T\left(\underline{w}_R\right)\right\}\right) \geq \{\underline{w}_R\}$. In conclusion, all equilibrium wages must lie in $\times_{R,i}\left[\underline{w}_{R,i}, \overline{w}_{R,i}\right]$.

Now define a strictly positive, compact domain for $\left\{c_R^T\right\}$, $\times_R\left[\underline{c}_R^T, \overline{c}_R^T\right]$, by

$$\underline{c}_R^T \equiv \inf_{\times_i\left[\underline{w}_{R,i}, \overline{w}_{R,i}\right]} c_R^T\left(w_R\right) = c_R^T\left(\underline{w}_R\right), \qquad \overline{c}_R^T \equiv \sup_{\times_i\left[\underline{w}_{R,i}, \overline{w}_{R,i}\right]} c_R^T\left(w_R\right) = c_R^T\left(\overline{w}_R\right).$$

Now consider the mapping $\mathbb{C}\left(\left\{c_R^T\right\}\right) \equiv \left\{c_R^T \circ \mathbb{W}\left(\left\{c_R^T\right\}\right)\right\}$ on $\times_R\left[\underline{c}_R^T, \overline{c}_R^T\right]$, which is continuous on this domain. By above, $\mathbb{W}_{R,i}\left(\left\{c_R^T\right\}\right) \leq \overline{w}_{R,i}$ for each R, i so $\mathbb{C}\left(\left\{c_R^T\right\}\right) \leq \left\{\overline{c}_R^T\right\}$. Also by above, $\mathbb{C}\left(\left\{c_R^T\right\}\right) \geq \left\{c_R^T \circ \mathbb{W}\left(\left\{c_R^T\left(\underline{w}_R\right)\right\}\right)\right\} \geq \left\{c_R^T\left(\left\{\underline{w}_R\right\}\right)\right\} = \left\{\underline{c}_R^T\right\}$. Thus $\mathbb{C}$ maps $\times_R\left[\underline{c}_R^T, \overline{c}_R^T\right]$ into itself and by Brouwer's fixed point theorem, there exists a fixed point $\left\{\widehat{c}_R^T\right\}$, which implies $\mathbb{W}\left(\left\{\widehat{c}_R^T\right\}\right)$ is an equilibrium wage vector. □

2.A.2 Model Simulation and Estimator Viability

A model simulation was constructed using parameters given in Table 2.7. In the simulation, firms maximize profits conditional on local market conditions, and applying the estimator above produces Tables 2.8 and 2.8. The Estimate column contains results while the model values are reported in the Predicted column. The estimates are very close to the predicted values. Figure 2.5 further confirms this by plotting the simulated and predicted differences in the share of workers hired. For ease of comparison, Figure 2.5 plots regional frequencies along the horizontal axis and (linearly) normalized wages for each worker type. As the Figure suggests, the R^2 in both cases are high: .99 for the first stage and .97 for the second stage.

FIGURE 2.5: Simulation Fit

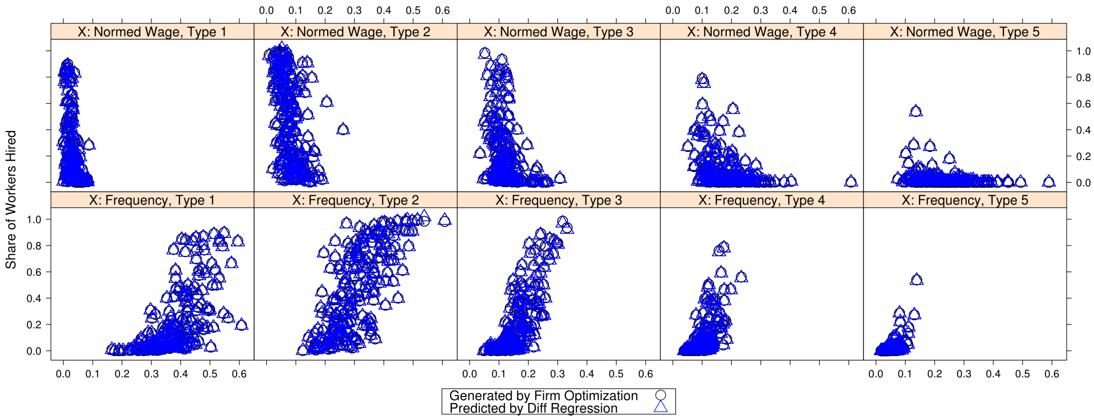


TABLE 2.7: Simulation details

Variable	Description	Value
θ^T	Technological parameter.	2
k	Pareto shape parameter.	1.5
$\{\underline{m}_i\}$	Human capital shifters.	$\{4, 8, 12, 16, 20\}$
$\{w_{R,i}\}$	Regional wages by type.	$\sim$LogNormal $\mu = (12, 24, 36, 48, 60)$, $\sigma = 13$.
$\{a_{R,i}\}$	Regional type frequencies.	$\sim$LogNormal $\mu = (.4, .3, .15, .1, .05)$, $\sigma = 13$, scaled so that frequencies sum to one.
K, M	Firm capital and materials.	$\sim$LogNormal $\mu = 1$, $\sigma = 1$.
L	Level of L employed by firm.	Profit maximizing given K, M and region.
$\alpha_M, \alpha_K, \alpha_L$	Production Parameters.	$\alpha_M = 1/6$, $\alpha_K = 1/3$, $\alpha_L = 1/2$.
Control	Misc variable for output.	$\sim$LogNormal $\mu = 0$, $\sigma = 1$.
Coeff	Exponent on Control.	Control Coeff$= \pi$.
$\{\omega_j\}$	Firm idiosyncratic wage costs.	$\sim$LogNormal $\mu = 0$, $\sigma = .1$.

Sample: 200 regions with 20 firms per region, with errors $\sim$LogNormal($\mu = 0$, $\sigma = 12$).

TABLE 2.8: Simulation Results

[Simulation First Stage Estimates: Technology and Human Capital]

Variable	Parameter	Estimate	Std Err	Predicted
$\{\ln a_{R,i}\}$	$\left(\theta^T/\beta^T\right)$	3.912	.0019	4
$\{\ln w_{R,i}\}$	$\left(-k/\beta^T\right)$	-2.922	.0021	-3
Dummy (Type = 1)	$\left(\theta^T/\beta^T\right) k \left(\ln \underline{m}_1/\underline{m}_5\right)$	-9.376	.0057	-9.657
Dummy (Type = 2)	$\left(\theta^T/\beta^T\right) k \left(\ln \underline{m}_2/\underline{m}_5\right)$	-5.295	.0045	-5.498
Dummy (Type = 3)	$\left(\theta^T/\beta^T\right) k \left(\ln \underline{m}_3/\underline{m}_5\right)$	-2.950	.0031	-3.065
Dummy (Type = 4)	$\left(\theta^T/\beta^T\right) k \left(\ln \underline{m}_4/\underline{m}_5\right)$	-1.274	.0024	-1.339

[Simulation Second Stage Estimates: Production Parameters]

Variable	Parameter	Estimate	Std Err	Predicted
$\ln M$	$\alpha_M/\left(1-\alpha_L\right)$	.3298	.0079	.3333
$\ln K$	$\alpha_K/\left(1-\alpha_L\right)$	.6680	.0080	.6667
$\ln c_{RT}$	$-\alpha_L/\left(1-\alpha_L\right)$	-.9303	.0748	-1
Control	Control Coeff	3.148	.0079	3.141

2.A.3 Model Estimates

TABLE 2.9: First Stage Estimates I

Industry	Beverage	Electrical Equip	Food	General Machines	Iron & Steel	Leather & Fur	Precision Equipment	Metal Products	Non-ferrous Metal
				Dependent Variable: $\ln(\%\text{type})$					
$\ln(w_{R,i})$	-1.808^a	-2.977^a	-0.870	-2.687^a	-2.150^a	-0.708^c	-4.517^a	-3.174^a	-3.096^a
$\ln(a_{R,i})$	1.673^a	1.878^a	1.489^a	1.794^a	1.018^a	0.636^a	3.358^a	1.439^a	1.627^a
m_1 (≤Junior HS: Fem)	-8.447^a	-9.491^a	-3.186	-10.170^a	7.190^a	-2.052	-13.450^a	-5.800^a	-1.189
m_2 (≤Junior HS: Male)	-5.947^c	-7.181^a	-1.504	-6.171^a	12.370^a	-1.089	-11.160^a	-2.176^c	3.768^c
m_3 (Senior High School)	-2.470	-4.475^a	1.123	-3.180^a	14.210^a	-2.058^c	-4.100^b	-0.758	6.119^a
m_1∗% Non-Ag Hukou	0.837	-7.619^a	-2.341^b	-5.957^a	-2.373^c	-4.544^a	-7.142^a	-6.038^a	-4.591^a
m_2∗% Non-Ag Hukou	0.306	-3.272^a	-1.880	-3.072^a	-1.355	-2.882^c	-3.957^c	-1.805^b	-0.370
m_3∗% Non-Ag Hukou	-1.102	-0.593	-0.837	-3.218^a	-2.394^a	-1.606^b	0.315	-1.104^b	-0.903
m_4∗% Non-Ag Hukou	-3.913	-4.572^a	-0.426	-7.026^a	10.130^a	-8.496^a	1.793	-2.491^b	3.403
$\underline{m}_1 *$ Urban Dummy	-0.271	-1.379^a	-1.462^a	-1.384^a	-1.393^a	-0.0822	-1.032^a	-1.408^a	-1.188^a
$\underline{m}_2 *$ Urban Dummy	-0.007	-0.991^a	-1.085^a	-0.980^a	-0.585^a	-0.128	-1.176^a	-0.533^a	-0.601^a
$\underline{m}_3 *$ Urban Dummy	0.286^c	0.139^b	0.175	0.427^a	0.503^a	0.220^c	-0.249	0.247^a	0.108
$\underline{m}_4 *$ Urban Dummy	2.212^a	1.513^a	1.743^a	2.336^a	3.275^a	0.683^a	1.053^a	2.147^a	1.791^a
m_1∗% Foreign Equity	0.531^a	1.030^a	0.841^a	0.934^a	0.751^a	-0.107	1.952^a	0.876^a	1.366^a
m_2∗% Foreign Equity	0.422^a	0.678^a	0.661^a	0.403^a	0.354^a	-0.0680	1.840^a	0.335^a	0.432^a
m_3∗% Foreign Equity	0.106	0.259^a	0.197^b	0.143^a	0.083	0.257^a	0.574^a	0.145^a	0.093
m_4∗% Foreign Equity	-0.005	0.232^a	0.015	0.351^a	-0.069	0.249	0.033	-0.150	0.589^a
$m_1 * \ln(\text{Firm Age})$	-2.803^a	-0.215	-0.983^a	-2.448^a	-2.160^a	0.113	0.727^b	-0.627^a	-2.156^a
$m_2 * \ln(\text{Firm Age})$	-2.290^a	-0.547^a	-0.494^c	-1.864^a	-1.662^a	-0.190^b	0.319	-0.788^a	-1.838^a
$m_3 * \ln(\text{Firm Age})$	0.714^a	-0.114	0.016	0.311^a	0.862^a	0.198	-0.510^b	0.417^a	0.695^a
$m_4 * \ln(\text{Firm Age})$	2.840^a	1.621^a	2.301^a	3.847^a	5.656^a	3.133^a	0.279	3.488^a	4.413^a
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,900	48,960	15,228	62,908	18,704	19,408	10,808	42,744	14,428
R-squared	0.124	0.117	0.098	0.139	0.168	0.208	0.246	0.124	0.145

Note: a, b and c denote 1, 5 and 10% significance level respectively.

TABLE 2.10: First Stage Estimates II

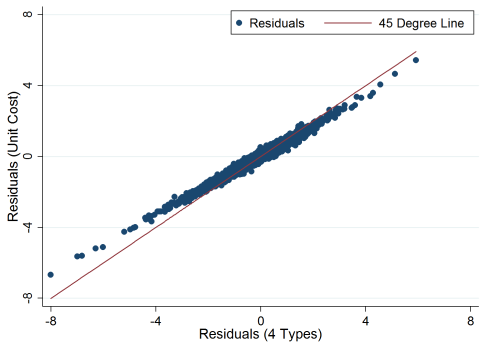
Industry	Other Non-metal	Paper	Plastic	Printing	PC & AV Equipment	Rubber	Specific Machines	Textile	Transport Equip	Wood
	Dependent Variable: $\ln(\%\text{type})$									
$\ln(w_{R,i})$	-1.693^{a}	-1.542^{a}	-3.324^{a}	-3.491^{a}	-3.371^{a}	-0.854	-1.260^{a}	-2.230^{a}	-0.372	-1.220^{b}
$\ln(a_{R,i})$	1.664^{a}	0.332^{b}	1.321^{a}	1.212^{a}	2.785^{a}	1.267^{a}	1.961^{a}	0.830^{a}	1.477^{a}	2.286^{a}
m_1 ($\leq$Junior HS: Fem)	-7.246^{a}	-3.469^{c}	-7.881^{a}	-5.515^{b}	-13.770^{a}	-1.997	-10.130^{a}	1.588	-6.326^{a}	-10.890^{a}
m_2 ($\leq$Junior HS: Male)	-3.128^{a}	-0.645	-4.596^{a}	-2.913	-11.970^{a}	0.188	-4.811^{a}	2.703^{b}	-3.359^{b}	-9.086^{a}
m_3 (Senior High School)	-0.808	0.076	-2.657^{b}	-1.849	-7.325^{a}	2.347	-1.515	3.468^{a}	-1.290	-6.106^{b}
m_1*% Non-Ag Hukou	-2.750^{a}	-6.210^{a}	-6.682^{a}	-5.979^{a}	-7.176^{a}	-5.162^{a}	-4.763^{a}	-6.271^{a}	-5.279^{a}	-0.301
m_2*% Non-Ag Hukou	-1.750^{a}	-6.148^{a}	-4.710^{a}	-4.386^{a}	-5.210^{a}	-2.819^{c}	-4.295^{a}	-5.555^{a}	-3.153^{a}	-0.308
m_3*% Non-Ag Hukou	-2.198^{a}	-3.251^{a}	-2.685^{a}	-1.835^{b}	0.597	-3.361^{a}	-1.463^{a}	-3.264^{a}	-1.039^{b}	-2.549^{a}
m_4*% Non-Ag Hukou	-3.926^{a}	-7.690^{a}	-7.074^{a}	-4.440^{c}	-3.291^{a}	-2.211	-2.447	-4.025^{a}	-3.450^{b}	-13.060^{a}
$\underline{m}_1 *$ Urban Dummy	-1.333^{a}	-0.691^{a}	-1.057^{a}	-1.711^{a}	-1.881^{a}	-0.819^{a}	-1.597^{a}	-0.650^{a}	-1.130^{a}	-1.630^{a}
$\underline{m}_2 *$ Urban Dummy	-0.834^{a}	-0.338^{b}	-0.590^{a}	-1.170^{a}	-1.619^{a}	-0.603^{a}	-1.234^{a}	-0.421^{a}	-0.714^{a}	-0.720^{a}
$\underline{m}_3 *$ Urban Dummy	0.250^{a}	0.350^{a}	0.272^{a}	0.198	-0.512^{a}	-0.035	0.216^{b}	0.285^{a}	0.233^{a}	0.129
$\underline{m}_4 *$ Urban Dummy	2.570^{a}	2.644^{a}	2.413^{a}	2.251^{a}	0.902^{a}	2.211^{a}	1.924^{a}	2.709^{a}	1.381^{a}	3.331^{a}
m_1*% Foreign Equity	0.834^{a}	0.407^{a}	0.877^{a}	0.193	1.340^{a}	0.620^{a}	1.588^{a}	0.214^{a}	1.023^{a}	0.415^{a}
m_2*% Foreign Equity	0.244^{a}	0.153^{c}	0.361^{a}	-0.029	1.072^{a}	0.234^{c}	0.750^{a}	0.202^{a}	0.547^{a}	0.176
m_3*% Foreign Equity	0.028	0.039	0.048	0.242^{a}	0.294^{a}	0.002	0.169^{a}	0.137^{a}	0.129^{a}	-0.142
m_4*% Foreign Equity	-0.310^{a}	-0.012	0.000	0.176	-0.160^{b}	-0.191	0.097	0.442^{a}	0.168^{b}	0.197
$m_1 * \ln(\text{Firm Age})$	-1.016^{a}	-1.899^{a}	-0.857^{a}	-0.247	0.310	-0.576	-1.601^{a}	-0.384^{a}	-1.266^{a}	-0.423
$m_2 * \ln(\text{Firm Age})$	-0.768^{a}	-0.819^{a}	-0.773^{a}	-0.402	0.223	-0.242	-1.675^{a}	-0.058	-1.171^{a}	0.066
$m_3 * \ln(\text{Firm Age})$	0.105	0.457^{a}	0.398^{a}	-0.023	-0.049	0.319	0.100	0.445^{a}	0.588^{a}	-0.468
$m_4 * \ln(\text{Firm Age})$	3.429^{a}	4.850^{a}	3.776^{a}	3.143^{a}	0.321^{a}	2.577^{a}	1.629^{a}	4.391^{a}	2.298^{a}	3.850^{a}
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,388	22,792	36,940	13,528	26,796	8,848	31,264	73,168	34,528	14,516
R-squared	0.150	0.164	0.130	0.107	0.188	0.120	0.177	0.221	0.129	0.245

Note: a, b and c denote 1, 5 and 10% significance level respectively.

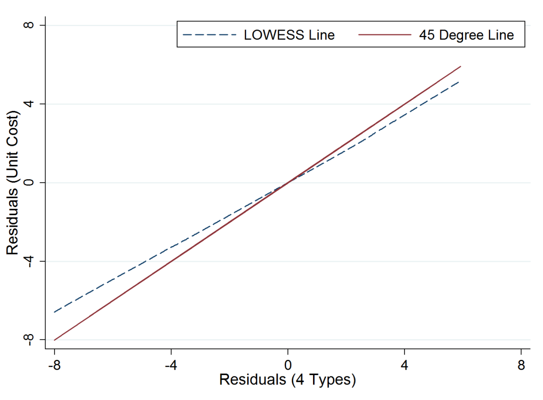
2.A.3.1 Residual Comparison: Unit Labour Costs vs Substitutable Labour

Of particular interest for work on productivity are the residuals remaining after the second estimation step, which are often interpreted as idiosyncratic firm productivity. Figure 2.6 contrasts unexplained productivity (estimation residuals) when unit labour costs are used with estimates that measure labour by including the employment of each worker type. Examining the 45 degree line also plotted in the Figure, a general pattern emerges: above average firms under the employment measure are slightly less productive under the unit cost approach, while below average firms are more productive. This suggests that a more detailed analysis of the role of local factor markets may substantially alter interpretation of differences in firm productivity.

FIGURE 2.6: Productivity: Unit Labour Costs vs Total Employment (General Machines)



(a) Residuals



(b) Fit

2.A.3.2 Comparison with Conventional Labour Measures

The estimates above reflect a procedure using regional variation to recover the unit cost of labour. Often, such information is not incorporated into production estimation. Instead, the number of employees or total wage bill are used to capture the effective labour available to a firm. The mean of the second stage estimates using these labour measures are contrasted with our method in Table 2.11 (full results in Table 2.19 of the Supplemental Appendix). The production coefficients using the total wage bill or total employment are very similar, reflecting the high correlation of these variables. However, both measures mask regional differences in factor markets. Once local substitution patterns are taken into account explicitly, substantial differences emerge.[32] Most notably, the capital share tends to be higher under our approach, while the labour share is substantially lower.

TABLE 2.11: Second Stage Estimates vs Homogeneous Labour Estimates

	Unit Labour Cost			Total Wage Bill			Total Employment		
	α_L	α_K	α_M	α_L	α_K	α_M	α_L	α_K	α_M
Average	0.18	0.13	0.55	0.29	0.09	0.54	0.28	0.09	0.58

Pushing this comparison further, Table 2.18 predicts the propensity to export of firms by residual firm productivity. The first column shows the results under our unit cost method. The second and third columns show the results when labour is measured as perfectly substitutable (either by employment of each type or wages). Note that in all cases, regional and industry effects are controlled for. The Table illustrates that productivity estimates which account for regional factor markets are almost twice as important in predicting exports as the other measures. Section 2.A.6.2 of the Appendix shows that similar results hold when examining sales growth and three year survival rate: productivity under the unit cost approach is more important in predicting firm performance, suggesting the other measures conflate the role of advantageous factor markets with productivity.

[32]The residuals remaining after the second estimation step, which are often interpreted as idiosyncratic firm productivity, are compared in Appendix 2.A.3.1.

TABLE 2.12: Explaining Propensity to Export with Productivity

	Export Dummy (2005)		
Productivity under Unit Cost method	0.0242***		
	(0.00393)		
Productivity under L = 4 Types		0.0131***	
		(0.00241)	
Productivity under L = Wage Bill			0.0168***
			(0.00252)
Prefecture and Industry FE	Yes	Yes	Yes
Observations	141,409	141,409	141,409
R-squared	0.202	0.201	0.202

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

2.A.4 Supplemental Derivations

2.A.4.1 Derivation of Region-Techonology Budget Shares

The expressions which fix the cutoff cost draw $\overline{\eta}_R^T$ and mass of entry $\mathbb{M}_R^T$ can be neatly summarized by defining the mass of entrants who produce, $\widetilde{\mathbb{M}}_R^T$, and the (locally weighted) average cost draw in each region, $\widetilde{\eta}_R^T$:

$$\widetilde{\mathbb{M}}_R^T \equiv \mathbb{M}_R^T G\left(\overline{\eta}_R^T\right), \qquad \widetilde{\eta}_R^T \equiv \int_0^{\overline{\eta}_R^T} \left(\eta_z^T u_R^T \left(U_R^T\right)^{1/\rho}\right)^{\rho/(\rho-1)} dG\left(z\right)/G\left(\overline{\eta}_R^T\right).$$

Using the profit maximizing price P_{Rj}^T and combining Equations (2.2.11), (2.3.2) and (2.3.1) then yields the equilibrium quantity produced,

$$Q_{Rj}^T = \rho I_{\text{Agg}} \left(u_R^T \eta_j \left(U_R^T/\sigma_R^T\right)^{1/\rho}\right)^{\rho/(\rho-1)} / u_R^T \eta_j \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t. \tag{2.A.2}$$

Aggregating revenues using Equation (2.A.2) shows that each consumer's budget share allocated to region R and industry T is

$$\text{Consumer Budget Share for R, T}: \quad \left(\sigma_R^T\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_R^T \widetilde{\eta}_R^T / \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t. \tag{2.A.3}$$

Consequently, since free entry implies expected profits must equal expected fixed costs, the mass of entrants $\mathbb{M}_R^T$ solves the implicit form[33]

$$\frac{1-\rho}{\rho} I_{\text{Agg}} \left(\left(\sigma_R^T\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_R^T \widetilde{\eta}_R^T / \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t \right) = \mathbb{M}_R^T u_R^T \left(f_e G\left(\overline{\eta}_R^T\right) + F_e \right), \tag{2.A.4}$$

while the equilibrium cost cutoffs $\overline{\eta}_R^T$ solve the zero profit condition[34]

$$\frac{1-\rho}{\rho} I_{\text{Agg}} \left(\sigma_R^T\right)^{1/(1-\rho)} \left(u_R^T \overline{\eta}_R^T \left(U_R^T\right)^{1/\rho} \right)^{\rho/(\rho-1)} = u_R^T f_e \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t. \tag{2.A.5}$$

Equations (2.A.4) and (2.A.5) fix $\overline{\eta}_R^T$ since combining them shows

$$\int_0^{\overline{\eta}_R^T} \left(\eta_z^T / \overline{\eta}_R^T\right)^{\rho/(\rho-1)} dG(z) / G\left(\overline{\eta}_R^T\right) = 1 + F_e / f_e G\left(\overline{\eta}_R^T\right).$$

In particular, $\overline{\eta}_R^T$ does not vary by region or technology. Thus, Equation (2.A.5) shows that

$$U_R^T u_R^T / \sigma_R^T = \left[(1-\rho) I_{\text{Agg}} / \rho f_e \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t \right]^{1-\rho} / \left(\overline{\eta}_R^T\right)^{\rho}. \tag{2.A.6}$$

where the RHS does not vary by region or technology. Combining this equation with (2.3.1) shows $Q_{Rj}^T = Q_{R'j}^{T'}$ for all (T, R) and (T', R'), so that $\mathbb{M}_R^T u_R^T / \sigma_R^T = \mathbb{M}_{R'}^{T'} u_{R'}^{T'} / \sigma_{R'}^{T'}$. At the same time, using Equation (2.A.6) reduces (2.A.3) to

$$\text{Consumer Budget Share for R, T}: \quad \mathbb{M}_R^T u_R^T / \sum_{t,r} \mathbb{M}_r^t u_t^t = \sigma_R^T / \sum_{t,r} \sigma_r^t = \sigma_R^T.$$

Since $\sum_{t,r} \sigma_r^t = 1$, each region and industry receive a share σ_R^T of consumer expenditure.

[33]To see a solution exists, note that for fixed prices, $\{\widetilde{\eta}_R^T\}$, and $\{\overline{\eta}_R^T\}$, necessarily $\mathbb{M}_R^T \in A_R^T \equiv \left[0, (1-\rho) I_{\text{Agg}} / \rho u_R^T F_e\right]$. Existence follows from the Brouwer fixed point theorem on the domain $\times_{R,T} A_R^T$ for $H\left(\left\{\widetilde{\mathbb{M}}_R^T\right\}\right) \equiv (1-\rho) I_{\text{Agg}} \left(\left(\sigma_R^T\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_R^T \widetilde{\eta}_R^T / \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t \right) / \rho u_R^T \left(f_e G\left(\overline{\eta}_R^T\right) + F_e \right)$.

[34]To see a solution exists, note that for fixed prices, $\left\{\mathbb{M}_{R'}^{T'}\right\}$ and $\{U_R^T\}$, the LHS ranges from 0 to ∞ as $\overline{\eta}_R^T$ varies, while the RHS is bounded away from 0 and ∞ when $\min\left\{\widetilde{\eta}_r^t G\left(\overline{\eta}_r^t\right)\right\} > 0$. $\widetilde{\eta}_R^T G\left(\overline{\eta}_R^T\right) > 0$ follows from inada type conditions on goods from each T and R.

2.A.4.2 Regional Variation in Input Use

Equation (2.4.1) specifies the relative shares of each type of worker hired. Since input markets are competitive, firms and workers take regional labour market characteristics as given. As characteristics such as wages worker availability and human capital vary, the share of each labour type hired differs across regions. These differences can be broken up into direct and indirect effects. Direct effects ignore substitution by holding the unit labour cost $\widetilde{c}_{RT}$ constant, while indirect effects measure how regional differences give rise to substitution. The direct effects are easy to read off of Equation (2.4.1), showing:

$$\text{Direct Effects}: \quad d\ln s_{R,T,i}/d\ln w_{R,i}|_{\widetilde{c}_{RT}\text{ constant}} = -k/\beta^T < 0, \tag{2.A.7}$$

$$d\ln s_{R,T,i}/d\ln a_{R,i}|_{\widetilde{c}_{RT}\text{ constant}} = \theta^T/\beta^T > 0, \tag{2.A.8}$$

$$d\ln s_{R,T,i}/d\ln \underline{m}_i^T|_{\widetilde{c}_{RT}\text{ constant}} = k\theta^T/\beta^T > 0. \tag{2.A.9}$$

These direct effects have the obvious signs: higher wages ($w_{R,i}$ ↑) discourage hiring a particular type while greater availability ($a_{R,i}$ ↑) and higher human capital ($m_{T,i}$ ↑) encourage hiring that type. The indirect effects of substitution through $\widetilde{c}_{RT}$ are less obvious as seen by

$$d\ln \widetilde{c}_{RT}^k/d\ln w_{R,i} = \left(k/\theta^T\right)\left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k-\beta^T/\theta^T}\right]^{\theta^T/\beta^T} \widetilde{c}_{RT}^{\,k\left(\theta^T/\beta^T\right)} > 0, \tag{2.A.10}$$

$$d\ln \widetilde{c}_{RT}^k/d\ln a_{R,i} = -\left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k-\beta^T/\theta^T}\right]^{\theta^T/\beta^T} \widetilde{c}_{RT}^{\,k\left(\theta^T/\beta^T\right)} < 0, \tag{2.A.11}$$

$$d\ln \widetilde{c}_{RT}^k/d\ln \underline{m}_i^T = -k\left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k-\beta^T/\theta^T}\right]^{\theta^T/\beta^T} \widetilde{c}_{RT}^{\,k\left(\theta^T/\beta^T\right)} < 0. \tag{2.A.12}$$

Thus, the indirect effects counteract the direct effects through substitution. To see the total of the direct and indirect effects, define the Type-Region-Technology coefficients $\chi_{i,R,T}$:

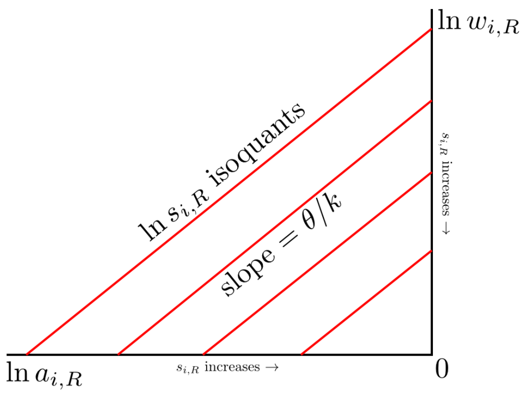
$$\chi_{i,R,T} \equiv 1 - \left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k-\beta^T/\theta^T}\right]^{\theta^T/\beta^T} \widetilde{c}_{RT}^{\,k\left(\theta^T/\beta^T\right)}.$$

Investigation shows that each $\chi_{i,R,T}$ is between zero and one. Combining Equations (2.A.7-2.A.9) and Equations (2.A.10-2.A.12) shows that the direct effect dominates since

$$\text{Total Effects}: \quad d\ln s_{R,T,i}/d\ln w_{R,i} = \left[-k/\beta^T\right]\chi_{i,R,T} < 0, \tag{2.A.13}$$
$$d\ln s_{R,T,i}/d\ln a_{R,i} = \left[\theta^T/\beta^T\right]\chi_{i,R,T} > 0, \tag{2.A.14}$$
$$d\ln s_{R,T,i}/d\ln \underline{m}_i^T = \left[k\theta^T/\beta^T\right]\chi_{i,R,T} > 0. \tag{2.A.15}$$

Equations (2.A.13-2.A.15) summarize the relationship between regions and labour market characteristics. For small changes in labour market characteristics, the log share of a type hired in linear in log characteristics with a slope determined by model parameters and a regional shifter $\chi_{i,R,T}$. These (local) isoquants for the share of type i workers hired in region R are depicted in Figure 2.7.

FIGURE 2.7: Local isoquants for Share of Workers Hired



2.A.4.3 Regional Variation in Theory: Isoquants

Equations (2.A.13-2.A.15) also characterize local isoquants of hiring the same share of a type across regions. It is immediate that for small changes in market characteristics, $\begin{pmatrix} \Delta_w, & \Delta_a, & \Delta_m \end{pmatrix}$, the share of a type hired is constant so long as

$$-\left(k/\theta^{T}\right)\Delta_{w}/w_{R,i}+\Delta_{a}/a_{R,i}+k\Delta_{m}/\underline{m}_{i}^{T}=0.$$

For instance, firms in regions R and R' will hire the same fraction of type i workers for small differences in characteristics (Δ_w, Δ_a) so long as

$$\Delta_{w}/\Delta_{a}=\left(\theta^{T}/k\right)w_{R,i}/a_{R,i}. \tag{2.A.16}$$

By itself, an increase in type i wages Δ_w would cause firms to hire a lower share of type i workers as indicated by the direct effect. However, Equation (2.A.16) shows that firms would keep the same share of type i workers if the availability Δ_a increases concurrently so that Equation (2.A.16) holds.

2.A.4.4 Derivation of Unit Labour Costs

Unit labour costs by definition solve

$$\text{Unit Labour Costs}: \quad c_{R}^{T}\equiv\min_{H}C_{T}\left(H|a_{R},w_{R}\right)\text{ subject to }L=\phi\left(\tilde{H},\theta^{T}\right)\cdot H_{\mathrm{TOT}}=1.$$

Under the parameterisation $\Psi\left(h\right)=1-h^{-k}$, Equations (2.2.1) become

$$H_{i}=a_{R,i}k/\left(k-1\right)\cdot\underline{m}_{i}^{T}\underline{h}_{i}^{1-k}\cdot N. \tag{2.A.17}$$

From above, $w_{R,i}H_i/\underline{m}_i^T\underline{h}_iC_T\left(H|a_R,w_R\right)=H_i^{\theta^T}/\sum_j H_j^{\theta^T}$, and $L=1=\left(\sum_j H_j^{\theta^T}\right)^{1/\theta^T}$ so

$$\underline{h}_{i}=w_{R,i}H_{i}^{1-\theta^{T}}/\underline{m}_{i}^{T}C_{T}\left(H|a_{R},w_{R}\right). \tag{2.A.18}$$

Substitution now yields

$$H_{i}=a_{R,i}k/\left(k-1\right)\cdot\underline{m}_{i}^{T}\left(w_{R,i}H_{i}^{1-\theta^{T}}/\underline{m}_{i}^{T}C_{T}\left(H|a_{R},w_{R}\right)\right)^{1-k}\cdot N. \tag{2.A.19}$$

Further reduction and the definition of β^T shows that

$$H_i^{\beta^T} = H_i^{\theta^T + k - k\theta^T} = a_{R,i}k/(k-1) \cdot \left(\underline{m}_i^T\right)^k w_{R,i}^{1-k} C_T\left(H|a_R, w_R\right)^{k-1} N. \quad (2.A.20)$$

Again using $\left(\sum_j H_j^{\theta^T}\right)^{1/\theta^T} = 1$ then shows

$$1 = \sum_i \left[a_{R,i}k/(k-1) \cdot \underline{m}_i^{Tk} w_{R,i}^{1-k} \left(c_R^T\right)^{k-1} N\right]^{\theta^T/\beta^T}. \quad (2.A.21)$$

From the definition of the cost function we have

$$c_R^T = N\left[\sum_i a_{R,i} w_{R,i} \underline{h}_i^{-k} + f c_R^T\right] = \sum_i w_{R,i}\left(\left(k-1\right)/k\right) H_i / \underline{m}_i^T \underline{h}_i + N f c_R^T.$$

Therefore from $w_{R,i} H_i / \underline{m}_i^T \underline{h}_i C_T\left(H|a_R, w_R\right) = H_i^{\theta^T}$ it follows

$$1 = \sum_i \left(k-1\right)/k \cdot H_i^{\theta^T} + Nf = \left(k-1\right)/k + Nf,$$

and therefore $N = 1/fk$. Now from Equation (2.A.21) c_R^T is seen to be Equation (2.2.7).

2.A.4.5 Derivation of Employment Shares

Combining Equations (2.A.18), (2.A.20) and $N = 1/fk$ shows

$$\underline{h}_i = a_{R,i}^{\left(1-\theta^T\right)/\beta^T} \left(\underline{m}_i^T\right)^{-\theta^T/\beta^T} w_{R,i}^{1/\beta^T} \left(c_R^T\right)^{-1/\beta^T} / \left(f\left(k-1\right)\right)^{\left(1-\theta^T\right)/\beta^T}. \quad (2.A.22)$$

Let $A_{R,i}^T$ be the number of type i workers hired to make $L = 1$, exclusive of fixed search costs. By definition, $A_{R,i}^T = N|_{L=1} a_{R,i}\left(1 - \Psi\left(\underline{h}_i\right)\right) = a_{R,i}\underline{h}_i^{-k}/fk$. Using Equation (2.A.22),

$$A_{R,i}^T = k^{-1}\left(k-1\right) a_{R,i}^{\theta^T/\beta^T} \left(\underline{m}_i^T\right)^{k\theta^T/\beta^T} w_{R,i}^{-k/\beta^T} \left(c_R^T\right)^{k/\beta^T} \left(k-1\right)^{-\theta^T/\beta^T} f^{-1}.$$

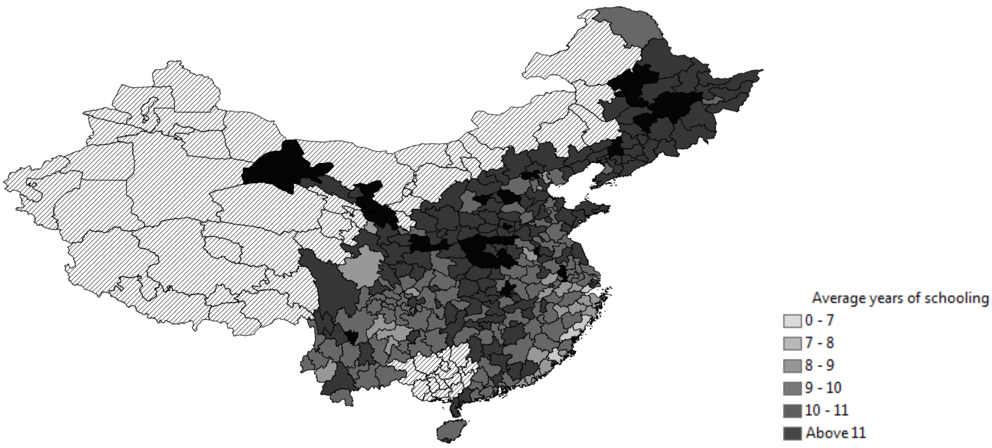
Labour is also consumed by the fixed search costs which consist of $N|_{L=1} \cdot f = 1/k$ labour units. Therefore, if $\widetilde{A}^T_{R,i}$ denotes the total number of type i workers hired to make $L = 1$, necessarily $\widetilde{A}^T_{R,i} = A^T_{R,i} + \widetilde{A}^T_{R,i}/k$ so $\widetilde{A}^T_{R,i} = k\,(k-1)^{-1} A^T_{R,i}$, and the total number of type i workers hired in region R using technology T is $L^T_R \widetilde{A}^T_{R,i}$. The total number of employees in R, T is $\sum_i L^T_R \widetilde{A}^T_{R,i} = L^T_R \left(c^T_R\right)^{k/\beta^T} \left(\widetilde{c}^T_R\right)^{-k\theta^T/\beta^T}$, where $\widetilde{c}^T_R$ denotes the unit labour cost function at wages $\left\{w^{k/(k-1)\theta^T}_{R,i}\right\}$[35].

2.A.5 Supplemental Summary Statistics

2.A.5.1 Educational Summary Statistics

UNICEF suggests that the typical Chinese primary school entrance age is 7 (Source: childinfo.org). Compulsory education lasts nine years (primary and secondary school) and ends around age sixteen. Figure 2.8 illustrates the average years of schooling for the Chinese labour force, while Table 2.13 displays the frequency of each worker type and their average monthly wages by Province.

FIGURE 2.8: Chinese Educational Attainment (Labour Force 2005)



[35]Formally $\widetilde{c}^T_R \equiv \min_H C_T\left(H|a_R, \left\{w^{-k/\theta^T(1-k)}_{R,i}\right\}\right)$ subject to $L = 1$.

TABLE 2.13: Educational and Wage Distribution by Province (2005)

Province	Fraction of Labour Force by Education				Avg Monthly Wage by Education			
	≤Junior HS (Female)	≤Junior HS (Male)	Senior HS	College or Above	≤Junior HS (Female)	≤Junior HS (Male)	Senior HS	College or Above
Anhui	0.296	0.485	0.155	0.063	581	862	866	1210
Beijing	0.140	0.284	0.299	0.277	796	1059	1314	2866
Chongqing	0.272	0.408	0.227	0.093	582	820	872	1379
Fujian	0.348	0.453	0.146	0.052	695	942	1103	1855
Gansu	0.216	0.399	0.271	0.114	507	738	869	1135
Guangdong	0.327	0.362	0.231	0.080	748	967	1281	2719
Guizhou	0.292	0.478	0.162	0.069	572	758	925	1189
Hainan	0.328	0.334	0.259	0.080	532	694	894	1527
Hebei	0.230	0.515	0.190	0.066	515	793	832	1233
Heilongjiang	0.217	0.393	0.285	0.104	515	740	797	1096
Henan	0.229	0.428	0.234	0.109	487	675	714	1079
Hubei	0.271	0.384	0.264	0.081	541	757	809	1262
Hunan	0.263	0.444	0.229	0.063	634	828	889	1267
Jiangsu	0.314	0.400	0.210	0.076	758	994	1086	1773
Jiangxi	0.291	0.456	0.196	0.056	525	783	794	1240
Jilin	0.204	0.382	0.307	0.107	522	745	809	1163
Liaoning	0.250	0.410	0.219	0.120	576	822	848	1366
Shaanxi	0.203	0.406	0.277	0.114	497	731	805	1149
Shandong	0.288	0.441	0.203	0.068	602	823	863	1398
Shanghai	0.221	0.321	0.272	0.186	891	1155	1450	3085
Shanxi	0.169	0.520	0.221	0.089	502	872	857	1113
Sichuan	0.277	0.480	0.162	0.081	541	737	829	1477
Tianjin	0.258	0.321	0.285	0.136	995	1019	1074	1617
Yunnan	0.275	0.495	0.160	0.070	504	697	896	1542
Zhejiang	0.357	0.469	0.129	0.045	817	1097	1299	2333

2.A.5.2 Provincial Summary Statistics

TABLE 2.14: Descriptive Statistics by Province (2005)

	Manufacturing		Population Census			
Province	Firm Count	Avg Workers	# of Regions	# Region-Industries	Monthly Wage	Avg Yrs School
Anhui	2,296	208	17	822	832	8.925
Beijing	3,676	145	2	128	1665	11.542
Chongqing	1,574	287	3	184	862	9.606
Fujian	7,534	212	9	504	945	8.170
Gansu	461	274	14	658	805	9.728
Guangdong	21,575	275	21	1269	1137	9.607
Guizhou	812	246	9	464	805	8.565
Hainan	126	149	3	151	830	9.772
Hebei	5,104	231	11	623	781	9.527
Heilongjiang	921	256	13	622	774	10.197
Henan	5,849	228	17	798	720	10.053
Hubei	2,685	247	14	742	789	9.731
Hunan	3,500	195	14	751	843	9.588
Jiangsu	22,197	170	13	756	1013	9.431
Jiangxi	1,501	245	11	556	766	9.208
Jilin	927	274	9	477	796	10.340
Liaoning	5,141	170	14	770	865	10.152
Shaanxi	1,207	368	10	548	787	10.068
Shandong	12,958	216	17	947	825	9.596
Shanghai	9,857	147	2	119	1577	10.569
Shanxi	1,118	386	11	619	847	9.895
Sichuan	3,209	238	21	887	800	9.149
Tianjin	2,671	195	2	128	1119	10.243
Yunnan	733	240	16	695	794	8.675
Zhejiang	27,639	144	11	629	1098	8.201

2.A.5.3 Industrial Summary Statistics

Table 2.15 presents the distribution of firms by industry and other descriptive statistics.

TABLE 2.15: Manufacturing Survey Descriptive Statistics (2005)

				Share of				
Industry	# of firms	# of Regions	Avg # of workers	Female	White Collar	Export	State Equity	Foreign Equity
Beverage	2,225	155	219.20	0.281	0.114	0.150	0.107	0.121
Electrical	12,241	166	201.58	0.289	0.106	0.351	0.030	0.195
Food	3,807	171	193.98	0.321	0.091	0.266	0.060	0.202
General Machines	15,727	195	152.68	0.205	0.117	0.262	0.047	0.115
Iron & Steel	4,676	160	227.40	0.148	0.088	0.101	0.032	0.056
Leather & Fur	4,852	89	320.70	0.362	0.036	0.682	0.005	0.335
Precision Tools	2,702	68	214.89	0.296	0.180	0.457	0.063	0.299
Metal Products	10,686	157	146.93	0.233	0.086	0.332	0.028	0.161
Non-ferrous Metal	3,607	139	157.75	0.186	0.093	0.180	0.035	0.093
Non-metal Products	15,347	259	195.57	0.207	0.090	0.169	0.059	0.088
Paper	5,698	159	151.05	0.269	0.061	0.127	0.026	0.131
Plastic	9,235	159	140.47	0.298	0.065	0.327	0.019	0.235
Printing	3,382	98	133.01	0.303	0.084	0.118	0.150	0.109
PC & AV	6,699	90	402.04	0.342	0.120	0.571	0.038	0.459
Rubber	2,212	79	226.25	0.294	0.067	0.377	0.027	0.218
Specific Machines	7,816	167	176.76	0.197	0.154	0.244	0.072	0.166
Textile	18,292	186	222.43	0.390	0.044	0.406	0.018	0.168
Transport	8,632	168	252.01	0.228	0.120	0.240	0.088	0.138
Wood	3,629	133	137.04	0.288	0.050	0.290	0.025	0.137

2.A.6 Supplemental Empirical Results

2.A.6.1 Verisimilitude of Census and Firm Wages

One of the main concerns about combining census data with manufacturing data is the representativeness of regional labour market conditions in determining actual wages within firms. It turns out they are remarkably good predictors of a firm's labour expenses. We construct a predictor of firm wages based on Census data and test it as follows: First, compute the average wages per prefecture. Second, make an estimate CensusWage by multiplying each firm's distribution of workers by the average wages of each type from the population census. Third, regress actual firm wages on CensusWage. The results are presented in Table 2.16 of Appendix 2.A.6.1. Not only is the R^2 of this predictor very high for each industry, but the coefficient on CensusWage is close to one in all cases, showing that one-for-one the census based averages are excellent at explaining the variation in the wage bill across firms.

TABLE 2.16: Census Wages as a Predictor of Reported Firm Wages

Industry	Dependent Variable: $\ln(\text{Firm Wage})$					
	$\ln(\text{Census Wage})$	Std Dev	Constant	Std Dev	Obs	R^2
Beverage	1.052***	(0.0147)	-0.904***	(0.204)	2223	0.85
Electrical	1.018***	(0.0103)	-0.370***	(0.138)	12213	0.86
Food	1.032***	(0.0104)	-0.602***	(0.144)	3766	0.83
General Machines	1.020***	(0.0063)	-0.365***	(0.091)	15711	0.84
Iron & Steel	1.049***	(0.0082)	-0.777***	(0.116)	4663	0.87
Leather & Fur	0.982***	(0.0112)	0.116	(0.165)	4851	0.87
Precision Tools	1.018***	(0.0221)	-0.332	(0.308)	2689	0.83
Metal Products	1.012***	(0.0094)	-0.286**	(0.130)	10654	0.83
Non-ferrous Metal	1.054***	(0.0092)	-0.833***	(0.127)	3588	0.88
Non-metal Products	0.981***	(0.0085)	0.16	(0.122)	15329	0.80
Paper	1.012***	(0.0086)	-0.335***	(0.120)	5695	0.82
Plastic	1.015***	(0.0129)	-0.340**	(0.170)	9214	0.85
Printing	1.055***	(0.0135)	-0.839***	(0.189)	3377	0.83
PC & AV	1.021***	(0.0172)	-0.354	(0.224)	6685	0.86
Rubber	1.000***	(0.0132)	-0.133	(0.182)	2195	0.87
Specific Machines	1.036***	(0.0105)	-0.580***	(0.139)	7780	0.83
Textile	0.981***	(0.0060)	0.132	(0.084)	18281	0.86
Transport	1.050***	(0.0071)	-0.755***	(0.099)	8618	0.86
Wood	0.965***	(0.0136)	0.309	(0.197)	3619	0.78

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

2.A.6.2 Firm Performance Characteristics and Productivity

TABLE 2.17: Explaining Growth with Productivity

	Sales Growth Rate (2005-7)		
Productivity under Unit Cost method	-0.0839**		
	(0.0372)		
Productivity under L = 4 Types		-0.0619***	
		(0.0239)	
Productivity under L = Wage Bill			-0.0607**
			(0.0258)
Prefecture and Industry FE	Yes	Yes	Yes
Observations	119,159	119,159	119,159
R-squared	0.027	0.027	0.027

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

TABLE 2.18: Explaining Survival with Productivity

	Survival Rate (2005-7)		
Productivity under Unit Cost method	0.0188***		
	(0.00230)		
Productivity under L = 4 Types		0.0115***	
		(0.00157)	
Productivity under L = Wage Bill			0.0103***
			(0.00157)
Prefecture and Industry FE	Yes	Yes	Yes
Observations	141,409	141,409	141,409
R-squared	0.023	0.023	0.022

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

2.A.6.3 Production Estimates by Method

Table 2.19 compares the production coefficients under three measures of labour: unit labour costs, total wages, and employment of each worker type. In the latter case, the coefficient for type i workers are labelled α_L^i.

TABLE 2.19: Second Stage Estimates vs Homogeneous Labour Estimates

	Unit Labour Cost			Total Wage Bill			Employment of Each Type					
Industry	α_L	α_K	α_M	α_L	α_K	α_M	α_L^1	α_L^2	α_L^3	α_L^4	α_K	α_M
Beverage	0.13	0.10	0.70	0.23	0.06	0.71	0.07	0.01	0.07	0.06	0.07	0.75
Electrical	0.25	0.14	0.47	0.34	0.12	0.47	0.06	0.02	0.08	0.12	0.12	0.53
Food	0.14	0.09	0.70	0.16	0.06	0.73	0.07	0.03	0.09	0.08	0.12	0.52
General Machines	0.17	0.12	0.60	0.25	0.09	0.61	0.03	0.01	0.09	0.03	0.06	0.76
Iron & Steel	0.40	0.07	0.48	0.25	0.07	0.68	0.04	0.03	0.06	0.08	0.10	0.66
Leather & Fur	0.10	0.13	0.59	0.27	0.09	0.55	0.01	0.07	0.11	0.05	0.06	0.71
Precision Tools	0.20	0.16	0.43	0.44	0.08	0.38	0.02	0.13	0.07	0.05	0.09	0.57
Metal Products	0.24	0.14	0.46	0.30	0.12	0.48	0.09	0.03	0.05	0.23	0.11	0.44
Non-ferrous Metal	0.40	0.08	0.43	0.17	0.10	0.65	0.03	0.04	0.06	0.02	0.06	0.71
Non-metal Products	0.20	0.07	0.61	0.20	0.06	0.67	0.04	0.04	0.10	0.07	0.11	0.55
Paper	0.18	0.14	0.53	0.28	0.11	0.52	0.09	0.02	0.10	0.08	0.14	0.47
Plastic	0.27	0.14	0.41	0.31	0.13	0.43	0.04	0.01	0.08	0.06	0.09	0.65
Printing	0.09	0.22	0.55	0.40	0.14	0.44	0.07	0.02	0.10	0.10	0.17	0.51
PC & AV	0.16	0.21	0.43	0.48	0.14	0.35	0.11	0.07	0.08	0.24	0.16	0.41
Rubber	0.06	0.13	0.63	0.31	0.07	0.55	0.05	0.07	0.08	0.11	0.06	0.56
Specific Machines	0.10	0.16	0.55	0.31	0.10	0.48	0.03	0.01	0.06	0.13	0.11	0.53
Textile	0.12	0.11	0.61	0.29	0.07	0.56	0.03	0.09	0.08	0.08	0.06	0.58
Transport	0.04	0.15	0.65	0.31	0.09	0.53	0.03	0.03	0.06	0.10	0.09	0.59
Wood	0.22	0.10	0.56	0.23	0.08	0.62	0.03	0.07	0.07	0.08	0.07	0.63
Average	0.18	0.13	0.55	0.29	0.09	0.54	0.05	0.03	0.08	0.09	0.10	0.59

Chapter 3

Education, Occupation and Children's Outcomes: The Impact of the Chinese Cultural Revolution

3.1 Introduction

Previous studies find that an increase in the availability of schooling raises educational attainment, which in turn reduces poverty and improves social mobility.[1] Higher educational attainment leads to better labour market outcomes, such as higher income and occupational status, and may have positive long-run effects on children's school performance. Therefore, many countries have carried out various reforms to improve the access to education.[2] In developing countries where early school drop-out rates are high, more emphasis is given

[1] See Birdsall (1985); Lavy (1996); Duflo (2001) for examples of the impact of education policy on schooling. Studies on the link between education reform and intergenerational mobility include Black et al. (2005); Pekkarinen et al. (2006); Holmlund (2008) and Maurin and McNally (2008).

[2] Examples of large-scale education reform in developing countries include the massive school construction in Indonesia in the 1970s and in India in the 1990s; the implementation of a compulsory schooling law in China in 1986; and the provision of free primary education in Kenya in 2003.

to the expansion of basic education as it benefits a larger social group and improves social mobility at the bottom of the income distribution.[3]

By exploiting the drastic education reform during the Chinese Cultural Revolution, this paper examines how changes in access to basic education affect schooling and their subsequent impact on occupational choice and children's educational attainment. In 1968-1976, a revolutionary education agenda was implemented in China to remove class differences and social inequality. In urban schools, ability tracks were abolished, schooling was restructured and the curriculum was simplified to increase the grade progression rate among proletarian families. New primary schools were built in rural areas to universalise education among the agricultural population. Although the quality of education suffered throughout the period, the new policies led to a significant rise in school enrolment and graduation rates. Between 1962 and 1975, primary and junior high school enrolment rates increased from 56.1% and 45.3% to 96.8% and 90% respectively (Ministry of Education).

The education reform in 1968-76 resulted in an exogenous change in the educational distribution among the school-aged cohorts, and the reform intensity was uneven across regions as different policies were adopted by the local governments. Using trend deviations of graduation rate as a proxy of education shock, I find that cohorts born in 1950-65 were most affected by the education reform and the impact was largest at primary and junior high school levels.[4] Moreover, the deviations from education trend varied significantly across

[3]Investment in higher education favours those with larger family endowment, and therefore has little redistributional effects. In fact, a number of studies suggest that reforms that promote equity in education improve intergenerational mobility (e.g. Holmlund (2008) and Pekkarinen et al. (2006)). Policies such as extension of compulsory years of schooling, abolishment of ability tracking system and introduction of standardised academic curriculum reduce intergenerational correlations in education and income.

[4]I do not consider the impact of university closure on educational attainment as less than 1% of the school-aged children entered university before the Cultural Revolution and most of them were from the elite class; therefore, the effect was confined to a very small group of people.

provinces and hukou type.[5] I use this variation in trend deviations as an instrument for individual's schooling to estimate the impact of education on occupational status and children's schooling outcomes. The key assumption of this identification strategy is the estimated education shock is uncorrelated with other regional characteristics that affect the individual's educational decision.

The results suggest that schooling has positive and significant impact on the status of first occupation and children's educational attainment. Each additional year of schooling increases the probability of obtaining an off-farm job by 3.11%, and increases the likelihood of acquiring a white collar job by 2.87%. Moreover, increasing parent's education by one year increases children's probability of completing junior high school and senior high school by 3.94% and 4.76% respectively.

This study is closely related to an existing literature which uses changes in education policy to identify the causal relationship between schooling and labour market outcomes. For example, Duflo (2001) finds that individual's education increases by 0.12-0.19 years for each new school built per 1000 children in Indonesia and generates returns to education of 6.8-10.6%. Maurin and McNally (2008) show that the temporary relaxation of French university entrance exam in 1968 led to an increase in years of higher education, which consequently increased wages and occupational status. Some studies also use changes in education system to examine the relationship between parents' and children's education. Maurin and McNally (2008) find that higher parental education reduces children's years of grade repetition in France. Oreopoulos et al. (2006) use changes in compulsory schooling law in the US as an instrument for parental education and find positive and significant effects of parental education on children's school performance. Black et al. (2005) adopt a similar approach and finds little causal relationship between parent's and children's education in Norway.

[5]A person's hukou type defines his region of permanent residence (urban or rural) and family's occupation (agricultural or non-agricultural). However, the link between one's hukou type and occupation is rather weak after the mid-1990s.

Finally, this paper is also related to a recent literature which uses the Cultural Revolution as a natural experiment to estimate the returns to education in China. Meng and Gregory (2007) use year of birth as an instrument for education disruption to estimate the education cost of the Cultural Revolution. They find that the impact of missed years of schooling or lack of normal curriculum on earnings is very small. The major disadvantage of their approach is they assume that the treatment intensity is the same within the cohorts, and therefore fail to exploit the regional variation in the education shock. In order to capture this variation, Giles et al. (2008) estimate the returns to education in urban China using city-wide birth-cohort average disruption to education as an instrument for schooling. They find that the IV estimate of returns to education was about 13%, much higher than the OLS estimate of 8%, which suggests that there was an under-investment in education in China.

The rest of the paper is organised as follows. Section 2 explains the background of the Cultural Revolution; Section 3 discusses the conceptual framework; and Section 4 describes the empirical strategy. Section 5 presents the empirical results and Section 6 concludes.

3.2 Background

3.2.1 Education System and Cultural Revolution

Before the Cultural Revolution, China's education system was characterised by a combination of academic and vocational schools to produce trained experts and educated labourers (Tsang, 2000). Rapid expansion of education among peasants and proletariat families was observed earlier in 1958-61; however, the government reverted to a more practical education policy after the failure of the Great Leap Forward in 1961. To make efficient use of the limited resources, urban schools were given priority over their rural counterparts to train specialists for the country's development goals. In urban 'key-point' schools, expertise was emphasized and competition for progression was tight. In contrast, the aim of rural education was to eradicate adult illiteracy and produce educated workers for agricultural production. Grade durations were shorter and educational quality was lower. Such regional disparities in education were reinforced by the hukou system which imposed huge institutional and monetary costs on migration, and therefore deprived rural households from higher quality education in urban areas.

The earlier education system was abruptly abolished after the outbreak of the Cultural Revolution. In 1966-68, urban schools were closed and normal teaching was suspended so that students could dedicate themselves to political activities. As one of the aims of the Cultural Revolution was to promote egalitarianism, a new education agenda was adopted in 1968 to provide peasants and proletarians with better educational opportunities. In primary and secondary schools, the education structure was unified and school curriculum was simplified to reduce the gaps between students from different social backgrounds. Normal school lessons were replaced by political and ideological education and manual farm work. To increase school progression rates, exams were abolished and students were given diplomas even though they missed schooling due to the initial school closure.[6] In rural areas, villages were pushed to build new schools and expand schooling to junior high school level (Tsang, 2000). Although teaching quality and school conditions were poor, the reform was quite successful in promoting mass education in rural areas. Between 1965 and 1976, rural enrolments in primary and junior high school increased from 80.9% to 88.5% and 30.2% to 72% respectively (Ministry of Education). It was not until 1977 that all schools returned to normal operations.

[6]The loss in university education was also tremendous during the Cultural Revolution. Many university professors were sent to the country-side for re-education and no formal teaching was undertaken throughout the period. Only a small number of students were recruited after 1972 on the basis of political attitude and social background. As only a very small fraction of population enters university before the outbreak of Cultural Revolution; therefore my analysis focuses on the initial interruption and subsequent expansion of primary and secondary education.

3.2.2 Impact on Schooling

This section discusses the factors that affect schooling decisions and how they are related to the education reform during the Cultural Revolution. The classical human capital theory suggests that investment in education is affected by four main factors: ability, returns to education, cost of schooling, and household liquidity constraint if there is imperfect capital market.[7] Either an increase in ability, parental income and returns to education, or decrease in cost of schooling would increase investment in schooling, holding other things constant.

The initial school closure in 1966-68 was a negative education shock to school-aged children, especially among those who lived in the urban areas or had an non-agricultural hukou. Although most schools were reopened in 1968, all 'key-point' schools and vocational schools remained closed throughout the period. Students might drop out of school permanently if they find it not worthwhile to re-enter schools after 1968, and these students tend to have higher cost of schooling or lower returns to education than their peers.

The subsequent education reform in 1968-76 can affect an individual's education decision in three ways. First, the abolition of exams and the change in school curriculum reduce the cost of effort for grade progression, which therefore increases the education level of students. Second, construction of new primary schools in rural areas reduces the cost of education and consequently increases the investment in education among the liquidity constrained families. Third, the poor teaching quality and removal of link between education and future earnings reduces the returns to education. Education no longer serves as a signalling device in the labour market and urban high school graduates were assigned to jobs directly by the government. Many of them were sent to

[7] See Becker (1962) and Becker and Tomes (1986) for a detailed discussion of the human capital model.

the countryside to work as peasants as there were insufficient jobs in the urban areas. This reduces the incentive to invest in education.[8]

The relative magnitude of the three effects depends on an individual's region of residence and family background. Under an exam-based system, students with a lower cost of exam preparation are more likely to progress to a higher grade. As children of intellectuals and government officials are best-equipped for the exams, they tend to have higher education levels than their peers. The removal of ability tracks reduces the importance of academic ability in determining schooling outcomes, which favours children from proletarian families. Next, primary school construction explicitly targeted areas where illiteracy rate was high and educational opportunities were limited. This would increase the educational level of the poor and narrow the education gap across regions. The impact of decline in returns to education is ambiguous. If labour market outcomes are independent of a student's academic performance during the Cultural Revolution, then the fall in returns to education is larger at higher education levels and education inequality would decrease.[9]

3.2.3 Variation in Treatment Intensity

There are two sources of variation in treatment intensity. The first one is year of birth. Cohorts affected by the reform ranged from students who attended senior high school in 1968 to children who were about to complete primary education in 1976. In China, children started primary schools at the age of 7 and completed senior high school at 18. Therefore, the treatment groups include 16 birth cohorts born between 1950 and 1965. The 1950-54 cohorts attended junior and/or senior high school during the Cultural Revolution; the 1955-59 cohorts

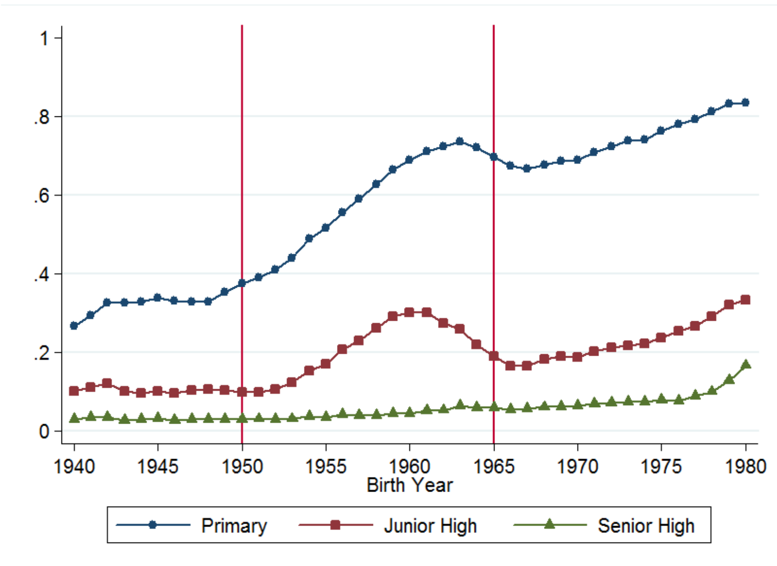
[8]Another factor that affects schooling decision but not related to the education reform is the struggle against intellectuals. During the Cultural Revolution, many intellectuals faced a negative income shock as their property was confiscated and their families were sent to rural areas for re-education. This reduces their demand for children's education if education is a normal good.

[9]Another policy that contributes to the reduction in education disparities is the disruption in university education which hinders children of intellectuals from obtaining higher education. When universities started recruiting a small number of new students in 1972, only those from peasants and proletarian families or closely related to government officials were recruited.

were fully exposed to the reform; and the 1960-65 cohorts attended primary and junior high schools before the end of the reform. Individuals born before 1950 had left school when the reform started, and those who were born after 1965 were too young to be affected by the reform.

Figures 3.1 displays the cohort graduation rates for individuals born between 1940 and 1980 at 3 education levels using the 0.95% sample of the 2000 population census. While average schooling increased over time, the educational attainment of the 1950-65 cohorts was much higher than the general trend.

FIGURE 3.1: Graduation Rates by Birth Cohort



Source: 0.95% Sample of 2000 Population Census

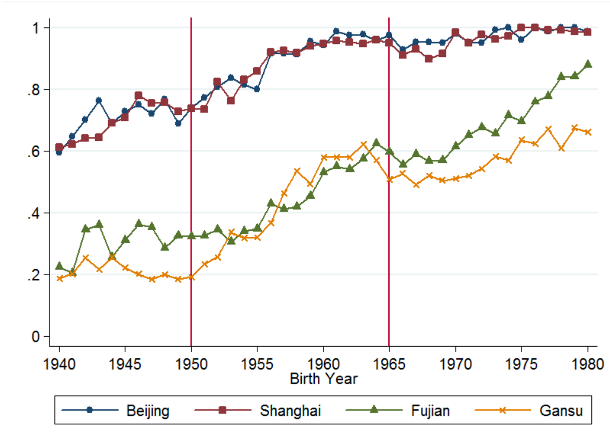
Apart from year of birth, the reform intensity also varied across provinces and households. Due to data limitations, it is still unclear how the new education policy was implemented by the local governments. However, the consensus in the literature is that poorer provinces and rural areas were less affected by the initial school closure.[10] Also, expansion of basic education was faster in less developed regions.

[10]Meng and Gregory (2007) suggest that most rural schools remained opened throughout the reform period although short-term interruptions may have occurred in some areas.

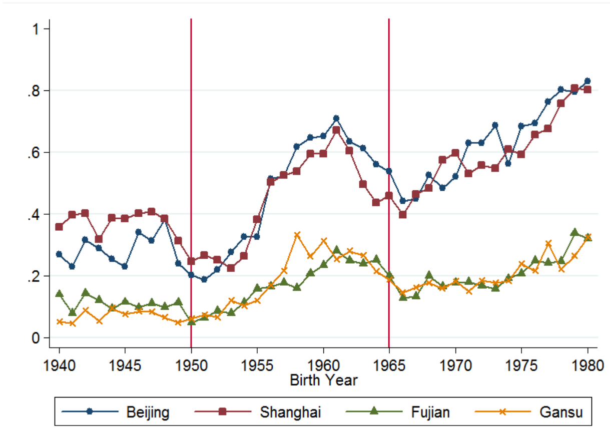
Figure 3.2 plots the cohort graduation rates across 4 of the 32 Chinese provinces and municipalities. The numbers are based on the reported province of birth as the census does not report region of education, . Beijing and Shanghai have a tradition of political activism and economic activities while Fujian and Gansu are far from the political centres and were relatively backward before China's market reform in 1978. In Beijing and Shanghai, the junior high school graduation rates among the 1950-54 cohorts fell below the education trend due to the initial school closure but increased rapidly afterwards until the end of the reform. Deviations from primary and senior high school trends were rather limited for all cohorts. In contrast, Fujian and Gansu were largely unaffected by the initial school interruptions; instead, their primary and junior high graduation rates were higher than the education trend throughout the reform period.

Next, figure 3.3 compares the cohort graduation rates between individuals with agricultural and non-agricultural hukou in Beijing and Fujian. Before the first wave of migration in mid-1990s, an individual's hukou type was highly correlated with his region of residence and family's occupation. Agricultural hukou holders mainly lived in the rural areas and engaged in farming while non-agricultural hukou holders resided in urban areas and worked in the industrial or service sectors. We see that the increase in primary school graduation rates was faster among agricultural hukou holders born in 1950-65. In contrast, the expansion in junior high school was more rapid among non-agricultural hukou holders during the reform.

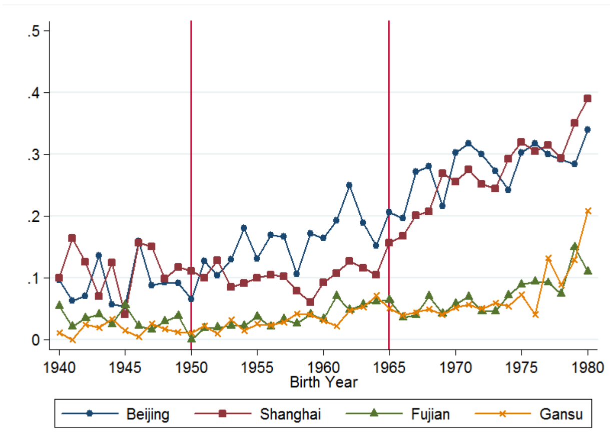
FIGURE 3.2: Graduation Rates by Province



(a) Primary School



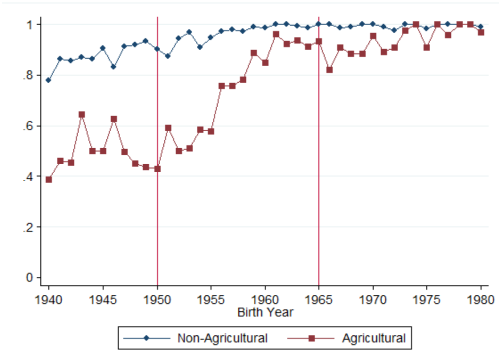
(b) Junior High School



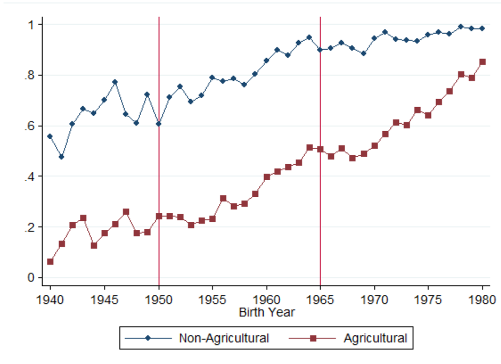
(c) Senior High School

Source: 0.95% Sample of 2000 Population Census

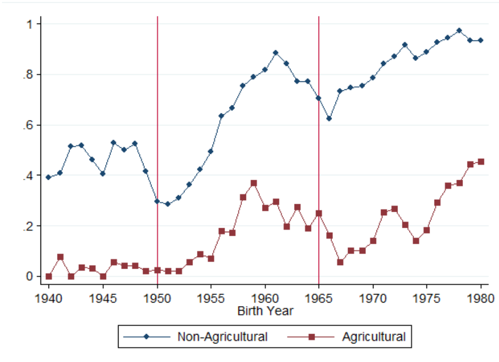
FIGURE 3.3: Graduation Rates by Hukou Type



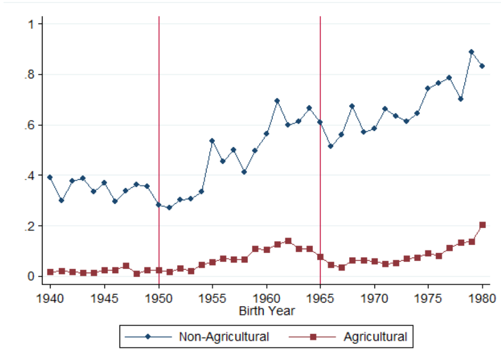
(a) Primary School: Beijing



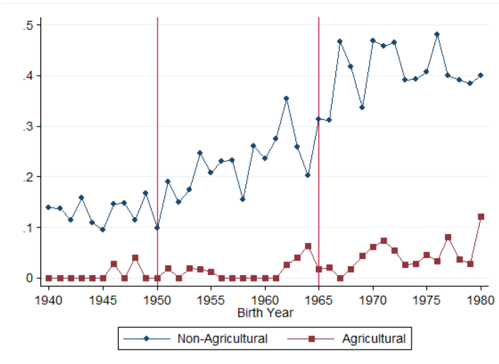
(b) Primary School: Fujian



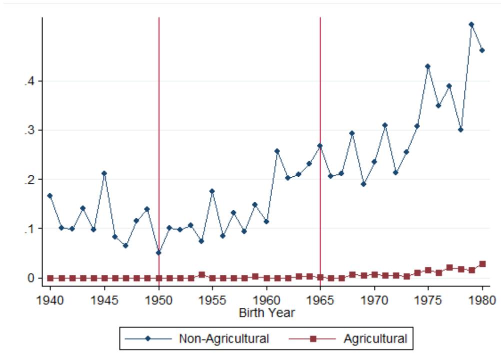
(c) Junior High School: Beijing



(d) Junior High School Fujian



(e) Senior High School: Beijing



(f) Senior High School: Fujian

Source: 0.95% Sample of 2000 Population Census

3.3 Empirical Strategy

3.3.1 Data

This paper uses data from the 2006 Chinese General Social Survey (CGSS) and the 0.95% sample of the 2000 Chinese population census. The 2006 CGSS is conducted jointly by the Survey Research Center of Hong Kong University of Science and Technology and the Sociology Department of the People's University of China.[11] It includes 10,015 individuals born between 1936 and 1988 who reside in 28 provinces and municipalities in China. Each individual reports his highest educational attainment, years of schooling, hukou type, first occupation and region of residence before migration. Recall information on father's hukou type and occupation when the individual was 18 years old are also provided. To control for migration and hukou changes, I assume that an individual's province of birth is the same as his province of residence before migration and use father's hukou when an individual was 18 as a proxy for his original hukou type.

The 2000 population census includes information about the respondent's age, province of birth, hukou type and educational attainment. The census data is aggregated by province, hukou and birth year and matched with the individual survey. Sample is restricted to those who were born between 1940 and 1980 to ensure that most individuals have completed education at the time of the census. Details of the computation and usage of census-based variables are discussed in the next section.

Table 3.1 presents the descriptive statistics of the individual survey. It shows that average years of schooling increases over time and there is a significant rise in educational attainment among the 1950-65 cohorts. The sample is over-represented by non-agricultural hukou holders; therefore, all regressions are

[11] The CGSS began in 2003 interviews about 5,000-10,000 individuals across 28 provinces and municipalities in China per year until 2008. Data in 2003, 2005 and 2006 are publicly available but only the 2006 survey is used in our paper. This is because the 2006 survey is the only survey that contains all the necessary information for our analysis, such as father's hukou type and observations from rural households.

weighted by population.[12] Descriptive statistics by hukou type is presented in Appendix Table 3.10.

TABLE 3.1: Descriptive Statistics of the 2006 Chinese General Social Survey

	1940-49		1950-65		1966-80	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Respondent						
Age	61.07	3.77	48.19	4.72	33.79	4.28
Female	0.492	0.500	0.546	0.498	0.562	0.496
Share of Non-Agricultural Hukou	0.576	0.494	0.509	0.500	0.470	0.499
Married	0.969	0.173	0.958	0.200	0.895	0.307
Years of Schooling	6.01	4.43	7.41	4.04	8.97	3.99
Highest Education Level Completed						
Primary School	0.270	0.444	0.169	0.375	0.175	0.380
Junior High School	0.203	0.402	0.330	0.470	0.334	0.472
Senior High School	0.118	0.322	0.230	0.421	0.231	0.421
College or Above	0.059	0.235	0.055	0.227	0.141	0.348
First Occupation						
Agricultural	0.497	0.497	0.445	0.500	0.378	0.485
Blue-collar	0.244	0.422	0.232	0.430	0.246	0.431
White-collar	0.192	0.408	0.210	0.394	0.306	0.461
Father When Respondent Was 18						
Share of Non-Agricultural Hukou	0.295	0.456	0.399	0.490	0.370	0.483
Occupation						
Agricultural	0.715	0.452	0.602	0.490	0.598	0.490
Blue-collar	0.146	0.353	0.22	0.414	0.189	0.391
White-collar	0.139	0.346	0.181	0.385	0.209	0.407
Observations	1,759		3,307		3,222	

Notes: Sample is restricted to individuals born in 1940-1980 and do not report missing values of the variables listed in the table above.

I focus on 3 types of occupation: agricultural, blue collar and white collar jobs. Table 3.2 shows that there is a strong persistence of occupational status over time.

[12]The share of non-agricultural hukou holders is 50% in the 2006 CGSS while the national average is less than 40%. Sample weights are provided by the 2006 CGSS data on the basis of the 2005 Chinese population census.

TABLE 3.2: Persistence in Occupational Sector

	First Occupation		
Current or Last Occupation	Agricultural	Blue-collar	White-collar
Agricultural	0.960	0.026	0.012
Blue-collar	0.122	0.796	0.072
White-collar	0.093	0.102	0.805

Notes: 2006 Chinese General Social Survey. Sample includes individuals born in 1940-1980 and reported first and current or last occupation.

Occupational status is strongly correlated with earnings. Table 3.3 illustrates the occupational prestige of the three occupations by comparing their average wages. As most of the 1940-49 cohorts have retired and half of the individuals do not report earnings, the estimates are based on a small sample of employees and therefore do not reflect the true returns to occupation in China. Unsurprisingly, white-collar workers have the highest average earnings, followed by blue-collar workers then agricultural employees.

TABLE 3.3: Wage Differences Across Occupations

	Log Hourly Wage
Age	0.0162**
	(0.0072)
Age Squared	-0.0210*
	(0.0119)
Female	-0.246***
	(0.0344)
Blue-collar	0.338**
	(0.166)
White-collar	0.543***
	(0.169)
Constant	1.482***
	(0.347)
Province × Hukou Fixed Effect	Yes
Observations	2,647
R-squared	0.228

Notes: Data from 2006 Chinese General Social Survey. Sample includes individuals born in 1940-1980. Standard errors clustered by province of employment and year of birth. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

3.3.2 Estimation

The impact of schooling on individual i born in province-hukou j and year t is estimated by a linear probability model:

$$Y_{ijt} = \alpha + \beta S_{ijt} + \varphi_j + \zeta_t + \varepsilon_{ijt} \tag{3.3.1}$$

where Y_{ijt} is either individual i's first occupation's status or his children's educational attainment, S_{ijt} is years of schooling; φ_j is the province $\times$ hukou fixed effect which captures any time invariant regional-hukou characteristics; and ζ_t is the cohort fixed effect. Standard errors are clustered by province and year of birth.

The first stage regression captures the relationship between the education shocks and individual's schooling:

$$S_{ijt} = \alpha_1 + \gamma_l \tilde{E}_{1jt} + \gamma_2 \tilde{E}_{2jt} + \varphi_j + \zeta_t + \mu_{ijt} \tag{3.3.2}$$

where $\tilde{E}_{1jt}$ and $\tilde{E}_{2jt}$ are measures of exogenous shocks to primary and junior high schools respectively. I exclude shocks to senior high school in my analysis as they were too small to pick up any variation in individual's schooling, as shown in figures 3.1-3.3 previously. $\tilde{E}_{1jt}$ and $\tilde{E}_{2jt}$ serve as the instruments for S_{ijt}.

As data on earlier school policies is unavailable, I use deviations of cohort graduation rates from predicted rates as a proxy for cohort-specific education shock. Graduation rates are census-based aggregated variables which vary across provinces of birth, hukou type and birth years. The cohort graduation rate is jointly determined by demand and supply of education; therefore, it is often correlated with other regional and time effects that affect either one or both forces. For example, richer provinces tend to have better access to schooling and larger demand for education at the same time. This problem can be tackled if these factors are regional and time-invariant. Any systematic differences across regions and between cohorts are captured by the province-hukou fixed effect and cohort fixed effect respectively. I also control for regional-hukou time trend by subtracting the predicted graduation rates from the actual rates. The difference between the two is my treatment intensity and is assumed orthogonal to an individual's occupation and children's education.

The computation of education shock is based on two assumptions: first, an individual's region of education is the same as his region of birth. Migration introduces measurement error which would lead to a downward bias in the OLS estimate. The census does not report region of education; however, the correlation between region of birth and region of education is very high in China. This is due to the fact that the hukou system was strictly enforced until the 1990s, and after the relaxation of hukou system, most of the migrants are adult job seekers instead of students. In the 2000 census, 15% of the individuals report that they live outside their county of birth. Among them, only 0.06% are students. This suggests that migration should have little impact on the estimation results.

The second assumption is change in hukou status is very limited before 2000. To capture the differences in the education shock between urban and rural areas, graduation rates are calculated separately for agricultural and non-agricultural hukou holders.[13] As the 2000 census only reports current hukou status, changes in hukou type before 2000 also lead to a downward bias in the OLS estimates. This is less of a concern as the cost of changing hukou registration is much higher than the cost of migration. Individuals who migrated to cities couldn't change their hukou type unless they have a university degree, are employed by a state-owned enterprise or have invested in local business or property market. Given the low educational attainment of rural population, the share of hukou switchers is very small in the population.

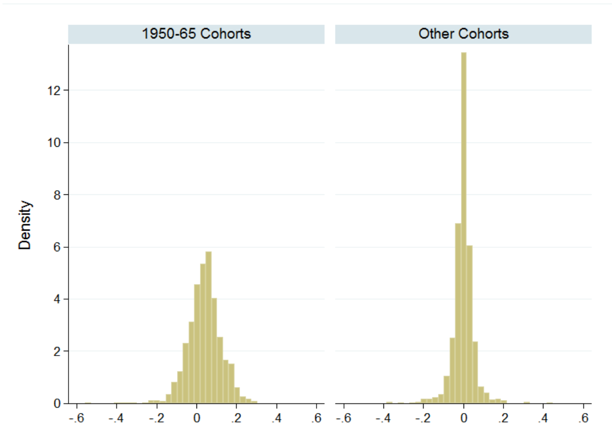
[13]Here I assume that an individual's hukou type is closely related to his region of education. Agricultural hukou holders are educated in rural areas and non-agricultural hukou holders are educated in urban areas. Argument for this assumption is the similar to the reasons which suggest that an individual's region of education highly correlated with his region of birth. Similar approach is also adopted by other studies such as Duflo (2001) and Qian (2003).

The education trend of each cohort group is estimated by the following equation:

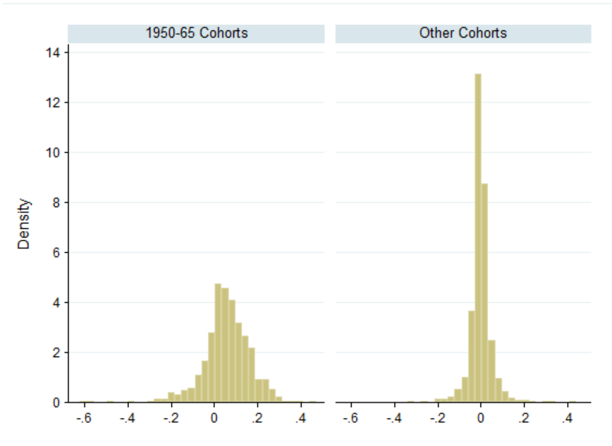
$$E_{ljt} = \alpha_{lj} + \theta_{1lj} E_{lj1940} \times [t - 1940] + \theta_{2lj} E_{lj1940} \times [t - 1940]^2 + \nu_{jt} \quad (3.3.3)$$

where E_{ljt} is the actual graduation rate of education level l for each province, hukou and birth cohort, and E_{jk1940} is the graduation rate of the 1940 cohort. θ_{2lj} captures the non-linear trends in educational attainment across cohorts. The instrumental variable $\tilde{E}_{ljt}$ is defined as the difference between the actual and predicted graduation rates. In order to isolate the education shocks during the Cultural Revolution, equation (3.3.3) is estimated for the control group only i.e. the 1940-49 and 1966-80 cohorts. Figure 3.4 presents the histograms of estimated trend deviations for three education levels. Each observation is a province, hukou and birth year cell. It suggests that education shock is larger for the 1950-65 birth cohorts and for primary schools and junior high schools. A breakdown of Figure 3.4 by hukou type is also shown in Appendix Figure 3.5.

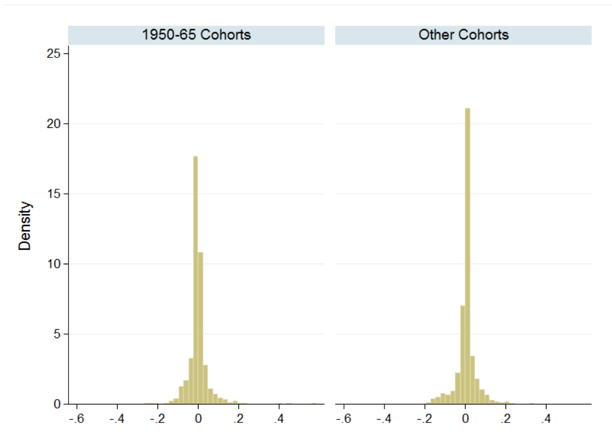
FIGURE 3.4: Distribution of Education Trend Deviations



(a) Primary School



(b) Junior High School



(c) Senior High School

Source: 0.95% Sample of 2000 Population Census and author's calculations

3.4 Results

Table 3.4 illustrates my IV strategy. Recall that education shock measures the differences in actual and predicted graduation rate, which is a proxy for changes in access to education. Column 1 presents the estimates of equation (3.3.2), which is the first stage regression. It shows that the instruments are strongly significant. A 1% increase in primary school graduation rate above the education trend is associated with an increase individual's schooling by 0.019 years, and a 1% increase in junior high school graduation rate increases schooling by 0.027 years. In columns 2 to 4, I estimate the probabilities of completing primary school, junior high school and senior high school using a probit model. The results also suggest that the education shocks to primary and junior high schools are positively correlated an individual's educational attainment.

TABLE 3.4: Relationship Between Education Shock and Individual Schooling

	OLS	Probit		
	Years of Education	Primary School	Junior High School	Senior High School
	(1)	(2)	(3)	(4)
Primary School Shock	0.0194**	0.0148***	0.00244	0.00178
	(0.00877)	(0.00446)	(0.00429)	(0.00567)
Junior High School Shock	0.0265**	0.0129**	0.0194***	0.0143***
	(0.0110)	(0.00608)	(0.00429)	(0.00485)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province × Hukou Fixed Effect	Yes	Yes	Yes	Yes
Observations	8,288	8,288	8,288	8,288
R-squared	0.246			

Notes: Sample includes individuals born in 1940-1980. Each dependent variable in columns 2 to 4 is a dummy for graduation. Education shocks are trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Standard errors clustered by province and year of birth. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

3.4.1 First Occupation

The regression results for equation (3.3.1) are presented in Table 3.5. I consider two types of occupational outcomes: non-agricultural job and white-collar job. Non-agricultural jobs include blue-collar and white-collar occupations. In columns 1 and 3, the OLS estimates indicate that an additional year of schooling increases the probability of obtaining a non-agricultural job by 3.11% and increases the probability of having a white-collar job by 2.87%. The IV estimates in columns 2 and 4 suggest a larger effect of schooling on occupational type (3.81% for non-agricultural job and 3.55% for white-collar job). This finding is consistent with the existing literature which suggest that the OLS estimates are biased downwards due to measurement error in schooling.

TABLE 3.5: Impact of Education on First Occupation

	Non-Agricultural Occupation		White Collar Occupation	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Years of Education	0.0311***	0.0381***	0.0287***	0.0355***
	(0.00141)	(0.00539)	(0.00173)	(0.00388)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province $\times$ Hukou Fixed Effect	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		16.5		16.5
Hansen J statistic		0.049		0.049
Observations	8,288	8,288	8,288	8,288

Notes: Sample includes individuals born in 1940-1980. Each dependent variable is a dummy for occupational outcome. Years of education are instrumented by trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Standard errors clustered by province and year of birth. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Occupational segregation between rural and urban residents has been a concern in China in the last few decades. The share of urban residents working in a non-agricultural job or white-collar occupation is much higher than their rural counterparts; therefore, the impact of schooling on occupational outcomes is likely to differ across households. To capture this, I estimate equation (3.3.1) by father's hukou type. For agricultural hukou holders, I focus on the probability of obtaining a non-agricultural job; and for non-agricultural hukou holders, I only consider the likelihood of having a white-collar job.[14] The results are shown in Table 3.6. The OLS and IV estimates are statistically significant and larger than the corresponding estimates in Table 3.5. This suggests that the marginal effects of schooling on obtaining an off-farm job are larger for agricultural hukou holders. However, the effects are smaller for white-collar jobs. This may be due to the fact that the quality of rural education is lower and there are less white collar jobs in rural areas.

TABLE 3.6: Impact of Education on First Occupation by Hukou Type

	Agricultural Hukou Holders:		Non-Agricultural Hukou Holders:	
	Non-Agricultural Occupation		White Collar Occupation	
	OLS (1)	IV (2)	OLS (3)	IV (4)
Years of Education	0.0361***	0.0380***	0.0426***	0.0445***
	(0.00173)	(0.00862)	(0.00313)	(0.0114)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province × Hukou Fixed Effect	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		14.6		12.3
Hansen J statistic		0.045		0.032
Observations	5,196	5,196	3,092	3,092

Notes: Sample includes individuals born in 1940-1980. Each dependent variable is a dummy for occupational outcome. Years of education are instrumented by trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Hukou type is defined as father's hukou status when the individual was 18. Standard errors clustered by province and year of birth. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

[14] I do not report the probability of obtaining a non-agricultural job among non-agricultural hukou holders and the probability of having a white-collar job among non-agricultural hukou holders as the number of observations in each subgroup are too small to obtain any meaningful estimates. Refer to Table 3.1 for more details.

3.4.2 Children's Education

There is a large literature documenting the persistence of educational outcomes across generations; therefore, one may wonder if increasing parents' education also increases children's educational attainment. To examine the causal relationship between the two, I estimate equation (3.3.1) for children's probability of school completion. I restrict my analysis to individuals born between 1940 and 1960 to ensure that their first child is old enough to complete senior high school by 2006. 85% of the 1940-60 cohorts reported having at least one child in 2006. As China implemented the compulsory schooling law in 1986, most children who were born after 1980 have completed primary education.[15] Therefore, I only consider the likelihood of completing junior high school and senior high school. Table 3.7 reports the estimation results. It shows that there is a positive and significant relationship between parent's and children's education. The IV estimates suggest that an additional year of parent's schooling increases children's probabilities of completing junior high school and senior high school by 3.94% and 4.76% respectively. The OLS estimates are smaller but still positive and significant.

3.4.3 Discussion and Robustness Checks

There are several caveats in interpreting the results. First, although the education reform in 1968-1976 increased the access to basic education, the quality of education was very poor. As data on teacher's quality and school curriculum is unavailable, I cannot control for changes in education quality. Therefore, the OLS and IV estimates should be interpreted as the lower bound of the impact of additional years of schooling on occupational and children's outcomes.

[15]The 1986 compulsory schooling law states that school-aged children are entitled to receive at least 9-years of education. The law was implemented unevenly across regions; therefore, junior high school drop-out rates were still quite high during the initial years, especially among the rural households.

TABLE 3.7: Impact of Education on Children's Schooling

	Children Completed Junior High School		Children Completed Senior High School	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Years of Education	0.0215***	0.0394***	0.0385***	0.0476***
	(0.00202)	(0.00516)	(0.00230)	(0.00856)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province × Hukou Fixed Effect	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		11.9		11.9
Hansen J statistic		0.038		0.038
Observations	3,155	3,155	3,155	3,155

Notes: Sample includes individuals born in 1940-1980. Each dependent variable is a dummy for children's outcome. Years of education are instrumented by trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Standard errors clustered by province and year of birth. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Second, many urban high school graduates were sent to rural areas to work as farmers during the rustication movement of the Cultural Revolution, and the candidates were often selected on the basis of family background (Li et al., 2010). The majority of students who were sent down were children of intellectuals, merchants and landlords. In contrast, children of well-connected families were more likely to escape from the rustication movement. To address this issue, I control for father's occupation and include a dummy for sent-down in the regressions for occupational outcomes. The results are shown in Tables 3.8 and 3.9. In all cases, the coefficients of schooling are very close to the previous findings. The estimates of father's occupation level are positive and significant, which suggest that intergenerational persistence in labour market outcomes is substantial.

TABLE 3.8: Education and First Occupation: Additional Controls

	Non-Agricultural Occupation		White Collar Occupation	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Years of Education	0.0309***	0.375***	0.0255***	0.0329***
	(0.00153)	(0.0147)	(0.00141)	(0.00975)
Father had Blue-Collar Job	0.423***	0.0984**	0.0641***	-0.0813***
	(0.0174)	(0.0434)	(0.0148)	(0.0294)
Father had White-Collar Job	0.339***	-0.0408	0.187***	0.0172
	(0.0173)	(0.0492)	(0.0175)	(0.0326)
Sent-Down	-0.0527*	-0.0870*	-0.0826**	-0.155***
	(0.0382)	(0.0565)	(0.0316)	(0.0372)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province × Hukou Fixed Effect	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		18.9		18.9
Hansen J statistic		0.036		0.036
Observations	8,288	8,288	8,288	8,288

Notes: Sample includes individuals born in 1940-1980. Each dependent variable is a dummy for occupational outcome. Years of education are instrumented by trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Standard errors clustered by province and year of birth. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 3.9: Education and First Occupation by Hukou Type: Additional Controls

	Agricultural Hukou Holders:		Non-Agricultural Hukou Holders:	
	Non-Agricultural Occupation		White Collar Occupation	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Years of Education	0.03734***	0.0369*	0.0418***	0.433**
	(0.00173)	(0.0271)	(0.00340)	(0.0576)
Father had Blue-Collar Job	0.130***	0.126***	-0.0880*	-0.201*
	(0.0389)	(0.0392)	(0.0454)	(0.105)
Father had White-Collar Job	0.123***	0.109**	0.0214	0.120
	(0.0348)	(0.0427)	(0.0454)	(0.126)
Sent-Down	0.241**	0.233*	-0.0886**	-0.140**
	(0.110)	(0.132)	(0.0363)	(0.0596)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province $\times$ Hukou Fixed Effect	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		15.8		15.8
Hansen J statistic		0.031		0.029
Observations	5,196	5,196	3,092	3,092

Notes: Sample includes individuals born in 1940-1980. Each dependent variable is a dummy for occupational outcome. Years of education are instrumented by trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Hukou type is defined as father's hukou status when the individual was 18. Standard errors clustered by province of birth and year. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

As discussed earlier, my measure of education shock relies on the assumption that there is no change in hukou status before the time of survey. If the probability of hukou switching is correlated with some regional factors which affect individual's occupation or children's schooling, my instruments would be endogenous and the IV estimates are biased. To tackle this problem, I estimate equations (3.3.1) on the basis of the 1% sample of 1990 population census. The main advantage of using the 1990 census is migration and hukou switching were strongly restricted before the mid-1990s, therefore the number of hukou switchers was much lower in 1990. However, I am forced to restrict my analysis to a smaller sample which excludes individuals born between 1971 and 1980. Appendix Figure 3.6 plots the histograms of the new estimates of education shocks. It shows that the distributions of education shocks based on the 1990 and 2000 census are very similar. In Appendix Tables 3.11-3.14, I present the regression results of equations (3.3.1) using the 1990 census-based education shocks as instruments for schooling. The results are robust to the new measures, which suggest that hukou switching is not a serious issue.

At last, my second stage estimation is based on a linear probability model. The advantage of this approach is that the magnitude of effects are easy to interpret. However, the linear least square method has an implicit assumption that the dependent variable is continuous and can take values other than zero and one. I re-estimate the second stage using a probit model and still find positive and significant effects of schooling on occupational status and children's educational performance. The results are shown in Appendix Tables 3.15-3.17 .

3.5 Conclusion

This paper studies the impact of education on occupational status and children's educational attainment. To tackle the problem of endogenous schooling, I use the education shock during the Cultural Revolution as an instrument for individual's schooling. The education reform in 1968-76 improved the access to basic education, which led to a significant growth in primary school and junior high school graduation rates for cohorts born in 1950-65. The trend deviations in primary school and junior school graduation rates are exogenous to other factors that are correlated with the individual's future outcomes. The estimation results show that increase in years of schooling leads to better occupational and children's outcomes. This finding suggest that public investment in education plays an important role in social mobility within and across generations.

3.A Appendix

3.A.1 2006 Chinese General Social Survey

Table 3.10 shows that educational disparities between individuals with agricultural and non-agricultural hukou are large and persistent across generations. Non-agricultural hukou holders have higher average years of schooling and more likely to complete junior or senior high school education. Also, the correlations between father's and children's educational attainment and hukou type are strong and positive.

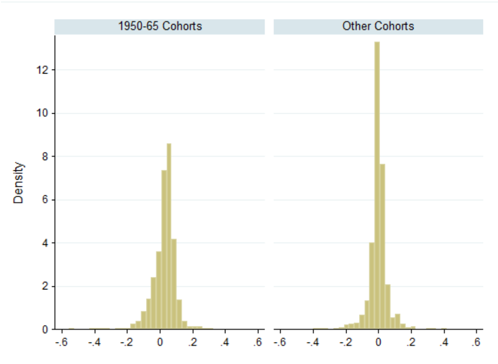
TABLE 3.10: Descriptive Statistics of the 2006 CGSS: Across Hukou

	Agricultural Hukou		Non-Agricultural Hukou	
	Mean	Std. Dev.	Mean	Std. Dev.
Respondent				
Age	42.80	12.24	44.31	13.07
Female	0.539	0.499	0.541	0.498
Married	0.913	0.282	0.858	0.349
Years of Schooling	5.965	3.763	10.036	3.867
Highest Education Level Completed				
Primary School	0.260	0.438	0.109	0.311
Junior High School	0.313	0.464	0.295	0.456
Senior High School	0.102	0.302	0.333	0.471
College or Above	0.014	0.117	0.188	0.391
First Occupation				
Agricultural	0.798	0.402	0.118	0.313
Blue-collar	0.175	0.380	0.465	0.491
White-collar	0.027	0.531	0.418	0.694
Father When Respondent Was 18				
Share of Non-Agricultural Hukou	0.0398	0.195	0.697	0.460
Sector of Occupation				
Primary	0.891	0.312	0.318	0.466
Secondary	0.0473	0.212	0.358	0.479
Tertiary	0.0620	0.241	0.324	0.468
Observations	4,162		4,126	

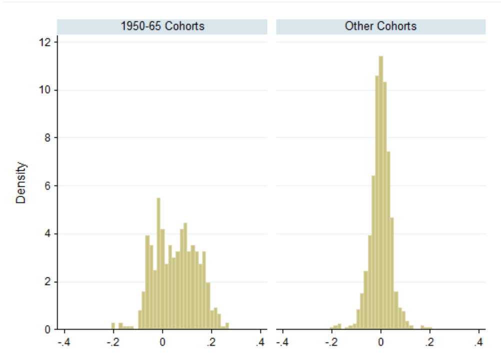
Notes: Sample is restricted to individuals born in 1940-1980 and do not report missing values of the variables listed in the table above.

3.A.2 Education Shock and Household Type

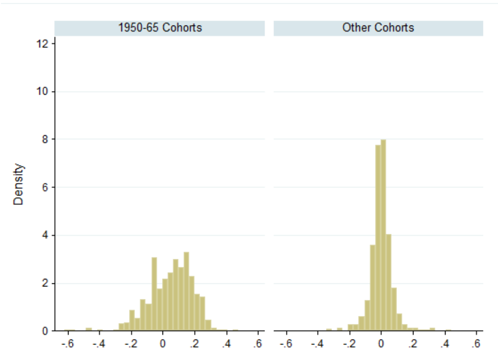
FIGURE 3.5: Distribution of Education Trend Deviations by Hukou Status



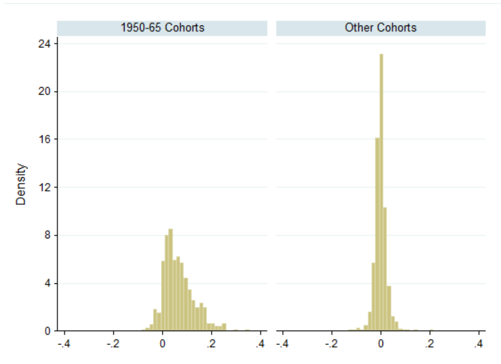
(a) Primary School: Non-Agricultural



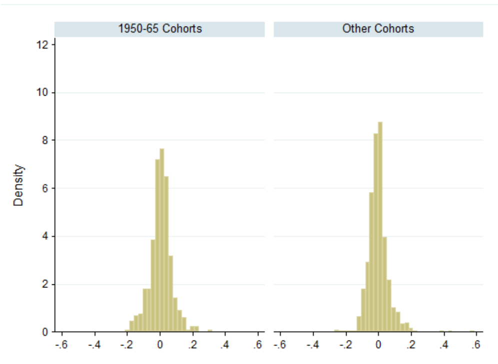
(b) Primary School: Agricultural



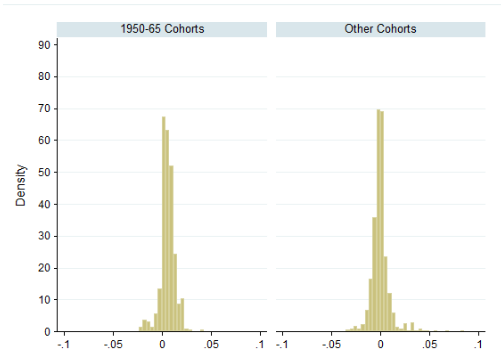
(c) Junior High School: Non-Agricultural



(d) Junior High School Agricultural



(e) Senior High School: Non-Agricultural

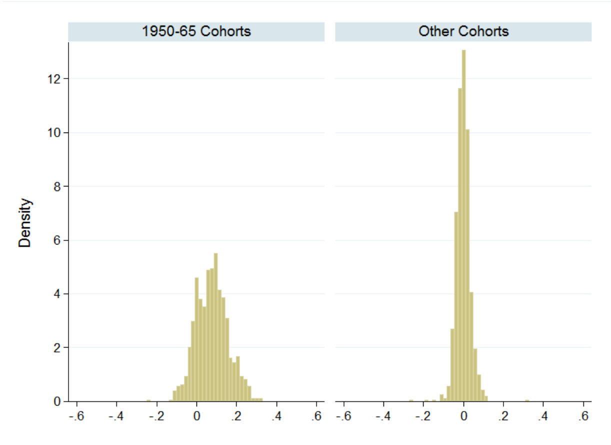


(f) Senior High School: Agricultural

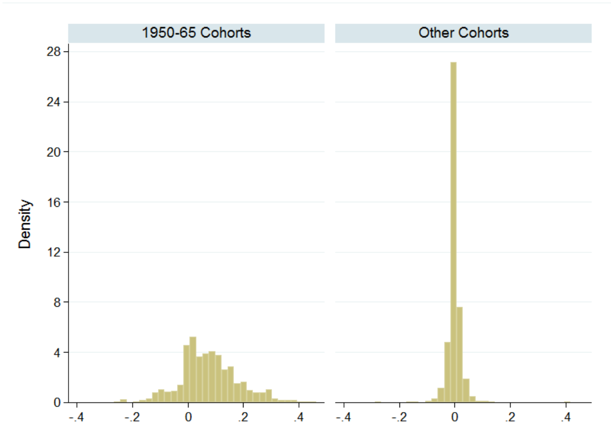
Source: 0.95% Sample of 2000 Population Census and author's calculations

3.A.3 Robustness Checks I

FIGURE 3.6: Distribution of Education Trend Deviations: 1990 Census-Based



(a) Primary School



(b) Junior High School

Source: 1% Sample of 1990 Population Census and author's calculations

TABLE 3.11: First Stage Results: 1990 Census

	OLS	Probit		
	Years of Education	Primary School	Junior High School	Senior High School
	(1)	(2)	(3)	(4)
Primary School Shock	0.0167*	0.0107***	0.00342	0.00245
	(0.00971)	(0.00405)	(0.00338)	(0.00600)
Junior High School Shock	0.0247**	0.0111***	0.0162***	0.0135***
	(0.0110)	(0.00419)	(0.00441)	(0.00381)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province × Hukou Fixed Effect	Yes	Yes	Yes	Yes
Observations	6,281	6,281	6,281	6,281
R-squared	0.207			

Notes: Sample includes individuals born in 1940-1970. Each dependent variable in columns 2 to 4 is an dummy for graduation. Education shocks are trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Standard errors clustered by province and year of birth. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 3.12: Education and First Occupation: 1990 Census

	Non-Agricultural Occupation		White Collar Occupation	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Years of Education	0.0331***	0.0360***	0.0304***	0.0357***
	(0.00165)	(0.00165)	(0.00144)	(0.00144)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province × Hukou Fixed Effect	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		15.7		15.7
Hansen J statistic		0.049		0.049
Observations	6,281	6,281	6,281	6,281

Notes: Sample includes individuals born in 1940-1970. Each dependent variable is a dummy for occupational outcome. Years of education are instrumented by trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Standard errors clustered by province and year of birth. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 3.13: Education and First Occupation by Hukou Type: 1990 Census

	Agricultural Hukou Holders: Non-Agricultural Occupation		Non-Agricultural Hukou Holders: White Collar Occupation	
	OLS (1)	IV (2)	OLS (3)	IV (4)
Years of Education	0.0348***	0.0377***	0.0376***	0.0411***
	(0.00182)	(0.00182)	(0.00350)	(0.00350)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province × Hukou Fixed Effect	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		14.2		11.4
Hansen J statistic		0.045		0.032
Observations	3,947	3,947	2,334	2,334

Notes: Sample includes individuals born in 1940-1970. Each dependent variable is a dummy for occupational outcome. Years of education are instrumented by trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Hukou type is defined as father's hukou status when the individual was 18. Standard errors clustered by province and year of birth. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 3.14: Education and Children's Schooling: 1990 Census

	Children Completed Junior High School		Children Completed Senior High School	
	OLS (1)	IV (2)	OLS (3)	IV (4)
Years of Education	0.0212***	0.0314***	0.0386***	0.0456***
	(0.00203)	(0.00203)	(0.00231)	(0.00231)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province × Hukou Fixed Effect	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		11.4		11.4
Hansen J statistic		0.038		0.038
Observations	3,155	3,155	3,155	3,155

Notes: Sample includes individuals born in 1940-1960. Each dependent variable is a dummy for children's outcome. Years of education are instrumented by trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Standard errors clustered by province and year of birth. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

3.A.4 Robustness Checks II

TABLE 3.15: Education and First Occupation: Probit Model

	Non-Agricultural Occupation		White Collar Occupation	
	Probit (1)	IV Probit (2)	Probit (3)	IV Probit (4)
Years of Education	0.185***	0.171***	0.184***	0.192***
	(0.00684)	(0.00470)	(0.00802)	(0.00786)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province × Hukou Fixed Effect	Yes	Yes	Yes	Yes
Wald Test of Exogeneity		8.44		8.44
Observations	8,288	8,288	8,288	8,288

Notes: Sample includes individuals born in 1940-1980. Each dependent variable is a dummy for occupational outcome. Years of education are instrumented by trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Standard errors clustered by province and year. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 3.16: Education and First Occupation By Hukou Type: Probit Model

	Agricultural Hukou Holders:		Non-Agricultural Hukou Holders:	
	Non-Agricultural Occupation		White Collar Occupation	
	Probit (1)	IV Probit (2)	Probit (3)	IV Probit (4)
Years of Education	0.134***	0.160***	0.183***	0.130***
	(0.0331)	(0.00848)	(0.0322)	(0.0111)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province × Hukou Fixed Effect	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		14.6		12.3
Hansen J statistic		0.045		0.032
Observations	5,196	5,196	3092	3,092

Notes: Sample includes individuals born in 1940-1980. Each dependent variable is a dummy for occupational outcome. Years of education are instrumented by trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Hukou type is defined as father's hukou status when the individual was 18. Standard errors clustered by province and year of birth. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 3.17: Education and Children's Schooling: Probit Model

	Children Completed Junior High School		Children Completed Senior High School	
	Probit	IV Probit	Probit	IV Probit
	(1)	(2)	(3)	(4)
Years of Education	0.0843***	0.169***	0.110***	0.237***
	(0.00858)	(0.0203)	(0.00751)	(0.0104)
Cohort Fixed Effect	Yes	Yes	Yes	Yes
Province × Hukou Fixed Effect	Yes	Yes	Yes	Yes
Wald Test of Exogeneity		5.18		5.18
Observations	3,155	3,155	3,155	3,155

Notes: Sample includes individuals born in 1940-1960. Each dependent variable is a dummy for children's outcome. Years of education are instrumented by trend deviations of cohort graduation rates which are measured at province-hukou level for each birth cohort. Standard errors clustered by province and year of birth. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Bibliography

Abowd, J. M., J. Haltiwanger, R. Jarmin, J. Lane, P. Lengermann, K. McCue, K. McKinney, and K. Sandusky (2005, December). The Relation among Human Capital, Productivity, and Market Value: Building Up from Micro Evidence. In *Measuring Capital in the New Economy*, NBER Chapters, pp. 153–204. National Bureau of Economic Research.

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999). High Wage Workers and High Wage Firms. *Econometrica 67*(2), pp. 251–333.

Abramovitz, M. (1956). Resource and Output Trends in the United States Since 1870. *American Economic Review*, 5–23.

Afridi, F., S. Li, and Y. Ren (2012). Social Identity and Inequality: The Impact of China's Hukou System. *Working Paper*.

Aghion, P., R. Burgess, S. Redding, and F. Zilibotti (2008). The Unequal Effects of Liberalization: Evidence from Dismantling the License Raj in India. *American Economic Review 98*(4), 1397–1412.

Amiti, M. and D. R. Davis (2012). Trade, Firms and Wages: Theory and Evidence. *Review of Economic Studies 79*(1), 1–36.

Amiti, M. and J. Konings (2007). Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia. *American Economic Review 97*(5), 1611–1635.

Atalay, E., A. Hortacsu, and C. Syverson (2012). Why Do Firms Own Production Chains? *NBER Working Paper No. 18020*.

Bandiera, O., I. Barankay, and I. Rasul (2009). Social Connections and Incentives in the Workplace: Evidence from Personnel Data. *Econometrica 77*(4), pp. 1047–1094.

Bas, M. and V. Strauss-Kahn (2012). Trade Liberalization and Export Prices: The Case of China. *Working Paper*.

Baum-Snow, N., L. Brandt, J. V. Henderson, M. A. Turner, and Q. Zhang (2012). Roads,RailroadsandDecentralizationofChineseCities. *Working Paper*.

Becker, G. S. (1962). Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy 70*(5), 9–49.

Becker, G. S. and N. Tomes (1986). Human Capital and the Rise and Fall of Families. *Journal of Labor Economics 4*(3), 1–39.

Bernard, A., S. Redding, and P. Schott (2007). Comparative Advantage and Heterogeneous Firms. *Review of Economic Studies 74*(1), 31–66.

Bernard, A. B., S. Redding, and P. K. Schott (2010). Multiple-product Firms and Product Switching. *American Economic Review 100*(1), 70–97.

Bernhofen, D. M. and J. C. Brown (2011). Testing the General Validity of the Heckscher-Ohlin Theorem: The Natural Experiment of Japan. *CESifo Working Paper Series 3586*.

Bernstein, J. R. and D. E. Weinstein (2002). Do Endowments Predict the Location of Production? Evidence from National and International data. *Journal of International Economics 56*(1), 55–76.

Bilbiie, F., F. Ghironi, and M. J. Melitz (2012). Endogenous Entry, Product Variety, and Business Cycles. *Journal of Political Economy 120*(2), 304–345.

Birdsall, N. (1985). Public Inputs and Children Schooling in Brazil. *Journal of Development Economics 18*, 67–68.

Black, S. E., P. J. Devereux, and K. G. Salvanes (2005). Why the Apple Doesn't Fall Far: Understanding Intergenerational Transmission of Human Capital. *American Economic Review 95*(1), 437–449.

Bloom, N., M. Schankerman, and J. van Reenen (2007). Identifying Technology Spillovers and Product Market Rivalry. *NBER Working Paper No. 13060*.

Bloom, N. and J. van Reenen (2007). Measuring and Explaining Management Practices across Firms and Countries. *Quarterly Journal of Economics 122*(4), 1351–1408.

Bombardini, M., G. Gallipoli, and G. Pupato (2012). Skill Dispersion and Trade Flows. *American Economic Review 102*(5), 2327–48.

Borjas, G. (2009). The Analytics of the Wage Effect of Immigration. *Working Paper*.

Borjas, G. J. (2003). The Labor Demand Curve Is Downward Sloping: Reexamining The Impact Of Immigration On The Labor Market. *Quarterly Journal of Economics 118*(4), 1335–1374.

Bowles, S. (1970). Aggregation of Labor Inputs in the Economics of Growth and Planning: Experiments with a Two-Level CES Function. *Journal of Political Economy 78*(1), 68–81.

Brandt, L., J. V. Biesebroeck, and Y. Zhang (2012). Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing. *Journal of Development Economics 97*(2), 339–351.

Chan, K. W. and W. Buckingham (2008). Is China Abolishing the Hukou System? *The China Quarterly 195*, 582–606.

Chan, K. W., T. Liu, and Y. Yang (1999). Hukou and Non-hukou Migrations in China: Comparisons and Contrasts. *International Journal of Population Geography 5*, 425–448.

Chow, G. C. (1993). Capital Formation and Economic Growth in China. *The Quarterly Journal of Economics 108*, 809–842.

Defever, F. and A. Riano (2012). Pure-Exporter Subsidies: The Non-Reform of China's Trade Policy. *Working Paper*.

Duflo, E. (2001). Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment. *American Economic Review 91*(4), 795–813.

Faber, B. (2012). Trade Integration, Market Size, And Industrialization: Evidence From China's National Trunk Highway System. *Working Paper*.

Fitzgerald, D. and J. C. Hallak (2004). Specialization, Factor Accumulation and Development. *Journal of International Economics 64*(2), 277–302.

Fleisher, B. M. and X. Wang (2004). Skill Differentials, Return to Schooling, and Market Segmentation in a Transition Economy: the Case of Mainland China. *Journal of Development Economics 73*(1), 315–328.

Fox, J. T. and V. Smeets (2011). Does Input Quality Drive Measured Differences in Firm Productivity? *NBER Working Paper No. 16853* (16853).

Garicano, L. and P. Heaton (2010). Information Technology, Organization, and Productivity in the Public Sector: Evidence from Police Departments. *Journal of Labor Economics 28*(1), 167–201.

Giles, J., A. Park, and M. Wang (2008). The Great Proletarian Cultural Revolution, Disruptions to Education, and Returns to Schooling in Urban China. *The World Bank Policy Research Working Paper 4729*.

Goldberg, P. K., A. Khandelwal, N. Pavcnik, and P. Topalova (2010). Imported Intermediate Inputs and Domestic Product Growth: Evidence from India. *Quarterly Journal of Economics 125*(4), 1727–1767.

Goldberg, P. K. and N. Pavcnik (2005). Trade, Wages and the Political Economy of Trade Protection: Evidence from Colombian Trade Reforms. *Journal of International Economics 66*(1), 75–105.

Grossman, G. M. and G. Maggi (2000). Diversity and Trade. *American Economic Review 90*(5), 1255–1275.

Helpman, E., O. Itskhoki, and S. Redding (2010a). Inequality and Unemployment in a Global Economy. *Econometrica 78*(4), 1239–1283.

Helpman, E., O. Itskhoki, and S. Redding (2010b). Unequal Effects of Trade on Workers with Different Abilities. *Journal of the European Economic Association Papers & Proceedings 8*(2-3), 421–433.

Hirschman, A. (1958). *The Strategy of Economic Development*. Encore Edition Series. Westview Press.

Holmlund, H. (2008). Intergenerational Mobility and Assortative Mating: Effects of an Educational Reform. *CEE Discussion Papers 0091*.

Horta, A. and C. Syverson (2007). Cementing Relationships: Vertical Integration, Foreclosure, Productivity, and Prices. *Journal of Political Economy 115*(2), 250–301.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and Manufacturing TFP in China and India. *Quarterly Journal of Economics 124*(4), 1403–1448.

Ilmakunnas, P. and S. Ilmakunnas (2011). Diversity at the Workplace: Whom Does it Benefit? *De Economist 159*(2), 223–255.

Iranzo, S., F. Schivardi, and E. Tosetti (2008). Skill Dispersion and Firm Productivity: An Analysis with Employer-Employee Matched Data. *Journal of Labor Economics 26*(2), 247–285.

Javorcik, B. S. (2004). Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages. *American Economic Review 94*(3), 605–627.

Karadi, P. and M. Koren (2012). Cattle, Steaks and Restaurants: Development Accounting when Space Matters. *Working Paper*.

Kennan, J. and J. R. Walker (2011). The Effect of Expected Income on Individual Migration Decisions. *Econometrica 79*(1), 211–251.

Kugler, M. and E. Verhoogen (2011). Prices, Plant Size, and Product Quality. *Review of Economic Studies 79*(1), 307–339.

Lavy, V. (1996). School Supply Constraints and Children's Educational Outcomes in Rural Ghana. *Journal of Development Economics 51*, 291–314.

Lazear, E. P. (2000). Performance Pay and Productivity. *The American Economic Review 90*(5), pp. 1346–1361.

Lewis, W. (1954). Economic Development with Unlimited Supplies of Labour. *The Manchester School 22*(2), 139–191.

Li, H., M. Rosenzweig, and J. Zhang (2010). Altruism, Favoritism, and Guilt in the Allocation of Family Resources: Sophie's Choice in Mao's Mass Send Down Movement. *Journal of Political Economy 118*(1), 1–38.

Ma, Y., H. Tang, and Y. Zhang (2012). Factor Intensity, Product Switching, and Productivity: Evidence from Chinese Exporters. *Working Paper*.

Manova, K. and Z. Zhang (2012). Export Prices Across Firms and Destinations. *Quarterly Journal of Economics 127*(1), 379–436.

Martins, P. S. (2008). Dispersion in Wage Premiums and Firm Performance. *Economics Letters 101*, 63–65.

Maurin, E. and S. McNally (2008). Vive la Rlution! Long Term Returns of 1968 to the Angry Students. *Journal of Labor Economics 26*(1), 1–33.

Melitz, M. J. (2003). The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity. *Econometrica 71*(6), 1695–1725.

Melitz, M. J. and G. I. P. Ottaviano (2008). Market Size, Trade, and Productivity. *Review of Economic Studies 75*(1), 295–316.

Meng, X. and B. Gregory (2007). Exploring the Impact of Interrupted Education on Earnings: The Educational Cost of the Chinese Cultural Revolution. *IZA Discussion Paper No. 2548*.

Moretti, E. (2004). Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions. *American Economic Review 94*(3), 656–690.

Moretti, E. (2011). Chapter 14 - Local Labor Markets. In *Handbook of Labor Economics*, Volume 4, Part B, pp. 1237 – 1313. Elsevier.

Morrow, J. (2010). Is Skill Disperison a Source of Productivity and Exports in Developing Countries? *Working Paper*.

Oreopoulos, P., M. E. Page, and A. H. Stevens (2006). The Intergenerational Effects of Compulsory Schooling. *Journal of Labor Economics 26*, 455–483.

Ottaviano, G. and G. Peri (2010). Rethinking the Effect of Immigration on Wages. *Working Paper*.

Overman, H. G. and D. Puga (2010). Labor Pooling as a Source of Agglomeration: An Empirical Investigation. In *Agglomeration Economics*, NBER Chapters, pp. 133–150. National Bureau of Economic Research, Inc.

Ozyurt, S. (2009). Total Factor Productivity Growth in Chinese Industry: 1952-2005. *Oxford Development Studies 37*(1), 1–17.

Parrotta, P., D. Pozzoli, and M. Pytlikova (2011). Does Labor Diversity affect Firm Productivity? *Norface Migration Discussion Paper No. 2011-22*.

Pekkarinen, T., R. Uusitalo, and S. Pekkala (2006). Education Policy and Intergenerational Income Mobility: Evidence from the Finnish Comprehensive School Reform. *IZA Discussion Paper No. 2204*.

Syverson, C. (2004). Market Structure and Productivity: A Concrete Example. *Journal of Political Economy 112*(6), 1181–1222.

Syverson, C. (2011). What Determines Productivity? *Journal of Economic Literature 49*(2), 326–365.

Topalova, P. (2010). Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India. *American Economic Journal: Applied Economics 2*(4), 1–41.

Trefler, D. (1993). Trade Liberalization and the Theory of Endogenous Protection: An Econometric Study of U.S. Import Policy. *Journal of Political Economy 101*(1), 138–160.

Trefler, D. (1994). Protection, Trade, and Wages: Evidence from U.S. Manufacturing. *Industrial and Labor Relations Review 47*(4), 574–593.

Trefler, D. (2004). The Long and Short of the Canada-U.S. Free Trade Agreement. *American Economic Review 94*(4), 870–895.

Vanek, J. (1968). The Factor Proportions Theory: The N-Factor Case. *Kyklos 21*(4), 749–756.

Verhoogen, E. A. (2008). Trade, Quality Upgrading and Wage Inequality in the Mexican Manufacturing Sector. *Quarterly Journal of Economics 123*(2), 489–530.

Yu, M. (2011). Processing Trade, Tarff Reductions, and Firm Productivity: Evidence from Chinese Products. *CCER Working Paper*.