ESSAYS IN DETERMINANTS OF COMPARATIVE ADVANTAGE AND WELFARE IMPLICATIONS OF TRADE WARS

KE GU

A DISSERTATION SUBMITTED TO
THE FACULTY OF GRADUATE STUDIES
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

GRADUATE PROGRAM IN ECONOMICS
YORK UNIVERSITY
TORONTO, ONTARIO

September 2021

Abstract

My main research areas are international trade and empirical microeconomics. In the first and second chapter of my PhD dissertation, I use similar empirical methodology clearly identify and analyzing comparative advantage among aging and female labor supply unbalanced countries. The third chapter focus on the effect of US – China trade war on the country welfare with intermediate and non-tradable goods.

In the first chapter, we investigate a particular mechanism through which differences in demographic composition across countries affect international trade flows. Some cognitive functions are known to vary across the adult life span, and in particular the ability to update skills and adapt to changes in working conditions. As a country's population is getting older, it becomes increasingly difficult for firms to find workers with up-to-date skills. As a result, countries with aging populations will start losing comparative advantage in industries that rely heavily on workers' ability to adapt to frequent changes in working conditions. We test this hypothesis and find robust empirical evidence for a significant negative effect of population aging on comparative advantage of a country in industries which are intensive in skill adaptability of the labor force, in both the cross-sectional and the dynamic panel data sets.

In the second chapter, we study the effect of female labor supply change on China's international trade. In 1979, the one-child policy (OCP) was introduced in China, many more boys than girls have been born, changing the relative female labor supply. Differences in sex ratios across cities, caused by differences in OCP enforcement, affect availability of gender-dependent skills. These regional differences interact with sector-specific differences in intensities in gender-dependent skills. Other things equal, cities with higher female population share specialize in industries which use female labor intensively. We empirically confirm this insight for the sample of 283 Chinese prefecture cities, using spatial variation in OCP stringency as an exogenous female labor supply shifter. We interpret our results as highlighting the importance of labor force gender composition for industry's productivity. Our results imply that the effect of gender imbalances in labor supply on labor market outcomes, observed in many parts of the world, can be mitigated through international trade by utilizing relatively abundant type of labor in export-oriented industries.

In the third chapter, we use a quantitative general equilibrium trade model to analyze the effect of the US – China trade war on welfare of the main countries affected by it. In 2018, the US introduced a 25% import tariff on certain imports from China in an attempt to reduce US – China trade deficits and to nudge the Chinese government to abandon its "unfair trade practices". Quantitative results suggest that after three rounds of import tariff increase both China and US suffered welfare reductions, by 0.3 and 0.0075 percentage points respectively. At the same time, some other economies benefited from the trade war, especially the ones that are close trade partners to either US or China. We use this model to simulate the effect of the same additional import tariff imposed on randomly selected industries, and find similar reduction in welfare.

Contents

List of Tables

List of Figures

Chapter 1

Skills, Population Aging, and the Pattern of Trade[1]

1 Introduction

Population aging is the most prominent global demographic trend of the 21^{st} century, which is expected to alter the labor force composition in a large number of countries. Along with population aging comes the structural change in the mix of skills that an average worker of a country possesses, as long as some of these skills change over a person's life cycle. Some skills are known to deteriorate with age, causing a decline in the aggregate supply of those skills in aging populations and altering age-earnings profiles. To understand better the economic implications of aging, one needs to know the effect of demographics on international trade flows since changes in the supply of a certain skill in a country may also affect the demand for that skill through exports and imports.[2]

In this study, we analyze the effect of population aging on trade flows through a reduction in the supply of a particular age-dependent skill – the ability of an individual to adapt to changes in working conditions. The neuroscience and behavioral literatures document that the ability of an individual to adjust to frequent changes in the workplace or in the job requirements is getting worse with age. This implies that younger workers, all else equal, are more productive in tasks that require workers to update their skills regularly. Throughout the paper, we call the worker ability to adapt to changes in the workplace the *adaptability skill*.

The age-induced decline in the adaptability skill implies two channels through which aging labor force affects the pattern of comparative advantage across countries with different demographic composition. First, population aging reduces the effective stock of adaptability skill and increases the skill premium, and industries that are intensive in the adaptability skill will face higher labor costs. This Heckscher-Ohlin channel implies that aging countries will lose their comparative advantage in industries that rely heavily on adaptability skills. Second, aging workers may become less productive in occupations that require adaptability skills. As a result, industries which rely on such occupations will lose the Ricardian comparative advantage as the pool of available workers becomes older. Therefore, regardless of the channel through which demographic changes affect comparative advantage, aging countries are expected to specialize less in industries in which adaptability skills are important.

In order to analyze the effect of aging on bilateral trade flows through adaptability skills, we construct an industry-level measure of intensity in the adaptability skill using two data sources. First, we use the O*NET data base, which surveys workers, occupational experts, and occupational analysts in the United States to measure the importance of various skills for different occupations. O*NET provides a direct measure of the relative importance of adaptability skill across occupations.

[1]This paper is joint with Professor Andrey Stoyanov.

[2]In the Heckscher-Ohlin model, a decrease in the supply of a factor of production deteriorates the comparative advantage of a country in industries that use that factor intensively. As a result, the demand for that factor decreases, countering the effect of the decline in the supply on the factor price.

Second, we use occupational composition in 4-digit NAICS industries in the US to construct a weighted-average measure of the adaptability skill intensity for each industry.

Testing our main hypothesis on a cross-section of bilateral trade data for a large set of countries in year 2000, we find that countries with relatively older labor forces tend to export less in industries which are intensive in adaptability skill. Interestingly, the effect of demographic differences across countries on trade is similar in magnitude to the effect of differences in physical capital and skilled labor, the two conventional factors of production. Furthermore, the role of cross-industry variation in adaptability skill in bilateral trade is similar to the effect of other age-dependent skills identified in previous literature, such as physical and cognitive skills. Our baseline results imply that if an industry has intensity in adaptability skill one standard deviation higher than the average in the economy, then a one year increase in a country's median age will decrease exports in that industry by 1.9% relative to other industries.

Another theoretical prediction that we test is that different rates of population aging across countries over time should change the patterns of comparative advantage. Specifically, if a country's population is aging faster than in other countries, then we should expect exports of the former to move away from industries that rely heavily on the adaptability skill. A test based on the dynamic panel structure has an additional advantage as it allows differentiating out country-specific factors, such as the level of development, with a proper set of fixed effects. Using the panel data on 80 exporting countries, 136 importing countries, and 71 industries for the time period from 1962 to 2010, we confirm that export structure of a country depends on the rate of population aging relative to other countries. The magnitude of the effect estimated from the dynamic model is nearly identical to that estimated from the static model: a one year increase in the median age of a country and a one standard deviation increase in industry's intensity in adaptability skill is associated with a 1.9% reduction in exports. This result confirms that while population aging decreases the relative supply of the adaptability skill, the effect of this change on labor markets is alleviated, to some extent, by a decrease in the demand for those skills through an increase in imports of goods which are intensive in the adaptability skill.

The results of our study complement the research investigating the sources of comparative advantage in international trade. Beck (2003), Manova (2008), Manova (2012) and Campello and Gao (2017) find that the level of financial market development, credit constraints, and the relationship between firms and their banks shape bilateral trade flows. Nunn (2007), Levchenko (2007), Antràs and Chor (2013) and Araujo et al. (2016) demonstrate that institutional differences across countries, such as the quality of contract enforcement, the strength of property rights protection, and shareholder protection, affect comparative advantage in trade. Helpman and Itskhoki (2010), Cuñat and Melitz (2012) and Tang (2012) show that countries with flexible labor markets enjoy comparative advantage in industries which are subject to frequent economic shock and require firms to adjust their labor force. In this work, we show that population aging is also a factor of comparative advantage that operates through the supply of adaptability skill in population.

The literature on the economic implications of population aging is large and varied, though mostly focused on macro effects and based on computational general equilibrium models. The evidence on the relationship between demographic factors and international trade is quite limited. Several studies show that aging countries observe not only a decrease in labor supply but also an increase in capital stock through accelerated savings, thus gaining a comparative advantage in capital-intensive industries.[3][4] Two papers that are most closely related to ours are by Wolff (2003) and Cai and Stoyanov (2016), which go beyond conventional factors of production and estimate a direct impact of unobservable age-dependent skills on the pattern of international trade. Wolff (2003) investigates empirically the factor content of US trade in various skills, and find that US is a net exporter of cognitive skills and an importer of motor skills. This could reflect the fact that aging US population accumulates cognitive skills and export them to other countries through trade in goods. However, age-induced changes in cognitive skills vary substantially across skill types: while some skills decline with age (such as memory), others improve (such as communication skills). The distinction between various types of cognitive skills for trade is supported by Cai and Stoyanov (2016), who take into account heterogeneous impact of aging on different cognitive skills. The authors find that aging population undermines comparative advantage in industries that are intensive in memory and the speed of information processing, but improves it in industries that are intensive in communication skills. In this paper, we identify adaptability skill as a novel channel through which demographic composition affects the pattern of international trade and determines the evolution of comparative advantage as the working population is getting older.

The paper contributes to the literature on population aging and international trade in three ways. First, the paper contributes to the trade literature by identifying a new factor of comparative advantage. It demonstrates that countries with younger working age populations specialize in industries that rely on the worker's ability to adapt to frequent changes in working conditions. This effect is empirically robust and economically sizable, and it explains as much variation in trade flows as previously identified sources of comparative advantage, such as differences in capital and labor endowments across countries. Second, the results of the paper imply that adaptability skill is an important input factor in the production process of many industries. The fact that comparative advantage in adaptability-intensive industries declines in aging countries suggests that firm-level productivity in those industries drops, either due to limited supply of workers with adaptability skill or due to declining productivity of aging workers in occupations that require adaptability skill. Finally, the finding that aging countries lose comparative advantage in adaptability-intensive industries also implies that the change in the supply of the skill mix, induced by demographic changes, is followed by the change in the demand for those skill on the side of exporting and importing industries. While the supply effect tends to increase the adaptability skill premium and the relative wage of junior workers in aging countries, the demand effect works in the opposite direction, meaning that international trade plays an important role in the effect of demographic changes on the labor markets.

The remainder of the paper is organized as follows: Section 2 describes the relationship between aging and adaptability skills, Section 3 discusses empirical methodology, Section 4 describes the data source, and Section 5 present the empirical results. Section 6 provides concluding remarks.

2 Aging and adaptability skills

A large body of literature demonstrates a negative relationship between aging and individual's ability to adapt to changes in working conditions. Four factors underlie this relationship. First,

[3] Sayan (2005), Naito and Zhao (2009) and Yakita (2012).

[4] A recent study by Chisik et al. (2016) analyses theoretically the effect of aging on consumer preferences and demand for imports.

research has shown that mental flexibility declines with age. For example, Wecker et al. (2005) document that in experiments in which individuals are required to systematically alternate between two response sets, the ability to switch between tasks is declining with respondents' age. Jones (2015) argues that aging is associated with an irreversible decrease in adaptability due to a cumulative decline in the exposure memory systems.

Second, the existing literature provides evidence on differences in the attitude towards new technologies among workers of different age. Older adults tend to rely more on their experiences than younger ones, and are less willing to accept new technologies or working methods if they resonate with their experiences. Czaja and Sharit (1998), among many others, find that the expansion of new computerized technologies was associated with discomfort and higher levels of frustration among older adults, even after controlling for the intensity of new technology use by an individual. Marcoulides et al. (1995) claimed that younger people could pick up computer skills quicker. During the spread of internet in 1990s, a series of studies report that younger adults used internet more frequently and perceived themselves more capable in learning this new tool (e.g. Zhang (2005)). Finally, various studies find that age works as a moderator in the attitude towards adoption of new technologies at the workplace (e.g. Elias et al. (2012)).

Third, older individual are not as good as younger ones in updating motor skills. Studies in behavioral, neurological, and neuroimaging literature consistently report negative relationship between aging and motor skill acquisition, whereby older adults learns slower, and in many cases, even when provided with extended practice, their performance levels do not reach those of younger adults.[5] In a recent review, King et al. (2013b) summarized that older adults (i) have deficits in motor skill updating when the task complexity is increasing, (ii) demonstrate impairments in consolidation of learned motor sequences, and (iii) do not perform well in tasks that feature frequent sensorimotor perturbations.

The fourth factor that affects adaptability skill of older individuals is the difference in acquisition of new information relative to younger individuals. For example, Gist et al. (1988), Sternberg and Berg (1992), Morris and Venkatesh (2000), Maurer (2001), Prenda and Stahl (2001), Skirbekk (2004), Brooke and Taylor (2005) and Charness (2006) find that older workers learn new skills at a slower pace than younger workers for a variety of reasons. Sternberg and Berg (1992) speculate that the slow acquisition of new information may occur to older workers because of their large knowledge base. First, older individuals are more likely to discard new information if it contradicts their beliefs formed long ago. Second, past experiences might be a handicap to learning, which may occur due to past habits or old ways of thinking. Maurer (2001) finds a decline in self-efficacy in career-relevant learning and skill development with age. Charness and Czaja (2006) show that some of the slowing in learning new tasks may be attributable to older adults preference for accuracy over speed.

3 Theoretical background and predictions

In this section, we discuss the theoretical mechanism underlying the effect of aging on comparative advantage in trade, and use the main predictions of the theoretical analysis to motivate the empirical

[5] See, for example, Buch et al. (2003), Harrington and Haaland (1992), Howard Jr and Howard (1997), McNay and Willingham (1998), Messier et al. (2007), Pratt et al. (1994), Ruch (1934), and Seidler (2006).

framework. Our theoretical framework follows Chor (2010), who combined both the Heckscher-Ohlin and the Ricardian determinants of comparative advantage to predict industry-level trade flows between country-pairs. Cai and Stoyanov (2016) extend framework to demographic differences across countries and argue that the combination of industry intensity in age-dependent skill and country's demographic composition is a factor of comparative advantage in trade. Applying the main argument put forward by the authors to adaptability skill, it follows that aging countries must lose comparative advantage in industries that rely heavily on the adaptability skill.

In the Heckscher-Ohlin model, bilateral trade flows are determined by the relative supply of the factors of production. It follows that differences in the supply of various skills across countries will also affect trade flows. If the stock of the adaptability skill of a worker is decreasing with age, the total supply of that skill must be decreasing in countries with rapidly aging populations. As a result, the skill premium for adaptability skill will be higher in countries with older populations, undermining their comparative advantage in industries that rely on that skill intensively.

In the Ricardian model, the comparative advantage is determined by the relative productivity of countries in different industries. If aging reduces workers' productivity in tasks that require frequent skill updating, then aging of the labor force will have disproportionately stronger adverse effect on productivity in industries that are intensive in the adaptability skill. Therefore the Ricardian comparative advantage of aging countries must decline in industries which need adaptability skill in the production process.

From above theoretical arguments, both models imply that export composition of aging countries must shift away from industries which require their workers to frequently update skills. Therefore we obtain the following two predictions:

1. In a static framework, countries with relatively younger labor forces must have stronger comparative advantage in industries which are intensive in adaptability skill than countries with older labor forces.

2. In a dynamic framework, countries with high rates of population aging must observe a decrease in exports in adaptability skill-intensive industries relative to countries with low rates of population aging.

4 Empirical methodology

In order to estimate the effect of population aging on trade flows, we follow Chor (2010), Bombardini et al. (2012), and Cai and Stoyanov (2016) and use the following empirical model:

$$\ln X_{cpi} = \alpha I_i \times Age_c + \sum_{k \in K} \beta_k I_i^k \times Age_c + \sum_{f \in F} \phi_f I_i^f \times F_c^f + \delta'_{cp}\lambda + \gamma_c + \gamma_{pi} + \varepsilon_{cpi} \tag{1}$$

In (1), X_{cpi} is the exports from country c to country p in industry i, and I_i is the intensity of industry i in the adaptability skill. Age_c is the variable that reflects the demographic structure of the labor force in country c. We use two alternative measures for Age_c, one is the median age of population in country c, and the other is the share of "senior workers" in the labor force, constructed as the share of 40-64 year-olds among 20-64 year-olds. The interaction term $I_i \times Age_c$ is the main variable of interest in equation (1). All else equal, countries with older labor forces and larger values of Age_c should have comparative disadvantage in adaptability-intensive industries (with high values of I_i), and we expect α to be negative.

I_i^k in (1) stands for the intensity of industry i in an age-dependent skill k. Cai and Stoyanov (2016) identify a set of age-dependent cognitive and physical skills which affect comparative advantage of a country, and we include $I_i^k \times Age_c$ interactions as controls to make sure that the adaptability skill does not capture the effect of other age-dependent skills on the patterns of trade. Other controls include capital and skilled labor endowments in exporting country, F_c^f, interacted with industry i intensity in these factors, I_i^f, where index f stays for either physical capital or skilled labor. We also control for geographic characteristics of each country-pair, δ_{cp}, that may affect bilateral trade cost.[6] Finally, equation (1) includes exporter and importer-industry fixed effects, γ_c and γ_{pi}, to control for the structural gravity effects, such as the factors of comparative advantage in importing countries.

We also estimate the dynamic specification of equation (1). Allowing exports, demographic structure, and the factor endowments to vary over time, we time-difference (1) and estimate the following model:

$$\triangle lnX_{cpi} = \alpha I_i \times \triangle Age_c + \sum_{k\in K} \beta_k I_i^k \times \triangle Age_c + \sum_{f\in F} \phi_f I_i^f \times \triangle F_c^f + \delta_{cp}^T \lambda + \nu_c + \nu_{pi} + \varepsilon_{cpi} \qquad (2)$$

where $\triangle$ is the time difference operator, δ_{cp}^T is the time trend in bilateral trade cost between counties c and p , and ν_c and ν_{pi} are the variations in exporter characteristics and importer-industry characteristics over time, respectively. Equation (2) shows how comparative advantage in trade responds to changes in demographic composition within a country over time. Since we expect aging countries to lose comparative advantage in adaptability-intensive industries, we expect $\alpha < 0$. The main advantage of the dynamic model (2) over the static model (1) is that the former differences out all country-specific factors, such as the level of development. The estimate of α from (2) would inform us about how a one year increase in the median age affects the pattern of trade, regardless of the level of economic development in a given base period.

5 Data

We estimate model (1) using bilateral trade data for the year 2000 at 4-digit North American Industry Classification system (NAICS) industry level. The data were downloaded from UN-TRAINS database at 6-digit Harmonized System classification, and then aggregated to 4-digit NAICS using concordance from Feenstra et al. (2002). The resulting trade data set contains 106 industries, 235 exporting and 204 importing countries, with the total of 42879 country pairs in the year 2000. Because these data are not available for years prior to 1988, we estimate the dynamic model (2) using bilateral trade flows from NBER-UN International Trade Database. These data cover 1962-2000 time period but fewer countries: 80 exporters, 135 importers, and 76 industries.

The intensity in adaptability skill for each industry i is constructed as the weighted average of the importance of the adaptability skill for different occupations, using occupational shares at the

[6]The bilateral trade cost vector δ_{cp} includes the log of the distance between exporter c and importer p, the common land border indicator, the common official language indicator, the pre-1945 colony relationship indicator, the current colony relationship indicator, and dummy variables for the presence of a Free Trade Agreement or a Customs Union.

industry level as weights:

$$I_i = \sum_j Occup\_share_{ij} \times (ImpAdapt_j - ImpRef_j) \tag{3}$$

In equation (3), $Occup\_share_{ij}$ is the share of occupation j in total employment in industry i. Cross-industry occupational composition is obtained at 7-digit Standard Occupational Classification (SOC) level from the Occupational Employment Statistics (OES) Survey by the US Bureau of Labor Statistics. $ImpAdapt_j$ is the standardized importance of the adaptability skill for occupation j. We obtain this measure from the Occupational Information Network (O*NET) database, which provides information on various job requirements for SOC occupations. Our adaptability ranking of occupations is based on the *Adaptability/Flexibility* O*NET descriptor, which specifies that "the job requires being open to change (positive or negative) and to considerable variety in the workplace." In order to capture comparative advantage of a country in age-dependent skills, we need to measure industry's intensity in these skills relative to some reference factor of production. Therefore, in construction of I_i variable we measure occupational intensity in adaptability skill relative to an standardized age-neutral reference skill $ImpRef_j$. We use four different age-neutral reference skills from the O*NET: inductive reasoning, deductive reasoning, fluency of ideas, and information ordering.[7] Table 1 lists ten industries with the largest and ten industries with the smallest values of intensity in adaptability skill.

We use two variables to capture demographic structure of a country, Age_c. The first one is the median age of population in a country, obtained from the United Nations. The second one is the share of senior workers in the labor force, defined as the fraction of residents aged 40-64 in 20-64 age group and obtained from the World Bank. The data of physical capital stock for each exporter are obtained from the Penn World Table in constant 2005 price, while the skilled labor endowment is calculated as the share of population with secondary and tertiary education, obtained from Barro and Lee (2013). The measures of intensity in age-dependent cognitive skills and physical ability at the industry level, as well as the intensities in capital and skilled labor, are obtained from Cai and Stoyanov (2016). All geographic variables are from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII), and information on the presence of a free trade agreement or a customs union between each country pair was collected from the WTO website.

If workers' adaptability skill depreciates with age, we would expect firms to employ more junior workers in industries that use adaptability skill intensively. Figure 1 plots intensity in the adaptability skill against age of a median employee for 51 US industries, constructed from 2000 Census data. The figure highlights substantial variation in age composition of the labor force across industries, with the median worker age varying from 37 to 46 years. The relationship between the adaptability skill intensity and the age of a median worker is negative and statistically significant, suggesting that aging workers lose relative productivity in tasks that require adaptability and relocate to industries that do not require that skill. Figure 2 plots the same relationship between the adaptability skill intensity and the median age for 299 occupations for the same Census year. The relationship is also negative, indicating that aging workers relocate not only across industries but also across occupations. Clearly, none of the figures is anything but suggestive of the important

[7] Cai and Stoyanov (2016) survey the literature on aging and age-dependent skills and identify inductive reasoning, deductive reasoning, fluency of ideas, and information ordering as the most likely characteristics that do not vary much over the life time of a typical worker.

role of demographics for industry productivity, and in the following section we study more systematically the relationship between demographics and productivity as reflected in observed trade flows.

6 Empirical results

6.1 The baseline results from static cross-sectional variance

Table 2 presents the baseline estimation results for equation (1). In columns (1)-(3), Age_c variable is measured with the median age of population in exporting country c, and in columns (4)-(6) it is measured with the share of senior workers in the labor force, calculated as the number of people aged 40-64 divided by the number of people aged 20-64. Both age measures are inversely related to the stock of the adaptability skill in exporting countries. In order to facilitate the comparison of the magnitudes of different determinants of trade flows, we standardize all variables.

The results in columns (1) and (4) of Table 2 show that, conditional on geography variables and exporter and importer-industry fixed effects, the coefficient α is negative and statistically significant at 1% confidence level. This result confirms that countries with older populations tend to export less in industries that are intensive in the adaptability skill. The coefficient estimate of -0.059 in column (1) implies that if one industry has a one standard deviation greater intensity in adaptability skill than another, then a one year increase in a country's median age will decrease exports in the former industry relative to the latter by 2.7%.[8]

In columns (2) and (5) we control for the two standard sources of comparative advantage: capital and skilled labor. We include interactions of physical capital and skilled labor intensity of an industry with capital and skill labor endowments of a country. The Heckscher-Ohlin model predicts that the coefficients on both interaction terms must be positive, and it is exactly what we observe in the data. More importantly, the estimation results reveal that the estimates of α coefficient remain negative and statistically significant. In columns (3) and (6), we control for three more age-dependent skills, introduced by Cai and Stoyanov (2016). Specifically, we include industry intensity in age-appreciating and age-depreciating cognitive skills and in physical ability, interacted with Age_c variable. The empirical results confirm prediction of Cai and Stoyanov (2016): the effects of aging on exports through cognitive age-appreciating and age-depreciating skills are statistically significant and of expected signs, while the effect of physical skills is insignificant. The estimates of α across all six specifications in Table 2 are remarkably stable.

Overall, the results from Table 2 point to a sizable effect of population aging on the pattern of comparative advantage, both statistically and economically. The stability of α estimate across specifications in Table 2 implies that the stock of the adaptability skill is an independent factor of comparative advantage when demographic composition of workers varies across countries. Negative α estimates indicate that a reduction in adaptability skills in aging countries undermines their comparative advantage in industries which require workers to frequently adapt to changes in working conditions.

[8]Because all variables are standardized, the relative export of the two industries is equal to $exp\left\{\alpha \times \frac{std(lnX_{cpi})}{std(Age_c)}\right\} = exp\left\{-0.059 \times \frac{3.361}{7.343}\right\} \simeq 0.973$.

6.2 Age threshold analysis

The theory informs us that countries with older populations should have comparative disadvantage in industries that use adaptability skill intensively. The previous section provides evidence in support of this prediction using two metrics of demographic structure of population – median age and the share of workers over 40 years of age in the labor force. In this section we utilize additional information on workers' age distribution to test the main hypothesis. Specifically, we divide the entire population of 20-64 year-olds in each country into nine five-year age groups: 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59 and 60-64. We then measure demographic structure of a country, Age_c, with the share of workers from a given age group among 20-64 year-olds, and trace out changes in α estimate as the definition of the Age_c variable changes.

Results are presented in Table 3.[9] All specifications include exporter and importer-industry fixed effects and trade costs controls. The standard errors are clustered by exporter-industry. In column (1), Age_c is measured with the share of 20-24 year-olds in the labor force of exporting country. From the estimation results, we obtain that the coefficient estimate of α is positive and statistically significant at 1% confidence level, with the point estimate of 0.047. This indicates that a larger share of 20-24 year-olds gives a country a comparative advantage in adaptability-intensive industries. In column (2), the estimated coefficient on the interaction of adaptability skill intensity of an industry and the share of workers in the 25-29 age group is also positive and statistically, but the point estimate decreases to 0.028. Insignificant estimates of α in columns (3) and (4) imply that cross-country variation in the share of workers aged 30-39 does not affect the pattern of trade. The estimate of α become negative and statistically significant in columns (5)-(9), implying that an increase in the share of workers in 40-59 age group is associated with comparative disadvantage in adaptability-intensive industries. The effect is getting stronger for more senior workers, peaks at 50-54 age group, and then the magnitude starts to decline. For the 60-64 age group, the estimate of α in column (9) is not statistically significant.

Since population shares are highly correlated across nine age groups within a country, and there are only 136 exporting countries in the estimation sample, we cannot jointly identify the effect of all nine age groups shares. In Table 4 we construct population shares for three age groups using insights from Table 3. The first group consists of 20-29 year-old, and includes two five-year age groups for which the individual α coefficients in Table 3 are estimated positive. The second group consists of individual aged 30 to 39, and the third group includes individuals aged 40 to 64. The estimation results in columns (1)-(3) of Table 4 support the findings of Table 3. In column (4) we include interactions of adaptability skill intensity with the share of workers in the first and the third groups, using the second group as the reference category. One can see that the coefficient estimate on the share of senior workers is negative, and on the share of junior workers is positive. Furthermore, the difference between the two coefficients is statistically different from zero, as underscored by a strong rejection of the Wald test of the equality in coefficients. To put these results into perspective, suppose industry A has a one standard deviation greater intensity in adaptability skill than industry B. Then a one percentage point increase in the share of senior workers combined with a one percentage point decrease in the share of junior workers will decrease

[9] In Table 3 we use the share of senior workers in labor force, as defined in the previous section, to construct interactions of Age_c with cognitive and physical skills.

exports in industry A relative to B by 2.5%.[10] The estimation results without the breakdown by age groups (column 6 of Table 2) imply a similar magnitude of 1.7%.[11]

The results from Tables 3 and 4 suggest that 30-39 is the critical age, or the turning point, for the effect of demographic composition on trade flows. A reduction in the share of workers from 20-29 age group or an increase in the share of workers in 40-59 age group leads to a loss of a comparative advantage of a country in industries which use the adaptability skill intensively.

6.3 Robustness tests

In Section (4) we justified the need to normalize the key explanatory variable in equation (1), I_i, by an age-neutral reference skill. The results in Table 2 are obtained with all age-dependent skills normalized by inductive reasoning. In columns (1)-(3) of Table 5 we explore the sensitivity of the main results to the choice of the reference factor. Following Cai and Stoyanov (2016), we use deductive reasoning, fluency of idea, and information ordering as alternative reference skills to estimate the effect of aging through workers' adaptability. The stock of the adaptability skill is measured by the median age of population in the exporting country. From the estimation results in columns (1)-(3), the coefficients on the interaction of the median age and the industry-level adaptability skill intensity, normalized by different reference skills, are all negative and statistically significant at 1 percent confidence level. Furthermore, the estimated coefficients on interactions of median age with other age-dependent skills are also not sensitive to the choice of the reference skill.

As an additional check on our results, in columns (4) and (5) of Table 5 we split the sample by exporting country groups and report results separately for OECD member and non-member countries. Since most OECD countries are developed and account for a disproportional fraction of exporter-industry observations, we want to verify that the variation in demographic composition within each group of countries has a similar effect on the pattern of trade as the variation between developed and developing countries. The estimated coefficients on the interaction of industry-level adaptability intensity and the median age in exporting country are similar to the estimation result in the baseline specifications in terms of the sign, the significance level and the economic magnitude.

At last, Costinot et al. (2011) advocate the use of country-pair fixed effects in the gravity model in order to account for unobserved time-invariant heterogeneity in trade costs across country-pairs. Of course, country-pair fixed effects absorb all geography controls except for the trade agreement covariates, however, it will not prevent identification of α coefficient since $I_i \times Age_c$ interaction varies by industry. The result, presented in column (6), shows that the estimated coefficient α remains negative and statistically significant at the 1% confidence level. Furthermore, the magnitude of the estimated coefficient is similar to the benchmark result, and the estimated coefficients on other age-dependent skills, physical capital and skill labor are all comparable to the baseline estimation results, both in terms of the magnitude and statistical significance.

[10] The relative exports of the two industries is equal to $exp\left\{\alpha_{young} \times 0.01 \times \frac{std(lnX_{cpi})}{std([20-29]\ Share_c)}\right\} - exp\left\{\alpha_{old} \times 0.01 \times \frac{std(lnx_{cpi})}{std([40-59]\ Share_c)}\right\} = exp\left\{0.022 \times 0.01 \times \frac{3.332}{0.0636}\right\} - exp\left\{-0.025 \times 0.01 \times \frac{3.332}{0.0597}\right\} \simeq 0.025$.

[11] The relative exports of the two industries in the presence of a 1 percentage point increase in the share of senior workers is equal to $exp\left\{\alpha \times 0.01 \times \frac{std(lnX_{cpi})}{std(Age_c)}\right\} = exp\left\{-0.039 \times 0.01 \times \frac{3.332}{0.0775}\right\} \simeq 0.017$.

6.4 Dynamic analysis

We now turn to the estimation of the dynamic model (2) and estimate the effect of over-time demographic transformations on bilateral trade flows. For that, we extend the time period of our analysis to 1962-2000. Since demographic changes are slow and it may take many years for the economy to adjust to those changes, we use 10, 20, 30, and 38 year differences to estimate equation (2).[12]

In columns (1) and (2) of Table 6 the changes in all dynamic variables are calculated between years 2000 and 1962. For both the median age and the share of senior workers as a measure of demographic structure, the coefficient α is estimated to be negative and statistically significant at least at 10% confidence level. These results demonstrate that regardless of the initial level of economic development of a country, population aging leads to economic restructuring of production activity across industries and a loss of a comparative advantage in sectors which require high degree of workers' adaptability to changes in working conditions. The estimation results shown in column (1) imply that if an industry's intensity in adaptability skill is one standard deviation higher than that of another industry, a one year increase in the median age in an exporting country will reduce exports of the former industry by 2.5% relative to the latter.[13] This magnitude is similar to what we found previously in the cross-sectional analysis.

In columns (3) and (4) we change the base year relative to which we time-difference trade flows and factor endowments from 1962 to 1970. The coefficients on the interaction of the adaptability skill intensity and Age_c variable remain negative and statistically significant at 10% level. When changes in the dynamic variables are constructed relative to 1980 and 1990 base years (columns 5-8), the coefficient α is estimated negative but is statically significant in only one out of four specifications. Similar to Cai and Stoyanov (2016), the coefficients on other age-dependent skills also decrease in magnitude and significance level with the shorter span for time difference. Low variation in demographic composition within a country over a short time span might be one possible reason for this result. Another explanation for obtaining weaker results in shorter panels might be that the adjustment period for an economy to respond to changes in demographic composition is more than ten years. Testing the dynamic response of trade flows to demographic transformations is outside the scope of what we can do with our data.

7 Conclusions

This paper finds evidence of different rates of population aging across countries being a source of comparative advantage in international trade. We argue that older workers are less likely to update their skills and adjust to changes in labor market requirements, and call the worker's ability to adapt to changes in the workplace the *adaptability skill*. It follows that countries with accelerated rates of population aging experience a decline in the effective endowment of the adaptability skill, and thus must lose their comparative advantage in industries which use that skill intensively. We test and confirm this prediction on a rich sample of countries. In particular, we find that industries vary substantially in adaptability skill intensity and that countries with older labor forces tend to export less in industries that rely heavily on the adaptability skill. According to the estimates,

[12] We use years 1968, 1970, 1980, 1990 and 2000 for the dynamic analysis.

[13] The relative exports of the two industries is equal to: $exp\left\{\alpha \times \frac{std(\triangle lnX_{cpi})}{std(\triangle Age_c)}\right\} = exp\left\{0.039 \times \frac{2.399}{3.716}\right\} \simeq 0.975$.

variation in demographic composition across countries is as important for international trade flows as the variation in the standard factors of production, such as physical capital and skilled labor. Furthermore, we find that heterogeneous rates of population aging across countries is a significant predictor of the changes in observed trade flows. This finding has important implications for the impact of trade on labor market. Our results imply that heterogeneous rates of population aging in different parts of the world must have differential impact on the supply of skill mix, the skill premium, sorting of workers into industries, and age-earning profiles across countries.

Pol Antràs and Davin Chor. Organizing the global value chain. *Econometrica*, 81(6):2127–2204, 2013.

Luis Araujo, Giordano Mion, and Emanuel Ornelas. Institutions and export dynamics. *Journal of International Economics*, 98:2–20, 2016.

Robert J Barro and Jong Wha Lee. A new data set of educational attainment in the world, 1950–2010. *Journal of development economics*, 104:184–198, 2013.

Thorsten Beck. Financial dependence and international trade. *Review of International Economics*, 11(2):296–316, 2003.

Matilde Bombardini, Giovanni Gallipoli, and Germán Pupato. Skill dispersion and trade flows. *The American Economic Review*, 102(5):2327–2348, 2012.

Libby Brooke and Philip Taylor. Older workers and employment: managing age relations. *Ageing & Society*, 25(3):415–429, 2005.

Ethan R Buch, Sereniti Young, and José L Contreras-Vidal. Visuomotor adaptation in normal aging. *Learning & memory*, 10(1):55–63, 2003.

Jie Cai and Andrey Stoyanov. Population aging and comparative advantage. *Journal of International Economics*, 102:1–21, 2016.

Murillo Campello and Janet Gao. Customer concentration and loan contract terms. *Journal of Financial Economics*, 123(1):108–136, 2017.

Neil Charness. Work, older workers, and technology. *Generations*, 30(2):25–30, 2006.

Neil Charness and Sara J Czaja. Older worker training: What we know and don't know.# 2006-22. *AARP*, 2006.

Richard Chisik, Harun Onder, and Dhimitri Qirjo. Aging, trade, and migration. 2016.

Davin Chor. Unpacking sources of comparative advantage: A quantitative approach. *Journal of International Economics*, 82(2):152–167, 2010.

Arnaud Costinot, Dave Donaldson, and Ivana Komunjer. What goods do countries trade? a quantitative exploration of ricardo's ideas. *The Review of economic studies*, 79(2):581–608, 2011.

Alejandro Cuñat and Marc J Melitz. Volatility, labor market flexibility, and the pattern of comparative advantage. *Journal of the European Economic Association*, 10(2):225–254, 2012.

Sara J Czaja and Joseph Sharit. Age differences in attitudes toward computers. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 53(5):P329–P340, 1998.

Steven M Elias, William L Smith, and Chet E Barney. Age as a moderator of attitude towards technology in the workplace: Work motivation and overall job satisfaction. *Behaviour & Information Technology*, 31(5):453–467, 2012.

Robert C Feenstra, John Romalis, and Peter K Schott. Us imports, exports, and tariff data, 1989-2001. Technical report, National bureau of economic research, 2002.

Marilyn Gist, Benson Rosen, and Catherine Schwoerer. The influence of training method and trainee age on the acquisition of computer skills. *Personnel Psychology*, 41(2):255–265, 1988.

Deborah L Harrington and Kathleen Y Haaland. Skill learning in the elderly: diminished implicit and explicit memory for a motor sequence. *Psychology and aging*, 7(3):425, 1992.

Elhanan Helpman and Oleg Itskhoki. Labour market rigidities, trade and unemployment. *The Review of Economic Studies*, 77(3):1100–1137, 2010.

James H Howard Jr and Darlene V Howard. Age differences in implicit learning of higher order dependencies in serial patterns. *Psychology and aging*, 12(4):634, 1997.

Dean P Jones. Redox theory of aging. *Redox biology*, 5:71–79, 2015.

Bradley R King, Stuart M Fogel, Geneviève Albouy, and Julien Doyon. Neural correlates of the age-related changes in motor sequence learning and motor adaptation in older adults. *Frontiers in human neuroscience*, 7, 2013b.

Andrei A Levchenko. Institutional quality and international trade. *The Review of Economic Studies*, 74(3):791–819, 2007.

Kalina Manova. Credit constraints, equity market liberalizations and international trade. *Journal of International Economics*, 76(1):33–47, 2008.

Kalina Manova. Credit constraints, heterogeneous firms, and international trade. *Review of Economic Studies*, 80(2):711–744, 2012.

George A Marcoulides, Bronston T Mayes, and Richard L Wiseman. Measuring computer anxiety in the work environment. *Educational and Psychological Measurement*, 55(5):804–810, 1995.

Todd J Maurer. Career-relevant learning and development, worker age, and beliefs about self-efficacy for development. *Journal of management*, 27(2):123–140, 2001.

Ewan C McNay and Daniel B Willingham. Deficit in learning of a motor skill requiring strategy, but not of perceptuomotor recalibration, with aging. *Learning & Memory*, 4(5):411–420, 1998.

Julie Messier, Sergei Adamovich, David Jack, Wayne Hening, Jacob Sage, and Howard Poizner. Visuomotor learning in immersive 3d virtual reality in parkinson disease and in aging. *Experimental brain research*, 179(3):457–474, 2007.

Michael G Morris and Viswanath Venkatesh. Age differences in technology adoption decisions: Implications for a changing work force. *Personnel psychology*, 53(2):375–403, 2000.

Takumi Naito and Laixun Zhao. Aging, transitional dynamics, and gains from trade. *Journal of Economic Dynamics and Control*, 33(8):1531–1542, 2009.

Nathan Nunn. Relationship-specificity, incomplete contracts, and the pattern of trade. *The Quarterly Journal of Economics*, 122(2):569–600, 2007.

Jay Pratt, Alison L Chasteen, and Richard A Abrams. Rapid aimed limb movements: age differences and practice effects in component submovements. *Psychology and aging*, 9(2):325, 1994.

Kimberly M Prenda and Sidney M Stahl. The truth about older workers. *Business and health*, 19 (5):30, 2001.

Floyd L Ruch. The differentiative effects of age upon human learning. *The Journal of General Psychology*, 11(2):261–286, 1934.

Serdar Sayan. Heckscher–ohlin revisited: implications of differential population dynamics for trade within an overlapping generations framework. *Journal of Economic Dynamics and Control*, 29 (9):1471–1493, 2005.

Rachael D Seidler. Differential effects of age on sequence learning and sensorimotor adaptation. *Brain research bulletin*, 70(4):337–346, 2006.

Vegard Skirbekk. Age and individual productivity: A literature survey. *Vienna yearbook of population research*, pages 133–153, 2004.

Robert J Sternberg and Cynthia A Berg. *Intellectual development*. Cambridge University Press, 1992.

Heiwai Tang. Labor market institutions, firm-specific skills, and trade patterns. *Journal of International Economics*, 87(2):337–351, 2012.

Nancy S Wecker, Joel H Kramer, Bradley J Hallam, and Dean C Delis. Mental flexibility: age effects on switching. *Neuropsychology*, 19(3):345, 2005.

Edward N Wolff. Skills and changing comparative advantage. *The Review of Economics and Statistics*, 85(1):77–93, 2003.

Akira Yakita. Different demographic changes and patterns of trade in a heckscher–ohlin setting. *Journal of Population Economics*, 25(3):853–870, 2012.

Yixin Zhang. Age, gender, and internet attitudes among employees in the business world. *Computers in Human Behavior*, 21(1):1–10, 2005.

Figure 1: Industry intensity in adaptability skills and the median worker age

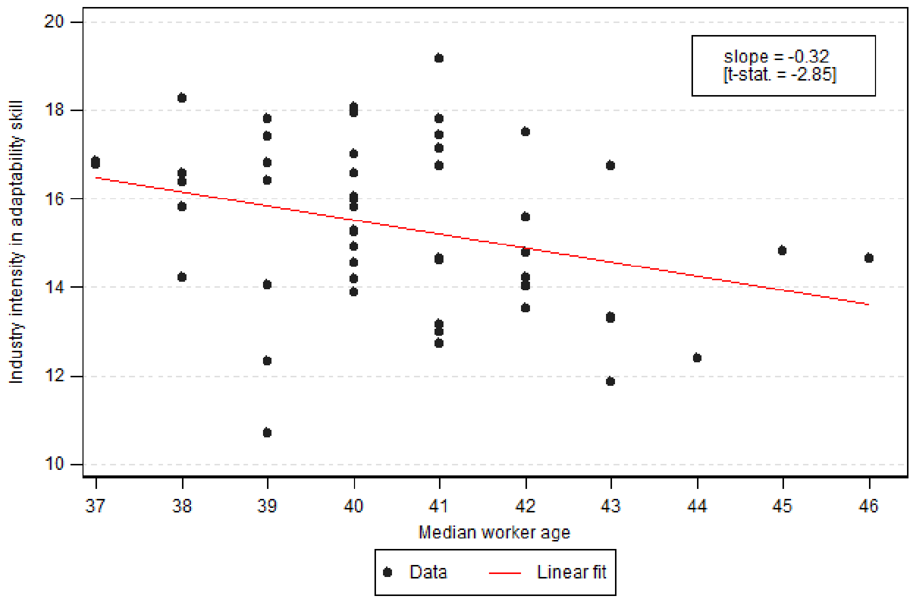

Figure 2: Occupation intensity in adaptability skill and the median worker age

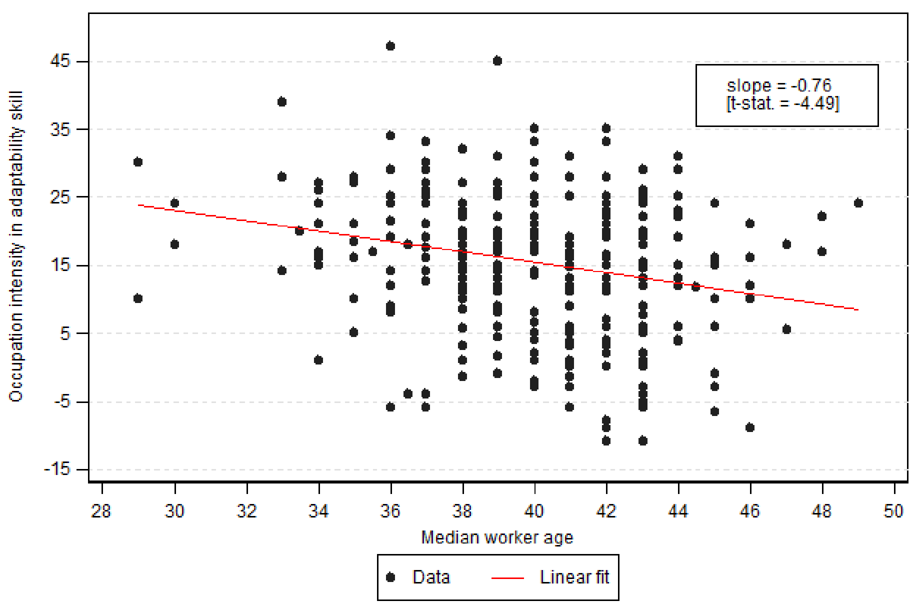

Table 1: Industries with the highest and the lowest intensities in adaptability skill.

10 industries with the highest intensity in adaptability skill		
Rank	NAICS4	Industry description
1	3341	Computer and Peripheral Equipment Manufacturing
2	3342	Communications Equipment Manufacturing
3	3364	Aerospace Product and Parts Manufacturing
4	3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
5	3254	Pharmaceutical and Medicine Manufacturing
6	3241	Petroleum and Coal Products Manufacturing
7	3344	Semiconductor and Other Electronic Component Manufacturing
8	3231	Printing and Related Support Activities
9	3255	Paint, Coating, and Adhesive Manufacturing
10	3332	Industrial Machinery Manufacturing

10 industries with the lowest intensity in adaptability skill		
Rank	NAICS4	Industry description
1	3361	Household Appliance Manufacturing
2	3161	Other Furniture Related Product Manufacturing
3	3365	Seafood Product Preparation and Packaging
4	3343	Apparel Knitting Mills
5	3159	Other Leather and Allied Product Manufacturing
6	3169	Apparel Accessories and Other Apparel Manufacturing
7	3151	Audio and Video Equipment Manufacturing
8	3117	Railroad Rolling Stock Manufacturing
9	3379	Leather and Hide Tanning and Finishing
10	3352	Motor Vehicle Manufacturing

Table 2: Baseline results.

	(1)	(2)	(3)	(4)	(5)	(6)
Age_c measure:		Median Age			Share Old	
Adaptability Skill Intensity$_i$	-0.059***	-0.047***	-0.040***	-0.055***	-0.044***	-0.039***
$\times Age_c$	(0.004)	(0.005)	(0.007)	(0.004)	(0.005)	(0.007)
Cognitive Appreciate Intensity$_i$			0.030***			0.030***
$\times Age_c$			(0.006)			(0.005)
Cognitive Depreciate Intensity$_i$			-0.049***			-0.055***
$\times Age_c$			(0.014)			(0.014)
Physical Ability Intensity$_i$			0.022			0.032*
$\times Age_c$			(0.017)			(0.017)
Capital Intensity$_i$		0.024***	0.016***		0.024***	0.019***
$\times Capital_c$		(0.005)	(0.005)		(0.005)	(0.005)
Skilled Labor Intensity$_i$		0.035***	0.020***		0.038***	0.024***
$\times Skilled\ Labor_c$		(0.005)	(0.006)		(0.005)	(0.005)
R^2	0.554	0.553	0.555	0.554	0.554	0.555
Observations	461,839	413,241	413,241	461,335	411,144	411,144

Notes: The dependent variable is the natural logarithm of exports from country country c to its partner p in industry i in year 2000. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by exporter-industry. All specifications include exporter and importer-industry fixed effects and trade costs controls. * significant at 10%, ** significant at 5% and *** significant at 1%.

Table 3: Baseline results by age group.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Adaptability\ Skill\ Intensity_i$	0.047***								
$\times [20-24]\ Share_c$	(0.006)								
$Adaptability\ Skill\ Intensity_i$		0.028***							
$\times [25-29]\ Share_c$		(0.006)							
$Adaptability\ Skill\ Intensity_i$			0.003						
$\times [30-34]\ Share_c$			(0.006)						
$Adaptability\ Skill\ Intensity_i$				-0.004					
$\times [35-39]\ Share_c$				(0.005)					
$Adaptability\ Skill\ Intensity_i$					-0.013**				
$\times [40-44]\ Share_c$					(0.006)				
$Adaptability\ Skill\ Intensity_i$						-0.036***			
$\times [45-49]\ Share_c$						(0.006)			
$Adaptability\ Skill\ Intensity_i$							-0.045***		
$\times [50-54]\ Share_c$							(0.007)		
$Adaptability\ Skill\ Intensity_i$								-0.025***	
$\times [55-59]\ Share_c$								(0.007)	
$Adaptability\ Skill\ Intensity_i$									-0.010
$\times [60-64]\ Share_c$									(0.007)
$Cognitive\ Appreciate\ Intensity_i$	0.031***	0.026***	0.018***	0.017***	0.019***	0.027***	0.032***	0.024***	0.020***
$\times Share\ Old_c\ [40-64]$	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$Cognitive\ Depreciate\ Intensity_i$	-0.055***	-0.047***	-0.032***	-0.030***	-0.034***	-0.050***	-0.058***	-0.044***	-0.036***
$\times Share\ Old_c\ [40-64]$	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)
$Physical\ Ability\ Intensity_i$	0.030**	0.015	-0.018	-0.023	-0.014	0.021	0.038**	0.009	-0.009
$\times Share\ Old_c\ [40-64]$	(0.015)	(0.016)	(0.016)	(0.014)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
$Capital\ Intensity_i \times Stock_c$	0.016***	0.020***	0.023***	0.023***	0.022***	0.020***	0.018***	0.021***	0.023***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$Skill\ Labor\ Intensity_i \times Stock_c$	0.022***	0.024***	0.023***	0.022***	0.022***	0.024***	0.025***	0.023***	0.023***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
R^2	0.555	0.555	0.554	0.554	0.554	0.555	0.555	0.555	0.554
Observations	411,144	411,144	411,144	411,144	411,144	411,144	411,144	411,144	411,144

Notes: The dependent variable is the natural logarithm of exports from country country c to its partner p in industry i in year 2000. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by exporter-industry. All specifications include exporter and importer-industry fixed effects and trade costs controls. * significant at 10%, ** significant at 5% and *** significant at 1%.

Table 4: Additional results by age groups.

	(1)	(2)	(3)	(4)
$Adaptability\ Skill\ Intensity_i$	0.045***			0.022
$\times [20-29]\ Share_c$	(0.006)			(0.015)
$Adaptability\ Skill\ Intensity_i$		-0.001		
$\times [30-39]\ Share_c$		(0.0096)		
$Adaptability\ Skill\ Intensity_i$			-0.046***	-0.025
$\times [40-59]\ Share_c$			(0.007)	(0.016)
$Cognitive\ Appreciate\ Intensity_i$	0.031***	0.017***	0.032***	0.033***
$\times Share\ Old_c\ [40-64]$	(0.005)	(0.005)	(0.005)	(0.005)
$Cognitive\ Depreciate\ Intensity_i$	-0.055***	-0.030**	-0.058***	-0.058***
$\times Share\ Old_c\ [40-64]$	(0.013)	(0.013)	(0.014)	(0.014)
$Physical\ Ability\ Intensity_i$	0.033***	-0.022	0.039**	0.039**
$\times Share\ Old_c\ [40-64]$	(0.016)	(0.015)	(0.016)	(0.016)
$Capital\ Intensity_i \times Stock_c$	0.017***	0.023***	0.018***	0.017***
	(0.005)	(0.005)	(0.005)	(0.005)
$Skill\ Labor\ Intensity_i \times Stock_c$	0.023***	0.022***	0.024***	0.024***
	(0.005)	(0.006)	(0.005)	(0.005)
R^2	0.555	0.554	0.555	0.555
Observations	411,144	411,144	411,144	411144
Wald Test				51.73
P-value				(0.000)

Notes: The dependent variable is the natural logarithm of exports from country country c to its partner p in industry i in year 2000. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by exporter-industry. All specifications include exporter and importer-industry fixed effects and trade costs controls. * significant at 10%, ** significant at 5% and *** significant at 1%. The null hypothesis of the Wald test is that the coefficients on $Adaptability\ Skill\ Intensity_i \times [20-29]\ Share_c$ and $Adaptability\ Skill\ Intensity_i \times [40-59]\ Share_c$ are the same.

Table 5: Robustness tests.

	(1)	(2)	(3)	(4)	(5)	(6)
Adaptability Skill Intensity$_i$	-0.041***	-0.050***	-0.028***	-0.038***	-0.030***	-0.040***
$\times$*Median Age*$_c$	(0.007)	(0.010)	(0.006)	(0.010)	(0.011)	(0.015)
Cognitive Appreciate Intensity$_i$	0.030***	0.0329***	0.060***	0.030***	0.006	0.031**
$\times$*Median Age*$_c$	(0.006)	(0.007)	(0.008)	(0.007)	(0.010)	(0.012)
Cognitive Depreciate Intensity$_i$	-0.055***	-0.072***	-0.024***	-0.041**	-0.041***	-0.049
$\times$*Median Age*$_c$	(0.013)	(0.017)	(0.011)	(0.018)	(0.020)	(0.034)
Physical Ability Intensity$_i$	0.027	0.038*	0.007	0.017	0.033	0.021
$\times$*Median Age*$_c$	(0.017)	(0.019)	(0.015)	(0.022)	(0.024)	(0.041)
Capital Intensity$_i$ $\times$ *Stock*$_c$	0.0169***	0.020***	0.013***	0.030***	0.022***	0.019
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.012)
Skill Labor Intensity$_i$ $\times$ *Stock*$_c$	0.0201***	0.020***	0.019***	0.023***	0.015*	0.022***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.006)
Sample	benchmark	benchmark	benchmark	OECD	NON-OECD	benchmark
Reference skill	Deductive reasoning	Fluency of ideas	Information ordering	Inductive reasoning	Inductive reasoning	Inductive reasoning
Exporter-Importer FE	No	No	No	No	No	Yes
Importer-Industry FE	Yes	Yes	Yes	Yes	Yes	No
R^2	0.555	0.555	0.555	0.611	0.465	0.510
Observations	413,241	413,241	413,241	276,649	136,021	411,614

Notes: The dependent variable is the natural logarithm of exports from country country c to its partner p in industry i in year 2000. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by exporter-industry. All specifications include exporter and importer-industry fixed effects and trade costs controls. * significant at 10%, ** significant at 5% and *** significant at 1%.

Table 6: Estimation results for dynamic model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\triangle Age_c$ measure:	$\triangle$Median Age	$\triangle$Share Old	$\triangle$Median Age	$\triangle$Share Old	$\triangle$Median Age	$\triangle$Share Old	$\triangle$Median Age	$\triangle$Share Old
$Adaptability\ Skill\ Intensity_i$	-0.039*	-0.049**	-0.028**	-0.024*	-0.016	-0.005	-0.027**	-0.013
$\times \triangle Age_c$	(0.020)	(0.021)	(0.012)	(0.014)	(0.010)	(0.009)	(0.012)	(0.011)
$Cognitive\ Appreciate\ Intensity_i$	0.037***	0.038***	0.037***	0.044***	0.030***	0.036***	0.006	0.008
$\times \triangle Age_c$	(0.012)	(0.013)	(0.009)	(0.009)	(0.008)	(0.007)	(0.0068)	(0.007)
$Cognitive\ Depreciate\ Intensity_i$	-0.001	0.011	-0.016	0.000	-0.014	-0.021*	0.011	-0.010
$\times \triangle Age_c$	(0.019)	(0.020)	(0.012)	(0.013)	(0.012)	(0.011)	(0.012)	(0.010)
$Capital\ Intensity_i \times Stock_c$	0.001	-0.009	-0.002	0.004	0.012	0.021***	0.020**	0.026***
	(0.011)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
$Skill\ Labor\ Intensity_i \times Stock_c$	-0.005	-0.003	-0.009	-0.011	-0.002	0.003	0.009	0.010
	(0.009)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
Start Year	1962	1962	1970	1970	1980	1980	1990	1990
End Year	2000	2000	2000	2000	2000	2000	2000	2000
R^2	0.450	0.450	0.426	0.426	0.409	0.408	0.309	0.309
Observations	61,619	62,279	84,372	85,763	102,838	104,902	93,804	95,971

Notes: The dependent variable is $\triangle lnX_{cpi}$ which is the change in the natural logarithm of exports from country country c to its partner p in industry i in year 2000 between the start and the end years. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by exporter-industry. All specifications include exporter and importer-industry fixed effects and trade costs controls. $\triangle X$ is the time operator for the difference in variable X between the start and the end year. * significant at 10%, ** significant at 5% and *** significant at 1%.

Chapter 2

Female Labor Supply and International Trade[14]

1 Introduction

In 1979 China introduced a unique population control policy – a one-child policy (OCP) – to curb population growth and advance economic development. While the OCP successfully lowered the population growth rate, it also had unintended consequences for gender composition. Since the OCP's commencement, the male to female ratio in Chinese population started to grow, and by 2000 the sex ratio at birth reached 120 males per 100 females, far away from the natural balance point of 105, which prevailed in the country prior to the policy. Previous research suggests that the main driving force behind distorted sex ratios is the traditional preference for sons in Chinese culture, so that the dual pressure to have a son and to comply with the OCP induces sex-selection behavior among parents. In this paper we find that the exogenous variation in the relative female labor supply across Chinese cities, caused by spatial variation in OCP stringency and preference for sons, is a source of comparative advantage.

Differences in female labor supply across cities matter for international trade so long as the relative demand for female labor varies across industries. Building upon previous literature, we identify two sets of gender-specific skills – social skills, in which women are relatively better than men, and physical skills, in which men have an advantage. The demand for these two skills varies importantly across industries. Using U.S. Census data on occupational employment by industry and the O*NET data on the importance of social and physical skills by occupation, we document substantial differences across industries in their use of occupations that require frequent social interactions or use of muscle force.

In the presence of differences in gender-dependent skill intensities across industries and differences in female labor supply across Chinese cities, we expect cities with more stringent OCP enforcement and scarce female labor supply to have a comparative advantage in industries that use physical skills intensively and disadvantage in industries which use social skills intensively. This prediction is consistent with both the Ricardian and the Heckscher-Ohlin models of comparative advantage, and we formalize this intuition in Section 4 using the theoretical model by Chor (2010). The Heckscher-Ohlin mechanism operates through the effect of the OCP on the endowment of gender-dependent skills. If workers have a certain amount of gender-dependent skills, then cities with more stringent OCP enforcement and low female population share would have high endowment and low premium for physical skills, providing physical-skill-intensive industries with a comparative advantage in the global market. Gender composition of a city may also affect labor productivity through the Ricardian channel. With a shortage of workers of a certain gender and in the presence of labor market frictions, firms may start filling positions that require a specific skill with more

[14] This paper is joint with Professor Andrey Stoyanov.

readily available workers who have disadvantage in that skill. In such case, distribution of workers by gender within industries will resemble that of a city, and cities with a shortage of female workers will have lower labor productivity in industries that require social skills. Both models establish a gravity-type relationship between city's gender composition and exports, and inform our approach to the data.

We estimate the model using exports data by 283 Chinese cities in 74 manufacturing industries to 205 destination countries/territories. We estimate the static version of the model for the year 2006, as well as the dynamic model in differences. Our empirical findings suggest that the OCP has a significant and robust effect on the pattern of Chinese exports. Cities with low share of female workers in total population, caused by strict OCP enforcement, lose comparative advantage in industries that require skills in which female workers are relatively better than male. In the baseline specification, we find that an increase in the share of female residents in total population of a city by one percentage point and a one standard deviation increase in skill intensity of an industry is associated with an increase in exports by 3.1% for social skills and a decrease by 9.2% for physical skills. In the dynamic model, we look at the change in the gender composition across cities between 1979, the year when the OCP was officially introduced, and 2006. The dynamic specification allows us to control for time-invariant city-industry sources of comparative advantage, and the results we obtain are very similar to those in the static model.

Our main concern with identifying a causal effect of gender differences in labor supply on trade is associated with migration of workers across cities. Local labor market conditions may shape the pattern of comparative advantage, while also attracting immigrants of a particular gender from other regions. In the absence of reliable data on internal migration flows, we use spatial variation in the OCP stringency as an exogenous shifter for the relative female labor supply. The two instruments that we use are the provincial fine rates on excess fertility and the number of local amendments to the country-wide policy, both being strong predictors of the gender imbalances among newborns at the city level. The intuition underlying this identification strategy is that the decisions on fertility fines and general implementation of the OCP were decentralized to local authorities, and were set in accordance with local fertility targets rather than economic conditions in the region. Therefore, the two instruments are plausibly exogenous to both the internal migration flows and the level of economic development of a city. The effect of gender imbalances in labor supply on trade becomes even stronger when we instrument the female share of the labor force with OCP stringency variables.

Our findings are not specific to China. Using country-level bilateral trade data, we also find strong support for the empirical predictions of the model. Specifically, we show that countries with low female labor supply, measured by the female labor force participation (FLFP), have comparative disadvantage in industries that use female labor intensively. Our approach to identifying the effect of female labor supply on trade is based on the insight of Alesina et al. (2013), who use differences in cultural norms across countries to predict female labor supply. They found that countries with traditional plough agriculture have gender norms that lead to greater gender inequality today, and result in less female participation in labor force. Using traditional plough agriculture prevalence as the instrument for the FLFP, we find that the effect of female employment on comparative advantage is even stronger across countries than across Chinese cities.

Our study of the effect of relative female labor supply on comparative advantage connects with three strands of related literature. First, it contributes to the large and growing literature examining the sources of comparative advantage. In addition to traditional factors of comparative advantage, such as cross-country differences in capital and skilled labor (Romalis, 2004), a number of non-traditional sources of comparative advantage were identified in recent literature, such as cross-country differences in institutions (Levchenko, 2007; Nunn, 2007; Manova, 2008; Bombardini et al., 2012), demographic composition (Cai and Stoyanov, 2016; Gu and Stoyanov, 2019), and fiscal policies (Sharma, 2017). We complement this line of research by showing that differences in gender composition of labor endowment across countries, emerging as a results of differences in gender norms within or across countries, is also a source of comparative advantage.

Second, our paper contributes to the vast literature on gender market outcomes. Our findings reveal the importance of gender composition of the labor force for exports in industries that differ in their use of social and physical skills. Underlying this result is the evidence coming from sociology and labor economics literatures that women have a comparative advantage in tasks that require social skills and disadvantage in tasks that require physical skills. Our results support this evidence by showing that excess supply of male labor in a local labor market raises productivity of firms that use physical skills intensively and boost their competitiveness in the global market, increasing demand for physical skills and balancing the skill premium. Thus, our findings fit into an important literature analyzing implications of differences in relative productivity of men and women in different tasks for labor market outcomes.

The paper is also related to the vast literature on the socio-economic implications of China's OCP. The main focus of this literature is on the effect of population aging associated with the OCP (İmrohoroğlu and Zhao, 2018; Ge et al., 2018; Mehlum et al., 2016). Existing research emphasizes the effect of the OCP on health, education, and macroeconomic outcomes. For example, Zhang (2017) and Li and Zhang (2017) find improvements in educational attainment due to the OCP as parents tend to invest more into education of their single child. As fertility rate decreases and life expectancy increases, acceleration of population aging stimulates households to raise their saving rate, by 50% on average between 1980 and 2010 (İmrohoroğlu and Zhao, 2018). Disparities in sex ratios, associated with the OCP, have been linked to higher crime rates (Edlund et al., 2013) and higher male labor force participation rate (Zhang, 2017). The effect of the OCP on comparative advantage that we identify in this paper suggests that an increase in the relative male labor supply can, to some extent, be alleviated by an increase in demand for male labor through expansion in the production and exports of goods that use male labor intensively. Moreover, the effect of gender disparities on Chinese trade will get even stronger as new cohorts, more affected by the OCP, start entering the labor market.

The paper is organized as follows. The next section introduces the brief history of China's OCP. Section 3 surveys the literature on gender-dependent skills. Section 4 describes theoretical mechanisms that link spatial gender imbalances to comparative advantage. Section 5 presents the empirical model and identification strategy, and Sections 6 discusses the data. Section 7 shows the empirical results, and Section 8 concludes.

2 China's one-child policy

China's OCP was officially introduced in 1979 as part of the policy to slow down population growth, and was relaxed in 2016 when the government allowed households to have two children. Figure 1 plots the annual fertility rate in China and the world between 1960 and 2016, and illustrates the evolution of population growth in China before and after the OCP. One can see that in the first half of 1960-s, following the famine of late 1950-s, the fertility rate in China was growing steadily and peaked at over six births per woman in 1965. Between 1965 and 1975, the fertility rate was in decline but remained higher than the world average. To curb population growth and promote human capital investment, in 1970s the Chinese government began to implement population control measures. In 1971, the government launched a family-planning campaign, encouraging later marriages, longer time laps between the first and the second children, and fewer children (two per couple at most). This largely voluntary family planning campaign was quite successful and fertility declined steadily over 1970s. However, it did not reach the target for the population growth rate reduction, and in 1979 the Chinese government moved to directly controlling the number of children per family by formalizing the official OCP (Wang and Zhang, 2018; Zhang, 2017; Liao, 2013). The policy imposed heavy fines on violators, typically 10-20 percent of the household income for a period lasting from 3 to 14 years, while also providing subsidies to single-child families (Ebenstein, 2010). As shown in Figure 1, the average fertility rate decreased from 2.75 in 1979 to 1.49 in 1999 and remained fairly constant since then, staying well below the global average of 2.69 children per woman over the same time period.

While successfully reducing the fertility rate, the OCP had also lead to a significant gender imbalance due to the presence of cultural preference for sons among Chinese parents.[15] During 1960s and 1970s, the fertility rate was high and the infant mortality low, making it likely for an average household to have at least one surviving son without resorting to gender selection. From early 1970s the gender selection begin to occur, albeit on a small scale due to unreliability of existing methods of determining sex in uterus (Ebenstein, 2010). This situation changed in early 1980s when portable ultrasound machines were introduced across the nation to improve the quality of prenatal care, but the same technology also introduced a reliable method of determining the sex in uterus from between 11-13 weeks of gestation (Guo et al., 2018; Piccini et al., 2018). In the presence of a dual need to have a son and to comply with the OCP, the sex determination technology allowed mothers to abort and reconceive with less time, increasing the prevalence of sex-selection behavior among parents. As a result, the share of boys among newborns started to increase: by 2000 almost 120 boys were born for every 100 girls, and there is a clear evidence that sex-selective abortion is the main reason for this imbalance. With approximately five percent of girls that should be born each year being missing, an estimated 30 millions “surplus” men under 21 were present in the population by 2000 (Edlund et al., 2013). Figure 2 illustrates the extent of gender imbalances by plotting the female population share for different age cohorts using 2000 Census data. It shows that in cohorts born prior to 1979 the female share varies around 0.49,[16] but the share began to decline following the introduction of the OCP. Between 1979 and 2000 it decreased from 0.50 to 0.45, or by 0.23 percentage points per year on average, and there is a strong evidence that the gender-selective abortion is the main cause.[17]

[15] This preference is even reflected in the OCP policy itself, which, in some provinces, allowed mothers of a daughter to have a second child (Zhang, 2017).

[16] Normally, the naturally higher proportion of boys at birth, around 0.51, is compensated by their higher mortality rate, and one would expect to see higher share of women in older cohorts. However, the female share in China is decreasing through ages. It may speak to the presence of son preference long before the OCP, whereby girls are more likely to be neglected and receive fewer medical treatments during childhood than boys.

[17] For example, using 2000 Chinese census data, Ebenstein (2010) shows that sons among second children are preceded by longer intervals between pregnancies, thus ruling our biological factors as a possible explanation for

The stringency and enforcement of the OCP had a substantial geographic variation in China. The central government set different fertility targets for different provinces, and the decisions on benefits and penalties for violations had been decentralized to the local authorities. The OCP was strictly enforced in urban regions, while in rural areas mothers of daughters were allowed to have a second child. The policy also had more lax limits on the number of children for ethnic minorities.[18] Since urban areas are concentrated in the coastal provinces and ethnic minorities tend to reside in the border provinces, the gender imbalances, implied by the OCP, vary substantially across cities. Some studies argue that the strength of preference for sons also varies across provinces in China. For example, Poston Jr et al. (1997) find that spatial variation in preference for sons is related to the sex ratio at birth, while Das Gupta et al. (2003) relate regional variation in sex ratios to cultural differences and the role of woman in a family.

Figures 3 and 4 demonstrate the extent of spatial variation in the sex ratio at birth across provinces and cities, respectively, using data on locally born residents from the 2000 Census data. The imbalances in spatial distribution of female share among residents are clear in the figures. In more rural Northern and Western regions with larger presence of ethnic minorities, the share is close to biologically natural 0.5. In contrast, the highly populous provinces in the center and the south, for which Poston Jr et al. (1997) and Das Gupta et al. (2003) find stronger son preference, have the female share of less than 0.465.

Figure 5 illustrates variation in the female share before and after introduction of the OCP. In the figure, we plot the histograms of the female population share across cities for age groups 0-21, born after the introduction of the policy (left panel), and 22-65, born prior to the policy (right panel), along with the fitted normal distribution densities. By comparing the female share distributions of the two population groups, we see that the OCP affected not only the mean of the female share, which was the main target of the policy, but also the variance. The cross-city coefficient of variation of the female share in post-1979 cohorts is twice as large as in the pre-1979 cohorts.[19] As the previous studies demonstrate, this increased variation is systematically related to spatial variation in son preference and the stringency of the OCP.

Consistently with the above findings, we observe that gender imbalances across provinces are persistent over time. In Figure 6, we split all cities into two categories based on whether the female population share is below or above the sample median for 1989 to 1991 cohorts.[20] The figure plots the average female share by the year of birth for these two groups of cities. One can see that for 1989-91 time period the difference in the female share between the two groups is stark, which follows directly from the way the two sub-samples were constructed. The gap in the female share falls considerably for birth cohorts 1992-2000. However, the difference in the female share

sex distortions. Also, he shows that the variation in OCP stringency across time and provinces is linked to gender imbalances.

[18]The OCP allowed for other more subtle exceptions from the strict limit of one child, which could also introduce geographic variation in OCP implementation. For example, "a second child is permitted under special conditions such as the first child is disabled, a spouse return from overseas, the first child is a girl and the couple has real difficulties, or one spouse is a deep-sea fisherman or works in underground mining for more than five years" (Liao, 2013; Ge et al., 2018; Zhang, 2017). The definition of "real difficulties" was open to interpretation by officials at the city level.

[19]The standard deviation of the cross-city female share distribution increased from 0.018 for people born during 1935-1978 to 0.028 for those born during 1979-2000.

[20]The main reasons that we choose the birth cohorts of 1989-1991 for categorizing cities into two groups is that the three age cohorts lie in the middle of the birth year interval affected by the OCP, and the three age groups provide enough observations to construct female share for all 340 cities in the data. We also try other birth year groups which are at least five years away from 1979 to reduce the initial OCP effect and the results are similar to Figure 6.

between the two groups remain consistently positive and persistent over time, reflecting importance of time-invariant factors of gender imbalances, such as son preference, the variation in fine rates and OCP enforcement, ethnic composition, and the share of parents with urban registration across cities. The persistence of the sex ratio imbalances across cities in the "post-policy" period implies that some cities accumulate excess female labor supply relative to other cities, altering comparative advantage in trade in the presence of gender-dependent skills.

3 Gender difference in social skills and physical abilities

The idea that men and women have comparative advantage in different tasks is not new to economics.[21] Although men and woman do not differ in general intelligence, specific cognitive tasks reveal sex differences. In this section we provide a brief overview of the literature on two skills for which there is a broad consensus on the presence of gender differences – social skills and physical abilities.

3.1 Social skills

Social and interpersonal skills are becoming increasingly important in labor markets, and the greater adoption of automation and artificial intelligence would only raise the value of social skills that machines do not posses, such as empathy, communication, negotiations, and ability to manage others. In a recent paper Deming (2017) argues that the demand of social skills – broadly defined as the ability to work with others – increases in the US labor market, as reflected in the growing share of occupations requiring social skills and higher wages in those occupations. The author argues that both the importance and the reward for social skills is increasing because they reduce the marginal cost of cooperation and increase the economy of scale.[22]

A growing body of work in physiology literature documents the presence of female's advantage in social skills. For instance, Baron-Cohen et al. (2005) analyze the difference in brain structure between women and men and claim that at the population level females are stronger empathizers and males are stronger systemizers. Woolley et al. (2010) show that after controlling for the average intelligence of group members, the group productivity increases with the social sensitivity of the group members, which is positively correlated to the share of female members in the group. After analyzing the data from the Early Child Longitudinal Study, DiPrete and Jennings (2012) claim that from the beginning of school, girls have an advantage in acquisition of social skills, which grows over time through elementary schooling and improves their academic achievements. Studying IQ test scores and self- and peer- reported questionnaires about social skills, Szymanowicz and Furnham (2013) conclude that both men and woman tend to rate female partners as being better at social skills than male ones. Van der Graaff et al. (2014) investigated adolescents' development of 283

[21] For example, Galor et al. (1996) analyze the role of complementary between capital and female-specific skills as the channel though which capital accumulation affects gender wage gap. Acemoglu et al. (2004), Niederle and Vesterlund (2010), Kuhn and Shen (2012), Card et al. (2015), and Blau and Kahn (2017) are among many other studies that analyze the role of gender-specific attributes in economics.

[22] A large number of other studies document the importance of social skills for economic outcomes. For example, Mobius and Rosenblat (2006) confirm the importance of social skills by decomposing the beautify premium in an experimental labor market, and claim that the social skills are crucial in smoothing interactions among people. Weinberger (2014) studies the complimentary of cognitive and social skills and shows that the adult outcomes are closely correlated with the social skills obtained in the adolescent period.

boys and 214 girls aged 13 to 18 in six consecutive years and found that girls show significantly higher level of empathetic concern than boys, which is an important social skill, and that the difference remained stable throughout adolescence. A large number of other studies in psychology demonstrates that women have higher scores than men in warmth, agreeableness, empathy and openness to feeling, which are all important attributes of social skills (Pohl et al., 2005; Rudman and Glick, 2012; Argyle, 2013; Merrell and Gimpel, 2014; Drydakis, 2017; Slater and Bremner, 2017).

Studies in behavioral and neuroscience literature confirm that women are better than men in understanding feelings and thoughts of other people, which enable them to better interact in the social world. These studies also find that women tend to have better performance than their male counterparts on verbal processing, emotion recognition and social interaction abilities (Beauchamp and Anderson, 2010; Berenbaum et al., 2011; Eagly and Wood, 2013; Li and Wong, 2016; Davis, 2018). In particular, Chapman et al. (2006) argue that the gender differences in social skills may in part reflect the developmental differences in brain structure and function. Mueser et al. (2010) analyze a community-dwelling sample of people older than 50 with severe mental illness and claim that aging was associated with worse social skills, whereas female gender was related to better social skills. Focusing on stress, which is a ubiquitous challenge in society where people consistently interact with others under the influence of stress, Tomova et al. (2014) show strong evidence that women flexibly disambiguate self and others under stress, enabling more accurate social responses, while men respond with increased egocentricity and less adaptive regulation. It explains gender difference in social skills such as empathy and pro-sociality.

Several recent studies analyze the economic implications of differences in social skills across genders. Cortes et al. (2018) argue that one of the factors contributing the gender wage gap reduction in the US is the growing demand for social skills: with increasing importance of social skills in many occupations, female advantage in those skills results in a greater employment outcomes for female workers. Deming (2017) also documents increasing demand for social skills in the US and develop a model of team production where employee with heterogeneous productivities can perform a variety of tasks required to produce final output. Workers with better social skills can specialize and trade tasks with other workers more efficiently, thus obtaining better reward by reducing coordination costs and allowing workers to exploit their comparative advantage. Several other studies show that female employees have better social skills than male, which give women an edge in competition for top positions (Sjöberg et al., 2001; Schaillée et al., 2015; Jerbashian, 2016; Drydakis, 2017; Krieger-Boden and Sorgner, 2018). In particular, Kim and Starks (2016) study the increasing proportion of women directors on the boards of S&P 1500 firms and conclude that women directors can bring advisory skills into the board, which enhances the board's advisory effectiveness and results in a positive impact on the firm value. Cortes et al. (2018) argues that on average women are good at building and maintaining a relationship with other members of the society, but Blau and Kahn (2017) claim that naturally men are stronger in body strength.

3.2 Physical abilities

Physical strength is one of those attributes where the sex difference is stark. It is widely know that men, on average, are physically stronger than woman, and the difference is well documented for various age groups, cultures and geographic locations (Björkqvist, 1994; Archer, 2004; Eckes and

Trautner, 2012). To a large extent, the difference is due to the relative amount of muscle weight in bodies. A study by Janssen et al. (2000) found that man have on average 12kg more of skeletal muscle mass than woman, and have 30-40% more body strength. In labor economics, the differences in physical abilities between genders was found to explain a substantial part of the gender wage gap (Welch, 2000; De Ruijter et al., 2003; England et al., 2002; Juhn et al., 2014). In the context of international trade, Juhn et al. (2013) find that trade liberalization in Mexico, associated with membership in the North American Free Trade Agreement, lowered the gender wage gap due to the presence of differences in physical abilities across genders. In particular, the authors claim that trade liberalization induced the most productive firms to adopt new IT-intensive technologies. This technological change lowers the demand for physical skills and narrows the gender wage gap. The same literature suggests that physical abilities are more substitutable with capital than cognitive skills, and a large skill premium for physical ability may stimulate firms to switch to technologies that rely more on using machines than physical labor.

4 Theoretical framework

The previous sections established that the OCP and the preference for sons in China increases the supply of male labor relative to female. In the presence of gender-dependent skills, the gender composition in local labor markets can affect the pattern comparative advantage through both the Heckscher-Ohlin and the Ricardian channels. Specifically, if a female population share of a city is higher than the country average, that city would have a comparative advantage (disadvantage) in industries which heavily rely on social (physical) skills.

To formally obtain this result, we follow the extension of the Eaton and Kortum (2002) model by Chor (2010), which uses a flexible theoretical framework with multiple industries, factors of production, importing and exporting countries. The model allows for two sources of comparative advantage: the Ricardian productivity differences and the Heckscher-Ohlin factor endowment differences across exporting cities. The representative consumer in an importing country has a nested utility function with the Cobb-Douglas preferences over goods and a constant elasticity of substitution (CES) sub-utility function over differentiated varieties of a good. Assuming that international markets for each variety are perfectly competitive and the production technologies are constant return to scale, the world price of each variety is proportional to its marginal cost of production, iceberg trade cost, and the inverse of productivity. Furthermore, assuming that the Ricardian productivity of each industry and city is drawn from the Gumbel distribution, for any pair of cities c_1 and c_2, their relative exports of good/industry i to country p is given by

$$\frac{X_{c_1pi}}{X_{c_2pi}} = \frac{\left(\varphi^i_{c_1}/mc^i_{c_1}d^i_{c_1p}\right)^\theta}{\left(\varphi^i_{c_2}/mc^i_{c_2}d^i_{c_2p}\right)^\theta}, \tag{4}$$

where X_{cpi} is the value of exports of industry i from city c to country p, d^i_{cp} is the iceberg trade cost of shipping one unit of i from c to p, and θ is the inverse of the productivity shock variance. The term mc^i_c is the unit production costs of city c in industry i, which captures the Heckscher-Ohlin comparative advantage, and φ^i_c is the Ricardian productivity of city c in industry i. Following Chor

(2010), we parameterize the Ricardian productivity term and the unit cost function as follows:

$$\ln \varphi_c^i = \mu_c + \mu_i + \sum_{k \in K} \rho_k^* I_i^k \times FS_c \tag{5}$$

$$mc_c^i = \prod_{k \in K} (\omega_{ck})^{s_{ki}} \prod_{f \in F} (\omega_{cf})^{s_{fi}} \tag{6}$$

In equation (5), μ_c and μ_i are the city- and industry-specific productivity components, respectively. The third term in equation (5) captures the effect of gender-dependent skills on production, where K is a set of gender-dependent skills, I_i^k is the intensity of industry i in the gender-dependent skill k, and FS_c is the female share in population of city c, which varies across cities due to differences in OCP enforcement stringency. If male workers are less productive in tasks that require a gender-specific skill k, the productivity term will depend on the interaction of industry's intensity in skill k, I_i^k, and the city's female population share, FS_c. As long as FS_c is decreasing in OCP stringency and industries inherit the gender distribution of a city, a decreasing female population share in a city would imply a productivity disadvantage in industries which use social skills intensively ($\rho_k^* > 0$) and a productivity advantage in industries which use physical skills intensively ($\rho_k^* < 0$). Therefore, industries requiring more social (physical) skills in the production process will lose (gain) the Ricardian comparative advantage in cities with more stringent OCP.

The unit cost function (6) is a Cobb-Douglas aggregator of input factor prices, where ω_{cj} is the price of factor j in city c, K is the set of gender-dependent factors of production, and F is the set of conventional factors of production, such as physical capital and skilled labor. s_{ji} is the share of factor j in the total production costs in industry i. The Heckscher-Ohlin comparative advantage operates through the endowment of production factors since differences in the supply of gender-dependent skills across cities in China affect the costs of producing and exporting the good to other markets. If the stock of social skills is decreasing with the female share in population, the supply of social skills in the city will decrease, thus raising the local skill premium for social skills. As a result, the marginal costs of production will increase, and more so in industries with larger expenditure share on social skills, thus deteriorating the city's comparative advantage in industries with high intensity in social skills.

If the Heckscher-Ohlin channel plays a role, the relative factor prices are inversely related to the relative factor endowments, and, as in Romalis (2004), the natural logarithm of the unit cost function becomes

$$\ln mc_c^i = -\sum_{k \in K} \phi_k^* s_{ki} \ln\left(FC_c^k\right) - \sum_{f \in F} \phi_f s_{fi} \ln\left(FC_c^f\right), \tag{7}$$

where FC_c^l is the endowment of factor $l \in K, F$ in city c, measured relative to some reference factor, and $\phi_k^* > 0$, $\phi_f > 0$. Substituting equations (5) and (7) into (4), we obtain

$$\begin{aligned} \frac{1}{\theta} \ln\left(\frac{X_{c_1pi}}{X_{c_2pi}}\right) \quad = \quad & \sum_{k \in K} \rho_k^* I_i^k \times (FS_{c_1} - FS_{c_2}) + \sum_{k \in K} \phi_k^* s_{ki} \ln\left(\frac{FC_{c_1}^k}{FC_{c_2}^k}\right) + \\ & \sum_{f \in F} \phi_f s_{fi} \ln\left(\frac{FC_{c_1}^f}{FC_{c_2}^f}\right) + (\mu_{c_1} - \mu_{c_2}) - \left(d_{c_1p}^i - d_{c_2p}^i\right) \end{aligned} \tag{8}$$

Equation (8) also allows to analyze the dynamic effect of the OCP on comparative advantage through changes in the gender composition of cities over time. It is easy to see that if the female population shares in cities c_1 and c_2 changes at different rates, their relative exports will also change for two reasons. First, cities with a more rapidly decreasing female population share should observe a reduction in social skill endowments and a boost in their premia. This, in turn, will shift the city's export structure away from industries which use social skills intensively through the Rybczynski effect. Second, different rates of female population share changes across cities affect relative industries' exports directly through the effect on gender composition and labor productivity of workers (the Ricardian effect).

The above discussion implies that if one city implements the OCP more stringently than another city, the former will have a deficit in female labor and must have a stronger comparative advantage in industries which are intensive in physical skills and disadvantage in industries which are intensive in social skills. Furthermore, a more rapid decline in the female share in one city relative to another should result in less exports in industries which use social skills intensively and more exports in industries which use physical skills intensively.

5 Empirical strategy

5.1 Static model

Equation (8) in the previous section demonstrates that the OCP can affect the comparative advantage of a city through the Ricardian productivity channel (the first term) and the Heckscher-Ohlin channel (the second and the third terms). In moving from theory to data, we face two challenges. First, estimation of the Heckscher-Ohlin effect in equation (8) requires information on the share of each gender-dependent skill in total costs of each industry, s_{ki}. Since information on gender-dependent skill premia is unavailable, following Chor (2010), Bombardini et al. (2012), and Cai and Stoyanov (2016) we assume that $s_{ki} = I_i^k$, since the expenditure shares on production factors are often used in the literature to measure industry intensity in those factors. Second, to construct the second variable in equation (8) we need information on city-level stocks of gender-dependent skills FC_c^k. This information is also unavailable to us, but we know that the skill stock is related to the female share in population. We assume that this relationship is linear, so that the city-level stock of gender-dependent skills is a linear function of the female population share in the city, FS_c:

$$\ln FC_c^k = \sigma_0^k + \sigma_1^k FS_c \tag{9}$$

where σ_0^k is the average level of the natural logarithm of the local stock of the gender-dependent skill k, and σ_1^k is the semi-elasticity of FC_c^k with respect to FS_c. Because the local stock of social skills is increasing with the local female population share, we expect $\sigma_1^k > 0$ if k is a social skill. At the same time, the local stock of physical skills is decreasing with the local female population share, and we expect $\sigma_1^k < 0$ for physical abilities. Therefore, the theoretical model (8) can be estimated with the following empirical model:

$$\ln X_{cpi} = \sum_{k \in K} \beta_k I_i^k \times FS_c + \sum_{f \in F} \phi_f I_i^f \times FC_c^f + \gamma_{cp} + \gamma_{pi} + \varepsilon_{cpi} \tag{10}$$

where $\beta_k = \rho_k^* + \phi_k^* \sigma_1^k$ are the main coefficients of interest which capture both the Ricardian and the Heckscher-Ohlin channels for each skill k. Based on our previous discussions for equation (9) and (8), both σ_1^k and ρ_k^* are positive for social skills and negative for physical abilities, while ϕ_k^* is always positive. Therefore, $\beta_k > 0$ for social and $\beta_k < 0$ for physical skills. With the available data, separating the Heckscher-Ohlin and the Ricardian channels is impossible. However, separate identification of the two channels is not critical for our study, which main objective is to measure the aggregated effect of China's OCP on exports patterns.

In equation (10), the estimates of β_k coefficients allow us to test the static theoretical prediction developed in Section 4. Since the intensity in gender-dependent skills, I_i^k, varies across industries i, and the female population share FS_c differs across cities c, we can derive β_k from a static empirical model (10) as follows

$$\beta_k = \frac{\partial^2 \left(\ln X_{cpi}\right)}{\partial \left(I_i^k\right) \partial \left(FS_c\right)} \tag{11}$$

If the difference in skill intensities across industries is positive $(\partial \left(I_i^k\right) > 0)$, then a higher female population share $(\partial \left(FS_c\right) > 0)$ must result in a higher exports value from city c if k is a social skill $(\beta_k > 0)$.

In equation (10), we also control for two standard Heckscher-Ohlin input factors, namely, physical capital and human capital. As long as cities export more in industries which intensively use their abundant factors, we expect $\phi_f > 0$ for these two factors of production. The exporter-importer fixed effect γ_{cp} in equation (10) capture iceberg trade cost between trading pairs, and the importer-industry fixed effect γ_{pi} capture product prices and other demand shifters in importing countries, including those which may be driven by cross-country differences in gender structure.

5.2 Dynamic model

In order to test the dynamic prediction of the theoretical model regarding the effect of a change in gender composition across cities over time, we time-difference equation (10) and estimate the following empirical model:[23]

$$\triangle \, lnX_{cpi} = \sum_{k \in K} \beta_k I_i^k \times \triangle FS_c + \sum_{f \in F} \phi_f I_i^f \times FC_c^f + \nu_{cp} + \nu_{pi} + \varepsilon_{cpi} \tag{12}$$

where Δ indicates the time-difference operator, ν_{cp} and ν_{pi} are the exporter-importer and importer-industry fixed effects that capture time trends in bilateral trade costs and demand shifters in importing countries. Our demographic data spans over 27 years, starting in 1979, which is the first year when China officially announced the OCP, and going to 2006, which is the latest year for which the city-level exports data is available to us. The change exports are constructed over the period 2000-2006, the time period for which the trade data are available to us. Allowing gender composition of population to change over time, we fist assume that the industries' factor intensities are constant in order to focus on the OCP as a single dynamic factor leading to changes in the comparative advantage. Then, we show that this assumption is not critical for the estimates of β_k, and demonstrate that changes in gender composition at the city level do not pick up the effect of changes in factor intensities on comparative advantage. The positive (negative) coefficients on the

[23]Because we have no historical data on city-level endowments of physical and human capital stocks, we use the levels of FC_c^f in the dynamic model.

variables of interest, β_k, shows that the cities with relatively larger changes in the female share due to more stringent OCP lead to stronger (weaker) comparative advantage in industries that heavily rely on social (physical) skills.

The main advantage of adding time dimension into the data structure is that it allows to control for the omitted time-invariant factors in the static model. In particular, many city-industry characteristics, which were shown to be important factors of comparative advantage in previous studies, are persistent over time. Among those factors are the differences in local institutions, the level of financial development, the quality of the judicial systems, education systems, and labor market regulations. Due to data limitations and different industry classifications used in this and the previous studies, we cannot control for these factors in the static cross-sectional model (10), but we can difference them out in a dynamic model (12) and alleviate a potential omitted variable bias.

5.3 Endogeneity problems

The main identification challenge in estimating equation (10) is the internal migration across cities in China. A large population of internal migrants may play an important role in determining gender composition of local labor markets. If there are any socio-economic factors co-determining city-level exports and the gender composition of migrants, these factors would confound the effect of the OCP on comparative advantage and lead to biased estimates of β_k coefficients. Therefore, internal migration is a crucial channel that links potential confounding factors to city-level female population share.

One such confounding factor is the economic system in China prior to 1979. Before 1979, China was a closed centrally planned economy. Many economic decisions, such as location for a new plant, were often driven by political considerations rather than market factors. As a result, economic activity in many industries was not spread evenly across cities but was often concentrated in geographic clusters. Since industries differ in their intensities in gender-dependent skills, establishment of a certain industrial cluster in a city may have a differential effect on the local demand for male and female workers. For instance, establishment of a large steel plant may attract disproportionately more male migrant workers who are better endowed with physical abilities, thus, lowering city's female population share. At the same time, opening of such plant will increase steel exports by that city for many years to come. Therefore, pre-1979 economic conditions that stimulate internal migration may have a long-lasting effect on both the female labor share and exports of a city, and incur a potential endogeneity problem.[24]

Another possible confounding factor is the improvement of inter-city public transit system, which reduces the cost of traveling within China. As a result, it stimulates internal migration between regions and makes it easier for young people to work far away from their hometowns and travel back home only occasionally to reunite with families. As such, transportation system is a factor facilitating internal migration and determining the city-level gender structure. At the same time, improving infrastructure reduces transportation cost and boosts exports, especially in industries with high share of transportation costs in value added.

[24]Of course, endogenous choice of geographic location by firms after 1979, when economy started its transition to a market economy, can also be a confounding factor if industries continue to clustered in certain areas and attract immigrant workers of a particular gender. However, this source of endogeneity will partially be alleviated by the fact that firms from gender-skill-intensive industries would have incentives to locate in cities with imbalanced sex ratios.

In both examples from above, the threat to identification of the OCP effect on trade is coming from the presence of third factors, which affects both the structure of exports and the gender composition of a city though internal migration. To address these endogeneity concerns, we seek to isolate the effect of the OCP on cross-city difference in gender composition from the effect of internal migration. For that, we construct two instruments for FS_c to identify changes in the female population share stemming from the OCP alone. We then instrument the interaction terms $I_i^k \times FS_c$ with $I_i^k \times \widehat{FS}_c$, where $\widehat{FS}_c$ is one of the instruments for the female population share.

Our first instrument for the female share in the labor force is the OCP violation fine rate. As previously discussed, the main factor behind growing sex ratio at birth in China is the combination of fertility control policy and the preference for sons. In regions with tighter fertility control measures parents are more likely to invest in sex selection, and the sex ratio at birth is likely to be higher. This logic suggests that the spatial variation in the OCP strictness can predict variation in the female labor share. One of the most important measures of policy strictness is the OCP violation fine rate. Families that exceeded their fertility limits were required to pay a fine, which was set by provincial authorities and formulated in multiples of household annual income. Ebenstein (2010) reports substantial variation in fine rates across provinces, ranging from 10% to 160% of the household annual income. Furthermore, he also documents strong positive relationship between provincial fine rates and the male fraction of births.[25]

The intuition underlying the validity of this instrument is the high degree of decentralization of the OCP implementation. While the population control was applicable throughout China, local authorities were left to formulate their own regulations and develop enforcement mechanisms. With such system of OCP administration, the violation fine rates were set not by the central government in accordance with certain economic criteria, but by the provincial authorities in accordance with local conditions. As a result, the variation in fines across provinces mostly comes from the variation in pre-OCP fertility rates and targets rather than economic conditions that may determine trade composition of a province. Furthermore, the fine rates were set many years before the affected cohorts entered labor market, and are thus unlikely to be related to future migration flows.

The main shortcoming of the above instrument is that the fine rates on excess fertility were set by provincial authorities and thus do not vary across cities within a province.[26] However, the implementation of the OCP was carried out by prefectural officials, who often set their own fertility target and instituted localized enforcement policies. For example, local authorities may include additional regulations on internal immigrants, monthly bonuses for families that obey the OCP, or some technical details regarding the enforcement of the OCP at the city level. While local variability in the policy is known to be important, it is hard to quantify and often unobservable.

In order to explore heterogeneity in the OCP intensity across prefectures, we complement the provincial fine rates with the second instrument that captures variation in the policy within provinces. That second instrumental variable is the number of city-level amendments to the country-wide OCP, announced in the local government printed media.

[25] Along with financial punishment for policy violation, there were non-financial enforcement mechanisms, such as dismissal from employment and disqualification from social benefits. However, fines were the major component of the enforcement policy, and the average fine rates have been shown to relate well to other enforcement mechanisms.

[26] Each province applied different fine rate on different categories of families. Ebenstein (2010) use this fact and constructed city-level fines from the variation in demographic composition across cities within the same province. However, the demographic composition, especially the share of ethnic minorities, is strongly correlated with the level of economic development, which may render the prefecture-level fine endogenous.

In general, high frequency of policy amendments is related to stronger incentives to comply with the OCP at the local level, and the relationship between this instrument and the female population share can be either positive or negative. On one hand, local amendments improve compliance rate, which is negatively related to the sex ratio at birth. On the other hand, local amendments to the OCP may signal that the policy fertility targets were not achieved in previous years due to weak enforcement or for some other reasons, thus making the sex ratio at birth closer to natural. Regardless of whether the relationship between the local policy amendments and the female share is positive or negative, this would be a valid instrument as long as it is uncorrelated with internal migration in future periods. While differences in policy enforcement across cities may affect the decision of a family to reside in one city over another and alter sex ratios at birth, it is difficult to think of any reasons for why enforcement may have differential effect on the internal migration of male and female workers in subsequent periods. Because in this study we use 2000 Census data and the effects of government regulation may manifest themselves prior to their official announcement due to disclosure, we count the number of local government amendments of the OCP before October 2000.

6 Data

In order to estimate the effect of the OCP on comparative advantage using equation (10), we construct a data set by bringing together four data sources: i) the industry-city-level Chinese exports flows, ii) the city-level China Population Census with information on gender composition by age group, iii) the measures of industry-level intensities in gender-dependent skills, and iv) the firm-level information on capital usage and employment by skill type in order to construct industry-level factor intensity variables and city-level factor endowments. We use exports data for the year 2006 and population demographic data for the year 2000. The resulting data set is comprised of 283 Chinese cities, 74 manufacturing industries and 205 export destinations for the year 2006. In what follows, we describe in detail the construction of the main variables for the static and the dynamic models.

6.1 Exports data

Estimation of equation (10) requires exports data by city, industry, and destination country. Since the objective of this paper is to relate demographic characteristic of workers in local labor markets to the comparative advantage of firms operating in these markets, we need to define a local labor market. Our definition is based on the 4-digit China Standard Location Identification System (CSLID), which divides China into 344 geographic units and includes all prefecture-level cities and four municipalities. For simplicity, we call these geographic units “cities”. Defined this way, each city is a sizable geographic area with most workers being employed in a city of their residence. Furthermore, the *hukou* policy of workers’ registration is conducted at the prefecture level, making it easier for workers to move and seek new employment within a city than across. This makes cities a logical choice of a geographic unit for local labor markets in our analysis.[27]

[27]For example, a study by Xu et al. (2006) finds that Chinese cities located as close as 50 kilometers to each other have segmented labor markets, reflected in differences in the gender wage gap, returns to education, and occupational premia.

The information on city-industry-level exports is obtained from the Chinese Customs Database (CCD), maintained by the China's General Administration of Customs. The CCD records firm-level export flows by destination country at 8-digit Harmonized System (HS) industry code, which we convert into 4-digit North American Industry Classification System (NAICS) using the Pierce and Schott (2009)'s concordance from 6-digit HS code to 4-digit NAICS. In the end, we construct the data set of Chinese exports by 4-digit CSLID city, 4-digit NAICS industry, and destination country for the year 2006, the most recent year for which the trade data are available.[28]

6.2 Industry-level intensities in social and physical skills

In constructing industry intensities in gender-specific skills, we rely on occupation-level data from the Occupational Information Network (O*NET). The database provides measures of importance of social and physical skills for over 900 occupations in the US. To obtain industry-level measures of skill intensities, we match O*NET occupation-specific importance scores to occupational composition of US 4-digit NAICS industries, and construct the employment-weighted scores of skill importance using the following formula:

$$I_i^k = \sum_j Occup\_share_{ij} \times Skill_j^k \tag{13}$$

where $Skill_j^k$ is the level of importance of the gender-dependent skill k for occupation j, $Occup\_share_{ij}$ is the share of occupation j in industry i, and I_i^k is the intensity of gender-dependent skill k for industry i. Equation (13) shows that the variation in each gender-dependent skill intensity across industries comes from the variation in the level of skill importance across occupations, as well from the variation in the occupational structure between industries.

We measure $Skill_j^k$ in equation (13) using O*NET information on the importance of social and physical skills for different occupations. In the O*NET database, both social and physical skills are complex categories that include multiple related measures. The category of social skills contains the following six basic skills: Coordination, Instructing, Negotiation, Persuasion, Service Orientation, and Social Perceptiveness. Specifically, Instructing, Negotiation and Persuasion reflect the importance of communication skills, Service Orientation and Social Perceptiveness capture the importance of understanding, and Coordination and Negotiation measure the importance of interpersonal relations. The category "Physical abilities" include nine basic skills: Dynamic Flexibility, Dynamic Strength, Explosive Strength, Extent Flexibility, Gross Body Coordination, Gross Body Equilibrium, Stamina, Static Strength and Trunk Strength. Due to high correlation between skills within each category, we combine all skills within each group into one aggregate measure using the principle component analysis (PCA).

The occupational employment shares for 4-digit NAICS industries come from the US Bureau of Labor Statistics. After matching occupational employment shares to the O*NET importance measures of social and physical skills at the 7-digit Standard Occupational Classification (SOC), we use the shares of occupational employment as weights in equation (13), and calculate the intensity of social and physical skills in 4-digit NAICS industries as a weighted average of social and physical

[28] The first cohort of workers who were affected by the OCP entered Chinese labor market either in 1997 (if they completed high school) or in 1995 (if they completed only middle school). Hence, we want to work with as recent trade data as possible, so that a larger share of the labor force would be affected by the OCP.

skills importance across occupations within an industry.

Using US employment shares instead of Chinese in equation (13) has its costs and benefits. The advantage of using US occupational shares is that these shares are independent of changes in the Chinese labor markets. A natural concern with using Chinese employment shares in equation (13) is that these occupational figures may reflect industries' response to changes in the relative supply of female labor by substituting away from the use of gender-dependent skills that become scarce. If industries differ in the ease with which they could substitute away from using gender-dependent skills, I_i^k constructed with the Chinese employment shares would be endogenous in equation (10). The disadvantage of using US employment shares is that they may not accurately reflect the demand for different occupations in China, in which case I_i^k with US employment shares will be noisy measures of the importance of gender-dependent skills for the industries. We assume that the relative ranking of industries in their use of gender-dependent skills in China is similar to that in the US, but we cannot test this assumption in the absence of information on the SOC occupational structure of Chinese industries.

In Table 2, we list ten industries with the highest and the lowest intensities in social and physical skills, and Table 3 reports ten occupations with the highest and the lowest intensities in those skills. For occupations which do not require much interaction with other workers, such as material moving workers, vehicle and machine operators, or assemblers, the importance of social skills is low. As a result, in industries where most workers enter in these occupations, the intensity in social skills is also low.[29] In contrast, industries that produce electronic equipment and machinery tend to be intensive in social skills because a relatively large share of workers in these industries enter in occupations that require social interactions, such as managers, sales/marketing specialist and engineers. Operations managers, business operation specialists, engineering technicians and engineers are among occupations with the highest intensity in social skills. These positions have relatively high employment share in industries such as navigational, measuring, electro-medical and control instruments manufacturing, communications equipment manufacturing and semiconductor manufacturing. More than 40% of workers in these industries enter as engineers and operation managers, making these industries among the most intensive in social skills. Table A1 in the Appendix provides detailed information on occupational employment composition for all 74 manufacturing industries used in our analysis. And in the Appendix Table 2 we show that our main results are not driven by outliers in the constructed I_i^k variables.

6.3 City-level gender composition

To construct the FS_c variable – the female population share among residents for each 4-digit CSLID prefecture/city – we use the 2000 China Population Census (CPC). The CPC records information on 1,180,111 individuals from 345,167 households, selected randomly by the National Bureau of Statistics of China (NBSC). Because we use exports data for the year 2006 while the CPC data is for the year 2000, we construct FS_c variable as a share of female residents in the total number of residents of city c for the 12-21 age cohort. We focus on this age group for two reasons. First, 12-year-olds in 2000 will enter the legal working age of 18 in 2006 and may enter the labor market.

[29]For example, in Apparel and Leather Tanning and Finishing industries more than half of the labor force work as operators of sewing and cutting machines. Both occupations are among ten occupations with the lowest levels of social skill importance.

Second, people aged 21 in 2000 is the first age cohort affected by the OCP, introduced in 1979. Constructed this way, FS_c variable is a good approximation for the female share in the 18-27 age group in 2006. For the sample of 283 cities that we use in the baseline regressions, FS_c has a mean of 0.50 and a standard deviation of 0.04. Table 1 lists distribution characteristics of the FS_c variable.

There are two issues with the above measure of female population share of a city that may affect the quality of the variable. First, as discussed in Section 5, there is a lot of internal migration in China. Some immigrants move permanently to a new place of residence which would be reflected in the Census data, but a large number of others stay registered in one city and work in another. Liang and Ma (2004) estimate the floating population, which are migrant workers residing in cities where they have no local registration, at 145 million, or more than 10 percentage of the Chinese total population. We rely on our instruments to deal with the issue of internal migration.

The second problem with the quality of FS_c variable is related to the problem of unregistered children who will be missing from Census data. The OCP requires parents who have out-of-plan birth to pay a hefty fine, and some parents may want to delay registration in order to avoid the penalty. Moreover, such parents are less likely to delay registration of sons because lack of registration can make it difficult to enroll a child into high school, and strong son preference suggests that parents are more willing to invest in education of sons. Indeed, many studies argue that unreported girts is an important factor of the sex ratio imbalance in China.[30] Unfortunately, the measurement error problem, induced by disproportionately unreported female births, not only distorts the FS_c variable, but also correlates with our instrumental variables. To address this problem, we rely on the fact that most unreported children get registered as teens in order to get immunization and attend high school. In Section 7.3 we show that our IV results are robust to using the female population share constructed for residents aged 16-20 in 2000 Census, which is the first cohort affected by the OCP and the least likely to suffer from measurement error resulting from unreported births.

6.4 City-level endowments and industry-level intensities in skilled labor and physical capital

The industry-level measures of intensity and the city-level measures of endowment in skilled labor and physical capital are all derived from the 2004 Chinese Industrial Enterprises Database (CIED), which is constructed by the NBSC and contains information on the location and industrial affiliation of all Chinese firms with annual sales over 5 million Chinese Yuan, or approximately $600,000 US dollars at 2006 exchange rate. The main reason of choosing the CIED for the year 2004 is that only in this year the CIED collects firm-level information on physical assets and employee educational attainment. For every firm in the data, we define capital stock as the value of firm-level fixed assets, which is then aggregated up to industries and cities. The industry-level capital intensity is constructed as the natural logarithm of the ratio of capital stock to total sales of an industry, while the city-level capital endowment is the natural logarithm of the ratio of capital stock to total

[30]For example, Cai and Lavely (2003) compare 1980 and 2000 Censuses and conclude that 12.8 million fewer girls were born over this period than would normally be expected, and that 8.5 million were truly missing due to sex selection, while the remaining 4.3 million were not reported at birth. Later studies by Goodkind (2004) and Shi and Kennedy (2016) find a larger share of unreported girls, between 20 and 30 million, and a smaller share of late registrations.

sales in a city. Similarly, the industry-level intensity in skilled labor and the city-level endowment of skilled labor are obtained as the natural logarithms of the share of skilled labor force in total employment of an industry and a city, respectively.[31] In total, the information on skilled labor and physical capital controls is available for 340 cities and 74 industries in 2004.

Because industry-level intensities in gender-dependent skills are available to us only for 4-digit NAICS industries (more details on the construction of these variable are in section 6.2), we need to convert CIED data into 4-digit NAICS. In CIED, firms are classified by the 4-digit Industrial Classification for National Economic Activities (ICNEA), which we map into the 4-digit NAICS in two steps. First, we convert 4-digit ICNEA into the 3-rd revision of the 4-digit International Standard Industrial Classification (ISIC) by applying concordance tables from China's National Bureau of Statistics. Second, we use the concordance tables from U.S. Census Bureau to convert 4-digit ISIC into 4-digit NAICS.

6.5 Instrumental variables

In order to address the endogeneity problem of the female share in local population, arising from its correlation with the flow of workers across cities, we employ two instrumental variables for FS_c. Information on the OCP violation fines, our first instrument, is taken from Ebenstein (2010). The fine on excess fertility is defined as a share of a household's annual income. Typically, the fines were collected as annual deduction over multiple years, and the rates that we use are the corresponding present value of a one-time penalty.

The second instrumental variable is the number of city-level amendments to the country-wide OCP. This instrument is a count variable, calculated as the number of announcement by local authorities, both province- and city-level, regarding modifications to the OCP and implemented between 1979 and 2000. All local government announcements are retrieved from the online database of local government legislation "Lawinforchina Weekly",[32] built in 1985 and maintained by the Peking University, using "China one-child policy" as a search key word. After breaking down provincial announcements into city-level announcements, we obtain 1,302 local government announcements regarding the OCP from 1979 to 2000 across 340 cities.

Table 1 provides the summary statistics for our baseline sample. Although the above instruments are pre-determined relative to future trade flows, one may still be concerned that the instruments are not completely exogenous if correlated with other economic characteristic that matter for trade. The conflation of the OCP stringency with the level of economic development is the greatest concern. For example, the OCP stringency, such as fertility targets, or OCP enforcement mechanisms, such as fine rates, may be different for high- and low-income regions. To gain a better understanding of how much variation exist in the female population share and our two instruments apart from income level, in column (1) of Table 4 we report the correlation coefficients between the GDP per capita of a city on one hand and the instrumental variables and the FS_c variable on the other. We find that sex ratios tend to be more distorted in less developed cities as the correlation between GDP per capita and FS_c is positive. The two instruments are also positively correlated with GDP per capita of a city but that correlation is weaker and statistically significant only at 10% confidence level.

[31]Skilled workers are those with at least a college degree. Information on skill composition of labor force is obtained from CIED.

[32]The website is www.pkulaw.com/law/lar

Since OCP implementation was carried out by local authorities, we do not find strong evidence that implementation varied across cities in a way that is related to their economic development. At the same time, both instruments have strong and statistically significant association with the female population share.

7 Empirical results

7.1 Baseline results

Table 5 presents the OLS estimation results for equation (10). For ease of comparison, we report standardized beta-coefficients in all tables. Since the dependent variable is defined at more disaggregated level than the main explanatory variables, the standard errors are clustered by city-industry to correct for correlation between export destinations for the same industry and city.

The first column includes only the two standard Heckscher-Ohlin factors of comparative advantage – the abundance of a city in physical capital interacted with the industry's capital intensity and the abundance of a city in skilled labor interacted with the industry's intensity in skilled labor. The coefficients on both interactions are estimated to be positive and statistically significant at five percent level, confirming that cities with relatively large endowments in physical capital and skilled labor force have comparative advantage in industries which use these two factors intensively.

Columns (2)-(3) add the two key variables, namely, the interactions of the industry-level intensities in gender-dependent skills and the city-level female population share. We find that the interaction of social skill intensity and female population share has a positive and statistically significant relationship with exports, which is consistent with the hypothesis that gender composition is a determining factor of a city's comparative advantage when demand for social skills varies across industries. The coefficient on the interaction of physical skill intensity and female labor share is negative, as expected, and also significant, meaning that cities with high share of female workers export less in industries with a strong reliance on physical abilities of the labor force. The magnitudes of both coefficients decline when the two interaction terms are included together in column (4), reflecting negative correlation between intensities in social and physical skills, but both coefficients remains statistically significant at 1% confidence level. This result suggests that the division of labor across cities, facilitated by international trade, to some extent mitigates the differences in local labor markets caused by disparities in female labor supply. Regions with relatively high female labor supply tend to employ more female workers by specializing and exporting products that require skills more commonly found in female workers, such as social skills.

To interpret the magnitudes of these coefficients, recall that in constructing the explanatory variables, both the female population share and the skill intensities are standardized across cities and industries, respectively, before being interacted in equation (10). Suppose a certain industry has a one standard deviation greater intensity in social skills than the rest of the economy. Focusing on the estimation results for the most complete specification in column (4), where the coefficient on the social skill interaction is equal to 0.02, a one standard deviation increase in the female population share of a city will increase city's export in that industry by

$$exp\left\{\beta_{social\ skills} \times std\left(lnX_{cdi}\right)\right\} = exp\left\{0.02 \times 2.75\right\} = 1.057$$

or by 5.7%, given that the standard deviation of the log of exports is equal to 2.75 (see Table 1). Since $std\,(FS_c)$ is equal to 4 percentage points, a one percentage point increase in FS_c will increase exports by $exp\,\{0.002 \times 0.25 \times 2.75\} = 1.014$, or by 1.4%.

Similarly, if an industry has a one standard deviation greater intensity in physical skills than the rest of the economy, a one standard deviation (a one percentage point) increase in city's female labor share will lower city-industry exports by 10.4% (2.7%).[33] In light of the delayed effect of the OCP on labor markets, the effect of the policy on trade flows may become even more disruptive in future when the cohorts with more distorted sex ratio, born after 1990, start entering the labor market.

7.2 IV results

As we discussed earlier, the female population share variable is likely to be endogenous in the presence of internal migration of workers. In this section we explore the instrumental variable strategy, described in Section 5.3.

The IV results are presented in Table 6, with column (1) showing the OLS results for comparison. We first instrument the female population share with the provincial OCP violation fine rate in column (2). The instrument is relevant, with the first-stage F-stat exceeding 10 for both variables. It is also valid, in that the fine rates are independent of the subsequent migration flows and are only weakly correlated with the level of economic development of a city. The second stage estimates in column (2) show that not only do the OLS results, hold up, but they are actually stronger when we instrument the female population share. Both coefficients on the social and physical skill interactions preserve expected signs and statistical significance, but they also raise (in absolute values) relative to OLS, roughly quadrupling to 0.08 for social skills and to -0.175 for physical skills. This suggests that the endogeneity concerns due to internal migration are not inflating our results but, if anything, biasing the OLS results toward zero. Column (3) reports the results with the city-level amendments to the OCP as an instrument for FS_c. The coefficient estimates support conclusions from column (2) that the distribution of both the social and the physical skills across cities matter for foreign trade.

In column (4) we use the two instruments together. The second stage results are consistent with the results in columns (2)-(3). Specifically, both coefficients of interest have expected signs and significant at five percent confidence level. The Hansen-J overidentification test does not reject the hypothesis of exogeneity of instruments, although it is not far from rejecting the null. To some extent, this result is not particularly surprising, given that our two instruments exploit variation across different administrative geographic areas.

Comparing the IV results in columns (2)-(3) to the OLS results allows us to make another important conclusion. We find that the IV estimates are always larger (in absolute value) than the OLS coefficients. If the OLS coefficients were overstated due to positive correlation between female population share and the level of economic development of a city, we would expect to see smaller coefficient estimates in IV specifications because both of our instruments have weaker correlation with the GDP per capita at the city-level than FS_c. Since we find the opposite, the positive

[33] For comparison, a one standard deviation increase in capital or skilled labor in a city will increase exports by 15.4% and 18.9% in industries which are one standard deviation more intensive in capital and skilled labor than other industries, although the former effect is not statistically significant

correlation between our instrument and the level of economic development of a city is unlikely to be a concern for identification.

Overall, the IV results in Table 6 provide strong support to the predictions of the theory. The IV approach provides evidence that the gender composition of a city has a causal effect on trade. Focusing on the most complete specification in column (4), the IV estimates imply an economically significant impact of female labor supply on exports. Specifically, a one percentage point increase in female population share of a city and a one standard deviation increase in social skill intensity of an industry will lead to a 3.1% increase in exports. Conversely, a one percentage point increase in city's female labor share combined with a one standard deviation increase in physical skill intensity of an industry will lead to an 9.2% reduction in exports. As such, we find compelling evidence for the hypothesis that the variation in female labor supply has a causal impact on foreign trade.

7.3 Extensions

7.3.1 Results with exports aggregated across destinations

In column (1) of Table 7 we estimate a reduced-form version of the gravity model (10) with exports aggregated across destination countries.[34] Since the key explanatory variables only vary by city and industry, we regress city c's exports in industry i, $\ln X_{ci}$, against the interaction terms capturing comparative advantage forces, while controlling for city and industry fixed effects. The standard errors are clustered by city. Column (1) shows that the estimates with data aggregated across destinations are less precise than the baseline IV results. Both coefficient estimates are of the expected signs and their magnitudes are very similar to those in column (4) of Table 6, but only the interaction on physical skills is statistically significant at 10% level. However, one should keep in mind that such specification may generate biased estimates, stemming from the relationship between the Ricardian productivity and the market conditions in destination countries. As Costinot et al. (2011) put it, the comparative advantage models do predict aggregate industry trade flows, but proper tests of these models should be based on exporter-importer-industry data with importer-industry fixed effects in order to control for the factors of comparative advantage in importing countries.

7.3.2 Unregistered births in Census data

As we discuss in Section 6.3, the official Census data may undercount the number of girls. Parents may not want to report a second birth in order to avoid OCP violation penalties, and the incentives to hide female births are stronger in a country with a preference for sons. Alternatively, some families may delay registration of a girl until they have a son. Although late registrations are prevalent and may distort official data on sex ratios, most studies suggest that the vast majority of missing girls are truly missing. For example, comparing Census data from different years, Cai and Lavely (2003) find that one-third of all girls missing in one Census wave are registered in the next one by the age of majority, while two-thirds are truly missing. They also find that unreported births are overwhelmingly registered by the age of fifteen. To verify that our results are not influenced by late registrations, we re-estimate the main IV regression using demographic data for residents aged

[34] All regressions in Table 7 are modifications of the baseline IV specification from Column (4) of Table 6. In Table A2 in the appendix we also demonstrate the robustness of our results to exluding observations with extreme values of the explanatory variables.

16-21 in 2000 Census. These are the first five cohorts affected by the OCP and the least likely to suffer from measurement error resulting from unreported births. The estimate on the social skill interaction from this specification, reported in column (2) of Table 7, is very similar to the baseline estimate, while the effect of physical skill, if anything, is even stronger.

7.3.3 Female employment share as a measure of intensity

Differences in the relative female labor supply across cities would affect exports only in the presence of gender-specific skills. The analysis so far focused on two skills, social and physical, at which men and women are likely to have different productivities. As an extension of the baseline result, we estimate a specification with an alternative measure of skill intensity I_i^k which does not require taking a stance on gender differences in a particular skill. Specifically, we construct a general measure of industry's intensity in female labor as a share of female workers in total sectorial employment using 2004 Chinese Industrial Enterprises Database. As long as there are gender differences in skill requirements of different jobs, be it social/physical or any other skill, women will select into industries that require female-specific skills, and it will be reflected in the female share of industry's labor force.[35]

Column (3) in Table 7 reports the results of this specification, and it confirms that differences in gender composition across cities affect their relative exports. The positive coefficient on the interaction term implies that an increase in the female population share of a city will result in more exports by industries which use female labor intensively. In column (4) we add the female labor intensity term to the main specification with social and physical skills. We find that the coefficient estimates on social and physical skill interactions remain largely unaffected. We also see that, controlling for social and physical skills, the coefficient on female labor intensity remains positive and significant. This result suggests that there are differences between male and female workers, other than in social and physical skills, that affect relative productivity of the two groups of workers and shape the pattern of comparative advantage.

7.3.4 Controlling for other skills

In our analysis we focus on two sets of skills, social and physical, for which we have substantial evidence on productivity differences by gender. We thus expect that the variation in gender composition across cities will have the strongest effect on relative exports of industries with the largest differences in social and physical skill intensities. In this section we explore the possibility that the sex ratio differences may affect trade through other skills. For that, we construct measures of industry intensities in cognitive, routine, and manual skills in the same way as we constructed intensities in social and physical skills using expression (13).[36] If one believes that none of these skills are male or female-oriented, then trade flows should be less responsive to variation in any of the new intensity measures in the presence of heterogeneity in sex ratios across cities, and the

[35] One may be concerned that the female employment share of an industry can be an endogenous response to the deficit of female workers in the local labor market conditions. Constructing female employment share from 2004 US IPUMS data avoids this problem and produces similar results.

[36] The PCA measure of cognitive skills is constructed from the O*Net measures of importance of "Management of Financial Resources," "Management of Personnel Resources," "Inductive Reasoning," "Information Ordering," "Oral Comprehension," and "Originality." Manual skill intensity is based on "Manual Dexterity," "Rate Control," "Reaction Time," "Response Orientation," and "Wrist-Finger Speed." Routine intensity is constructed from "Importance of repeating same tasks," "Work schedule", and "Level of competition."

exercise can be viewed as a placebo test. Columns (5)-(8) of Table 7 show the estimates from this test, and the results are broadly consistent with our expectations. None of the new skills are individually or jointly significant. Including all three additional measures of skill into the baseline specification in column (8) does not change the sign and significance of coefficient on social skill interaction, although it increases in magnitude. The point estimate on physical skills, however, becomes substantially smaller and statistically insignificant. The most likely reasons is a high degree of correlation between the measures of intensity in physical and manual skills, which makes it difficult to separately identify the effects of these two skills. At the same time, the coefficients on cognitive and routine skill interactions are never statistically significant, confirming that these two skills are not associated with relative productivity differences by gender.

7.3.5 Controlling for differences in economic development

Table 4 reveals that our instruments are correlated with income per capita of a city. Since the industrial structure changes with the level of economic development, it may raise a concern about exogeneity of instruments. To mitigate this concern, we show that our results are robust to conditioning on the city's level of economic development. Specifically, we include in (10) the interactions of industry intensity in social and physical skills with the log of city's GDP per capita. Because the OCP fine rates may also be related to other characteristics of a city, such as factor endowments, we control for the interaction of social and physical skill intensities with city's endowment in physical and human capital. Similarly, the underlying industry characteristic of interest, the intensity in gender-dependent skills, could be correlated with other industry characteristics, such as intensity in capital and skilled labor. To show that the variation in female labor supply across cities affects exports through gender-dependent skills, we include in model (10) the interactions of female labor share of a city with industries' intensity in capital and skilled labor. We report the result of specification with the above control variables in column (9) of Table 7. We only report the estimates on the interactions of GDP per capita with skill intensities in the table, and do not report the estimates on the remaining six interaction coefficients for brevity. We observe that the interactions of GDP per capita with social and physical skill intensities are not statistically significant, while the two main coefficients of interest preserve expected signs and significance. Therefore, there is no evidence that the variation in OCP implementation across cities picks up cross-city heterogeneity in economic development or other omitted interaction variables.

7.3.6 Additional instruments for female labor share

In this section we employ three additional instruments for female population share that rely on different identifying assumptions. Given that these instruments exploit different sources of data variation, we view this as a stringency test.

Locally-born female population share. Another instrumental variable that we use for FS_c is the locally-born female population share, defined as the share of women who were born in the city among the total locally-born population. The 2000 CPS, from which we retrieve demographics data, records whether an individual was born in the city of current residence or not. This allows separating locally-born city residents from immigrants. However, the Census does not provide information on the city of birth, which prevents us from constructing complete cross-city migration flows. Therefore, the locally-born female population share can isolate the effect of immigration into a city from the FS_c variable, but it cannot control for the migration of workers out of the city. Hence, this instrumental variable offers only a partial solution to a possible endogeneity of FS_c variable.

Minority share. One of the factors related to the stringency of OCP enforcement is the share of ethnic minority groups in a city. Minority groups were exempted from the OCP until 1989, which is the time period of our study (Skalla, 2004). This implies that in cities with large share of ethnic minorities a substantial fraction of population is not covered by a one-child limit, resulting in less sex selection and closer to normal gender ratios. This motivates our second additional instrument, which is the share of non-Hun locally born residents in total population of a city. One may be concerned that the ethnic composition of a city may be related to the level of economic development and to a pattern of comparative advantage, a concern that need to be kept in mind in interpreting our estimation results with this instrument. The minority share of a city is constructed as a share of non-Han residents in the 12-21 years old age group, using data from 2000 CPC.

OCP violation rate. Our third additional instrument for the female labor share is the rate of the OCP violations at the city level. We define an OCP violating household as the household with at least two children and the youngest one born after 1979, the year when the OCP was officially introduced. In the presence of a strong son preference and high penalties for OCP violations, some families may be willing to violate the OCP and accept the penalty as long as the newborn is a boy, in which case they would be more likely to invest more in gender planning and selection.[37] It follows that a higher OCP violation rate indicates a stronger son preference, resulting in a higher gender determination and selection rates at pregnancy. Therefore, high rates of the OCP violations should have negative relationship to the local female population share.[38] While the OCP violations at birth are independent of subsequent internal migration, it may be affected by local economic conditions, such as income levels and the ability or inability to pay the penalties, and can thus matter for the factors determining comparative advantage. The advantage of this instrument is that it is the only one available to us that captures son preference in the area. However, that instrument may capture not only the variation in preference for sons across cities but also other factors not fully exogenous to the determinants of comparative advantage. This implies that our results using this instrument need to be interpreted with caution.

The results with additional instrumental variables are presented in Table 8. The first-stage results for all instruments are strong, with F-stat well over ten for both endogenous variables. When the female population share is instrumented with the locally-born female share in column (2), both coefficients on skill interactions preserve expected signs and statistical significance. However, this instrumental variable addresses the problem of internal migration only partially by controlling for the inflow of workers into a city but not the outflow.

Column (3) uses the share of ethnic minorities in a city to instrument for the local female share. The coefficient on the physical skill interaction is negative, significant, and substantially larger than

[37] Consistently with this expectation, we find in our data that the share of girls among children born after 1979 is 0.48 for the first child in the family, and it decreases to 0.44 for the second. Using survey data, Junhong (2001) also find evidence of stronger sex selection at birth among second children: 39% of women had ultrasound during the first pregnancy and 55% for the second. The author also found that ten percent of determined female fetuses were aborted.

[38] It is important to note that, technically, not all second children are born in violation of the policy. In some regions families were allowed a second child if the first one is a girl. However, the logic behind the instrument still applies: families would have stronger incentives for gender planning with the second child. With that in mind, we call all cases when a second child is born after 1979 as "OCP violation".

the OLS estimate. In contrast, the coefficient estimate on the social skill interaction, while still positive and larger in magnitude than the OLS estimate, is statistically insignificant. The third additional instrumental variable that we use is the city-level share of the households that violate OCP by having a second child after the policy was officially introduced in 1979. The results with this instrument are presented in column (4). As with the baseline IV results, not only both coefficients preserve expected signs and remain significant, but the estimates are also larger in absolute value than the OLS estimates.

In column (5) we use all five instruments together, along with an interaction of the OCP fine and the minority share as an additional instrument. The intuition being this interaction as an additional instrument is that ethnic minorities were often exempted from a strict one-child limit. As such, the same OCP violation fine should have more impact on fertility and sex ratios in cities where the share of ethnic minorities is small. At the first stage, each instrument, except for the fine rate, has a significant impact on the interaction term it was supposed to predict, and the F-stat is greater than ten for both interactions. The second stage results with all instruments together are reassuringly consistent with the results in Table 6. Specifically, both coefficients of interest have expected signs and significant at five percent confidence level.

We should note that the Hansen-J overidentification test rejects the hypothesis of exogeneity of instruments, and the difference-in-Hansen test reveals that it is the share of OCP violating households instrument that is likely to be invalid. To some extent, this result is not particularly surprising, given that this instrument produces estimates that are notably different from other instruments. It could be that the family's decision to violate the policy captures not only the OCP penalties and family's preference for sons, but also other potentially endogenous factors, such as income level.

Although none of our additional instruments is perfect, the results are consistent with our previous findings. Taken together, these IV approaches provide further evidence that gender composition of the labor force has causal effect on foreign trade.

7.4 Estimates from the dynamic model

In this section, we focus on estimating the dynamic model (12), described in Section 5.2, and relate changes in gender composition of a city to changes in its exports. Changes in the city-level female population shares were construct over the time period between 1979, the year the OCP was introduced, and 2006, the final year of our sample. The Chinese customs trade data is available to us only for the 2000-2006 period and the change in exports is constructed over this six-year period. It should be noted that the first five cohorts, affected by the OCP, were already in the labor market in 2000, and our dependent variable may not fully reflect the response of trade flows to labor market shock. As such, one might expect our results to be attenuated.

7.4.1 Results with time-invariant factor intensities

Following the structure outlined in Section 5.2, we start by assuming that factor intensities are constant over time, so that exports respond only to changes in the gender composition of a city.

Column (1) of Table 9 reports the OLS results. We find that changes in the female population share of a city during the first ten years of the OCP had a significant effect on exports only through the physical skills channel. The coefficient on the physical skill interaction is statistically significant and equals to -0.037, which is similar to the OLS estimate of -0.04 based on the cross-sectional data (column 4 of Table 5). The estimate of the coefficient on the social skill interaction from the dynamic model remains positive but is smaller than in the static model and is not statistically significant. In column (2) we report IV estimates using the two instruments from Table 6, both in levels. As in the static model, the coefficients on the social and physical skill interactions are positive and negative, respectively, and both are significant at 5% level. Consistently with the results in Table 6, the IV estimates are larger in magnitude than the OLS estimates. Overall, the results in Table 9 confirm that changes in the gender structure within a city over time have significant implications for comparative advantage.

7.4.2 Results with time-varying factor intensities

Analysis in the previous section rests on the assumption that industries' skill intensities are stable over time, so that changes in trade flows react only to changes in the female population share of a city. Next, we check if trade responds to changes in factor intensities as well. Since skill intensities are constructed from skill importance measures weighted by occupational shares, we allow for both the occupational importance of gender-related skills and the occupation composition of an industry to change over time. In Appendix A2 we decompose the changes in the explanatory variables, $\Delta\left(I_i^k \times FS_c\right)$, into (i) changes in the gender composition of a city, (ii) changes in the importance of social and physical skills within occupations, and (iii) changes in the occupational composition of industries. This allows us to refine the previous analysis of comparative advantage dynamics by studying the impact of structural changes within industries as well as the demographic changes within cities.

Equation (16) in the appendix represents the empirical model with the $\Delta\left(I_i^k \times FS_c\right)$ interaction decomposed into three effects described above. In order to construct the first term in equation (16), the change in the occupational composition at the industry level, we collected historical data on sectorial occupation structure from the US Bureau of Labor Statistics. Changes in sectorial occupation structure are constructed for the time period between 1980 and 2006. Data for the second term, the change in the importance of gender-dependent skills by occupation, is obtained from the O*NET. The earliest year for which the O*NET data is available is 1998, and we choose it as the base year for constructing the time difference. Because the general trends in occupational requirements may not be measured accurately in short differences, we also try using the difference between 1998 and 2018 as a robustness exercise.

The IV estimation results for equation (16) are presented in Table 10. Column (1) shows the results when the difference in skill importance measures are constructed over 1998-2006 time period, while results in column (2) are for the 1998-2018 period. As in the previous section, even controlling for changes in skill intensities, city-level changes in the female population share leads to changes in the pattern of exports in a way predicted by the theory. For example, in column (1) only changes in $\Delta\left(I_i^k \times FS_c\right)$ interaction that are caused by changes in gender composition of a city have a significant effect on exports. Perhaps surprisingly, neither changes in occupational composition of industries nor changes in skill importance of occupations have any heterogeneous effect on trade in cities with different gender structure. The data shows no evidence that an increase in social skill intensity or a decrease in physical skill intensity of an industry leads to more exports by cities with higher female population share.

7.5 Country-level evidence

In this section we extend our analysis to cross-country setting and use variation in the relative female labor supply across countries to test the hypothesis that gender composition of labor force is a factor of comparative advantage. Estimation of model (10) at the country level requires data on bilateral trade flows by industry and a measure of the relative female labor supply by country. We obtained bilateral trade flows data from the UN-TRAINS database at 6-digit Harmonized System classification, which we map into 4-digit NAICS industries using concordance from Pierce and Schott (2009). As a measure of relative female labor supply we use female labor force participation (FLFP) in manufacturing, taken from the World Banks's *World Development Indicators*. This measure is constructed as the rate of female participation in the workplace multiplied by the share of manufacturing sector in total employment.

The realized level of the FLFP is formed under the influence of both the supply and the demand factors. In order to isolate the cross-country variation in the FLFP that stems from variation in the female labor supply, we employ an instrumental variable approach. As an IV for the FLFP we use a measure of the prevalence of traditional plough agriculture in a country from Alesina et al. (2013). In their study, the authors find that societies that traditionally used plough agriculture have lower female participation in the workplace, and they attribute these differences to gender norms developed within societies over centuries. Since plough agriculture is intensive in physical labor in which men have an advantage, it encouraged division of labor along gender lines in which men work outside the home in the field and women specialize in activities inside the home. Over time, such division of labor generated social norms that require women to work from within a house, reducing female labor supply. The authors find that these norms are still prevalent in modern societies and show that traditional plough agriculture is a strong predictor of lower FLFP in a country and women' participation in other economic and political activities. Furthermore, these relationships are not sensitive to conditioning on income per capita of a country, suggesting that plough use is not just pre-determined relative to present-day trade flows, but is also unlikely to affect trade through channels other than the relative female labor supply.

Columns (1) and (2) of Table 11 report cross-sectional estimation results for the year 2000. Consistently with Alesina et al. (2013), traditional plough use in agriculture is a good predictor of the FLFP and the instruments are strong. The estimates in column (1) show that countries where women are less likely to participate in the labor market are also less likely to export in industries that use social skills intensively and more in industries that are intensive in physical skills. Not only both coefficients of interest are statistically significant and have expected signs, but they are also economically meaningful. If an industry has one standard deviation greater intensity in social skills than the rest of the economy, then a one percentage point increase in the FLFP will increase relative exports of that industry by 8%. Similarly, if that industry has one standard deviation greater intensity in physical skills, its relative exports will decline by 14.9%. These magnitudes are even stronger than 3% and 9%, implied by the estimated using data on Chinese cities in column (4) of Table 6.

In columns (3) and (4) of Table 11 we estimate how changes in the FLFP over time within a country affect its exports composition. We collect data on the FLFP, trade flows and factor endowments from 1990 to 2005 at five year intervals, and estimate equation (10) on the panel data, holding industry factor intensities constant. Both columns include exporter-importer-year and importer-industry-year fixed effects. Therefore, our empirical specification identifies the role of female labor supply on trade entirely from the variation within exporter-industry cells over time, allowing us to address additional omitted variable bias concerns. In particular, these fixed effects control for time-invariant importer-industry characteristics, such as persistent determinants of importers' comparative advantage, as well as many exporters' characteristics, including institutional factors. It is important to emphasize that since the traditional plough use is also time-invariant, we continue to use this instrument to predict changes in the FLFP over time. Comparing columns (3) and (1), we find that the coefficient estimates are remarkably similar to the cross-sectional results for the year 2000. The first-stage results are strong, and the estimated magnitudes of the second stage coefficients and similar to the estimates reported in column (1) and (2).

8 Conclusions

This paper demonstrates that the composition of trade across industries responds to exogenously-driven changes in female labor supply. If industries differ in their use of female labor, we would expect a shortage of female labor supply to put female-labor-intensive industries into comparative disadvantage. We confirm this insight using trade data for Chinese cities. Our identification strategy relies on the spatial variation in female labor share in population across cities that results from variations in population control measures, imposed by the central government of China, combined with the traditional preference for sons. Several measures of city-level OCP stringency serve as reasonably exogenous IVs for female population share. Our results indicate that if in 1980-s a city enforced OCP more strictly than the rest of the country, by 2006 its female population share will be lower. As a result, the city will tend to export less in industries that are intensive in female-oriented skills, such as social skills, and more in industries dominated by male-specific skills, such as physical abilities. We show that these results economically sizable and are robust to using different instrumental variable strategies.

Our results speak to several topics on literatures in international trade and labor economics. While many economic implications of the OCP, associated with a reduction in labor supply and population aging, have been well studied, we show that changes in the gender composition of the labor force also have important implications for trade and labor markets. We demonstrate that the combination of restrictions on fertility, whether economic or administrative, and social preference for sons, observed not only in China but in many developing countries around the world, shapes the pattern of comparative advantage. This suggests that a decline in relative female labor supply can, to some extent, be balanced by an increase in the relative demand for male-oriented skills, utilized in exporting sectors that take advantage of falling premia for those skills. Thus, the effect of imbalances in sex ratios on labor markets can be offset, at least partially, through trade in products that embed gender-specific skills.

Daron Acemoglu, David H Autor, and David Lyle. Women, war, and wages: The effect of female labor supply on the wage structure at midcentury. *Journal of political Economy*, 112(3):497–551, 2004.

Alberto Alesina, Paola Giuliano, and Nathan Nunn. On the origins of gender roles: Women and the plough. *Quarterly Journal of Economics*, 128(2):469–530, 2013.

John Archer. Sex differences in aggression in real-world settings: A meta-analytic review. *Review of general Psychology*, 8(4):291, 2004.

Michael Argyle. *The social psychology of everyday life*. Routledge, 2013.

Simon Baron-Cohen, Rebecca C Knickmeyer, and Matthew K Belmonte. Sex differences in the brain: implications for explaining autism. *Science*, 310(5749):819–823, 2005.

Miriam H Beauchamp and Vicki Anderson. Social: an integrative framework for the development of social skills. *Psychological bulletin*, 136(1):39, 2010.

Sheri A Berenbaum, Judith E Owen Blakemore, and Adriene M Beltz. A role for biology in gender-related behavior. *Sex Roles*, 64(11-12):804, 2011.

Kaj Björkqvist. Sex differences in physical, verbal, and indirect aggression: A review of recent research. *Sex roles*, 30(3-4):177–188, 1994.

Francine D Blau and Lawrence M Kahn. The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, 55(3):789–865, 2017.

Matilde Bombardini, Giovanni Gallipoli, and Germán Pupato. Skill dispersion and trade flows. *American Economic Review*, 102(5):2327–48, 2012.

Jie Cai and Andrey Stoyanov. Population aging and comparative advantage. *Journal of International Economics*, 102:1–21, 2016.

Yong Cai and William Lavely. China's missing girls: Numerical estimates and effects on population growth. *China Review*, pages 13–29, 2003.

David Card, Ana Rute Cardoso, and Patrick Kline. Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women. *The Quarterly Journal of Economics*, 131(2):633–686, 2015.

Emma Chapman, Simon Baron-Cohen, Bonnie Auyeung, Rebecca Knickmeyer, Kevin Taylor, and Gerald Hackett. Fetal testosterone and empathy: evidence from the empathy quotient (eq) and the "reading the mind in the eyes" test. *Social Neuroscience,*, 1(2):135–148, 2006.

Davin Chor. Unpacking sources of comparative advantage: A quantitative approach. *Journal of International Economics*, 82(2):152–167, 2010.

Guido Matias Cortes, Nir Jaimovich, and Henry E Siu. The" end of men" and rise of women in the high-skilled labor market. Technical report, National Bureau of Economic Research, 2018.

Arnaud Costinot, Dave Donaldson, and Ivana Komunjer. What goods do countries trade? a quantitative exploration of ricardo's ideas. *The Review of Economic Studies*, 79(2):581–608, 2011.

Monica Das Gupta, Jiang Zhenghua, Li Bohua, Xie Zhenming, Woojin Chung, and Bae Hwa-Ok. Why is son preference so persistent in East and South Asia? A cross-country study of China, India and the Republic of Korea. *The Journal of Development Studies*, 40(2):153–187, 2003.

Mark H Davis. *Empathy: A social psychological approach*. Routledge, 2018.

Judith MP De Ruijter, Anneke van Doorne-Huiskes, and Joop J Schippers. Size and causes of the occupational gender wage-gap in the netherlands. *European Sociological Review*, 19(4):345–360, 2003.

David J Deming. The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, 132(4):1593–1640, 2017.

Thomas A DiPrete and Jennifer L Jennings. Social and behavioral skills and the gender gap in early educational achievement. *Social Science Research*, 41(1):1–15, 2012.

Nick Drydakis. Brain types and wages. *The Manchester School*, 85(2):183–211, 2017.

Alice H Eagly and Wendy Wood. The nature–nurture debates: 25 years of challenges in understanding the psychology of gender. *Perspectives on Psychological Science*, 8(3):340–357, 2013.

Jonathan Eaton and Samuel Kortum. Technology, geography, and trade. *Econometrica*, 70(5): 1741–1779, 2002.

Avraham Ebenstein. The "missing girls" of China and the unintended consequences of the one child policy. *Journal of Human Resources*, 45(1):87–115, 2010.

Thomas Eckes and Hanns M Trautner. Social role theory of sex differences and similarities: A current appraisal. In *The developmental social psychology of gender*, pages 137–188. Psychology Press, 2012.

Lena Edlund, Hongbin Li, Junjian Yi, and Junsen Zhang. Sex ratios and crime: Evidence from China. *Review of Economics and Statistics*, 95(5):1520–1534, 2013.

Paula England, Michelle Budig, and Nancy Folbre. Wages of virtue: The relative pay of care work. *Social problems*, 49(4):455–473, 2002.

Oded Galor, David N Weil, et al. The gender gap, fertility, and growth. *American Economic Review*, 86(3):374–387, 1996.

Suqin Ge, Dennis Tao Yang, and Junsen Zhang. Population policies, demographic structural changes, and the chinese household saving puzzle. *European Economic Review*, 101:181–209, 2018.

Daniel M Goodkind. China's missing children: the 2000 census underreporting surprise. *Population studies*, 58(3):281–295, 2004.

Ke Gu and Andrey Stoyanov. Skills, population aging, and the pattern of international trade. *Review of International Economics*, 2019.

Jiajun Guo, Shengjie Lin, and Yawei Guo. Sex, Birth Order, and Creativity in the Context of China's One-Child Policy and Son Preference. *Creativity Research Journal*, 30(4):361–369, 2018.

Ayşe İmrohoroğlu and Kai Zhao. The chinese saving rate: Long-term care risks, family insurance, and demographics. *Journal of Monetary Economics*, 96:33–52, 2018.

Ian Janssen, Steven B Heymsfield, ZiMian Wang, and Robert Ross. Skeletal muscle mass and distribution in 468 men and women aged 18–88 yr. *Journal of applied physiology*, 89(1):81–88, 2000.

Vahagn Jerbashian. Automation and job polarization: On the decline of middling occupations in europe. Technical report, papers.ssrn.com, 2016.

Chinhui Juhn, Gergely Ujhelyi, and Carolina Villegas-Sanchez. Trade liberalization and gender inequality. *American Economic Review*, 103(3):269–73, 2013.

Chinhui Juhn, Gergely Ujhelyi, and Carolina Villegas-Sanchez. Men, women, and machines: How trade impacts gender inequality. *Journal of Development Economics*, 106:179–193, 2014.

Chu Junhong. Prenatal sex determination and sex-selective abortion in rural central China. *Population and Development Review*, 27(2):259–281, 2001.

Daehyun Kim and Laura T Starks. Gender diversity on corporate boards: Do women contribute unique skills? *American Economic Review*, 106(5):267–71, 2016.

Christiane Krieger-Boden and Alina Sorgner. Labor market opportunities for women in the digital age. *Economics: The Open-Access, Open-Assessment E-Journal*, 12(2018-28):1–8, 2018.

Peter Kuhn and Kailing Shen. Gender discrimination in job ads: Evidence from China. *The Quarterly Journal of Economics*, 128(1):287–336, 2012.

Andrei A Levchenko. Institutional quality and international trade. *The Review of Economic Studies*, 74(3):791–819, 2007.

Bingjing Li and Hongliang Zhang. Does population control lead to better child quality? Evidence from China's one-child policy enforcement. *Journal of Comparative Economics*, 45(2):246–260, 2017.

Rebecca Y Hei Li and Wang Ivy Wong. Gender-typed play and social abilities in boys and girls: Are they related? *Sex Roles*, 74(9-10):399–410, 2016.

Zai Liang and Zhongdong Ma. China's floating population: new evidence from the 2000 census. *Population and development review*, 30(3):467–488, 2004.

Pei-Ju Liao. The one-child policy: A macroeconomic analysis. *Journal of Development Economics*, 101:49–62, 2013.

Kalina Manova. Credit constraints, equity market liberalizations and international trade. *Journal of International Economics*, 76(1):33–47, 2008.

Kalina Manova. Credit constraints, heterogeneous firms, and international trade. *Review of Economic Studies*, 80(2):711–744, 2012.

Halvor Mehlum, Ragnar Torvik, and Simone Valente. The savings multiplier. *Journal of Monetary Economics*, 83:90–105, 2016.

Kenneth W Merrell and Gretchen Gimpel. *Social skills of children and adolescents: Conceptualization, assessment, treatment.* Psychology Press, 2014.

Markus M Mobius and Tanya S Rosenblat. Why beauty matters. *American Economic Review*, 96 (1):222–235, 2006.

Kim T Mueser, Sarah I Pratt, Stephen J Bartels, Brent Forester, Rosemarie Wolfe, and Corinne Cather. Neurocognition and social skill in older persons with schizophrenia and major mood disorders: an analysis of gender and diagnosis effects. *Journal of Neurolinguistics*, 23(3):297–317, 2010.

Muriel Niederle and Lise Vesterlund. Explaining the gender gap in math test scores: The role of competition. *Journal of Economic Perspectives*, 24(2):129–44, 2010.

Nathan Nunn. Relationship-specificity, incomplete contracts, and the pattern of trade. *The Quarterly Journal of Economics*, 122(2):569–600, 2007.

Paola Piccini, Carlotta Montagnani, and Maurizio de Martino. Gender disparity in pediatrics: a review of the current literature. *Italian journal of pediatrics*, 44(1):1, 2018.

Justin R Pierce and Peter K Schott. A concordance between ten-digit u.s. harmonized system codes and sic/naics product classes and industries. Working Paper 15548, National Bureau of Economic Research, 2009.

Rüdiger F Pohl, Michael Bender, and Gregor Lachmann. Autobiographical memory and social skills of men and women. *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition*, 19(6):745–759, 2005.

Dudley L Poston Jr, Baochang Gu, Peihang Peggy Liu, and Terra McDaniel. Son preference and the sex ratio at birth in China: a provincial level analysis. *Social biology*, 44(1-2):55–76, 1997.

John Romalis. Factor proportions and the structure of commodity trade. *American Economic Review*, 94(1):67–97, 2004.

Laurie A Rudman and Peter Glick. *The social psychology of gender: How power and intimacy shape gender relations.* Guilford Press, 2012.

Hebe Schaillée, Marc Theeboom, and Jelle Van Cauwenberg. What makes a difference for disadvantaged girls?: investigating the interplay between group composition and positive youth development in sport. *Social Inclusion*, 3(3):51–66, 2015.

Rishi R Sharma. Does the vat tax exports? *Economic Inquiry*, 2017.

Yaojiang Shi and John James Kennedy. Delayed registration and identifying the "missing girls" in China. *The China Quarterly*, 228:1018–1038, 2016.

Lennart Sjöberg et al. Emotional intelligence and life adjustment: A validation study. *Sweden: Center for Economic Psychology Stockholm School of Economics*, 2001.

Nicole M Skalla. Chna's one-child policy: Illegal children and the family planning law. *Brook. J. Int'l L.*, 30:329, 2004.

Alan Slater and J Gavin Bremner. *An introduction to developmental psychology.* John Wiley & Sons, 2017.

Agata Szymanowicz and Adrian Furnham. Gender and gender role differences in self-and other-estimates of multiple intelligences. *The Journal of Social Psychology*, 153(4):399–423, 2013.

Livia Tomova, Bernadette von Dawans, Markus Heinrichs, Giorgia Silani, and Clauss Lamm. Is stress affecting our ability to tune into others? evidence for gender differences in the effects of stress on self-other distinction. *Psychoneuroendocrinology*, 43:95–104, 2014.

Jolien Van der Graaff, Susan Branje, Minet De Wied, Skyler Hawk, Pol Van Lier, and Wim Meeus. Perspective taking and empathic concern in adolescence: Gender differences in developmental changes. *Developmental psychology*, 50(3):881, 2014.

Xuebo Wang and Junsen Zhang. Beyond the quantity–quality tradeoff: Population control policy and human capital investment. *Journal of Development Economics*, 2018.

Catherine J Weinberger. The increasing complementarity between cognitive and social skills. *Review of Economics and Statistics*, 96(4):849–861, 2014.

Finis Welch. Growth in women's relative wages and in inequality among men: One phenomenon or two? *American Economic Review*, 90(2):444–449, 2000.

Anita Williams Woolley, Christopher F Chabris, Alex Pentland, Nada Hashmi, and Thomas W Malone. Evidence for a collective intelligence factor in the performance of human groups. *science*, 330(6004):686–688, 2010.

Wei Xu, Kok-Chiang Tan, and Guixin Wang. Segmented local labor markets in postreform China: gender earnings inequality in the case of two towns in zhejiang province. *Environment and Planning A*, 38(1):85–109, 2006.

Junsen Zhang. The evolution of China's one-child policy and its effects on family outcomes. *Journal of Economic Perspectives*, 31(1):141–60, 2017.

Figure 1: The average annual fertility rate in China.

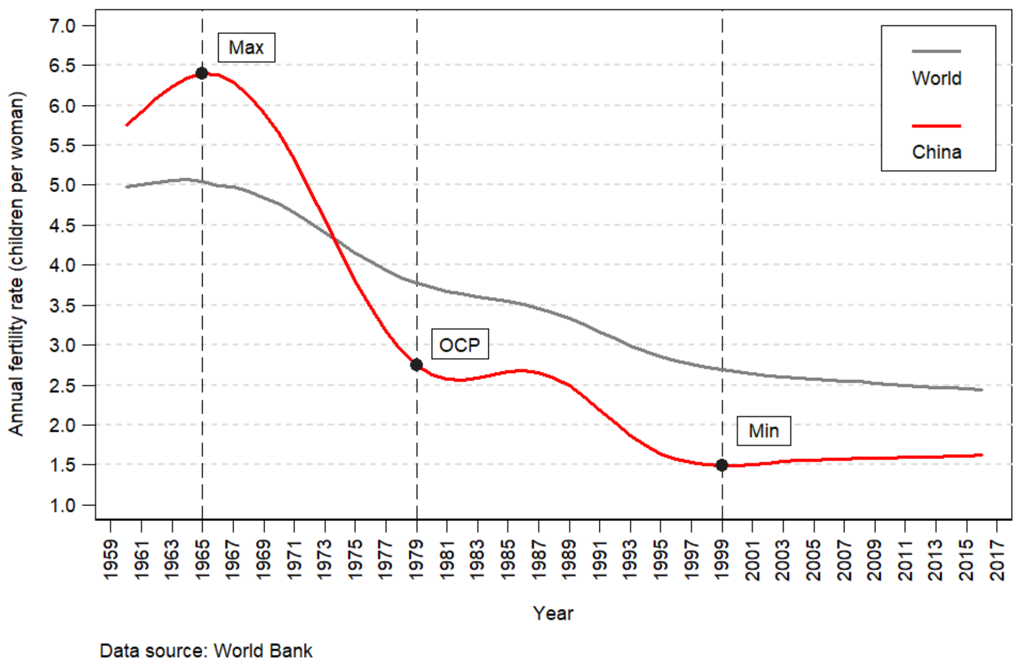

Figure 2: The female population share in China by the year of birth.

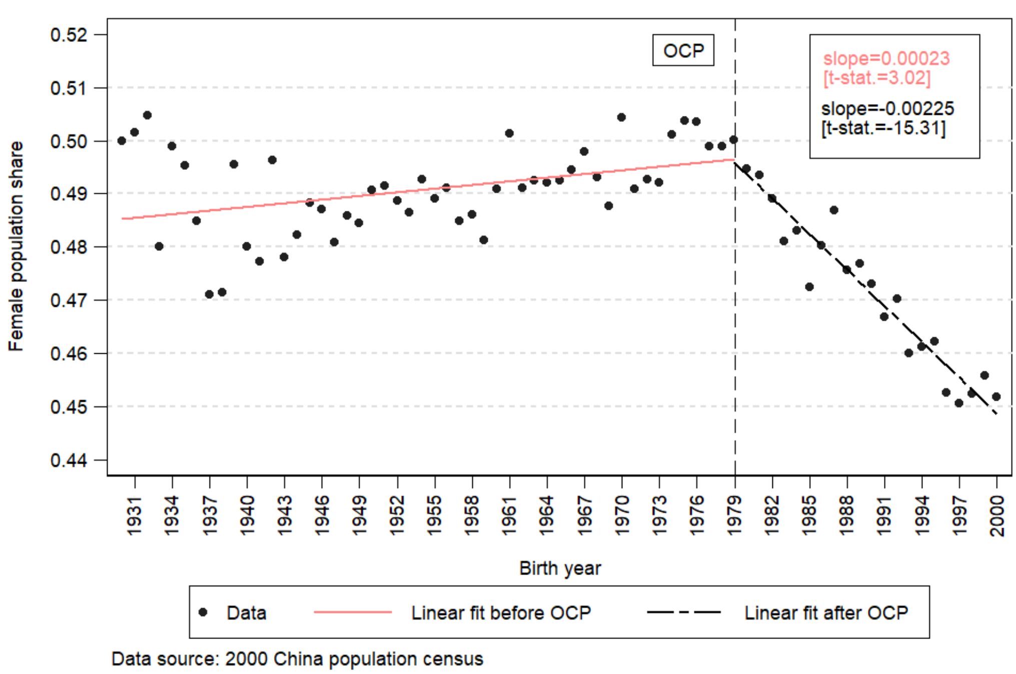

Figure 3: The geographic distribution of locally born Chinese female population share in 2000 across provinces (age group 0-21).

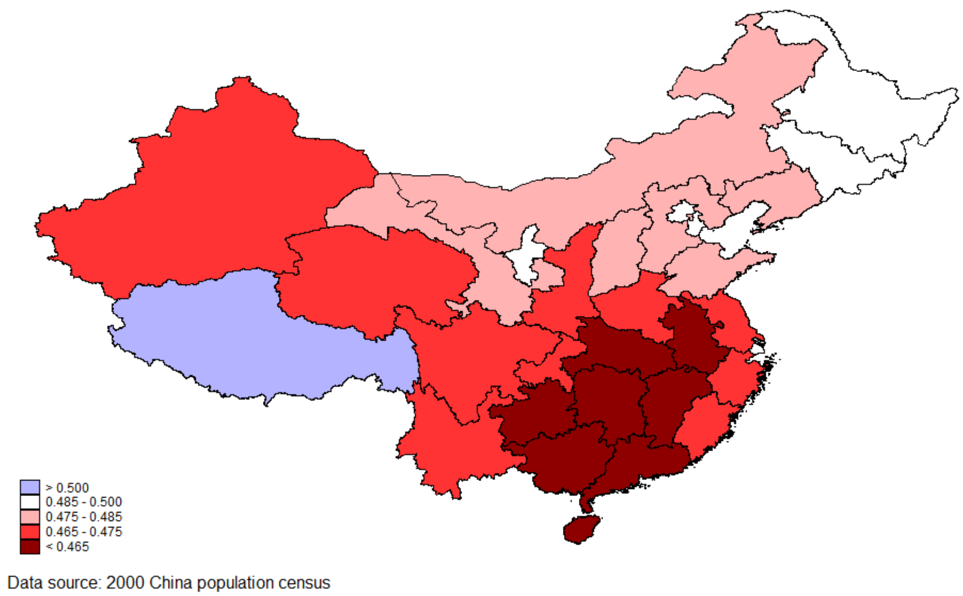

Figure 4: The geographic distribution of Chinese female population share in 2000 across cities (age group 12-21).

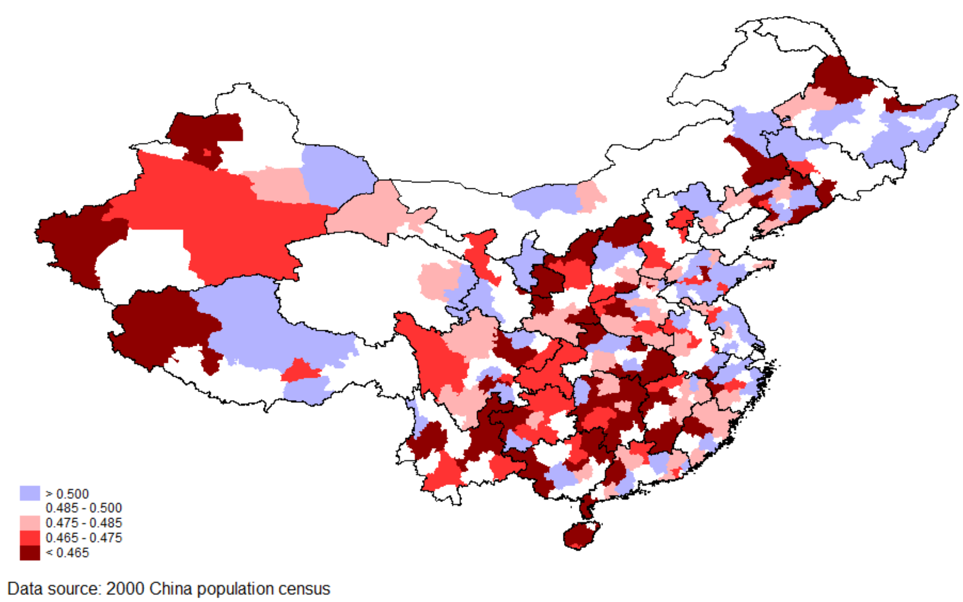

Figure 5: The distribution of the locally born female population share in China across cities for age groups 0-21 and 22-65.

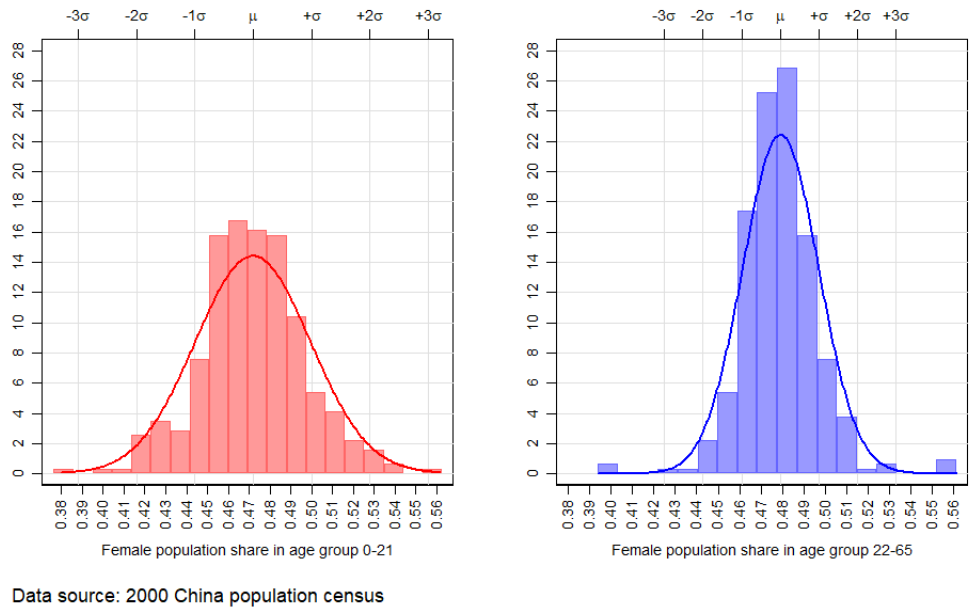

Figure 6: The locally born female population share in China by the year of birth in cities with the share above and below the median in 1989-1991.

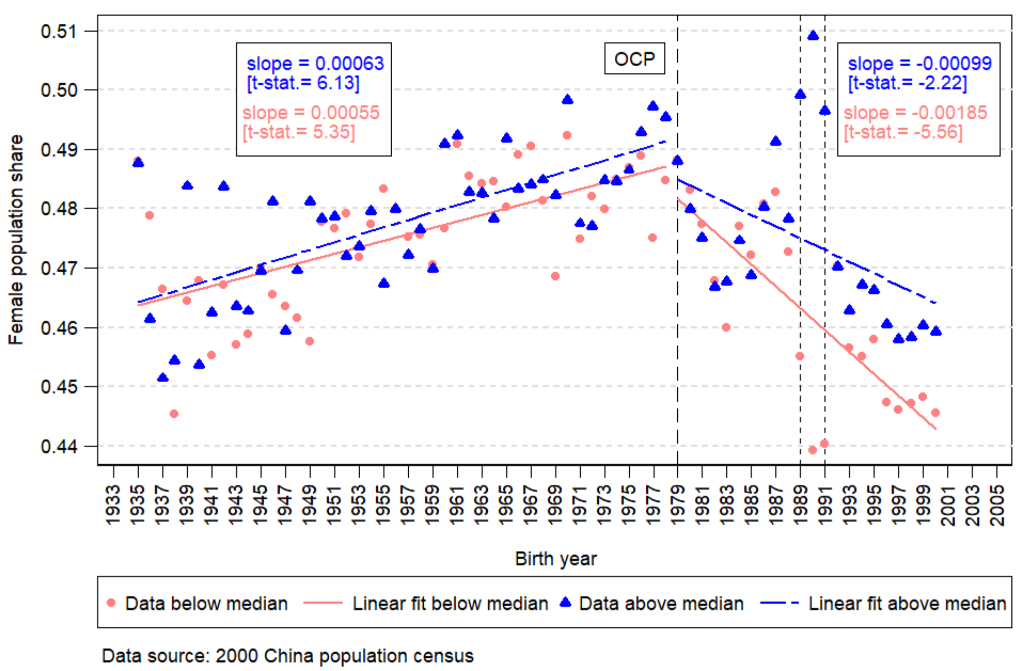

Table 1: Summary statistics.

	mean	std	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Main variables							
Female population share, age 12-21	0.50	0.04	0.46	0.48	0.50	0.52	0.54
Log total value	10.93	2.75	7.46	9.22	10.95	12.75	14.40
Trade flows by city							
Number of export destinations	143.49	43.14	75	120	156	177	191
Number of industries	60.51	12.36	43	57	64	69	72
Log total value	21.77	1.78	19.43	20.66	22.12	23.23	23.71
Trade flows by export destinations							
Number of cities	157.30	56.81	78	116	163	207	220
Number of industries	65.86	7.71	59	63	66	72	73
Log total value	21.26	2.00	18.78	20.07	21.41	22.73	23.71
Trade flows by industries							
Number of cities	162.73	47.59	92	131	171	196	209
Number of export destinations	167.29	23.83	138	158	172	186	189
Log total value	22.34	1.11	21.04	21.57	22.28	22.93	23.67
Instrumental variables							
Locally-born female share	0.52	0.08	0.43	0.46	0.51	0.58	0.62
The OCP violation punishment fine	1.76	0.47	1.15	1.49	1.87	1.99	2.17
Ethic minority share	0.02	0.08	0.00	0.00	0.01	0.01	0.05
Number of OCP amendments	5.06	3.91	2	2	4	7	8
Rate of OCP violations	0.19	0.12	0.05	0.10	0.16	0.27	0.37
Physical capital							
Log of industry intensities	-1.15	0.40	-1.59	-1.42	-1.13	-0.88	-0.60
Log of city endowments	-0.94	0.37	-1.35	-1.20	-0.95	-0.74	-0.47
Skilled labors							
Log of industry intensities	-2.20	0.52	-2.96	-2.55	-2.14	-1.85	-1.62
Log of city endowments	-2.21	0.45	-2.71	-2.57	-2.27	-1.92	-1.50

Table 2: Manufacturing industries with the highest and the lowest intensities in social skills and physical abilities.

10 industries with the highest intensity of gender-dependent skills			10 industries with the lowest intensity of gender-dependent skills		
Rank	NAICS4	Industry description	Rank	NAICS4	Industry description
		Social Skills			
1	3254	Pharmaceutical and Medicine Manufacturing	1	3162	Footwear Manufacturing
2	3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	2	3161	Leather and Hide Tanning and Finishing
3	3342	Communications Equipment Manufacturing	3	3169	Other Leather and Allied Product Manufacturing
4	3344	Semiconductor and Other Electronic Component Manufacturing	4	3151	Apparel Knitting Mills
5	3364	Aerospace Product and Parts Manufacturing	5	3117	Seafood Product Preparation and Packaging
6	3241	Petroleum and Coal Products Manufacturing	6	3116	Animal Slaughtering and Processing
7	3251	Basic Chemical Manufacturing	7	3132	Fabric Mills
8	3341	Computer and Peripheral Equipment Manufacturing	8	3274	Lime and Gypsum Product Manufacturing
9	3332	Industrial Machinery Manufacturing	9	3152	Cut and Sew Apparel Manufacturing
10	3231	Printing and Related Support Activities	10	3212	Veneer, Plywood, and Engineered Wood Product Manufacturing
		Physical Abilities			
1	3131	Fiber, Yarn, and Thread Mills	1	3341	Computer and Peripheral Equipment Manufacturing
2	3273	Cement and Concrete Product Manufacturing	2	3342	Communications Equipment Manufacturing
3	3371	Household and Institutional Furniture and Kitchen Cabinet Manufacturing	3	3346	Manufacturing and Reproducing Magnetic and Optical Media
4	3262	Rubber Product Manufacturing	4	3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
5	3212	Veneer, Plywood, and Engineered Wood Product Manufacturing	5	3344	Semiconductor and Other Electronic Component Manufacturing
6	3315	Foundries	6	3364	Aerospace Product and Parts Manufacturing
7	3219	Other Wood Product Manufacturing	7	3333	Commercial and Service Industry Machinery Manufacturing
8	3116	Animal Slaughtering and Processing	8	3391	Medical Equipment and Supplies Manufacturing
9	3328	Coating, Engraving, Heat Treating, and Allied Activities	9	3169	Other Leather and Allied Product Manufacturing
10	3221	Pulp, Paper, and Paperboard Mills	10	3332	Industrial Machinery Manufacturing

Table 3: Selected occupations with the highest and the lowest importance in social skills and physical abilities.

10 occupations with the highest intensity of gender-dependent skills			10 occupations with the lowest intensity of gender-dependent skills		
Rank	SOC	Occupation position description	Rank	SOC	Occupation position description
Social Skills					
1	112	Advertising, Marketing, Promotions, Public Relations, and Sales Managers	1	537	Material Moving Workers
2	111	Top Executives	2	517	Woodworkers
3	411	Supervisors of Sales Workers	3	514	Metal Workers and Plastic Workers
4	113	Operations Specialties Managers	4	516	Textile, Apparel, and Furnishings Workers
5	491	Supervisors of Installation, Maintenance, and Repair Workers	5	513	Food Processing Workers
6	414	Sales Representatives, Wholesale and Manufacturing	6	512	Assemblers and Fabricators
7	413	Sales Representatives, Services	7	372	Building Cleaning and Pest Control Workers
8	131	Business Operations Specialists	8	352	Cooks and Food Preparation Workers
9	511	Supervisors of Production Workers	9	533	Motor Vehicle Operators
10	191	Life Scientists	10	493	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers
Physical Abilities					
1	372	Building Cleaning and Pest Control Workers	1	112	Advertising, Marketing, Promotions, Public Relations, and Sales Managers
2	493	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers	2	413	Sales Representatives, Services
3	517	Woodworkers	3	172	Engineers
4	537	Material Moving Workers	4	113	Operations Specialties Managers
5	514	Metal Workers and Plastic Workers	5	131	Business Operations Specialists
6	492	Electrical and Electronic Equipment Mechanics, Installers, and Repairers	6	192	Physical Scientists
7	352	Cooks and Food Preparation Workers	7	414	Sales Representatives, Wholesale and Manufacturing
8	516	Textile, Apparel, and Furnishings Workers	8	111	Top Executives
9	513	Food Processing Workers	9	191	Life Scientists
10	533	Motor Vehicle Operators	10	411	Supervisors of Sales Workers

Notes: This table includes occupations with at least 0.5% share of employment in the manufacturing sector.

Table 4: Correlation between female population share and instrumental variables.

	Log GDP per capita	*Female population share*	*The OCP violation fine*	*Number of OCP amendments*
Log GDP per capita	1	-	-	-
Female population share	0.180**	1	-	-
The OCP violation fine	0.132*	0.198***	1	-
Number of OCP amendments	0.125*	0.390***	0.472***	1

Notes: * significant at 10%, ** significant at 5% and *** significant at 1%.

Table 5: Baseline OLS results.

	(1)	(2)	(3)	(4)
$Social\ Skill\ Intensity_i$		0.036***		0.020***
$\times[12-21]\ Female\ Share_c$		(0.010)		(0.007)
$Physical\ Ability\ Intensity_i$			-0.047***	-0.040***
$\times[12-21]\ Female\ Share_c$			(0.009)	(0.008)
$Capital\ Intensity_i$	0.066***	0.067***	0.049***	0.052***
$\times Capital_c$	(0.012)	(0.012)	(0.011)	(0.012)
$Skilled\ Labor\ Intensity_i$	0.055***	0.063***	0.059***	0.063***
$\times Skilled\ Labor_c$	(0.006)	(0.007)	(0.006)	(0.007)
R^2	0.435	0.436	0.437	0.437
Observations	246,038	246,038	246,038	246,038

Notes: The dependent variable is the natural logarithm of exports from Chinese city c to destination country d in industry i in year 2006. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by city-industry. All specifications include city-destination and industry-destination fixed effects. * significant at 10%, ** significant at 5% and *** significant at 1%.

Table 6: Results with instrumental variables.

	(1) OLS	(2) IV	(3) IV	(4) IV
Social Skill Intensity$_i$	0.020***	0.080**	0.046**	0.044**
$\times$ [12 − 21] *Female Share*$_c$	(0.007)	(0.034)	(0.020)	(0.020)
Physical Ability Intensity$_i$	-0.040***	-0.175***	-0.141***	-0.141***
$\times$ [12 − 21] *Female Share*$_c$	(0.008)	(0.047)	(0.034)	(0.034)
Capital Intensity$_i$	0.052***	0.004	0.015	0.015
$\times$*Capital*$_c$	(0.012)	(0.024)	(0.019)	(0.019)
Skilled Labor Intensity$_i$	0.063***	0.087***	0.076***	0.076***
$\times$*Skilled Labor*$_c$	(0.007)	(0.011)	(0.009)	(0.009)
Instruments for Female Share	-	The OCP Violation Fine Rate (VFR)	Number of OCP Amendments (NMA)	VFR & NMA
First Stage F-stat for Social Skills	-	20.4	19.7	10.1
First Stage F-stat for Physical Skills	-	15.9	10.5	6.2
Hansen J Test P-Value	-	-	-	0.187
R^2	0.437	-	-	-
Observations	246,038	246,038	242,551	242,551

Notes: The dependent variable is the natural logarithm of exports from Chinese city c to destination country d in industry i in year 2006. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by city-industry. All specifications include city-destination and industry-destination fixed effects. * significant at 10%, ** significant at 5% and *** significant at 1%.

Table 7: Extensions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Social Skill Intensity$_i$	0.055			0.073***	0.133	0.043**	0.058	0.177**	0.071***
$\times [12-21]$ *Female Share*$_c$	(0.037)			(0.028)	(0.089)	(0.020)	(0.067)	(0.088)	(0.022)
Physical Ability Intensity$_i$	-0.180*			-0.110***	-0.129***	-0.069	-0.135***	-0.015	-0.050***
$\times [12-21]$ *Female Share*$_c$	(0.101)			(0.034)	(0.036)	(0.075)	(0.047)	(0.077)	(0.018)
Social Skill Intensity$_i$		0.056*							
$\times [16-21]$ *Female Share*$_c$		(0.031)							
Physical Ability Intensity$_i$		-0.220***							
$\times [16-21]$ *Female Share*$_c$		(0.062)							
CN Industry Female Intensity$_i$			0.068***	0.062**					
$\times [12-21]$ *Female Share*$_c$			(0.022)	(0.028)					
Cognitive Skill Intensity$_i$					-0.091			-0.151	
$\times [12-21]$ *Female Share*$_c$					(0.090)			(0.105)	
Manual Skill Intensity$_i$						-0.073		-0.114	
$\times [12-21]$ *Female Share*$_c$						(0.085)		(0.089)	
Routine Skill Intensity$_i$							-0.014	0.013	
$\times [12-21]$ *Female Share*$_c$							(0.064)	(0.075)	
Capital Intensity$_i$	0.024	-0.020	0.055***	0.016	0.013	0.016	0.015	0.013	0.016
$\times$*Capital*$_c$	(0.015)	(0.031)	(0.013)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.016)
Skilled Labor Intensity$_i$	0.092***	0.091***	0.045***	0.070***	0.075***	0.077***	0.076***	0.075***	0.051***
$\times$*Skilled Labor*$_c$	(0.014)	(0.013)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)
Social Skill Intensity$_i$									0.015
$\times$*GDP Per Capita*$_c$									(0.011)
Physical Ability Intensity$_i$									-0.009
$\times$*GDP Per Capita*$_c$									(0.013)
Destination Countries	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-stat for Social Skills	1.2	7.4	-	8.9	7.5	6.8	7.6	5.1	71.9
First Stage F-stat for Physical Skills	1.8	5.3	-	4.7	5.4	7.6	7.2	5.5	69.3
First Stage F-stat for US Female Employee	-	-	26.3	9.5	-	-	-	-	-
First Stage F-stat for Cognitive Skills	-	-	-	-	7.4	-	-	5.3	-
First Stage F-stat for Manual Skills	-	-	-	-	-	4.6	-	4.2	-
First Stage F-stat for Routine Skills	-	-	-	-	-	-	6.6	5.8	-
Hansen J Test P-Value	0.484	0.433	0.239	0.042	0.262	0.219	0.213	0.192	0.004
Observations	9,429	242,551	242,551	242,551	242,551	242,551	242,551	242,551	220,319

Notes: The dependent variable in columns (2) – (8) is the natural logarithm of exports from Chinese city c to destination country d in industry i in year 2006. In column (1) exports is aggregated across destinations to city-industry level. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by city-industry. Column (1) includes city and industry fixed effects. Columns (2)-(8) include city-destination and industry-destination fixed effects. * significant at 10%, ** significant at 5% and *** significant at 1%. In all specifications, city-level female share is instrumented with the OCP violation fine and the number of city-level OCP amendments. In column (9), industry-level physical assets or skilled labor multiplying city-level female share, and industry-level social or physical skills intensity multiplying city-level physical assets or skilled labor endowments are controlled.

Table 8: Results with additional instrumental variables.

	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV
Social Skill Intensity$_i$	0.020***	0.038**	0.070	0.116***	0.054***
$\times [12-21]$ *Female Share*$_c$	(0.007)	(0.019)	(0.077)	(0.031)	(0.017)
Physical Ability Intensity$_i$	-0.040***	-0.055***	-0.160***	-0.091**	-0.107***
$\times [12-21]$ *Female Share*$_c$	(0.008)	(0.021)	(0.055)	(0.036)	(0.020)
Capital Intensity$_i$	0.052***	0.047***	0.009	0.035*	0.028*
$\times$*Capital*$_c$	(0.012)	(0.014)	(0.025)	(0.019)	(0.015)
Skilled Labor Intensity$_i$	0.063***	0.068***	0.084***	0.087***	0.075***
$\times$*Skilled Labor*$_c$	(0.007)	(0.007)	(0.015)	(0.009)	(0.008)
Instruments for Female Share	-	Locally-born Female Share (LFS)	Ethnic Minority Share (EMS)	Share of Household Violating OCP (SHV)	LFS, NMA VFR, EMS VFR× EMS, SHV
First Stage F-stat for Social Skills	-	28.1	18.3	46.0	21.7
First Stage F-stat for Physical Skills	-	19.9	34.5	32.3	18.8
Hansen J Test P-Value	-	-	-	-	0.000
R^2	0.437	-	-	-	-
Observations	246,038	245,926	246,030	246,038	242,439

Notes: The dependent variable is the natural logarithm of exports from Chinese city c to destination country d in industry i in year 2006. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by city-industry. All specifications include city-destination and industry-destination fixed effects. * significant at 10%, ** significant at 5% and *** significant at 1%.

Table 9: Estimates of the dynamic model.

	(1) OLS	(2) IV
Social Skill Intensity$_i$	0.012	0.070**
$\times\triangle$ *Female Share*$_c$	(0.011)	(0.033)
Physical Ability Intensity$_i$	-0.037***	-0.069**
$\times\triangle$ *Female Share*$_c$	(0.012)	(0.029)
Capital Intensity$_i$	-0.009	-0.009
$\times$*Capital*$_c$	(0.011)	(0.011)
Skilled Labor Intensity$_i$	0.023***	0.014**
$\times$*Skilled Labor*$_c$	(0.006)	(0.006)
Instruments for Skills Endowment	-	VLF & NMA
First Stage F-stat for Social Skill	-	42.1
First Stage F-stat for Physical Ability	-	41.8
Hansen J Test P-Value	-	0.211
R^2	0.296	-
Observations	106,658	105,501

Notes: The dependent variable is the time difference of the natural logarithm of exports from Chinese city c to destination country d in industry i between the year 2006 and 2000. The change in female share of a city is calculated between age cohort 18-21 and 12-21. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by city-industry. All specifications include city-destination and industry-destination fixed effects. * significant at 10%, ** significant at 5% and *** significant at 1%. The results in columns (2)-(4) are estimated using the OCP violation fine and the number of city-level OCP amendments as instrumental variables for $\triangle$ *Female Share*.

Table 10: Decomposition of the dynamic effect.

	(1)		(2)	
	IV		IV	
Time period of occupation share	1990 - 2006		1980 - 2006	
Time period of skills level	1998 - 2006		1998 - 2018	
	Social Skills	Physical Skills	Social Skills	Physical Skills
Change in industry occupational	0.014	-0.097	-0.117	-0.107
structure	(0.055)	(0.064)	(0.160)	(0.074)
Change in occupational skill	0.065	0.093	-0.361	0.278
importance	(0.049)	(0.100)	(0.519)	(0.425)
Change in city's female	0.136**	-0.178**	0.074	-0.099*
share	(0.056)	(0.086)	(0.054)	(0.060)
$Capital\ Intensity_i$	0.079		-0.031	
$\times Capital_c$	(0.068)		(0.060)	
$Skilled\ Labor\ Intensity_i$	0.000		0.019	
$\times Skilled\ Labor_c$	(0.022)		(0.015)	
First Stage F-stat for Skill Structure	7.1	8.1	8.3	10.2
First Stage F-stat for Skill Level	3.0	3.2	4.7	5.1
First Stage F-stat for Skill Stock	23.4	18.5	24.4	33.1
Hansen J Test P-Value	0.074		0.069	
Observations	47,320		47,320	

Notes: The dependent variable is the time difference of the natural logarithm of exports from Chinese city c to destination country d in industry i between the year 2006 and 2000. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by city-industry. All specifications include city-destination and industry-destination fixed effects. The time difference of occupation structure and O*NET skills importance measures are indicated in the header of each column. The time difference of the female population share is obtained from the difference between 18-21 and 12-21 age groups in 2000 census. * significant at 10%, ** significant at 5% and *** significant at 1%. All results are estimated using the OCP violation fine and the number of city-level OCP amendments as instrumental variables for $\triangle$ *Female Share*.

Table 11: Baseline IV results with country-level data.

	(1)	(2)	(3)	(4)
$Social\ Skill\ Intensity_i$	0.075**		0.088***	
$\times Female\ Labor\ Force\ Participation_{tc}$	(0.032)		(0.019)	
$Physical\ Skill\ Intensity_i$	-0.158***		-0.147***	
$\times Female\ Labor\ Force\ Participation_{tc}$	(0.036)		(0.021)	
$Female\ Employee\ Intensity_i$		0.057**		0.044***
$\times Female\ Labor\ Force\ Participation_{tc}$		(0.027)		(0.017)
$Capital\ Intensity_i$	0.034***	0.040***	0.034***	0.039***
$\times Capital_c$	(0.005)	(0.005)	(0.003)	(0.003)
$Skilled\ Labor\ Intensity_i$	0.037***	0.069***	0.040***	0.071***
$\times Skilled\ Labor_c$	(0.010)	(0.005)	(0.006)	(0.003)
First Stage F-stat				
Social Skill Intensity Interaction	25.5		80.1	
Physical Skill Intensity Interaction	30.8		97.6	
Female Labor Intensity Interaction		48.8		149.1
Sample Period	2000		1990, 1995, 2000, 2005	
Fixed Effects	exporter-importer, importer-industry		exporter-importer-year, importer-industry-year	
Observations	433,748	318,062	1,230,699	902,582

Notes: The dependent variable is the natural logarithm of exports from country c to destination country d in industry i in year t. In all specifications the female labor force participation rate of a country is instrumented with an index of the traditional use of plough in that country's agricultural sector. * significant at 10%, ** significant at 5% and *** significant at 1%. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by exporter-industry in column (1), (2) and by exporter-industry-year in column (3), (4).

9 Appendix A: Additional results

9.1 A1. Robustness tests

For the baseline results, we constructed the skill intensity measures using 6 social skills and 9 physical skills from the O*NET database. In the column (1) of the Table A2, the results are estimated using different measures of industry-level intensities by four social skills that contributed the most variation to the PCA (Coordination, Negotiation, Persuasion, and Social Perceptiveness) and two physical abilities (Dynamic Strength and Explosive Strength). The estimation results are consistent with the baseline IV results not only in terms of the magnitude and statistical significance of the key coefficients, but also in terms of the strength of the first stage results.

Next, we demonstrate the robustness of our results are not driven by a small number of cities/industries with extreme values of skill intensities or demographic composition. First, we present estimation results from the regressions that exclude seven industries with the highest and seven industries with the lowest intensities in social skills (column 2), thus reducing the sample of industries from 40 to 26. In column (3), we perform the same sensitivity analysis for physical skills, and in column (4) we exclude the top and bottom seven industries in terms of both social and physical skills. The results reveal that the magnitudes of the coefficients of interest are consistent with the benchmark results, although statistical significance declines to 10% for both skill variables.

Lastly, we check the sensitivity of the results to excluding cities with extreme gender ratios. In column (5) we exclude 10 cities with the highest and 10 cities with the lowest female population share from the sample. The magnitudes of both coefficients change notably, with the estimate on social skills nearly doubled relative to benchmark, and the estimate on physical skills declining by a third. Furthermore, both coefficients are estimated with much lower precision, and the one on physical skills is becoming insignificant.

9.2 A2. Decomposition of the dynamic effect

In this section, we decompose over-time changes in the main explanatory variables into three parts: the change in female population share of a city, the change in occupational importance of social and physical skills, and the change in occupational composition of an industry. Allowing for two time periods, labelled as t and 0, the time difference of the interaction of the industry's skill intensity and the city's female share can be written as:

$$\sum_j \left(OS_{ij}^t \times SI_j^t\right) \times FS_c^t - \sum_j \left(OS_{ij}^0 \times SI_j^0\right) \times FS_c^0 \tag{14}$$

where OS_{ij} is the share of occupation j in industry i, SI_j is the measure of importance of a gender-specific skill for occupation j, and FS_c is the female population share of city c. To start, we expand (14) to get:

$$\frac{1}{2}\left(\sum_j \left(OS^t_{ij}SI^t_J\right)FS^0_c - \sum_j \left(OS^t_{ij}SI^t_j\right)FS^0_c + \sum_j \left(OS^0_{ij}SI^0_j\right)FS^t_c - \sum_j \left(OS^0_{ij}SI^0_j\right)FS^t_c\right) + \sum_j \left(OS^t_{ij}SI^t_j\right)FS^t_c - \sum_j \left(OS^0_{ij}SI^0_j\right)FS^0_c$$

After simplification, we can write the above expression as follows:

$$\frac{FS^t_c + FS^0_c}{2}\left(\sum_j \left(OS^t_{ij}SI^t_j\right) - \sum_j \left(OS^0_{ij}SI^0_j\right)\right) + \frac{\sum_j \left(OS^t_{ij}SI^t_j\right) + \sum_j \left(OS^0_{ij}SI^0_j\right)}{2}\left(FS^t_c - FS^0_c\right) \quad (15)$$

In equation (15) the first term shows the portion of the change in the explanatory variable due to the change in OS and LS, and the second term shows the effect of the change in female share of a city. Decomposing the first term further into changes in OS and LS, we arrive at the following expression:

$$\frac{FS^t_c + FS^0_c}{2}\sum_j OS^t_{ij}\left(SI^t_j - SI^0_j\right) + \frac{FS^t_c + FS^0_c}{2}\sum_j LS^0_{ij}\left(SI^t_j - SI^0_j\right) + \frac{\sum_j \left(OS^t_{ij}SI^t_j\right) + \sum_j \left(OS^0_{ij}SI^0_j\right)}{2}\left(FS^t_c - FS^0_c\right) \quad (16)$$

Equation (16) separates the full dynamic effect into three effects which come from changes in the importance of skills (the first term), changes in occupation composition of industries (the second term), and changes in gender composition of cities (the third term).

The empirical model corresponding to decomposition equation (16) is

$$\begin{aligned} \triangle\, lnX_{cpi} = \sum_{k\in K}\beta^1_k \frac{FS^t_c + FS^0_c}{2}\sum_j OS^t_{ij}\left(SI^t_j - SI^0_j\right) + \\ + \beta^2_k \frac{FS^t_c + FS^0_c}{2}\sum_j LS^0_{ij}\left(SI^t_j - SI^0_j\right) + \\ + \beta^3_k \frac{\sum_j \left(OS^t_{ij}SI^t_j\right) + \sum_j \left(OS^0_{ij}SI^0_j\right)}{2}\left(FS^t_c - FS^0_c\right) + \\ + \sum_{f\in F}\left(\phi_f I^f_i \times FC^f_c\right) + \nu_{cp} + \nu_{pi} + \varepsilon_{cpi} \end{aligned} \quad (17)$$

Table 12: Robustness tests.

	(1)	(2)	(3)	(4)
$Social\ Skill\ Intensity_i$	0.064***	0.065*	0.047	0.140*
$\times [12-21]\ \ Female\ Share_c$	(0.022)	(0.036)	(0.053)	(0.074)
$Physical\ Ability\ Intensity_i$	-0.133***	-0.107***	-0.250***	-0.173*
$\times [12-21]\ \ Female\ Share_c$	(0.031)	(0.035)	(0.091)	(0.102)
$Capital\ Intensity_i$	0.030*	0.021	0.021	0.058**
$\times Capital_c$	(0.017)	(0.018)	(0.018)	(0.025)
$Skilled\ Labor\ Intensity_i$	0.075***	0.069***	0.034***	0.047***
$\times Skilled\ Labor_c$	(0.009)	(0.010)	(0.011)	(0.017)
Sample	benchmark	64/74 NAICS4 (social skills)	64/74 NAICS4 (physical skills)	57/74 NAICS4 (5 soc-5 phy)
6 or 4 social skills for PCA	4	6	6	6
9 or 2 physical abilities for PCA	2	9	9	9
First Stage F-stat for Social Skills	9.8	10.9	8.4	9.3
First Stage F-stat for Physical Skills	7.8	4.6	10.8	9.1
Hansen J Test P-Value	0.178	0.016	0.353	0.081
Observations	242,551	213,952	213,952	195,619

Notes: The dependent variable is the natural logarithm of exports from Chinese city c to destination country d in industry i in year 2006. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by city-industry. All specifications include city-destination and industry-destination fixed effects. * significant at 10%, ** significant at 5% and *** significant at 1%. In columns (2) and (3), industries with 5 highest and lowest intensities in social and physical skills, respectively, are excludes from the sample. In column (4), 17 industries with 5 highest and lowest intensities in social and physical skill are excluded from the sample. All results are estimated by using the OCP violation fine and the number of city-level amendments as instrumental variables.

Table 13: Baseline OLS results with possible more interaction controls.

	(1)	(2)	(3)	(4)
$Social\ Skill\ Intensity_i$	0.020***	0.050***		0.038***
$\times [12-21]\ Female\ Share_c$	(0.007)	(0.014)		(0.012)
$Physical\ Ability\ Intensity_i$	-0.040***		-0.037***	-0.030***
$\times [12-21]\ Female\ Share_c$	(0.008)		(0.010)	(0.010)
$Capital\ Intensity_i$	0.052***	0.054***	0.033***	0.040***
$\times Capital_c$	(0.012)	(0.013)	(0.013)	(0.014)
$Skilled\ Labor\ Intensity_i$	0.063***	0.053***	0.060***	0.053***
$\times Skilled\ Labor_c$	(0.007)	(0.010)	(0.007)	(0.010)
$Capital\ Intensity_i$		-0.025*	-0.005	-0.007
$\times [12-21]\ Female\ Share_c$		(0.013)	(0.013)	(0.013)
$Skilled\ Labor\ Intensity_i$		-0.029**	0.002	-0.028***
$\times [12-21]\ Female\ Share_c$		(0.012)	(0.008)	(0.011)
$Social\ Skill\ Intensity_i$		-0.032***		-0.019*
$\times Capital_c$		(0.009)		(0.011)
$Social\ Skill\ Intensity_i$		0.018		0.014
$\times Skilled\ Labor_c$		(0.012)		(0.012)
$Physical\ Ability\ Intensity_i$			0.040***	0.030**
$\times Capital_c$			(0.011)	(0.013)
$Physical\ Ability\ Intensity_i$			-0.016*	-0.013
$\times Skilled\ Labor_c$			(0.009)	(0.009)
R^2	0.437	0.437	0.438	0.438
Observations	246,038	246,038	246,038	246,038

Notes: The dependent variable is the natural logarithm of exports from Chinese city c to destination country d in industry i in year 2006. Standardized beta coefficients are reported. Robust standard errors in parentheses are clustered by city-industry. All specifications include city-destination and industry-destination fixed effects. * significant at 10%, ** significant at 5% and *** significant at 1%.

Chapter 3

US – China Trade War

1 Introduction

Since China adopted a market economy and became a member of the World Trade Organization (WTO), its role in the global trade system has been steadily growing. In 2013 China surpassed the US in terms of both foreign trade and trade surplus. In the base year 2016, the value of trade between the US and China was 598 billion US dollars, comprised of 482 billion Chinese exports to the US and 116 billion US exports to China. To reduce the trade deficit with China and stimulate the outsourced manufacturing industries to restore to North America, President Donald Trump decides to increase the import tariff on selected Chinese merchandise goods up to 25% in three rounds. The affected trade flows were 50, 200, and 300 billion US dollars each round, respectively. The Chinese government retaliated by increasing its tariff on US imports to the same level of 25% and the same coverage in terms of value in the first two rounds of the US – China trade war.

The decision to increase import tariffs is a double-edged sword that affects the welfare of the exporting country and the importing country. Questions such as how to estimate the effect of the trade war welfare of involved countries and the exact amount of welfare change are crucial. In the paper, we follow a general equilibrium model by Caliendo and Parro (2015), which considers the role of intermediate goods in the international supply chains and the non-tradable sector to estimate the effect of the US – China trade war on welfare. We find that both countries suffered serious welfare, but the reduction in Chinese welfare resulted from the trade war ten times larger than that in the US. We also find that despite disruption in the global supply chains, the leading trade partners of China and the US, including Canada, Mexico, South Korea, and Japan, gained from the trade war.

In the theoretical model, 30 major countries and the rest of the world trade in 20 industries, with 20 more industries being non-tradable. We analyze the response of each country's imports and exports to changes in the US – China import tariffs by the estimated trade elasticities for each tradable sector. To consider the role of intermediate and non-tradeable goods, we incorporate the input-output table into the production process. Also, to satisfy the theoretical model and bring in the variance of profitability and production scales among sectors and countries, the value-added and gross output tables are needed as simulating inputs. In our counterfactual analysis, we assume the global trade conditions remain the same as in 2016 and calculate the response of the global trade system to the increase in tariffs between the US and China.

Because the trade policy effects usually are not linear to the increasing import tariffs and demanding to be explicitly derived from the equation system, the advantage of the simulation model is that, by modeling the international trade among multi sectors and countries, we can analyze the effect of changing trade policy when the complicated global trade system reaches a new equilibrium. In the model, the effect of US – China trade operates not only through consumption goods but also through the increasing cost of imported intermediate goods. By introducing the IO table, the model allows us to analyze the effect of the trade war on country welfare through the international supply chains. If the entire industry supply chain is not located in the same country, the existing international supply chain may amplify the increased import tariff effects. On the other hand, in the model, we also consider non-tradable goods in the global trade system. As an essential input of production, non-tradable goods also accumulate the effect of trade war through the material imported. Therefore, we can obtain more accurate estimation results by considering the international supply chain through intermediate goods and the channel of non-tradable goods.

After entering the estimated bilateral import elasticities with input-output table, bilateral tariff and trade amount among 30 countries and rest of world, and value-added amount in the internal trade flows, we calculate the amount of affected country welfare and real wage for the US, China, and main developed and developing countries. From the simulated results, we find that the magnitude of the reduction in Chinese welfare due to the trade war is ten times larger than that in the US, and a relative reduction in the real wage is very similar. On the other hand, developed countries and leading trade partners of China, South Korea, and Japan can easily substitute the US and export to China. Therefore, after three rounds of import tariffs increase between the US and China, South Korea and Japan benefit from the US – China trade war in 0.0039 and 0.002 percentage respectively. Moreover, similar results are derived for the leading US trade partners, such as Mexico and Canada.

As an extension of the model, we random draw 50 sample sets in the total trade records between China and the US with a similar number of trade items and total trade amount with five percentage tolerance and then estimate the affected country welfare. The estimation results show that without changing the affected total trade amount and the percentage of increasing import tariffs, the US government could make China suffer more than what occurred in the real world, but the US has to pay more for it. These results show that the US government does not follow that the US will pressure China immensely during the trade war. On the other hand, some industries have the power to persuade the US government to avoid applying import tariffs on their related sectors.

The paper is closely related to the growing literature on the trade war between the United States and China. From Bown (2021), the US – China trade war started on February 2018 when the US rises import tariff on solar panels and washing machines by 30 percent and 20 percent respectively. Before the tariffs change, there are lots of clues and activities make the economic relationship between the US and China strained (Bown, 2019). Before and in the initial stage of trade war, some economists predict the possible trade war results to alert relevant governments and try to reduce the possibility of serious trade conflicts. Handley and Limão (2017) documents that the trade policy uncertainty would affect aspects of US society including trade volumes market prices, real incomes, and firm investment which suffer one-third of autarky economy and make the economy worse than autarky. Ossa (2014) uses equilibrium model which is introduced in Dekle et al. (2007) to analyze country welfare when countries turn to autarky economies and the main economies such as the US, China, the European Union and Japan will loss -13.5, -12.9, -12.3 and -13 percent of current country welfare respectively. Other articles claim the trade war effects in other dimensions, for examples, Steinbock (2018) documents risks on US – China relations, existing international order, and the American democracy; Liu and Woo (2018) claim that weaken China's technology development for the US national security also weak the US itself in the long run; and Taheripour and Tyner (2018) show that the possible 25% Chinese retaliatory tariff is a lose – lose proposition for both China and the US.

In the literature of US – China trade war, some papers focus on analyzing the effects on US economy. Applying different theoretical model and various data set, Cavallo et al. (2021); Fajgelbaum et al. (2020); Amiti et al. (2019); Besedes et al. (2020) all conclude that during the trade war, Chinese exporters do not reduce their US dollar price and imply that tariffs are completely pass-through into the US domestic market prices. In addition, Cavallo et al. (2021) claim that import tariff pass-through is much higher than exchange rate pass-through and the US exports significantly reduce their price affected by foreign retaliatory tariffs. Fajgelbaum et al. (2020) further estimate that the total losses of US consumer and firms in buying imports is \$51 billion or 0.27% of GDP and the net real income loss after accounting tariff revenue and gains of domestic producer is \$7.2 billion or 0.04% of GDP. Amiti et al. (2019) show that the entire incident tariffs fall on US consumers and importers in 2018 and no impacts on foreign exporters. Besedes et al. (2020) explain that the entire tariff pass-through is in the short run, and an adjustment will happen in the long run. While tariffs are not pass-through in all sectors, Amiti et al. (2020) claim that foreign exporters pay US tariff in steel sector. Balistreri et al. (2020) and Kim and Margalit (2021) both conclude that the trade war effects are not evenly distributed across the US, for example farmers and ranchers receive bulks of benefits, but tax revenues falls on all citizens, and Republican-support counties suffer more from Chinese retaliatory tariffs. Grant et al. (2021), Carter and Steinbach (2020), and Gopinath (2021) focus on the hurts on US agriculture sector. Benguria and Saffie (2020) and Flaaen and Pierce (2019) document the effects on US local labor market and the employment in manufacture sectors.

While some authors focus on the trade war effects on Chinese economy. Comparing the results of US − Japan trade friction in the history, Chong and Li (2019) and Urata (2020) both conclude that the trade war cannot be easily resolved. Furthermore, Chong and Li (2019) applies a scenario analysis and concludes that China will suffer a 1.1 percent decrease in employment and 1 percent GDP loss. Urata (2020) predicts that Chinese firms may stop forced technology transfer after trade war. Nti et al. (2019) focus on the Chinese pork market and argue that because of the outbreak of Africa Swine Fever and the retaliatory import tariffs, Chinese port production and pork import from the US are both significantly reduced. Feenstra and Hong (2020) analyze the Phase One trade agreement between the US and China and show that the increased agriculture imports from the US is away from other countries such as Australia, Canada, Brazil, Indonesia, Malaysia, Thailand and Vietnam. Shen et al. (2020) document that the trade destruction effects are mainly concentrated on high tech-intensive manufactures. Liu and Woo (2018) analyze China's exchange rate and trade imbalance and conclude that the meaning of "equilibrium exchange rate" is weak and China need find other ways to strength its technology capability.

In the literature a large amount of papers document the trade war effects on different sectors. Flaaen and Pierce (2019) argue that because the import protection is offset by the rising price of inputs, US manufacturing industries experience reduction in employment and outputs. Authors focus on different sectors, for example, Waugh (2019) on auto market, Flaaen and Pierce (2019) on washing machine production, and Amiti et al. (2020) on steel sector. In financial market, Huang et al. (2018) analyze the effect on stock market, Bouri et al. (2021) study the volatility of bitcoin trading, and Reyes-Heroles et al. (2020) focus on investment goods. Because there is a large amount US exports to China in agriculture sector, Feenstra and Hong (2020); Grant et al. (2021); Regmi (2019); Westhoff et al. (2019); Carter and Steinbach (2020) all focus on agriculture sector and claim that China's retaliatory import tariffs significantly hurt the exports amount and commodity price, increase the stock level and reduce the future farm input. Lots of articles analyze specific agriculture sectors as well, for example Hitchner et al. (2019) and Adjemian et al. (2019) on soybeans, Nti et al. (2019) and Grant et al. (2018) on pork, Sumner et al. (2019) on tree nut, Muhammad et al. (2019) on cotton, and Muhammad and Jones (2021) on US lumber and log exports. For market facilitation program compensation delivery, Balistreri et al. (2020) argue the benefit distribution is not equivalent across the United States and Janzen and Hendricks (2020) claim that the amount of compensation cannot bear long-run losses in Chinese agriculture market. At last, Handley and Limão (2017); Furceri et al. (2020); Gopinath (2021); Bouri et al. (2021); Nong (2021) document the policy uncertainty along with trade war significantly reduce the global economic forecast and weak the connections among countries.

The US – China trade is always applied as a tool of natural experience to analyze causal relation in the international trade. Lechthaler and Mileva (2021) use a dynamic trade model to show that the sector where the workers are employed along with their class determine their benefits from protectionism tariffs. Specifically, unskilled workers in the unskilled-intensive sector benefit the most in the trade war. Ossa (2014) and Grant et al. (2018) both analyze the importance of price elasticity in the international trade. Authors conclude that lower elasticities give countries more monopoly power in the world market and corp and meat are more price elastic than previous estimation during the US – China trade war. Finkelstein and Hendren (2020) use the measure of marginal value of public funds to analyze how government decides to increase import tariffs during the US – China trade war. Besedes et al. (2020) and Cavallo et al. (2021) are both obtain the estimation result that almost all tariffs pass-through to the US domestic market and conclude that it against the term-of-trade theory in some goods where the US holds market power and the US retail companies and customers are hurt most in the trade war. Furceri et al. (2020) argue that the global growth has slowed in the trade war; Mikic et al. (2020) and Bown et al. (2020) claim that COVID-19 lock-down policy and trade war affect healthcare-industry upstream supply and domestic value-added growth in foreign production affected by tariff trade war. Balistreri et al. (2020) and Kim and Margalit (2021) both document the trade war costs are unevenly distributed across states of the US and hurt more on political support for the president's party. Qiu et al. (2019) predict what will happen in the trade from trade literature and Nong (2021) show the connection between the US and China is non-negligible, asymmetric and non-linear.

A large trend of trade war literature, use different equilibrium models to simulate the outcomes after setting import tariffs on the new level. In sum, during the trade war, the US and China welfare are both suffered due to the adjustment in international trade pattern. Some small economies may benefit from the trade war, but the whole world economy decreases. Carvalho et al. (2019) use Global Trade Analysis Project model to show that while the imbalance trade between the US and China reduces, all sectors in both countries are hurt. Li et al. (2018) claim that the only way that the US have benefits is no retaliation from China. Zheng et al. (2018) apply Global Simulation Model to estimate the loss of main US agriculture exporters to China. Li and Whalley (2021) document the US manufacturing employment loss by demand reducing. Guo et al. (2018) claim that the Chinese economy may gain if the trade surplus exists. Bellora and Fontagné (2020) apply model MIRAGE-e version to show US has sizable gain in iron and steel, electronics, machinery or metal products. Itakura (2020) estimates -1.41% and -1.35% GDP loss in the US and China respectively. Wu et al. (2021) simulate the results of US – China decoupling and conclude that China suffer more than the US if the US – China bilateral trade is replaced by the surrounding economies. Dinopoulos et al. (2020) claim that trade war results a larger income inequality. Chang (2020) documents a lose – lose game and China receives a greater impact in high probability. Firooz and Heins (2020) obtain a small US welfare losses on 0.1% or 0.04 % level and a slightly gain for Chinese economy. Archana (2020) argues that the losses in the US are higher than those in China and both of them gains from trade liberalization.

In the current literature of US – China trade war, Caliendo and Parro (2015) and Guo et al. (2018) are the most similar to the paper. The paper share the main frame of the theoretical model applied in Caliendo and Parro (2015) but analyze different events. Specifically, Caliendo and Parro (2015) focus on the country welfare effects when NAFTA is signed, but this paper study the impacts of US – China trade war. Guo et al. (2018) also analyze the trade war between the US and China, but they focus on the effect of the existing US – China bilateral trade imbalance. While the paper use the model to analyze the decision rule of US government in the trade war.

The paper is organized as follows. The next section briefly introduces the main methodology used in the paper. Section 3 discusses the data. Section 4 shows the main results, and Section 5 concludes.

2 Methodology

The paper follows the model introduced in Caliendo and Parro (2015) to estimate the country welfare effects of the US – China trade war from July 2018 to February 2020. In the first step, we estimate import tariff elasticity of trade-in NAICS 2-digit by using import expenditure and import tariff information. Next, we input trade expenditures, import tariff in the base year 2016, gross output, share of value-added, input and output coefficients, and estimated trade elasticity for 31 countries and 40 tradable and non-tradable sectors to obtain trade war effect on country welfare and real wages.

2.1 Theoretical model

The consumption side of the model is set by the following utility function:

$$u\left(C_n\right) = \prod_{j=1}^{J} \left(C_n^j\right)^{\alpha_n^j}$$

where C_n is the consumption final goods and $\sum_{j=1}^{J} \alpha_n^j = 1$. In each country n representative persons maximizing their utility by choosing final goods C_n. Following literature, the production function is as follows:

$$Q_n^j = \left[\int r_n^j \left(\omega^j\right)^{1-\frac{1}{\sigma^j}} d\omega^j\right]^{\frac{\sigma^j}{\sigma^j - 1}}$$

where $\sigma^j > 0$ is the substitution elasticity across intermediate goods ω^j in each industry j and $r_n^j\left(\omega^j\right)$ is the demand for intermediate good ω^j under the price $p_n^j\left(\omega^j\right)$. In addition, the price of the intermediate goods is determined by the supplier with the lowest costs, then we can show the price as follows

$$p_n^j\left(\omega^j\right) = \min_i \left\{\frac{c_i^j \kappa_{ni}^j}{z_i^j\left(\omega^j\right)}\right\}$$

where $\kappa_{ni}^j = \left(1+\tau_{ni}^j\right) d_{ni}^j$ interpreted as the trade costs including import tariff τ_{ni}^j and iceberg trade cost d_{ni}^j between importer n and exporter i for sector j. Note for non-tradable goods the trade costs $\kappa_{ni}^j = \infty$. Assuming the productivity $z_i^j\left(\omega^j\right)$ is a random variable which follows Frechet distribution and c_i^j denotes the cost of an input bundle from the production function of intermediate goods. Therefore we obtain following equations for composite intermediate good and the cost of input bundle by the properties of Frechet distribution.

$$P_n^j = A^j \left[\sum_{i=1}^{N} \lambda_i^j \left(c_i^j \kappa_{ni}^j\right)^{-\theta^j}\right]^{-\frac{1}{\theta^j}} \tag{18}$$

$$c_i^j = \Upsilon_i^j w_i^{\Upsilon_i^j} \prod_{k=1}^{J} \left(P_i^k\right)^{\Upsilon_i^{k,j}} \tag{19}$$

where $\Upsilon_i^j \equiv \prod_{k=1}^J \left(\Upsilon_i^{k,j}\right)^{-\Upsilon_n^{k,j}} \left(\Upsilon_i^j\right)^{-\Upsilon_i^j}$, constant number A^j and parameter λ_i^j for Frechet distribution, wage w_i and import tariff elasticity of trade value θ^j.

Therefore we can obtain equations for total expenditure X_n^j, and country n's share of expenditure on goods j from country i, $\pi_{ni}^j = \frac{X_{ni}^j}{X_n^j}$ as follows

$$X_n^j = \sum_{k=1}^{J} \Upsilon_n^{j,k} \sum_{i=1}^{N} X_i^k \frac{\pi_{in}^k}{1+\tau_{in}^k} + \alpha_n^j I_n \tag{20}$$

$$\pi_{ni}^j = \frac{\lambda_i^j \left[c_i^j \kappa_{ni}^j\right]^{-\theta^j}}{\sum_{h=1}^N \lambda_h^j \left[c_h^j \kappa_{nh}^j\right]^{-\theta^j}} \tag{21}$$

where country income $I_n = w_n L_n + R_n + D_n$ which is the sum of labor income, tariff revenues and trade deficit. Specifically, the labor income is $w_n L_n = \sum_{j=1}^J \Upsilon_n^j \sum_{i=1}^N X_i^j \frac{\pi_{in}^j}{1+\tau_{in}^j}$.

At last, we have an international market clear condition as the total expenditure of country n equals the total income from country n. The market clear equation is as follows

$$\sum_{j=1}^{J}\sum_{i=1}^{N} X_n^j \frac{\pi_{ni}^j}{1+\tau_{ni}^j} - D_n = \sum_{j=1}^{J}\sum_{i=1}^{N} X_i^j \frac{\pi_{in}^j}{1+\tau_{in}^j} \tag{22}$$

2.2 Empirical estimation of trade elasticity

In this section, we derive the empirical model for estimating the trade elasticity θ^j for each industry j. Suppose there are three countries n, i and h, all produce and trade in industry j. The exports chain of goods j is from country n to i, i to h and h to n. In addition, the other way around also exists as from country n to h, h to i and i to n. By the definition of $\pi_{ni}^j = \frac{X_{ni}^j}{X_n^j}$, we can obtain equation as follows:

$$\frac{X_{ni}^j X_{ih}^j X_{hn}^j}{X_{in}^j X_{hi}^j X_{nh}^j} = \frac{\frac{X_{ni}^j}{X_n^j}\frac{X_{ih}^j}{X_i^j}\frac{X_{hn}^j}{X_h^j}}{\frac{X_{in}^j}{X_i^j}\frac{X_{hi}^j}{X_h^j}\frac{X_{nh}^j}{X_n^j}} = \frac{\pi_{ni}^j \pi_{ih}^j \pi_{hn}^j}{\pi_{in}^j \pi_{hi}^j \pi_{nh}^j} \tag{23}$$

And then substitute equation (21) we can derive equation:

$$\frac{X_{ni}^{j}X_{ih}^{j}X_{hn}^{j}}{X_{in}^{j}X_{hi}^{j}X_{nh}^{j}}=\left(\frac{\kappa_{ni}^{j}\kappa_{ih}^{j}\kappa_{hn}^{j}}{\kappa_{in}^{j}\kappa_{hi}^{j}\kappa_{nh}^{j}}=\right)^{-\theta^{j}} \tag{24}$$

Taking natural logarithm both sides, $\kappa_{ni}^{j}=\left(1+\tau_{ni}^{j}\right)d_{ni}^{j}$ and the fact $d_{ni}^{j}=d_{in}^{j}$, we get the empirical model for estimating trade elasticity θ^{j} as follows:

$$\ln\left(\frac{X_{ni}^{j}X_{ih}^{j}X_{hn}^{j}}{X_{in}^{j}X_{hi}^{j}X_{nh}^{j}}\right)=-\theta^{j}\ln\left(\frac{\tilde{\tau}_{ni}^{j}\tilde{\tau}_{ih}^{j}\tilde{\tau}_{hn}^{j}}{\tilde{\tau}_{in}^{j}\tilde{\tau}_{hi}^{j}\tilde{\tau}_{nh}^{j}}\right)+\tilde{\varepsilon}^{j} \tag{25}$$

where n, i and j indicates different countries, X is the import expenditure and τ is the import tariff rate for industry j. From the empirical model, we can learn that if we have the information of bilateral trade flows and import tariffs for each country n, i and h and industry j, we can estimate trade elasticity θ^{j} for each industry j by OLS.

2.3 Estimation of trade war effect on country welfare and real wage

The derivation of simulation equations follows the extended multi sectors Eaton and Kortum (2002) model in Caliendo and Parro (2015). From the equations (18), (19), (20), (21) and (22), we can derive main theoretical equations as follows:

Cost of the input bundles:

$$\hat{c}_{n}^{j}=\hat{w}_{n}^{\gamma_{n}^{j}}\prod_{k=1}^{J}\hat{P}_{n}^{k\gamma_{n}^{k,j}} \tag{26}$$

Price index:

$$\hat{P}_{n}^{j}=\left[\sum_{i=1}^{N}\pi_{ni}^{j}\left[\hat{k}_{ni}^{j}\hat{c}_{i}^{j}\right]^{-\theta^{j}}\right]^{-\frac{1}{\theta^{j}}} \tag{27}$$

Bilateral trade shares:

$$\hat{\pi}_{ni}^{j}=\left[\frac{\hat{c}_{i}^{j}\hat{k}_{ni}^{j}}{\hat{P}_{n}^{j}}\right]^{-\theta^{j}} \tag{28}$$

Total expenditure in each country n and sector j:

$$X_{n}^{j'}=\sum_{k=1}^{J}\gamma_{n}^{j,k}\sum_{i=1}^{N}\frac{\pi_{in}^{k'}}{1+\tau_{in}^{k'}}X_{i}^{k'}+\alpha_{n}^{j}I_{n}^{'} \tag{29}$$

Trade balance:

$$\sum_{j=1}^{J}\sum_{i=1}^{n}\frac{\pi_{ni}^{j'}}{1+\tau_{ni}^{j'}}X_{n}^{j'}-D_{n}=\sum_{j=1}^{J}\sum_{i=1}^{N}\frac{\pi_{in}^{j'}}{1+\tau_{in}^{j'}}X_{i}^{j'} \tag{30}$$

where $\hat{k}_{ni}^{j}=\frac{1+\tau_{ni}^{j'}}{1+\tau_{ni}^{j}}$ and $I_{n}^{'}=\hat{w}_{n}w_{n}L_{n}+\sum_{j=1}^{J}\sum_{i=1}^{N}\tau_{ni}^{j'}\frac{\pi_{ni}^{j'}}{1+\tau_{ni}^{j'}}X_{n}^{j'}+D_{n}$

In the equations (w, P) is an equilibrium under tariff structure τ and let (w', P') is an equilibrium under tariff structure τ'. Define $\left(\hat{w}, \hat{P}\right)$ as an equilibrium under τ' relative to τ, where a variable with a hat "$\hat{x}$" represents the relative change of the variable, namely $\hat{x}=\frac{x'}{x}$. Using the above 5 equations with data of import tariff (τ), bilateral expenditure share $\left(\pi_{ni}^{j}\right)$, the share of value added in production $\left(\Upsilon_n^j\right)$, value added $(w_n L_n)$, the share of intermediate consumption $\Upsilon_n^{k,j}$ and the estimated demand elasticity $\left(\theta^j\right)$ for each industry j, we can simulate the parameters to calculate country welfare and real wage after modification of trade policy.

From above equations (26) and (28) we can derive real wages $\frac{\hat{w}_n}{\hat{P}_n^j}$ as follows

$$\ln \frac{\hat{w}_n}{\hat{P}_n^j} = -\sum_{j=1}^{J} \frac{\alpha_n^j}{\theta^j} \ln \hat{\pi}_{nn}^j - \sum_{j=1}^{J} \frac{\alpha_n^j}{\theta^j} \frac{1-\Upsilon_n^j}{\Upsilon_n^j} \ln \hat{\pi}_{nn}^j - \sum_{j=1}^{J} \frac{\alpha_n^j}{\Upsilon_n^j} \ln \prod_{k=1}^{J} \left(\frac{\hat{P}_n^k}{\hat{P}_n^j}\right)^{\Upsilon_n^{k,j}} \tag{31}$$

The country welfare is defined as $W_n = \frac{I_n}{P_n}$, where country income is $I_n = w_n L_n + R_n + D_n$ and country consumption price index is given by $P_n = \prod_{j=1}^{J} \left(\frac{P_n^j}{\alpha_n^j}\right)^{\alpha_n^j}$. Therefore, we can obtain the percentage change of country welfare as follows

$$d \ln W_n = \frac{1}{I_n} \sum_{j=1}^{J} \sum_{i=1}^{N} \left(E_{ni}^j \cdot d \ln c_n^j - M_{ni}^j \cdot d \ln c_i^j\right) + \frac{1}{I_n} \sum_{j=1}^{J} \sum_{i=1}^{N} \tau_{ni}^j \cdot M_{ni}^j \left(d \ln M_{ni}^j - d \ln c_i^j\right) \tag{32}$$

where E_{ni}^j and M_{ni}^j are exports and imports from country n to i for industry j. And the trade deficits D_n^j for sector j is the difference between E_{ni}^j and M_{ni}^j.

3 Data

For estimating trade elasticities in all 20 tradable industries using equation (25), the data set of trade value and import tariffs should be merged in country and industry (2-digit ISIC version 3) level in 2016. Refer to the empirical model equation (25), trade value and import tariffs must be available for all three countries (n, i and h) that constitute as a "trade-chain" which import and export goods in a loop for each industry. After data cleaning, 127,194 unique three-country tuples in 20 tradable industries are available for running the regression.

3.1 Countries and industries

Before estimating the trade war effect on country welfare and real wage, we use equations (26), (27), (28), (29) and (30) to simulate the trade war effects among 31 countries, in 20 tradable and 20 non-tradable industries (2-digit ISIC version 3). For analyzing the trade war effects on country welfares, we aim to cover the diversity of all countries, such as the traditional European developed countries, the large developing countries in population size, and countries with relatively large trade volume with the United States and/or China. The countries on our final list include Argentina, Australia, Austria, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Turkey, UK, US, and an aggregated rest of the world.

3.2 Trade value and tariff

In the paper the bilateral trade flow and import Most Favored Nation (MFN) and preferential tariff are all obtained from World Integrated Trade Solution (WITS) in 6-digit harmonized system (HS) code. For the import tariff data set, we use both MFN and preferential tariff data set and use preferential tariff instead of MFN tariff if the information of these two data is both available. The trade flow and import tariff data are used in both estimating trade elasticity and 620 by 31 input matrix which is constructed by 31 by 31 countries matrix in 20 tradable industries. Therefore we use country 3-digit ISO code to identify all 30 selected countries, then aggregated the rest of trade flow as a constructed represented country – rest of world for all 20 tradable industries. In the paper, we use the concordance tables from WITS to convert 6-digit HS to 4-digit ISIC in version 3 and then aggregated into 4-digit ISIC industry classification. All trade and tariffs data are for the base year 2016.

3.3 Value added, gross production and IO table

In order to simulate country welfare effects, we still need value-added, gross production and IO table as input matrices to construct parameters Υ_n^j, $w_n L_n$ and $\Upsilon_n^{k,j}$ in equations (26), (27), (28), (29) and (30). The dimension for gross output and value-added input matrices is 40 by 31 which indicates all 31 countries in 40 tradable and non-tradable industries. But for Input-Output (IO) table, the dimension is 1240 by 40. The first 40 by 40 sub-matrix is for the first country, and then following sub-matrices are in sequence until the 31 country – rest of world.

For OECD countries, the value-added and gross production data are both downloaded from the OECD STAN database for industrial analysis. And for the rest of none OECD countries, similar data sets are obtained from the Industrial Statistics Database INDSTAT2. We also aggregate the industry to 2-digit ISIC version 3 level for all 31 countries. The IO table is downloaded from the World Input-Output Database (WIOD) and the OECD Input-Output Database. We use the year 2016 as our base year for computing all the three matrix data sets.

4 Empirical results

4.1 Results of trade elasticity

Table 2 presents the estimated trade elasticities (the negative of estimated coefficients), standard deviations in parenthesis, and the number of observations for every 20 tradable industries. For estimating the trade elasticities in 2-digit ISIC Revision 3, we need to convert import tariffs from 6-digit HS to 2-digit ISIC Revision 3. In the first 3 columns, we use the share of trade value as the corresponding weight when import tariffs are aggregated into 2-digit ISIC Revision 3 industry classification. At the same time, for the last 3 columns, equal weights are assigned to all 6-digit HS classification in aggregating the import tariffs.

From the estimated results in table 2, we can learn that estimated trade elasticities are all statistically significant, and the magnitudes range from 3 to 23 (except petroleum 40.32) which is reasonable. From the definition of elasticity, the larger magnitude of elasticity, the bigger decrease of import flow under the same amount of shift import tariffs. In the table, the relatively small trade elasticities are reported in Agriculture, Food, and Auto sectors, which reflects the inelastic demand of food and auto importing from the monopolistic exports in these industries by nature and brand loyalty effect. Comparing the estimated trade elasticities from the first and last 3 columns, we find that the estimated results are consistent. Therefore, we use the estimated trade elasticities using weighted average tariffs as inputs of the next stage.

4.2 Baseline results for country welfare and real wages

Table 3, 4, and 5 report the simulated country welfare and real wage effects after 3 rounds of trade barriers strength in the US – China trade war from July 2018 to Feb 2020. In the first column, we report the total country welfare effects which are calculated by equation (32). Also, the first and second items of the equation (32) show that the country welfare effects are from trade terms and volumes respectively. The first item which indicates the change of country welfare due to trade terms is from the changing of export price relative to import price. And the second item in equation (32) shows the change of country welfare through the decreasing of trade volume due to import tariffs increasing. Therefore, we list the sub-country welfare effects in the next two columns. At last, the real wage effect which is derived from equation (31) is presented in the last column.

To illustrate the big picture of the trade war effects between U.S. and China, besides country welfare effects and real wages for US and China, we list those for other closely related countries such as Japan and South Korea which exports multiple intermediate goods to China in auto, electrical and communication industries; Mexico and Canada which integrate their economies with the US; France, Germany and United Kingdom which own a significant part of the whole world economy pie, and India, Indonesia and Rest of world which have a large part of the population of the world.

From the estimated results in table 3, we can learn that after the Chinese and US government increase 25 percent import tariffs on selected imported goods from the US and China in total trade amount 50 billion each, China suffered in both trade terms and volume items and the total magnitude of country welfare is decreased by 0.079 percentage. Since the country's welfare includes labor income, trade deficits, and tariffs incomes, and in China the total national income in 2016 is 2172.6 billion US dollars, China will lose more than 1.8 billion US dollars in the first round US – China trade war. But the US only suffered from the change of trade volume but after compensation from trade terms, the total country welfare increases by 0.0017 percentage. At last, on average, the workforce in both US and China are suffered from a reduced real wage in 0.053 and 0.0046 percentage respectively. The increasing US country welfare mainly benefits from the increasing tariff income, but the increasing market price reduces the real wage in the US. In conclusion, the average losses among the workforce in China are larger than those in the U.S. by 7 percentage.

As the main trade partners and upstream suppliers of China, Japan, and South Korea experience different shocks after the first round of trade war. Since Japan and South Korea have high-tech barriers and work as a monopoly in the upstream of the supply chain in some industries, they can keep their profits as before or even gain during US – China trade war. From the estimated results, Japan would benefit from the first round trade war in both terms and volume, and the corresponding real wages increases in a small amount. However, South Korea would lose in all aspects, although the magnitude of decrease is less than 10 percent of China. The circumstances for Mexico and Canada are similar to Japan and South Korea. In total, Canada and Mexico both would benefit from the first round of trade policy changes, but Canada would lose in trade terms and workforce real wages. From the estimated results of these 4 countries, we can learn that the closed related economies may share the loss or gain from the trade war, but intermediate goods suppliers have different results which depend on the industry and their cooperation positions in the supply chains. On average, developed countries would benefit, but developing countries lose after the first round of trade war.

Table 4 reports the cumulative US – China trade war effects after the second round of punishment import tariffs increasing in total of 200 billion trade flows from both US and China. The pattern of results are similar, but the huge amount of increasing import tariffs also suffered the US economy and its real wage. For South Korea and India, the country's welfare and real wage effects change from loss to gain. The developed countries also keep gaining in the trade war but they benefit less compared to what they gain in the first round of trade war. Therefore, on average, the trade war reduces the global country's welfare in total. From the results in table 5, the third round trade war does not affect the global economy much. To satisfy the target of setting trade barriers on another 300 billion trade flows, the US government has to increase import tariffs on some industries again which reduces the trade war effects. Besides, the Chinese government does not set the corresponding trade policy against the US is another reason for the insignificant trade war effect in the third round.

4.3 Counterfactual results

In this extension, we try to analyze whether the US government carefully selected the affected industries during the US – China trade war. Table 6, 7, and 8 report counterfactual results derived as the average of estimated results in 50 randomly drawn trade war affected industry lists. The randomly selected data set must satisfy the declare of the US government that the total trade amount in 3 rounds is 50, 200, and 300 billion US dollars (5% tolerance). Comparing the actual first-round trade war effects to its corresponding counterfactual effects, we can learn that the pattern of effects is similar, but China will suffer more than actual effects in 83.54 percentage. On the other hand, the US country welfare effect will change from positive to negative which means the US will also suffer more than before in 133.53 percentage in total. Compared to the first round of trade war in table 3, we can learn that the US government avoids the industries which make China and the US suffer more in the first round. But considering the related small magnitude trade war effects on the US economy and the tough attitude of President Trump in the trade war, we can also conclude that the US government does not carefully follow what president Trump said.

Comparing results in the second and third-round trade war, we can conclude that the actual trade war effects on both China and the US do not have a significant difference to the counterfactual ones. For other countries except the US and China, the country welfare effects are similar as well. Therefore, we can confirm that trade war must significantly reduce the global welfare in total. Also, no parts could win in the trade war no matter the selection of the strategies.

5 Conclusions

This paper estimates the pains of the two parts in the US – China trade war response to the trade policy changes in import tariff. Given the trade policies are consistent among other countries the sharply increasing import tariffs on selected trading goods significantly reduced the country's welfare and real wages in both China and U.S. but other countries in which the substitution effect dominates income effect benefit from this trade war. But in the view of the world, the benefits cannot overcome the total loss, because the optimal trade system is broken and the total cost of the trade system is higher than before. From our main results, we confirm that there is no absolute winners in the trade war, and both parts of the trade war are suffered from it. Also, it could be some countries or some industries benefit from the trade war, but the aggregated global welfare reduced.

We also study the different country welfare effect between following actual U.S. government trade policy and the average country welfare effect from randomly increasing import tariffs on the same total amount of import goods. The estimation results show that as the first moving part, the U.S. government carefully selects the affected industries in the trade war to control the total loss in the trade war. At last, since the U.S. dominates China in military power, total economy, and international relations, the loss of the U.S.A is much smaller than China in the trade war.

Michael K Adjemian, Shawn Arita, Vince Breneman, Rob Johansson, and Ryan Williams. Tariff retaliation weakened the us soybean basis. *Choices*, 34(316-2020-229):1–9, 2019.

Mary Amiti, Stephen J Redding, and David E Weinstein. The impact of the 2018 tariffs on prices and welfare. *Journal of Economic Perspectives*, 33(4):187–210, 2019.

Mary Amiti, Stephen J Redding, and David E Weinstein. Who's paying for the us tariffs? a longer-term perspective. In *AEA Papers and Proceedings*, volume 110, pages 541–46, 2020.

Vani Archana. Who will win from the trade war? analysis of the us–china trade war from a micro perspective. *China Economic Journal*, 13(3):376–393, 2020.

Edward J Balistreri, Wendong Zhang, and John Beghin. The state-level burden of the trade war: Interactions between the market facilitation program and tariffs. *Agricultural Policy Review*, 2020(1):1, 2020.

Cecilia Bellora and Lionel Fontagné. Shooting oneself in the foot? trade war and global value chains. 2020.

Felipe Benguria and Felipe Saffie. The impact of the 2018-2019 trade war on us local labor markets. *Available at SSRN 3542362*, 2020.

Tibor Besedes, Tristan Kohl, and James Lake. Phase out tariffs, phase in trade? *Journal of International Economics*, 127:103385, 2020.

Elie Bouri, Konstantinos Gkillas, Rangan Gupta, and Christian Pierdzioch. Forecasting realized volatility of bitcoin: The role of the trade war. *Computational Economics*, 57(1):29–53, 2021.

Chad P Bown. The 2018 us-china trade conflict after forty years of special protection. *China Economic Journal*, 12(2):109–136, 2019.

Chad P Bown. The us–china trade war and phase one agreement. *Journal of Policy Modeling*, 2021.

Chad P Bown, Aksel Erbahar, and Maurizio Zanardi. Global value chains and the removal of trade protection. 2020.

Lorenzo Caliendo and Fernando Parro. Estimates of the trade and welfare effects of nafta. *The Review of Economic Studies*, 82(1):1–44, 2015.

Colin A Carter and Sandro Steinbach. The impact of retaliatory tariffs on agricultural and food trade. Technical report, National Bureau of Economic Research, 2020.

Monique Carvalho, André Azevedo, and Angélica Massuquetti. Emerging countries and the effects of the trade war between us and china. *Economies*, 7(2):45, 2019.

Alberto Cavallo, Gita Gopinath, Brent Neiman, and Jenny Tang. Tariff pass-through at the border and at the store: Evidence from us trade policy. *American Economic Review: Insights*, 3(1): 19–34, 2021.

Winston W Chang. Inner workings of the chinese economy and the us–china trade war. *Review of Pacific Basin Financial Markets and Policies*, 23(02):2050016, 2020.

Terence Tai Leung Chong and Xiaoyang Li. Understanding the china–us trade war: causes, economic impact, and the worst-case scenario. *Economic and Political Studies*, 7(2):185–202, 2019.

Davin Chor. Unpacking sources of comparative advantage: A quantitative approach. *Journal of International Economics*, 82(2):152–167, 2010.

Robert Dekle, Jonathan Eaton, and Samuel Kortum. Unbalanced trade. *American Economic Review*, 97(2):351–355, 2007.

Elias Dinopoulos, Gunnar Heins, and Bulent Unel. Tariff wars, unemployment, and income distribution. *Unemployment, and Income Distribution (November 09, 2020)*, 2020.

Jonathan Eaton and Samuel Kortum. Technology, geography, and trade. *Econometrica*, 70(5): 1741–1779, 2002.

Pablo D Fajgelbaum, Pinelopi K Goldberg, Patrick J Kennedy, and Amit K Khandelwal. The return to protectionism. *The Quarterly Journal of Economics*, 135(1):1–55, 2020.

Robert C Feenstra and Chang Hong. China's import demand for agricultural products: The impact of the phase one trade agreement. Technical report, National Bureau of Economic Research, 2020.

Amy Finkelstein and Nathaniel Hendren. Welfare analysis meets causal inference. *Journal of Economic Perspectives*, 34(4):146–67, 2020.

Hamid Firooz and Gunnar Heins. Profit shifting, import and export markups, and the gains from trade. *Import and Export Markups, and the Gains from Trade (November 25, 2020)*, 2020.

Aaron Flaaen and Justin R Pierce. Disentangling the effects of the 2018-2019 tariffs on a globally connected us manufacturing sector. 2019.

Davide Furceri, Swarnali A Hannan, Jonathan D Ostry, and Andrew K Rose. Are tariffs bad for growth? yes, say five decades of data from 150 countries. *Journal of policy modeling*, 42(4): 850–859, 2020.

Munisamy Gopinath. Does trade policy uncertainty affect agriculture? *Applied Economic Perspectives and Policy*, 43(2):604–618, 2021.

Jason H Grant, Xin Ning, and Everett B Peterson. Trade elasticities and trade disputes: New evidence from tariffs and relative preference margins. 2018.

Jason H Grant, Shawn Arita, Charlotte Emlinger, Robert Johansson, and Chaoping Xie. Agricultural exports and retaliatory trade actions: An empirical assessment of the 2018/2019 trade conflict. *Applied Economic Perspectives and Policy*, 43(2):619–640, 2021.

Ke Gu and Andrey Stoyanov. Skills, population aging, and the pattern of international trade. *Review of International Economics*, 2019.

Meixin Guo, Lin Lu, Liugang Sheng, and Miaojie Yu. The day after tomorrow: Evaluating the burden of trump's trade war. *Asian Economic Papers*, 17(1):101–120, 2018.

Kyle Handley and Nuno Limão. Policy uncertainty, trade, and welfare: Theory and evidence for china and the united states. *American Economic Review*, 107(9):2731–83, 2017.

Joanna Hitchner, Keith Menzie, and Seth Meyer. Tariff impacts on global soybean trade patterns and us planting decisions. *Choices*, 34(316-2020-228):1–9, 2019.

Yi Huang, Chen Lin, Sibo Liu, and Heiwai Tang. Trade linkages and firm value: Evidence from the 2018 us-china trade war. Technical report, Graduate Institute of International and Development Studies Working Paper, 2018.

Ken Itakura. Evaluating the impact of the us–china trade war. *Asian Economic Policy Review*, 15 (1):77–93, 2020.

Joseph P Janzen and Nathan P Hendricks. Are farmers made whole by trade aid? *Applied Economic Perspectives and Policy*, 42(2):205–226, 2020.

Sung Eun Kim and Yotam Margalit. Tariffs as electoral weapons: The political geography of the us–china trade war. *International organization*, 75(1):1–38, 2021.

Wolfgang Lechthaler and Mariya Mileva. The dynamic and distributional aspects of import tariffs. *International Economic Review*, 62(1):199–241, 2021.

Chunding Li and John Whalley. Trade protectionism and us manufacturing employment. *Economic Modelling*, 96:353–361, 2021.

Chunding Li, Chuantian He, and Chuangwei Lin. Economic impacts of the possible china–us trade war. *Emerging Markets Finance and Trade*, 54(7):1557–1577, 2018.

Tao Liu and Wing Thye Woo. Understanding the us-china trade war. *China Economic Journal*, 11 (3):319–340, 2018.

Mia Mikic, Alexander Puutio, and James Gallagher. Healthcare products trade and external shocks: The us-china trade war and covid-19 pandemic. 2020.

Andrew Muhammad and Keithly G Jones. The end of the trade war? effects of tariff exclusions on us forest products in china. *Forest Policy and Economics*, 122:102350, 2021.

Andrew Muhammad, SA Smith, and Stephen MacDonald. How has the trade dispute affected the us cotton sector? *Choices*, 34(316-2020-231):1–9, 2019.

Huifu Nong. Have cross-category spillovers of economic policy uncertainty changed during the us–china trade war? *Journal of Asian Economics*, 74:101312, 2021.

Frank Kyekyeku Nti, Lindsay Kuberka, and Keithly Jones. Impact of retaliatory tariffs on the us pork sector. *Choices*, 34(316-2020-233):1–8, 2019.

Ralph Ossa. Trade wars and trade talks with data. *American Economic Review*, 104(12):4104–46, 2014.

Larry D Qiu, Chaoqun Zhan, and Xing Wei. An analysis of the china–us trade war through the lens of the trade literature. *Economic and Political Studies*, 7(2):148–168, 2019.

Anita Regmi. Retaliatory tariffs and us agriculture. *CRS Report*, (R45903), 2019.

Ricardo Reyes-Heroles, Sharon Traiberman, and Eva Van Leemput. Emerging markets and the new geography of trade: The effects of rising trade barriers. *IMF Economic Review*, 68(3):456–508, 2020.

Guobing Shen, Peijie Wang, and Yuanhan Xu. Trade destruction and deflection effects of us-china trade frictions on china's tariff-targeted products. *The World Economy*, 2020.

Dan Steinbock. Us-china trade war and its global impacts. *China Quarterly of International Strategic Studies*, 4(04):515–542, 2018.

Daniel A Sumner, Tristan Hanon, and William A Matthews. Implication of trade policy turmoil for perennial crops. *Choices*, 34(316-2020-232):1–9, 2019.

Farzad Taheripour and Wallace E Tyner. Impacts of possible chinese 25% tariff on us soybeans and other agricultural commodities. *Choices*, 33(2):1–7, 2018.

Shujiro Urata. Us–japan trade frictions: The past, the present, and implications for the us–china trade war. *Asian Economic Policy Review*, 15(1):141–159, 2020.

Michael E Waugh. The consumption response to trade shocks: Evidence from the us-china trade war. Technical report, National Bureau of Economic Research, 2019.

Patrick Westhoff, Patricia Tracey Davids, and Byung Min Soon. Impacts of retaliatory tariffs on farm income and government programs. 2019.

Jie Wu, Jacob Wood, and Xianhai Huang. How does gvc reconstruction affect economic growth and employment? analysis of usa–china decoupling. *Asian-Pacific Economic Literature*, 35(1): 67–81, 2021.

Yuqing Zheng, Dallas Wood, H Holly Wang, and Jason PH Jones. Predicting potential impacts of china's retaliatory tariffs on the us farm sector. *Choices*, 33(2):1–6, 2018.

Table 1: Summary statistics for the year 2016.

	Weighted average using trade value				Simple average			
	Mean	Std.	Min	Max	Mean	Std.	Min	Max
Main variable								
log import expenditure	12.844	3.992	0	24.400	12.848	3.994	0	24.414
Import tariffs	7.102	12.670	0	423.293	7.377	8.975	0	128.360
Log import expenditure, averaged by								
Import country	21.220	2.148	14.379	25.533	21.218	2.139	14.382	25.539
Export country	21.272	2.218	9.900	25.197	21.268	2.212	9.900	25.202
Industry	26.085	0.154	25.930	26.238	26.073	0.173	25.900	26.245
Import tariffs, averaged by (%)								
Import country	7.102	5.336	0	22.332	7.377	5.233	0	20.832
Export country	7.102	2.213	0.188	12.109	7.377	2.108	0.75	10.977
Industry	7.102	0.655	6.444	7.755	7.377	0.567	6.808	7.942

Table 2: Estimated elasticity in industry level.

	Weighted average tariff by trade value			Simple average tariff		
	Elasticity	**Std errors**	**Observations**	**Elasticity**	**Std errors**	**Observations**
Agriculture	2.917	(0.597)	3241	6.611	(0.863)	3241
Mining	29.303	(3.617)	1806	30.816	(4.032)	1806
Manufacturing						
Food	6.476	(0.494)	3754	5.881	(0.525)	3754
Textile	16.999	(0.650)	3982	19.102	(0.701)	3982
Wood	23.286	(1.380)	1983	23.581	(1.463)	1983
Paper	20.775	(1.435)	2756	23.902	(1.528)	2756
Petroleum	40.320	(5.466)	1189	46.248	(5.566)	1189
Chemicals	18.719	(1.249)	3694	22.900	(1.326)	3694
Plastic	22.217	(1.141)	3393	28.459	(1.232)	33.93
Minerals	21.176	(1.196)	2430	24.921	(1.298)	2430
Basic metals	23.474	(2.162)	2337	38.017	(2.427)	2337
Metal products	22.948	(1.090)	3293	26.143	(1.187)	3293
Machinery	12.136	(1.180)	3745	18.900	(1.334)	3745
Office	14.571	(3.344)	2187	8.939	(3.420)	2187
Electrical	22.346	(1.239)	3440	27.638	(1.380)	3440
Communication	11.246	(1.543)	2238	14.681	(1.788)	2238
Medical	17.727	(1.644)	3158	21.548	(1.843)	3158
Auto	4.321	(1.085)	2566	12.268	(1.412)	2566
Other Transport	10.024	(1.421)	1708	11.487	(1.635)	1708
Other	14.926	(0.792)	3261	17.364	(0.877)	3261

Table 3: Welfare effects from US – China trade war round 1 (50 billions) tariff strength.

	Country welfare			
Country	Total effects	Effects by terms	Effects by volume	Real wages
China	-0.079%	-0.031%	-0.049%	-0.053%
Japan	0.00077%	0.0005%	0.00027%	0.00054%
South Korea	-0.0015%	-0.0011%	-0.00038%	-0.0011%
United States	0.0017%	0.0029%	-0.0012%	-0.0046%
Canada	0.0002%	-0.00033%	0.00053%	-0.00027%
Mexico	0.00229%	0.000576%	0.00171%	0.000639%
France	0.00028%	0.000062%	0.00022%	0.000083%
Germany	0.00073%	0.00033%	0.0004%	0.00036%
United Kingdom	0.00022%	0.00015%	0.00007%	0.00016%
India	-0.0012%	-0.0006%	-0.00057%	-0.00066%
Indonesia	-0.004%	-0.0019%	-0.0021%	-0.0021%
Rest of world	0.00027%	-0.00007%	0.00035%	-0.00000077%

Table 4: Welfare effects from US – China trade war round 2 (200 billions) tariff strength.

	Country welfare			
Country	Total effects	Effects by terms	Effects by volume	Real wages
China	-0.28%	-0.079%	-0.2%	-0.22%
Japan	0.0019%	0.0013%	0.00066%	0.0014%
South Korea	0.0044%	0.0012%	0.0032%	0.002%
United States	-0.0078%	0.0053%	-0.013%	-0.02%
Canada	0.0013%	-0.00017%	0.0015%	0.000013%
Mexico	0.00376%	0.00191%	0.00185%	0.00203%
France	0.0011%	0.0004%	0.00069%	0.00049%
Germany	0.0021%	0.00093%	0.0012%	0.0011%
United Kingdom	0.00083%	0.00053%	0.0003%	0.00059%
India	0.0022%	0.0011%	0.0011%	0.0012%
Indonesia	-0.0046%	-0.0014%	-0.0031%	-0.0015%
Rest of world	0.0039%	0.0013%	0.0027%	-0.0016%

Table 5: Welfare effects from US – China trade war round 3 (300 billions) tariff strength.

Country welfare				
Country	Total effects	Effects by terms	Effects by volume	Real wages
China	-0.3%	-0.09%	-0.21%	-0.23%
Japan	0.002%	0.0013%	0.00072%	0.0015%
South Korea	0.0039%	0.00085%	0.003%	0.0017%
United States	-0.075%	0.064%	-0.14%	-0.21%
Canada	0.0015%	-0.00024%	0.0017%	0.000013%
Mexico	0.00376%	0.00189%	0.00187%	0.00201%
France	0.0012%	0.00041%	0.00077%	0.00052%
Germany	0.0023%	0.001%	0.0013%	0.0012%
United Kingdom	0.00087%	0.00056%	0.00031%	0.00063%
India	0.0022%	0.0011%	0.0012%	0.0013%
Indonesia	-0.006%	-0.0022%	-0.0039%	-0.0023%
Rest of world	0.0041%	0.0013%	0.0029%	0.0017%

Table 6: Average welfare effects from 50 random draws round 1 (50 billions) tariff strength.

Country welfare				
Country	Total effects	Effects by terms	Effects by volume	Real wages
China	-0.13%	-0.054%	-0.074%	-0.077%
Japan	0.00065%	0.00035%	0.0003%	0.00042%
South Korea	-0.0013%	-0.0012%	-0.000023%	-0.001%
United States	-0.00057%	0.0051%	-0.0056%	-0.0068%
Canada	0.00056%	-0.00056%	0.0011%	-0.00043%
Mexico	0.0011%	0.00036%	0.000731%	0.000395%
France	0.0005%	0.00012%	0.00038%	0.00017%
Germany	0.0011%	0.00043%	0.00071%	0.0005%
United Kingdom	0.00025%	0.00017%	0.000078%	0.0002%
India	0.00036%	0.00018%	0.00017%	0.00019%
Indonesia	-0.0052%	-0.0022%	-0.003%	-0.0024%
Rest of world	0.0011%	0.00012%	0.001%	-0.00028%

Table 7: Average welfare effects from 50 random draws round 2 (200 billions) tariff strength.

Country welfare				
Country	Total effects	Effects by terms	Effects by volume	Real wages
China	-0.3%	-0.087%	-0.21%	-0.23%
Japan	0.002%	0.0013%	0.0007%	0.0015%
South Korea	0.0038%	0.00087%	0.003%	0.0017%
United States	-0.0076%	0.0062%	-0.014%	-0.021%
Canada	0.0014%	-0.00022%	0.0017%	-0.0000065%
Mexico	0.0036%	0.00185%	0.00179%	0.00197%
France	0.0012%	0.0004%	0.00075%	0.00051%
Germany	0.0023%	0.00098%	0.0013%	0.0011%
United Kingdom	0.00085%	0.00054%	0.00031%	0.00061%
India	0.0024%	0.0012%	0.0012%	0.0013%
Indonesia	-0.0059%	-0.0021%	-0.0038%	-0.0023%
Rest of world	0.0041%	0.0012%	0.0028%	0.0017%

Table 8: Average welfare effects from 50 random draws round 3 (300 billions) tariff strength.

Country welfare				
Country	Total effects	Effects by terms	Effects by volume	Real wages
China	-0.3%	-0.094%	-0.21%	-0.23%
Japan	0.0021%	0.0013%	0.00075%	0.0015%
South Korea	0.0037%	0.0007%	0.003%	0.0016%
United States	-0.073%	0.068%	-0.14%	-0.22%
Canada	0.0015%	-0.00028%	0.0018%	-0.0000039%
Mexico	0.00368%	0.00185%	0.00183%	0.00198%
France	0.0012%	0.00041%	0.0008%	0.00053%
Germany	0.0024%	0.001%	0.0014%	0.0012%
United Kingdom	0.00088%	0.00056%	0.00032%	0.00064%
India	0.0024%	0.0012%	0.0012%	0.0013%
Indonesia	-0.0066%	-0.0024%	-0.0042%	-0.0025%
Rest of world	0.0042%	0.0013%	0.003%	0.0017%