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Abstract

In this paper 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.

JEL Classification codes: F14, F16, J11, J24

Keywords: worker adaptability, comparative advantage, population aging

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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.[1]

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. 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

[1] 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.

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, Mion, and Ornelas (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.[2][3] 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

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

[3] A recent study by Chisik, Onder, and Qirjo (2016) analyses theoretically the effect of aging on consumer preferences and demand for imports.

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, research has shown that mental flexibility declines with age. For example, Wecker, Kramer, Hallam, and Delis (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, Mayes, and Wiseman (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, Smith, and Barney (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.[4] In a recent review, King, Fogel, Albouy, and Doyon (2013) 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, Rosen, and Schwoerer (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 (2016) 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 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

[4] See, for example, Buch, Young, and Contreras-Vidal (2003), Harrington and Haaland (1992), Howard Jr and Howard (1997), McNay and Willingham (1998), Messier, Adamovich, Jack, Hening, Sage, and Poizner (2007), Pratt, Chasteen, and Abrams (1994), Ruch (1934), and Seidler (2006).

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, Gallipoli, and Pupato (2012), and Cai and Stoyanov (2016) and use the following empirical model:

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

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.[5] 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.

[5]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.

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:

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

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, Romalis, and Schott (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 industry level as weights:

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

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 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 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.[6] 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 is from Saggi, Yildiz, and Stoyanov (2015).

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 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

[6] 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.

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%.[7]

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.

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.[8] 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

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

[8] 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.

(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 exports in industry A relative to B by 2.5%.[9] The estimation results without the breakdown by age groups (column 6 of Table 2) imply a similar magnitude of 1.7%.[10]

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.

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

[10] 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 $exp\left\{\alpha \times 0.01 \times \frac{std(lnX_{cpi})}{std(Age_c)}\right\} = exp\left\{-0.039 \times 0.01 \times \frac{3.332}{0.0775}\right\} \simeq 0.017.$

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, Donaldson, and Komunjer (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.

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).[11]

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.[12] 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

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

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

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, 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.

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

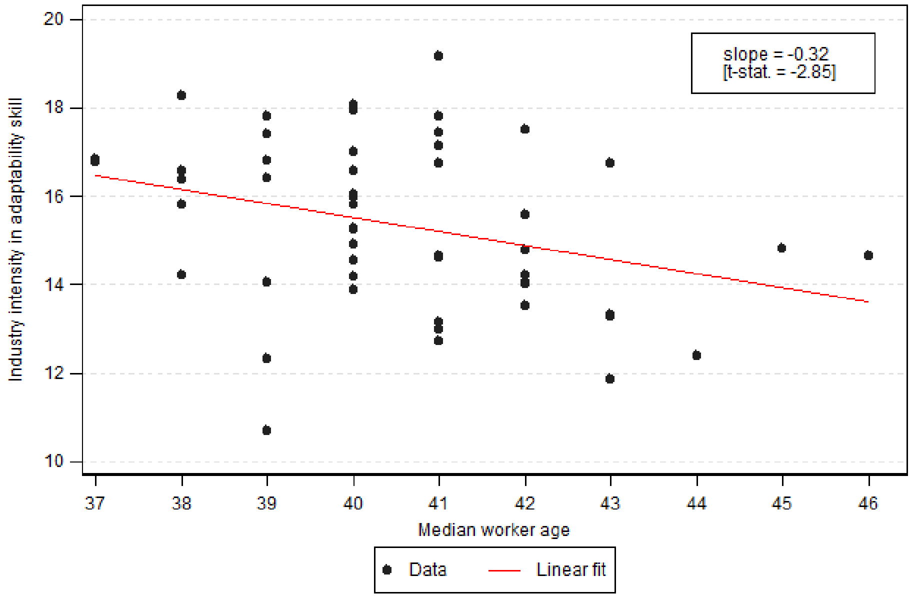

Figure 2. Occupation intensity in adaptability skill and the median worker age

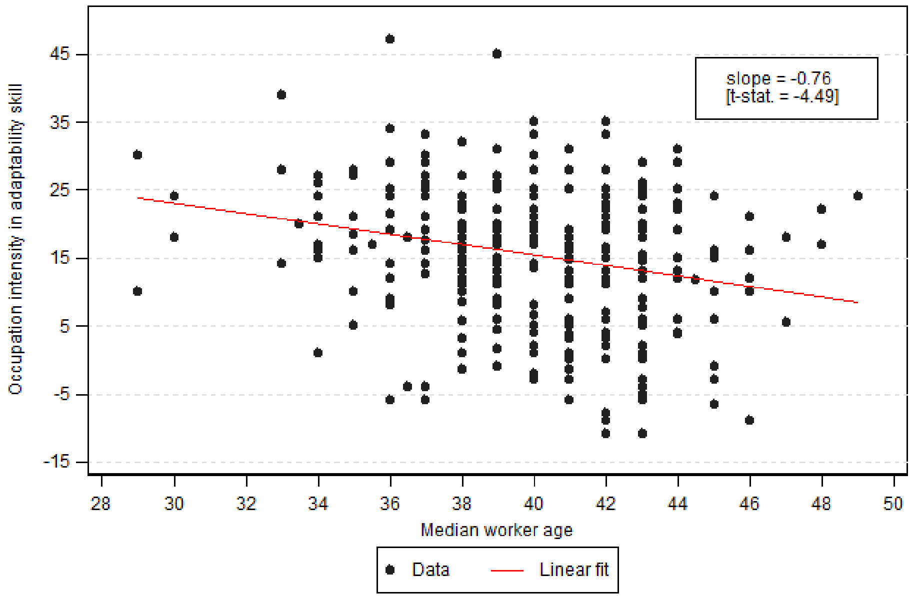

Table 1: Industries with the highest and the lowest intensities in adaptability skill.

		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%.