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Population aging and comparative advantage☆

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ABSTRACT

In this paper we show that demographic differences between countries are a source of comparative advantage in international trade. Since many skills are age-dependent, population aging decreases the relative supply and increases the relative price of skills which depreciate with age. Thus, industries relying on skills in which younger workers are relatively more efficient will be more productive in countries with a younger labor force and less productive in countries with an older population. Building upon the neuroscience and economics literature, we construct industry-level measures of intensities in various age-dependent skills and show that population aging leads to specialization in industries which use age-appreciating skills intensively and erodes comparative advantage in industries for which age-depreciating skills are more important.

1. Introduction

Many countries observe major changes in the demographics of their populations as aging leads to a shift in the age structure of the labor force towards older workers. These changes are likely to have a profound influence on the structure of economic activity within countries and on the pattern of trade between them through a change in the relative supply of age-dependent skills. Recent research on aging suggests that there is a negative relationship between age and some cognitive abilities, with a number of studies showing that cognitive decline begins as early as the age of 25. This implies that aging societies experience a more rapid decline in the quality and the stock of certain cognitive skills and may thus lose comparative advantage in industries which use those skills intensively. In this paper, we study how differences in age structure of populations between countries affect global trade flows. Specifically, we find a novel and empirically sizeable source of comparative advantage: the relative supply and quality of age-dependent skills that vary across countries with different demographic compositions.

This article links economics, with its focus on skills and productivity, and psychology, where the idea of different skills changing differently with age first originated. A series of studies on cognitive abilities and aging consistently report that speech and language abilities improve with age, while memory, multitasking, and the speed of information processing decline with age. Furthermore, a decline in physical strength with age is well documented in the medical literature. Knowing the importance of those skills for various occupations and the composition of occupations across industries, we are able to pin down industry-level demand for each age-dependent skill. For instance, among the occupations which rely heavily on age-depreciating cognitive skills are various types of machine operators, where coordination, divided attention, and perceptual speed are very important. As a result, in industries where most workers enter as *machine setters and operators*, such as yarn mills or wood product manufacturing, age-depreciating skills are used intensively. Other industries, such as printing or beverages and tobacco, employ many

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workers in occupations which require good written and/or oral communication skills (e.g. *technical writers* or *sales representatives*) and use age-appreciating cognitive skills intensively.

One such mechanism operates through the effect of population aging on the stocks of age-dependent skills. If individuals are endowed with certain stocks of age-dependent skills which they supply to the market, then a country with an older labor force, all else being equal, will have lower endowments and higher relative prices of age-depreciating skills and thus specialize in the production of goods which utilize age-appreciating skills intensively. The second mechanism through which demographics operate is the effect on labor productivity. If aging affects the quality rather than the quantity of age-dependent skills, then older workers become less productive in tasks which require age-depreciating skills, and the age composition of the labor force would determine the relative productivity of an industry. In the presence of labor market frictions which prevent perfect sorting of workers into industries based on their age, industries would inherit the national age distribution, in which case population aging would shift the age distribution of employees in all sectors and increase (decrease) labor productivity in industries which rely on age-appreciating (age-depreciating) skills.

Both the Heckscher–Ohlin and the Ricardian mechanisms imply that countries with older (younger) populations will specialize in industries which use age-appreciating (age-depreciating) skills intensively. Figs. 1 to 3 illustrate this prediction and plot the relationship between export shares and skill intensities across industries for countries with the median age below 20 (young) and above 35 (old) in the year 2000. As we expect, countries with older populations export more in industries which use age-appreciating cognitive skills intensively, and less in industries with a greater dependence on physical and age-depreciating cognitive skills. The opposite pattern is observed among countries with younger populations, which specialize more in commodities that rely on age-depreciating skills. Fig. 1A in the online Appendix also shows that industries with high intensity in age-appreciating (age-depreciating) skills tend to employ older (younger) workers.[1] This pattern suggests that as workers age, their productivity in tasks that require age-depreciating skills declines and the return to their skills falls, making older workers more likely to move to industries where age-appreciating skills are important.

The relationship between skill development and aging allows us to analyze the effect of unobservable endowments of cognitive skills on trade flows by using observable cross-country variation in demographic composition as a proxy. Surveying behavioral and neuroscience literature, we identify cognitive skills which are known to change over the course of an individual's life. To measure sectorial intensities in those skills, we retrieve the indicators of their importance for different worker occupations from the O*NET database. We then use occupational composition for each 4-digit NAICS industry, obtained from the US Bureau of Labor Statistics, to construct the weighed-average measure of importance of each age-dependent skill for every 4-digit NAICS industry. Since many of these skill importance variables are highly correlated and their impacts cannot be separately identified with our data, we group all age-dependent skills into three main categories using the principal component analysis: physical abilities, age-appreciating cognitive skills, and age-depreciating cognitive skills.

We confirm the main theoretical prediction about the effect of aging on comparative advantage using rich bilateral trade data which include 86 industries and cover the time period between 1962 and 2010. We find that countries with older (younger) populations capture larger shares of world trade in commodities that more intensively use age-appreciating (age-depreciating) skills. In the baseline regressions that include 136 exporting countries, we show that the interaction of a country's median age and the industry's intensity in age-dependent skills is an important determinant of bilateral trade flows, both statistically and economically. [2] This finding is robust to the inclusion of the standard determinants of comparative advantage such as endowments of physical and human capitals, as well as institutional factors such as financial development and the quality of the legal system. Moreover, age-appreciating and age-depreciating cognitive skills often explain more variation in trade flows than physical and human capitals. Furthermore, the magnitude of the impact of age differences on trade flows, estimated in this study, is comparable to institutional determinants of comparative advantage identified in recent literatures, such as that on product market institutions (Nunn, 2007; Costinot, 2009), financial market institutions (Manova, 2008), and labor market institutions (Cunat and Melitz, 2012). The main finding of this paper is robust to different definitions of human capital and holds for different time periods.

Availability of historical demographic data allows us to test the dynamic predictions of the model. Specifically, we would expect fast(slow)-aging countries to observe a decrease in the relative price of age-appreciating (age-depreciating) skills and an increase in the relative productivity of industries which use those skills intensively, thus making them more competitive in the global market. Analyzing the effect of population aging on changes in comparative advantage allows us to address many omitted variable concerns in the estimation, and in particular the effect of institutional factors which do not vary over time. We also pay close attention to other potential sources of endogeneity in the empirical model, and explore the robustness of our results using an instrumental variable approach and alternative measures of countries' effective endowment in age-dependent skills.

We find substantial support for the dynamic predictions of the model in the data. We demonstrate that an increase in the median age between 1962 and 2000 is associated with a shift in a country's production and export structure towards commodities that more intensively use age-appreciating skills and away from commodities that rely more on age-depreciating skills. This result implies that although population aging leads to a reduction in premia for skills that are inherent to older workers, the problem can be alleviated by an increase in demand for those skills through expansion in the production and exports of goods which use them intensively.

This paper contributes to the fast-growing literature that formally tests the relationship between factor proportions and trade flows. Specifically, it is related to the classical works documenting the important role of physical and human capital endowments in comparative advantage.[3] More recent developments in this literature emphasize non-traditional sources of comparative advantage, such as the cross-country variations in contract enforcement (Levchenko, 2007; Nunn, 2007), the quality of financial systems (Beck, 2003; Manova, 2008), the extent of labor market frictions (Helpman and Itskhoki, 2010; Cunat and Melitz, 2012; Tang, 2012), skill dispersion (Bombardini et al., 2012), and water resources (Debaere, 2014). Our study contributes to this literature by proposing a novel factor of comparative advantage stemming from the differences in endowments of cognitive and physical skills between countries. Using the variation in demographic composition across countries and the variation in age-dependence of different cognitive skills, we are able

[1] The relationship between the median age of the labor force and intensity in three age-dependent skills is constructed for eighty-three four-digit NAICS industries from the U.S. Census Public Use Micro-Samples for the year 2000.

[2] Similar results are obtained when a country's endowment of age-dependent skills is proxied by the share of workers below a certain age threshold in the labor force.

[3] See Trefler (1993), Harrigan (1997), Davis and Weinstein (2001), and Debeare (2003) for the empirical evidence based on the factor content of trade analysis. Romalis (2004) and Blum (2010) analyze the role of capital and skilled labor in specialization and comparative advantage using commodity trade and output data, respectively.

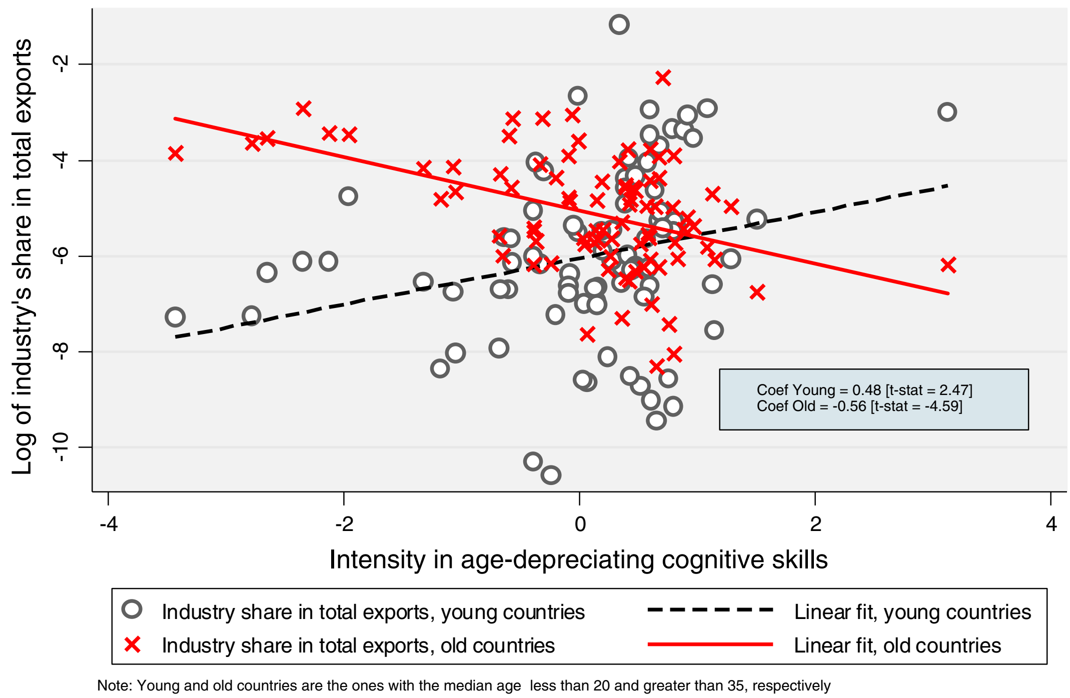

Fig. 1. Correlation between intensity in age-depreciating cognitive skills and exports for old and young countries.

to construct a reliable proxy for a country's effective endowment in unobservable cognitive and physical skills. We thus demonstrate that demographics can affect cross-country differences in effective endowments of cognitive and physical skills and is an equally important determinant of comparative advantage as are the differences in physical and human capitals.

The only study on the role of cognitive skills in trade we are aware of is by Wolff (2003), who estimates the content of cognitive and physical skills in US exports. Wolff demonstrates that the US has comparative advantage in cognitive and interactive skills and disadvantage in motor skills. However, without reliable data on factor endowments in other countries, these results are hard to interpret as an empirical test of the role of cognitive skills in the Heckscher–Ohlin model. Our model, in contrast, provides a theoretical underpinning for Wolff's finding on interactive and motor skills. Since interactive skills improve with age while motor skills deteriorate, a country with a relatively old population, such as the US, must be abundant in interactive and scarce in physical skills.

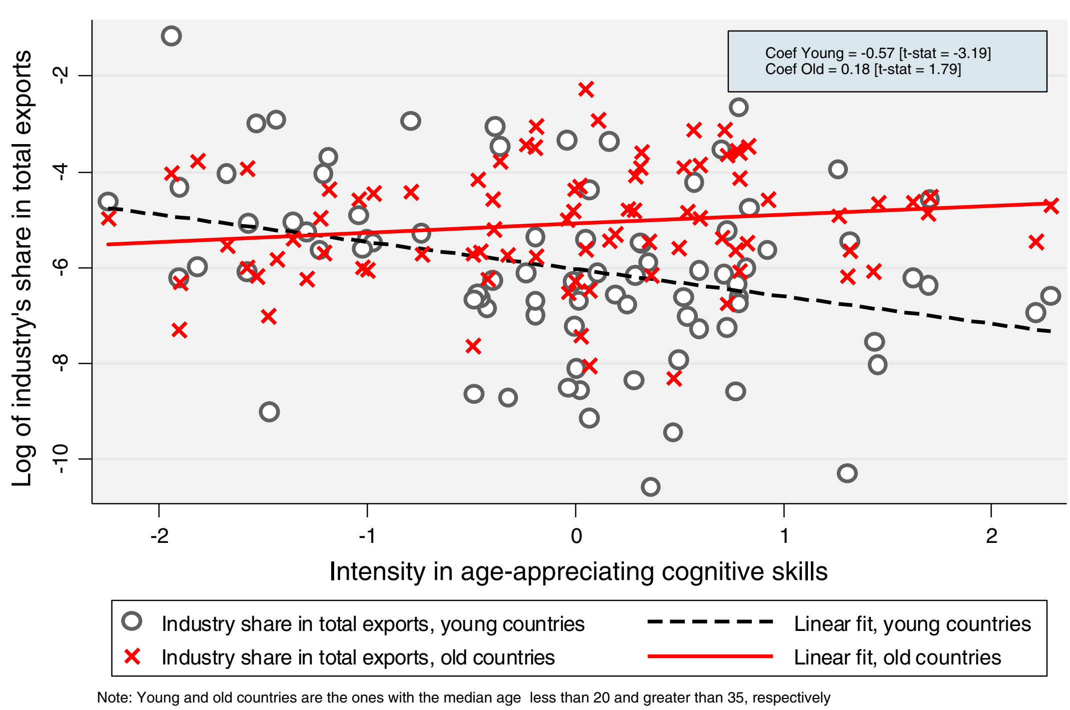

Fig. 2. Correlation between intensity in age-appreciating cognitive skills and exports for old and young countries.

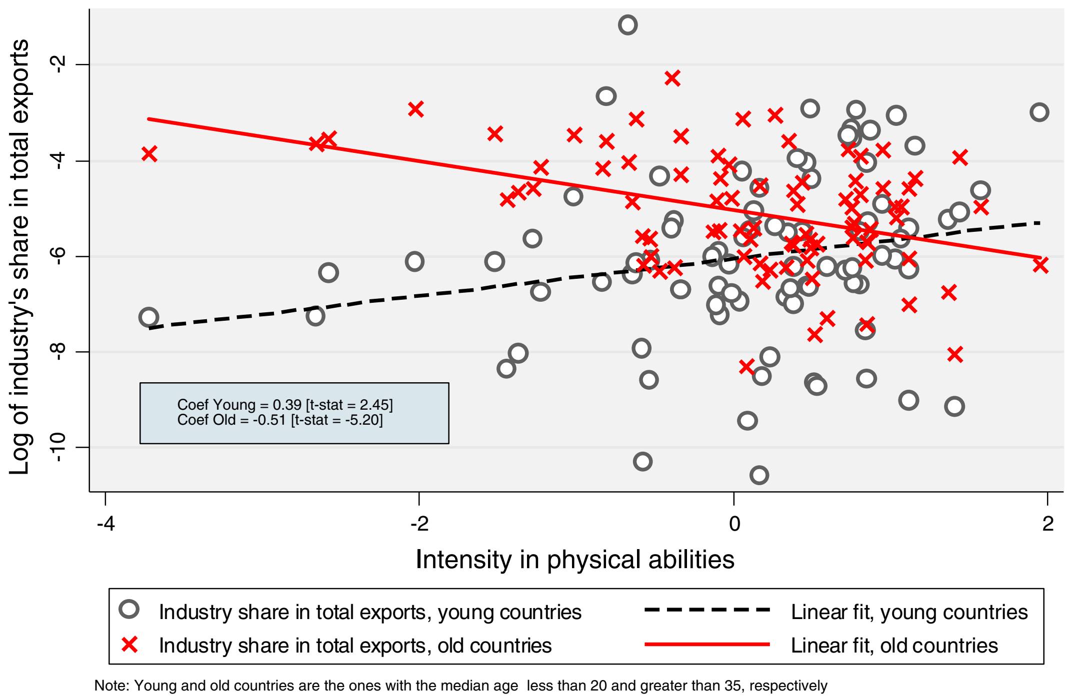

Fig. 3. Correlation between intensity in physical abilities and exports for old and young countries.

Therefore, the US demographic composition can explain why this country has a positive factor content of trade for communication skills and negative for physical skills. We also show, using more comprehensive data, that failure to distinguish various cognitive skills by their age-dependence may confound the effect of demographics on comparative advantage.

Our research also relates to the literature on macroeconomic impacts of population aging. Papers studying the role of aging in international capital and immigration flows using an overlapping generations framework[4] conclude that more rapid population aging in Northern countries increases the rate of capital accumulation, stimulating capital flow to Southern countries, where the return on capital is higher.[5] Higgins (1997) and Narciso (2013) empirically investigate this prediction and confirm that demographic structure has significant effect on capital flows. In the context of international trade, Helliwell (2004) shows with a theoretical model that demographic changes are associated with intensified outsourcing of labor-intensive processes to countries with younger populations and thus affect a country's comparative advantage. Our theoretical framework is also based on the effect of aging on trade through changes in relative factor prices but goes beyond the two-factor model and introduces multiple age-dependent factors of production.

The paper is organized as follows. Section 2 discusses the empirical strategy for testing the main predictions of the theoretical model, which details are presented to the Appendix. Section 3 describes the data and Sections 4 presents the baseline empirical results, along with extensions, robustness checks, and solutions to endogeneity problems. Section 5 shows the effect of changes in age composition of a country's labor force on comparative advantage. Section 6 concludes.

2. Theoretical background and empirical methodology

In the presence of age-dependent skills, demographic composition can affect a country's comparative advantage through two different channels. First, there is a Heckscher–Ohlin channel whereby population aging can affect the stocks and relative supply of age-dependent skills. When certain skills change over the course of an individual's life, the stocks of those skills will vary across individuals and hence across countries with the age structure of their populations. The Heckscher–Ohlin model then implies that with cross-industry variation in skill intensities, the age structure of a country becomes a source of comparative advantage. For example, a country with a young population will have a comparative advantage in products which intensively use age-depreciating skills. In this case, comparative advantage stems from cross-country variation in skill premia.

Second, demographics can affect comparative advantage through the Ricardian channel. Workers of different ages may not be equally productive in tasks that require age-dependent skills, which may affect relative labor productivities of industries with different compositions of tasks. As long as industry-specific skills or other labor market frictions prevent workers of different ages from moving freely from one industry to another, the workers' age distribution in every industry will resemble the country's distribution. In this case, population aging will shift the age distribution of employees in all sectors and increase (decrease) labor productivity in industries which rely on age-appreciating (age-depreciating) skills. Therefore, countries with older populations will have higher Ricardian productivities and stronger comparative advantage in industries which are intensive in age-appreciating skills.

[4] Holzmann (2002), Boersch-Supan et al. (2001), Boersch-Supan et al. (2006), Domeij and Floden (2006), Attanasio et al. (2007), Ludwig et al. (2007), among others.

[5] Ludwig and Vogel (2010) and Ludwig et al. (2012) point out that intensified accumulation of human capital in the North can mitigate the decline in the marginal return to capital and slow down capital outflow.

We introduce age-dependent skills into the theoretical model of Ricardian and Heckscher–Ohlin comparative advantage by Chor (2010) (see the Appendix for details). In that extension, population aging affects country's comparative advantage both through a reduction in relative supply and an increase in relative price of age-depreciating skills (Heckscher–Ohlin channel) and through a direct effect on labor productivity in tasks that rely on age-dependent skills (Ricardian channel). The empirical specification implied by the model is similar to Chor (2010) and Bombardini et al. (2012):

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

where X_{cpi} is exports from country c to country p in industry i, K is the set of age-dependent skills and F is the set of other factors of production, I_i^k is the intensity of industry i in factor of production k, Age_c is the demographic structure in country c assumed to be increasing as population is getting older, F_c^f is endowment of country c in factor f, and δ_{cp} is bilateral trade costs. Coefficients ϕ_f reflect the importance of conventional determinants of comparative advantage, such as human and physical capital endowments.

In Eq. (1), the coefficients β_k on interactions $I_i^k \times Age_c$ capture both the Ricardian and the Heckscher–Ohlin channels. Separating the two effects is neither critical nor feasible for this study. In either case, the estimates of model (1) are valid for the purpose of evaluating the effect of population aging on trade flows and comparative advantage. Whether this effect operates through changes in skill premia or labor productivity is irrelevant for the main finding of this paper that aging countries experience structural changes in their production and trade patterns away from industries which rely on age-depreciating skills. Isolating one effect from the other would require micro data and a good measure of individual productivity to evaluate the relationship between aging, skill premia and labor productivity, which is outside the scope of this paper. Thus, we leave this questions for future research.[6]

The interaction $I_i^k \times Age_c$ is the main variable of interest and the sign of β_k allows us to test the key theoretical prediction that younger countries have a comparative advantage in industries which intensively use age-depreciating skills. The theoretical model predicts that $\beta_k < 0$ for skills that worsen with age and $\beta_k > 0$ for skills that improve with age. Furthermore, Eq. (1) implies that for any pair of countries c_1 and c_2 exporting goods i and j to a third country p the following holds

$$E\left[\ln\left(\frac{X_{c_1pi}}{X_{c_2pi}}\right) - \ln\left(\frac{X_{c_1pj}}{X_{c_2pj}}\right)\right] = \sum_{k \in K} \beta_k \left(I_i^k - I_j^k\right) \times \left(Age_{c_1} - Age_{c_2}\right). \quad (2)$$

If country c_1 has a younger population than country c_2, $(Age_{c_1} - Age_{c_2}) < 0$, and industry i is more intensive in skill k than industry j, $\left(I_i^k - I_j^k\right) > 0$, then we would expect country c_1 to export relatively more (less) of good i than j if skill k depreciates (appreciates) with age, which would be the case when $\beta_k < 0$ ($\beta_k > 0$).

In our baseline specifications we control for two standard Heckscher–Ohlin factors of comparative advantage — the cross-country differences in physical capital and skilled labor. Given that countries export more in industries which use their abundant factors intensively, we expect $\phi_f > 0$ for all standard factors of production. The vector δ_{cp} in Eq. (1) captures bilateral trade frictions between countries c and p. Exporter fixed effects γ_c control for exporter's aggregate productivity level, size, remoteness from other countries, and other characteristics that do not vary across industries. Importer-industry fixed effects γ_{pi} control for product prices in the importing country and all other demand shifters, including those which may be driven by cross-country demographic differences.

There are two potential endogeneity concerns with $I_i^k \times \mathrm{Age}_c$ variables in Eq. (1). The first one relates to the demographic composition of a country's population. A country's median age is predetermined relative to industry-level trade flows, and it is difficult to think of other reasons why the median age could affect the export structure other than through the effect on either supply or demand.[7] However, it may be related to other unobservable countries' determinants of comparative advantage which may have differential impact on productivities in industries with different skill intensities. In Section 4.3 we discuss how we address potential endogeneity issues with demographic composition using instrumental variable approach and alternative measures of effective endowment of age-dependent skills. Second, the skill intensity measures constructed from the occupational structures in the US industries are plausibly exogenous, as long as the US employment composition is unaffected by bilateral trade flows between other countries. In Section 4.2 we provide evidence in support of this assumption. In particular, if there is feedback from trade flows to employment structure, the simultaneity would especially be a problem for the US trade flows. However, removing the US from the set of importing and exporting countries does not affect our results. Moreover, skill intensities, constructed with 2010 data, predict trade flows in 1970 just as well as in 2010, suggesting that our results are unlikely to be subject to the reverse causality.

It is also important to emphasize that while the focus of this study is on the effect of population aging on supply, the demographic composition, in principle, can also affect trade through the effect on demand if consumer preferences change with age. We explore this possibility in Section 4.2 and find that although consumption behavior does change with age, there is little evidence that age-related changes in preferences are systematically related to production technology or skill intensities in manufacturing industries.

To test the prediction regarding the effect of demographic transformations on trade flows, we introduce exporter and importer-industry trends in Eq. (1) and estimate it in differences:

$$\Delta \ln X_{cpi} = \sum_{k \in K} \beta_k I_i^k \times \Delta Age_c + \sum_{f \in F} \phi_f I_i^f \times \Delta F_c^f + \delta_{cp}^{T}\lambda + \mu_c + \mu_{pi} + \varepsilon_{cpi}, \quad (3)$$

where Δ is the time-difference operator, δ_{cp}^{T} is the subset of country-pair characteristics that vary over time, $\mu_c = \gamma_c t - \gamma_c(t-1)$ and $\mu_{pi} = \gamma_{pi} t - \gamma_{pi}(t-1)$. Eq. (3) thus assumes that while trade structure, age composition, and factor stocks can change within a country over time, industries' factor intensities are constant. Thus, rapidly aging countries should lose comparative advantage in industries which rely on age-depreciating skills and specialize in industries which

[6] A specific feature of the setup with multiple age-dependent skills is that the workers arrive with a bundle of skills. Ohnsorge and Trefler (2007) demonstrate that in a setting with multiple skills embedded in workers, a country's comparative advantage is determined not only by its relative skill endowments but also by the second moments of skill distributions. In the Appendix we use the Ohnsorge and Trefler (2007) framework to show that in the presence of multiple skills the pattern of comparative advantage remains consistent with the Heckscher–Ohlin theorem for the plausible range of the parameters on the second moments of the multivariate distribution of skill endowments, and hence empirical methodology employed in the current study remains valid.

[7] Galor and Mountford (2008) find that trade openness, measured by the ratio of total trade flow over GDP, may have a differential effect on the fertility rate and investment in human capital in developed and developing countries. Do et al. (2015) also find that trade affects demographic composition if industries differ in relative demand for female labor. However, the potential feedback from trade openness to demographic composition is not a concern for us because our focus is not the level of openness but the share of trade across industries for a given level of openness.

use age-appreciating skills intensively. Therefore, β_k are expected to be positive for age-appreciating and negative for age-depreciating skills. For physical capital and skilled labor the Rybczynski prediction implies $\phi_f > 0$.

The advantage of adding a panel dimension to our data structure is that it allows us to address additional omitted variable concerns in the estimation; in particular, time differencing controls for time-invariant exporter-industry characteristics, such as the effect of some institutions on industry-level productivity. Many institutional factors which previous literature identified as important determinants of comparative advantage vary little over time for a vast majority of countries in our sample and cannot be studied in a panel data analysis. Time differencing transformation will also eliminate the effect of any geographic characteristics on productivity of different industries, such as proximity to main markets or to natural resources.

3. Data

Estimation of the main model Eq. (1) requires four sets of data: industry-level data on bilateral trade flows; determinants of bilateral trade costs; industries' intensities in age-dependent skills and other factors of production; and country-level measures of abundance in those factors. Eq. (1) is estimated with bilateral trade data for the year 2000. To estimate Eq. (3), we employ the change in trade structure, age composition, and factor endowments between 1962 and 2000. In what follows we describe the data sources for this study and discuss the issues with construction of the key variables.

3.1. Trade data

The data on industry-level bilateral trade flows for estimation of Eq. (1) are obtained from the UN-TRAINS database at 6-digit Harmonized System classification and aggregated into 4-digit North American Industry Classification System (NAICS) using concordance from Feenstra et al. (2002). The resulting data is an unbalanced panel of 235 exporters, 159 importers, and 85 industries for the year 2000. While UN-TRAINS database provides comprehensive country and industry coverage, it does not report data prior to 1989. To estimate dynamic Eq. (3), we use bilateral trade flows between 1962 and 2000 obtained from NBER-UN International Trade Database, with the NBER concordance tables employed to convert 4-digit SITC data into 4-digit NAICS. Eq. (3) is estimated for 80 exporters, 135 importers, and 76 industries.

Bilateral trade costs are controlled for with the standard set of geographical and institutional variables used in the gravity model literature. The vector δ_{cp} in Eqs. (1) and (3) includes the log of distance, defined as the distance between the major cities of the two countries, common land border indicator, common official language binary variable, colonial ties binary variable (separately for before and after 1945), and a binary variable taking the value of one if importer and exporter were ever part of the same country.[8] We also use two binary variables, which we constructed from the WTO database on Regional Trade Agreements, for the presence of a free trade agreement or a customs union between a pair of countries.

3.2. Intensities in cognitive skills and physical abilities

Estimating the effect of age-dependent skills on trade flows is the main focus of this paper, and in what follows we provide a detailed discussion of how the industry-level measures of intensities in age-dependent skills were constructed.

The online Appendix A describes two categories of age-dependent skills – cognitive and physical – and reviews the literature that analyses the evolution of these skills over the course of an individual's life. For cognitive skills, the existing empirical evidence suggests that while some cognitive functions decline with increasing age, others improve. Nearly all studies that analyze the relationship between verbal abilities and communication skills on one hand and age on the other document improvement in those skills for workers of all ages. In contrast, there is convincing evidence that many other cognitive skills deteriorate significantly with age. A series of studies that rely on large-scale longitudinal data from various countries and using different cognitive tests report that memory, divided attention,[9] and the speed of information processing decline after the age of 30–50.[10] Finally, the negative impact of aging on nearly all aspects of physical and psychomotor skills – such as muscular strength, stamina, coordination, and dexterity – is well documented in the medical literature.[11]

To construct industry-level measures of intensity in cognitive skills and physical abilities,[12] we use information on occupational composition for every industry, obtained from the US Bureau of Labor Statistics. Occupational employment shares were matched though a common occupational classification (7-digit Standard Occupational Classification) to the information on the importance of different skills and abilities across occupations, retrieved from the Occupational Information Network (O*NET) database. Using occupational employment shares as weights, we construct an industry-level measure of intensity in a particular skill as a weighted average of the importance of that skill across occupations within an industry. Therefore, for a given skill, the variation in intensity of its use across industries comes from the differences in occupational composition between industries. At the same time, the within-industry variations in intensities of different skills comes from the variation in the importance of those skills between occupations.

To quantify the importance of cognitive skills and physical abilities for different occupations, we use the O*NET database. O*NET ranks all occupations in several dimensions which are closely related to the age-depreciating skills. The importance of speech and language abilities between occupations is captured by the following four skill indicators from the O*NET database: *oral comprehension*, *oral expression*, *written comprehension*, and *written expression*. The intensities in memory and divided attention are constructed from the O*NET indicators of importance of *memorization* and *time sharing*, respectively. The speed of information processing is captured by the indicators on *perceptual speed* and *speed of closure*. Averaging these indicators across occupations within industries, we obtain eight measures of industry-level intensities in cognitive skills. Given the high degree of correlation between cognitive skill indicators (see Tables 1A and 2A in the online Appendix), we group four language indicators into a single indicator for age-appreciating cognitive skills, cog_app_i, using the principle component analysis (PCA).[13] Similarly, the four indicators associated with age-declining cognitive skills were also grouped into one measure for age-depreciating cognitive skills, cog_dep_i. Panels A and B of Table 3A report the results of the PCA. The third column shows the total variance accounted for by each factor and the last column reports factor loadings.

[8] All of these variables were obtained from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII).

[9] Divided attention is the ability to process information from two or more sources at the same time or to switch from one task to another.

[10] See, for example, Schaie (1986), Schaie (1994), Salthouse (1998), Salthouse (2009), and Singh-Manoux et al. (2012).

[11] See de Zwart and Frings-Dresen (1995) and Hedge (2005) for a survey of literature that documents declining physical capabilities with age.

[12] The online Appendix B describes the construction of the skill intensity variables in more details.

[13] See Jolliffe (2002).

For physical abilities, we construct nine industry-level measures of skill intensities based on the O*NET questions capturing the importance of dynamic flexibility, dynamic strength, explosive strength, extent flexibility, gross body coordination, gross body equilibrium, stamina, static strength, and trunk strength. As with the cognitive skills, all nine indicators were combined into a single indicator for physical abilities, $physical_i$, through the PCA.

The industry-level intensity in age-dependent skills is constructed relative to a reference cognitive skill the choice of which is determined by two considerations. First, it should not be affected by aging; otherwise, it could confound the effect of the age-dependent variables. Second, because cog_app_i and cog_dep_i are highly correlated, most likely due to high degree of complementarity between the two groups of cognitive skills, the reference skill should also be positively correlated with age-dependent skills in order to break multicollinearity between cog_app_i and cog_dep_i. We choose inductive reasoning as the benchmark reference factor. While some studies find that older individuals perform worse on reasoning tests, Salthouse (2010) (and many subsequent studies) demonstrates that this finding simply reflects the slower speed of information processing by older individuals because reasoning tests are usually administered under tight time limits. Salthouse (2010) confirms that reasoning and ability to process complex problems show no little evidence of decline with age when test participants are given enough time to respond to questions. In Section 4.2 we demonstrate the robustness of our results to alternative reference skills, such as deductive reasoning, fluency of ideas, and information ordering.

Table 1 lists the ten most and the ten least intensive occupations for physical and both types of cognitive skills. Many of the occupations that are the most intensive in age-appreciating skills are related to sales, where oral and written communication skills are critical. The top of the list for age-depreciating skills is dominated by various machine setters and operators, for whom coordination, divided attention, and perceptual speed are the most important. It is important to note that many of the least age-depreciation intensive occupations are high-skill occupations that are not intensive in physical skills. This results in strong positive correlation between cog_dep_i and $physical_i$ measures and negative correlation with human capital measures (see Table 2). Therefore, multicollinearity between factor

Table 1
Occupations with extreme skill intensities.

10 most skill intensive occupations			10 least skill intensive occupations		
Rank	SOC	Occupation	Rank	SOC	Occupation
Age-appreciating cognitive skills					
1	273042	Technical writers	1	516051	Sewers, hand
2	113111	Compensation and benefits managers	2	191022	Microbiologists
3	434151	Order clerks	3	517021	Furniture finishers
4	414012	Sales representatives, except technical and scientific products	4	499071	Maintenance and repair workers, general
5	414011	Sales representatives, technical and scientific products	5	514052	Pourers and casters, metal
6	519083	Ophthalmic laboratory technicians	6	519031	Cutters and trimmers, hand
7	113061	Purchasing managers	7	517041	Sawing machine setters and operators
8	113121	Human resources managers	8	519198	Helpers–production workers
9	439031	Desktop publishers	9	519123	Painting, coating, and decorating workers
10	433061	Procurement clerks	10	518093	Petroleum pump system operators, refinery operators, and gaugers
Age-depreciating cognitive skills					
1	514194	Tool grinders, filers, and sharpeners	1	191022	Microbiologists
2	516064	Textile winding, twisting, and drawing out machine setters, operators, and tenders	2	172031	Biomedical engineers
3	519041	Extruding, forming, and pressing machine setters and operators	3	452041	Graders and sorters, agricultural products
4	519021	Crushing, grinding, and polishing machine setters and operators	4	191021	Biochemists and biophysicists
5	537051	Industrial truck and tractor operators	5	172131	Materials engineers
6	519111	Packaging and filling machine operators	6	111011	Chief executives
7	434151	Order clerks	7	172071	Electrical engineers
8	537072	Pump operators, except wellhead pumpers	8	192031	Chemists
9	514021	Extruding and drawing machine setters, operators, and tenders, metal and plastic	9	172041	Chemical engineers
10	519121	Coating, painting, and spraying Machine setters and operators	10	172112	Industrial engineers
Physical abilities					
1	475051	Rock splitters, quarry	1	131081	Logisticians
2	453011	Fishers and related fishing workers	2	271024	Graphic designers
3	499044	Millwrights	3	172131	Materials engineers
4	537062	Laborers and freight, stock, and material movers, hand	4	112021	Marketing managers
5	472211	Sheet metal workers	5	271021	Commercial and industrial designers
6	472111	Electricians	6	173013	Mechanical drafters
7	499096	Riggers	7	172141	Mechanical engineers
8	519197	Tire builders	8	172031	Biomedical engineers
9	512011	Aircraft structure, surfaces, rigging, and systems assemblers	9	173012	Electrical and electronics drafters
10	519012	Separating, filtering, and still machine setters, and operators	10	273042	Technical writers

Note: Only occupations with at least 10% employment in manufacturing sector are included in the rankings.

Table 2
Correlation between industry-level intensities in factor inputs.

		(1)	(2)	(3)	(4)	(5)
(1)	*cog_app*	1				
(2)	*cog_dep*	−0.23	1			
(3)	*physical*	−0.40	0.93	1		
(4)	*capital intensity*	0.39	−0.91	−0.24	1	
(5)	*skill intensity*	0.63	−0.70	−0.83	0.35	1

Note: correlation coefficients are calculated over 86 3-digit manufacturing NAICS industries.

intensities remains a problem and will be a concern in the empirical analysis.

3.3. Other data

Our primary measure of a country's age structure is the median age, obtained from the United Nations.[14] As an alternative, we also use the share of young workers in the labor force, constructed as a fraction of 20–40 year-olds in the 20-to-65 age group. The information on the age structure of population comes from the World Development Indicators database, maintained by the World Bank.

Industry-level measures of intensities in skilled labor and physical capital are derived from the US Census of Manufacturers for 1998.[15] Capital-intensity is constructed as the ratio of capital stock over total employment, and skill intensity as the share of non-production workers in total employment.

Data on a country's stock of physical capital, measured in 2005 prices, is retrieved from the Penn World Table. Human capital stock for the year 2000 is obtained from Barro and Lee (2013) and is measured as a share of population with secondary and tertiary education.[16] The full sample includes 136 exporting countries, 155 importing countries, and 83 industries.

4. Results

4.1. Baseline results

Table 3 reports estimation results for Eq. (1) with the country's median age used as a proxy for the stock of age-depreciating skills.[17] For comparability, all tables report standardized coefficients. The first column confirms the main prediction of the Heckscher–Ohlin model for capital and skilled labor: countries that are abundant in capital and skilled labor export more in industries which use those factors intensively.[18] Adding $I_i^k \times \mathrm{Age}_c$ interactions to the main specification in columns (2) to (5), we find that all coefficients are consistent with the theoretical model and are statistically significant,[19] thus supporting the hypothesis that age differences across countries are the source of comparative advantage in international trade. The estimates in columns (2)–(5) reveal that older countries export more in industries which use age-appreciating cognitive skills intensively and less in industries which are intensive in physical and age-depreciating cognitive skills.

Column (6) of Table 3 reports results for a complete specification with all skill measures included in the regression. This extension does not substantially affect the coefficient estimates for the two types of cognitive skills, but the coefficients on physical skills become insignificant. However, the latter result is likely to be plagued by strong multicollinearity arising from high correlation between physical and age-depreciating cognitive skill intensities. In a regression of $physical_i \times Age_c$ on $cog\_dep_i \times Age_c$ and other explanatory variables from Eq. (1), we find an R-square of 0.93, indicating a high degree of linear relationship between the two variables, which prevents us from identifying partial effects of either variable.

Because median age and skill intensities are standardized across countries and industries, respectively, we can use the estimates for Eq. (2) in Table 3 to directly compare the magnitudes of the effect of different factors of production on trade. Suppose industry i has one standard deviation higher intensity in all factors of production. Then, focusing on the most complete specification in column (6), a country which has one standard deviation higher median age than another will export 11% more in industries which are intensive in age-appreciating skills, 15.2% less in industries which use age-depreciating skills intensively, and 6.2% and 5.2% more in capital and labor intensive industries, respectively. [20,21]

4.2. Robustness tests

In Table 4 we present several extensions of the main specification and explore the robustness of our results to changes in econometric specification and definitions of the key variables.

4.2.1. Alternative measures of human capital

In column (1) of Table 4 we report the estimates of Eq. (1) with the age composition being measured by the share of young workers in the labor force, which we define as the fraction of 20–40 year-olds in the 20-to-65 age group. The advantage of this measure over the median age is that it represents the age structure of the working-age population only. At the same time, since we do not know the exact onset of the age-related cognitive decline, which may also vary across age-dependent skills, the age threshold of 40 in the definition of young workers is somewhat ad hoc.[22] The estimates in column (1) are similar in magnitude to those obtained with the median age (note that since the share of young workers is inversely related to the population's median age, the coefficient estimates are of opposite signs when median age and the share of young workers are used). In column (2) we include the interaction of industries' skill intensity and countries' abundance in skilled young workers (the share of young workers with secondary and tertiary education) to control for the differences in human capital of young workers across countries. The coefficients of interest remain broadly the same as before.

[14] See Table 7A in the online Appendix for information on median age in 2000 and change in median age between 1962 and 2000 for all exporting countries in our sample.

[15] Under the assumption of no factor intensity reversals, the ranking of factor intensities across industries does not vary by country.

[16] Our three alternative measures are the average years of schooling attained, the share of workers with at least primary education, and the share of workers having completed tertiary schooling.

[17] Results remain qualitatively similar when Eq. (1) is estimated with exports aggregated across destination countries. These results are reported in Table 4A in the online Appendix.

[18] In Table 5A in the online Appendix we show that the results are robust to alternative measure of human capital.

[19] The estimates remain statistically significant if standard errors are clustered by exporter.

[20] With the standard deviation of log exports being equal to 3.36, the difference in exports of k-factor intensive industry between the two countries is $exp(3.36 \cdot \beta_k)$. The standard deviation of the median age is equal to 7.4 in our sample.

[21] It is not unusual in the literature to find the effect of various institutional factors of trade to be more important than the effect of capital and skilled labor (see for example Bombardini et al., 2012, and Nunn, 2007). One possible explanation is the measurement problem inherent to both variables: the definitions of physical capital vary a lot across countries and the number of years of schooling does not reflect cross-country differences in the quality of education systems.

[22] This threshold level is motivated by studies on aging and cognition, surveyed in the online Appendix A, which show that cognitive decline begins at around 30 and after 40 reaches the level of 20 year olds. Changing the threshold to 35 or 45 does not alter our main estimation results.

Table 3
Baseline specification with median age.

	(1)	(2)	(3)	(4)	(5)	(6)
$Cog\_app_{\,i}\times$		0.040**			0.030**	0.031**
$(Median\ age)_c$		(8.17)			(6.10)	(5.73)
$Cog\_dep_{\,i}\times$			−0.058**		−0.029*	−0.042**
$(Median\ age)_c$			(−10.59)		(−2.10)	(−2.83)
$Physical_{\,i}\times$				−0.063**	−0.036*	−0.013
$(Median\ age)_c$				(−10.62)	(−2.46)	(−0.83)
$(Capital\ int.)_i\times$	0.030**	0.018**	0.029**	0.024**		0.018**
$(Capital\ abund.)_c$	(6.23)	(3.60)	(5.83)	(4.66)		(3.46)
$(Skill\ int.)_i\times$	0.049**	0.038**	0.023**	0.018**		0.015**
$(Skill\ abund.)_c$	(10.31)	(7.59)	(4.16)	(3.17)		(2.64)
ln(*Distance*)	−0.358**	−0.359**	−0.358**	−0.358**	−0.353**	−0.358**
	(−107.13)	(−106.94)	(−106.92)	(−107.15)	(−110.99)	(−107.20)
Customs union dummy	0.189**	0.192**	0.190**	0.191**	0.188**	0.192**
	(21.20)	(21.61)	(21.44)	(21.56)	(22.05)	(21.65)
FTA dummy	0.110**	0.109**	0.108**	0.108**	0.105**	0.108**
	(16.44)	(16.15)	(16.09)	(16.06)	(16.14)	(16.11)
Common border	0.218**	0.215**	0.214**	0.214**	0.213**	0.214**
	(32.43)	(31.66)	(31.63)	(31.60)	(33.92)	(31.53)
Common language	0.095**	0.097**	0.097**	0.097**	0.066**	0.097**
	(13.44)	(13.68)	(13.59)	(13.60)	(9.73)	(13.66)
Common ethnicity	0.036**	0.035**	0.036**	0.035**	0.069**	0.035**
	(5.27)	(5.17)	(5.25)	(5.22)	(10.68)	(5.18)
Ever in colonial relationship	0.195**	0.196**	0.196**	0.197**	0.175**	0.197**
	(22.74)	(22.77)	(22.90)	(22.92)	(20.87)	(22.91)
Common colonizer	0.242**	0.243**	0.241**	0.241**	0.242**	0.242**
	(26.01)	(25.83)	(25.76)	(25.76)	(28.01)	(25.84)
Current colony	0.234**	0.231**	0.230**	0.230**	0.143**	0.230**
	(5.90)	(5.80)	(5.78)	(5.79)	(4.06)	(5.77)
Ever same country	0.047**	0.050**	0.049**	0.049**	0.053**	0.049**
	(4.47)	(4.69)	(4.68)	(4.65)	(5.28)	(4.66)
Importer-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Trade costs controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.551	0.553	0.554	0.554	0.557	0.555
N	414,918	413,466	413,466	413,466	462,045	413,466

Notes: The dependent variable is the normalized natural logarithm of exports from country *c* to country *p* in industry *i* in year 2000. Standardized beta coefficients are reported, with t-statistics in parentheses. Robust standard errors are clustered by exporter-industry.
* Significant at 5%.
** Significant at 1%.

4.2.2. Alternative reference skills

In Section 3 we emphasized the need to normalize age-dependents skill intensities by a reference age-neutral skill. In the benchmark specification *inductive reasoning* was used as a reference skill. We now demonstrate the robustness of our main results to alternative reference skills. Column (3) reports regression estimates when all age-dependent skill intensities are normalized by the O*Net measure of *deductive reasoning*. The estimates of the key coefficients are very similar to the benchmark results, both in terms of the magnitudes and significance levels. Unfortunately, for other cognitive skill measures available in the O*Net there is no reliable evidence on their age-neutrality. In columns (4) and (5) we show results with age-dependent skills normalized by *fluency of ideas* and *information ordering* O*Net indicators. Both are reflective of reasoning and problem solving skills but may also be capturing importance of some other, potentially age-dependent, cognitive skills. Taking these data limitations into consideration, the results are still supportive of the main hypotheses — coefficient estimates on cognitive skill interactions preserve expected signs and are statistically significant at a 90% confidence level.

4.2.3. Controlling for bilateral trade costs

In column (6) of Table 4 we estimate Eq. (1) with importer-product and exporter–importer fixed effects. The latter is used to account for unobserved country-pair heterogeneity that does not vary across industries and is not captured by distance and other controls for bilateral trade costs. While this extension of the model substantially improves the fit to the data, it does not materially affect the coefficients of interest.

4.2.4. Zero trade flows

A potential problem with estimating Eq. (1) by the OLS is that it discards observations with zero trade flows, which constitute about two-thirds of the data. Excluding those observations from the sample can result in systematically biased OLS coefficients (Silva and Tenreyro, 2006; Helpman et al., 2008). We address this problem by using a two-step procedure to correct for sample selection as in Helpman et al. (2008).[23] The second stage results, reported in column (7) of Table 4, do not suggest that sample selection affects the OLS estimates as all coefficients remain unchanged.

4.2.5. Results for other time periods

In columns (8) and (9) we demonstrate that the results are not confined to a particular time period by estimating Eq. (1) using trade and median countries' age data for the years 2010 and 1970, respectively. The coefficients on cognitive skills remain qualitatively unchanged. An important difference with the benchmark results

[23] As in Helpman et al. (2008), we use the interactions of market entry regulation costs in importing and exporting countries to identify variation in the extensive export margin at the first stage of the estimation procedure.

Table 4
Robustness tests.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$Cog\_app_i \times$	−0.029**	−0.028**	0.030**	0.015^{+}	0.011^{+}	0.034**	0.037**	0.040**	0.034**	0.031**	0.051**
$(Age)_c$	(−5.66)	(−5.38)	(6.14)	(1.75)	(1.88)	(6.06)	(6.12)	(7.24)	(3.74)	(5.80)	(3.38)
$Cog\_dep_i \times$	0.045**	0.046**	−0.040*	−0.050**	−0.089**	−0.044**	−0.051**	−0.052**	−0.041*	−0.040**	−0.121**
$(Age)_c$	(3.12)	(3.19)	(−2.43)	(−4.81)	(−4.60)	(−2.88)	(−3.12)	(−3.41)	(−2.05)	(−2.73)	(−8.72)
$Physical_i \times$	0.005	−0.000	−0.022	−0.013	0.016	−0.011	−0.017	−0.005	−0.038^{+}	−0.016	
$(Age)_c$	(0.34)	(−0.02)	(−1.28)	(−0.93)	(0.83)	(−0.64)	(−0.94)	(−0.28)	(−1.65)	(−0.95)	
$(Capital\ int.)_i \times$	0.021**	0.021**	0.017**	0.026**	0.027**	0.019**	0.018**	0.010^{+}	−0.090	0.019**	0.158**
$(Capital\ abund.)_c$	(4.30)	(4.41)	(3.33)	(5.06)	(5.19)	(3.61)	(2.76)	(1.90)	(1.40)	(3.58)	(8.88)
$(Skill\ int.)_i \times$	0.019**	0.015**	0.015**	0.018**	0.017**	0.018**	0.024**	0.025**	0.024**	0.008	0.043^{+}
$(Skill\ abund.)_c$	(3.54)	(2.94)	(2.64)	(3.23)	(2.91)	(2.91)	(3.86)	(4.58)	(2.43)	(1.42)	(1.78)
$(Skill\ int.)_i \times$		−0.022**									
$(Skill\ abund.\ young)_c$		(−4.63)									
$(External\ fin.\ Depend.)_i \times$											0.202**
$(Fin.\ development)_c$											(16.77)
$(Contract\ intensity)_i \times$											0.219**
$(Judicial\ quality)_c$											(14.25)
$(Job\ complexity)_i \times$											0.170**
$(Judicial\ quality)_c$											(8.09)
$(Sales\ volatility)_i \times$											0.062**
$(Flexible\ lab.\ markets)_c$											(5.05)
Sample	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	2010	1970	No USA	Chor (2010)
Exporter FE	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Importer–exporter FE	No	No	No	No	No	Yes	No	No	No	No	No
R-squared	0.555	0.555	0.555	0.555	0.555		0.548	0.574	0.529	0.525	0.596
N	411,362	411,362	413,466	413,466	413,466	419,401	297,485	453,390	160,718	395,666	42,332

Notes: In columns (1)–(7) and (10)–(11) the dependent variable is the normalized natural logarithm of exports from country c to country p in industry i in year 2000 IN columns (8) and (9) the dependent variable is exports in years 2010 and 1970, respectively. Standardized beta coefficients are reported, with t-statistics in parentheses. Robust standard errors are clustered by exporter-industry. All specifications include exporter-industry fixed effects and trade costs controls. In columns (1) and (2), $(Age)_c$ is the share of workers 20–40 year-olds in the 20-to-65 age group in country c. In columns (3)–(8) $(Age)_c$ is the median age of population in country c. In columns (3), (4), and (5) industry intensities in all age dependent skills are normalized, respectively, by alternative age-neutral O*Net measures of "deductive reasoning", "fluency of ideas", and "information ordering". Specification (7) includes additional unreported probability of exports obtained from the first stage. Column (11) uses data and empirical specification from Chor (2010).

$^{+}$ Significant at 10%.
* Significant at 5%.
** Significant at 1%.

is the insignificant coefficient on physical capital in both time periods.[24]

4.2.6. Results without the USA

The result that skill-intensities, constructed with the US data for 2000, can equally well predict bilateral trade flows in 1970 and in 2010 suggests that the reverse causality from trade to occupational composition across industries is unlikely to be a problem. Furthermore, if reverse causality were present, it would be stronger for the US trade data. However, excluding the US from the sample (column (10) of Table 4) produces virtually identical results to those in the benchmark specification, which corroborates the conjecture that our main results are not subject to simultaneity bias.

4.2.7. Other determinants of comparative advantage

Recent studies on comparative advantage have identified a number of institutional determinants of trade flows. In what follows we consider four such factors and show that our results are robust to inclusion of these factors. The first one is the level of a country's financial development interacted with industry's dependence on external finance. Manova (2008) proposed that more financially developed countries have a comparative advantage in industries that rely heavily on external financing. The second control is the interaction of a country's ability to enforce contracts and industry-level measure of contract intensity (Nunn, 2007) to capture the holdup problem that may undermine productivity in industries in which relationship-specific investments are important. The third measure is the strength of a country's legal system interacted against a measure of industry's task complexity. Costinot (2009) argued that countries where firms are better able to monitor workers will gain more from task specialization and thus specialize in industries which require many tasks. Lastly, following Cunat and Melitz (2012), we include the interaction of the flexibility of a country's labor markets and industry's output volatility. The data on all four interactions is from Chor (2010)[25] and is recorded at 2-digit SIC-87. We use US Census Bureau concordance to convert our measures of skill-intensities into that format, which results in a reduction in the number of industries from 85 to 20.[26] The estimated coefficients on all four institutional factors are positive and statistically significant, in line with previous studies (column (11) of Table 4). More importantly, the signs and statistical significance of cognitive age-dependent skills remain unchanged.

4.3. Addressing endogeneity of the median age

4.3.1. Instrumenting intensities in age-dependent skills

The key variables in our analysis are the measures of intensity in various skills. Each skill intensity measure is constructed as the weighted average of importance of that skill across occupations within an industry. For the benchmark specification, the data on occupational composition come from the US Bureau of Labor

[24] The cross-section regressions of Eq. (1) for the years 1962, 1980, and 1990, not presented in the paper but available upon request, produce similar results: the coefficients on $(cog\_app_i \times Age_c)$ and $(cog\_dep_i \times Age_c)$ variables are always positive and negative, respectively, and are statistically significant.

[25] We thank Davin Chor for sharing the data with us.

[26] We exclude physical skills from this specification because with only 20 SIC industries the measure becomes highly collinear with the intensity in age-depreciating skills.

Statistics for the year 2012. A potential concern is that these occupational shares could reflect industries' adjustments to changes in relative supply of age-dependent skills caused by accelerated population aging in the US during the last two decades. This would result in endogeneity if industries differ in their ability to adjust to demographic changes. We address this concern by instrumenting I_i^k with factor intensities constructed from occupational shares from 1980, 1990, and 2000 US Census years.

A major issue with using older Census data is the difference between Census occupation classification (COC) and Standard Occupational Classification (SOC) used by the O*Net. Therefore, in order to obtain consistent occupational categories over time and occupational employment shares that could be matched to the O*Net measure of importance of age-dependent skills, we need occupational crosswalks from COS to SOC. COC occupations from 2000 Census data were mapped into SOC using US Census Bureau concordance tables. However, COC occupations from 1980 and 1990 Census are substantially different from SOC and no official crosswalks between the two classifications are available. In this study we employ a crosswalk constructed by Firpo et al. (2011). The limitation of this approach is that pre-2000 COC occupations cannot be precisely mapped to SOC, introducing a serious measurement error in factor intensity measures.[27] However, if the measurement error resulting from imprecise concordance tables is independent of the error term in Eq. (1), it should not affect the quality of instruments. Another source of measurement error in the instruments results from different industry classifications used in 1980 and 1990 Census data, that were first converted into 1987 SIC and then into 1997 NAICS using crosswalk tables provided by the US Census Bureau.[28] The interactions of country' median age and industry' skill intensities in model (1) are instrumented with $\hat{I}_i^k \times Age_c$ variables, where $\hat{I}_i^k$ is the intensity in factor k constructed with either 1980, 1990, or 2000 employment shares.

Columns (1), (2) and (3) of Table 5 present the estimation results for Eq. (1) when instruments for industry-level intensity in age-dependent skills are constructed with occupational composition in years 1980, 1990, and 2000, respectively. Column (4) reports results with all three sets of instruments together, and column (5) shows the estimates for the benchmark OLS specification using the same sample as in column (4). In this exercise, we do not report the estimates for physical skill interaction because it cannot be identified separately from the coefficient on cognitive age-depreciating skills due to strong multicollinearity in instruments. The first stage results are very strong across all specifications — all of our instruments have correct signs and are highly significant. The results of the second stage are consistent with previous findings, with both coefficients on age-dependent cognitive skills preserving correct signs and statistical significance. Results are similar when all instruments are used together in column (4), and the Hansen overidentification test does not reject the hypothesis of exogeneity of instruments.

A notable difference between the IV and OLS results is the magnitude of the coefficient estimates. When I_i^k are instrumented with factor intensities constructed from 2000 data, the magnitudes of coefficients are very similar to the benchmark estimates. However, when instruments are constructed with 1980 and 1990 data, the coefficient on age-appreciating skills falls by half and the coefficient on age-depreciating cognitive skills doubles. The implications of the changes in the magnitudes of the coefficients are unclear. It is hard to understand the striking difference between the IV estimates for 1990 and 2000, given that there is little change in magnitudes from 1980 to 1990 and from 2000 to 2010. It seems very unlikely that there was a sharp structural change in employment composition in the decade from 1990 to 2000, but not in the decades before 1990 and after 2000. The more plausible explanation for the difference in pre- and post-2000 results is the measurement error in 1980 and 1990 instruments caused by a major change in occupational codes in 2000 Census, and this concern reinforces the attractiveness of an estimator that does not rely on instrumental variables for factor intensities.

4.3.2. Instrumenting demographic composition

The OLS estimates of Eq. (1) provide consistent estimates only if age composition is independent of other country characteristics which may have a differential effect on productivity in industries depending on their intensities in age-dependent skills. While this may be the case, in this and the following sections we explore two additional strategies to identify the effect of age composition on comparative advantage using the instrumental variable approach and alternative measure of a country's effective endowment in age-dependent skills.

It is hard to find a purely exogenous instrument for demographic composition — we lack measures that can be convincingly argued to affect trade flows only through the effect on a population's age structure. Given that limitation, our strategy is to employ several instruments which explain different sources of variation in the median age and rely on weaker identification assumptions than the OLS. The first instrument is the birth rate per capita in 1960, which is highly correlated with the median age in 2000 but is independent of many socioeconomic influences that took place between 1960 and 2000, such as changes in industrial policies or reduction in gender disparities in education system.[29] The data for this instrument is obtained from the World Development Indicators database.

Our second instrument for a country's demographics is the religious composition. It is well established that religious families have higher fertility rates than non-believers. Many demographic studies also demonstrate that religious affiliation is an important determinant of demographic behavior. In particular, countries with large Muslim and Catholic populations tend to experience higher fertility rates. Our instrument for median age is based on six variables measuring the share of population in five main religious groups – Buddhism, Christianity, Hinduism, Islam and Judaism – plus the share unaffiliated with any religion.[30] Other religion groups serve as an omitted category. We instrument the interactions of a country's median age and industry's skill intensities in model (1) with $I_i^k \times \widehat{Age}_c$, where $\widehat{Age}_c$ is obtained as fitted values from the cross-country regression of median age on religious group shares.[31]

The choice of our third instrument is motivated by Spolaore and Wacziarg (2014), who argue that the variation in fertility decline among European countries is related to their cultural distance to France, where the demographic revolution had begun. The authors confirm that genetic distance from France, which captures ancestral and cultural differences, is a strong predictor of the onset of demographic transition to lower fertility levels. We use the data from Spolaore and Wacziarg (2009) to construct genetic distance of each

27 The significance of the measurement error caused by different occupational classifications becomes apparent when factor intensities constructed with employment shares from different census years are compared with each other. The coefficient of correlation in skill intensities across industries in 1980 and 1990, which are based on a very similar COC classifications that can be easily mapped one-to-one, is 0.96–0.97. However, the correlation with the measure based on SOC occupational classification in 2012 is 0.61 for age-appreciating and 0.74 for age-depreciating cognitive skills.

28 Because Census industry classification is more aggregated than 4-digit NAICS, we exclude industries that cannot be precisely mapped to the broader NAICS classification. 2000 Census data record industrial affiliation at both Census and NAICS industry classifications. However, many observations are recorded at 3-digit NAICS only, and we drop those from our sample.

29 We continue to assume that industry factor intensities are exogenous and instrument $I_i^k \times Age_c$ variables with interactions of I_i^k and the instruments for median age.

30 The data is retrieved from the Pew Research Center.

31 The R-squared from this regression is 0.34 and the p-value of the F-test for joint significance of religious group share variables is 0.00.

Table 5
Instrumenting demographic composition and factor intensities.

	(1) IV-GMM	(2) IV-GMM	(3) IV-GMM	(4) IV-GMM	(5) OLS	(6) IV-GMM	(7) IV-GMM	(8) IV-GMM	(9) IV-GMM
$Cog\_app_{\,i}\times$	0.017^{**}	0.015^{*}	0.021^{**}	0.034^{**}	0.042^{**}	0.037^{**}	0.038^{**}	0.036^{*}	0.031^{**}
$(Median\ age)_c$	(2.88)	(2.26)	(3.32)	(4.54)	(6.18)	(5.85)	(3.98)	(2.32)	(4.95)
$Cog\_dep_{\,i}\times$	-0.083^{**}	-0.093^{**}	-0.029^{**}	-0.062^{**}	-0.036^{**}	-0.040^{**}	-0.057^{*}	−0.004	-0.045^{*}
$(Median\ age)_c$	(−8.49)	(−10.50)	(−2.98)	(−8.06)	(−5.16)	(−2.62)	(−1.97)	(−0.11)	(−2.54)
$Physical_{\,i}\times$						−0.013	−0.026	−0.004	−0.010
$(Median\ age)_c$						(−0.58)	(−0.82)	(−0.09)	(−0.55)
$(Capital\ int.)_i\times$	0.019^{**}	0.020^{**}	0.020^{**}	0.010	0.007	0.016^{**}	0.013^{+}	0.017^{*}	0.016^{*}
$(Capital\ abund.)_c$	(3.69)	(3.05)	(3.02)	(1.16)	(0.94)	(3.00)	(1.92)	(1.96)	(2.55)
$(Skill\ int.)_i\times$	0.004	0.001	0.031^{**}	0.012	0.021^{**}	0.016^{*}	0.001	0.031^{*}	0.007
$(Skill\ abund.)_c$	(0.53)	(0.05)	(3.97)	(1.64)	(3.07)	(2.50)	(0.05)	(2.27)	(1.05)
Instruments for facor intensities	Factor intensities from 1980	Factor intensities from 1990	Factor intensities from 2000	All	–	–	–	–	–
Instrument for median age	–	–	–	–	–	Birth rate, 1960	Religious composition	Genetic distance to France	All
Hansen J-test (p-value)				0.00					0.48
N	299,483	299,483	255,453	235,587	235,587	409,910	409,545	309,736	309,736

Notes: The dependent variable is the normalized natural logarithm of export from country c to country p in industry i in year 2000. Standardized beta coefficients are reported, with t-statistics in parentheses. Coefficients on $Physical_i \times (Median\ age)_c$ are not reported in columns (1)–(5) due to high multicollinearity of first stage instruments. All standard errors are obtained by bootstrap with 100 replications and are clustered by exporter-industry. All specifications include exporter fixed effects, importer-industry fixed effects, and controls for bilateral trade costs.
$^{+}$ Significant at 10%.
* Significant at 5%.
** Significant at 1%.

country in our sample to France and use it as a source of exogenous variation in demographic composition to predict the median age of populations in different countries. That instrument performs well in the first stage. As expected, the coefficient on the genetic distance in the regression for median is negative and the t-statistics of the test of significance equals −9.31. It is important to emphasize that genetic distance and religious composition capture different sources of variation in median age as the coefficient of correlation between the median age predicted from these two models is only 0.16.

We present the results with the birth rate in 1960 in column (5) of Table 5. The instrument performs well in the first stage: the p-value for the Angrist–Pischke weak instrument test is always equal to 0.0 and the F-statistics from the first stage regression are in the range from 93 to 112.[32] The IV estimations results are consistent with our previous findings: the coefficient on age-appreciating cognitive skills is positive and highly significant, and the coefficients on age-depreciating cognitive and learning skills are negative.

Results with religious composition and genetic distance as instruments are presented in columns (6) and (7) of Table 5. The corresponding Kleibergen–Paap F-statistics for the endogenous variables is always greater than 20, which is well above the critical values tabulated by Stock and Yogo (2005), and suggests that a bias from weak instruments is unlikely to be a concern. As can be seen, the estimates with the religious composition are very similar to OLS and are consistent with our earlier findings about the effect of demographics on comparative advantage. When the median age is instrumented with genetic distance, the effect of age-appreciating is also in line with our expectations; however, the coefficient on age-depreciating cognitive skills becomes small and insignificant. This result should not be particularly surprising. Although genetic distance from France is a statistically significant determinant of the median age, it is not capturing many other sources of exogenous variation in demographic composition across countries which may affect comparative advantage. Results with all three instruments together are reported in column (8) of Table 5. Again, these results provide little evidence for the endogeneity of median age: the coefficient estimates are not much different from the OLS estimates and the overidentification test cannot reject the hypothesis of exogeneity of instrument.

Overall, while the exclusion assumptions underlying our instruments can be argued, the three instruments that we employ isolate different sources of potentially endogenous variation in the median age, and yet the results paint a similar picture to that documented previously in Section 4.1.

4.3.3. An alternative measure of the stock of age-depreciating cognitive skills

Our second strategy to confirm that the main result of this paper is not driven by correlation between age composition and other unobservable determinants of a country's comparative advantage is to use an alternative measure for a country's relative productivity in age-dependent skills. To this point, we have used a country's age structure to proxy for its effective endowment of age-dependent skills in all regression specifications. In what follows we use an alternative proxy variable for a country's effective endowment of one of the age-depreciating skills – memory – and show that trade data is still consistent with predictions of our theoretical model.

The proposed measure is based on a standardized memory test conducted in 27 different countries among seniors.[33] The test consists of verbal registration and recall of a list of ten words 1 min after an interviewer read them to respondents. The test score is the fraction of the number of words recalled correctly. This test provides an alternative measure of cross-country differences in effective memory stocks and in aggregate productivities in memory-intensive tasks. Therefore, all else being equal, countries with higher memory

[32] The full set of the first stage results is presented in Table 8A in the online Appendix.

[33] The detailed test description can be found in the online Appendix C. Although the sample is overrepresented by countries with high median age, there are four countries from the first and second quartiles of the median age distribution.

tests scores, both unconditional and conditional on observable characteristics, are expected to have comparative advantage in memory-intensive industries, just like countries with a younger labor force. However, the main advantage of the memory test is that, for a given age cohort, it provides a cross-country variation in the quantity and quality of skill endowment which is largely independent of the variation in population aging and demographic composition, and is thus not susceptible to the possible omitted variable bias which may be inherent to the median age variable. Furthermore, memory test score is a measure of memory quality and is directly related to workers' productivity in tasks that are intensive in memory use. Hence, the test could in principle be used to separate the Ricardian effect of population aging from the Heckscher–Ohlin effect. However, it is practically difficult to separately identify the two effects given the small number of countries in the sample, so we do not pursue this approach here.

In column (1) of Table 6 we present the results for the benchmark specification (1) using median age as a proxy for skill endowment but with memory as a single cognitive skill. As with the composite age-depreciating skill variable, the coefficient on memory intensity interacted with a country's median age is negative and statistically significant. Thus, consistent with our previous findings, younger countries capture larger market shares in industries where employees are required to have good memory. In column (2) we use the unconditional word recall test score as a measure of skill endowment, averaged among individuals of 50–55 years of age within each country in order to control for different age composition of respondents across countries. The effect of the interaction remains large and statistically significant at a 5% confidence level.[34] Column (3) shows that results of column (1) remain robust when estimated for the sample of countries for which the memory test scores are available. It is also important to note that the coefficient estimates with memory test scores are remarkably similar to the estimates with the median age. Since the two variables rely on different sources of variation in memory endowment to identify country's comparative advantage in memory-intensive industries, we believe that the similarity of the estimates is reassuring that neither set of results is driven by the omitted variable bias.

To make our results with the memory test more comparable to those for the median age, we use memory test scores to identify the contribution of demographic structure on comparative advantage. All test participants complete a survey questionnaire, which includes information on individuals' age and gender. The survey also collects standard data on the highest completed education and the number of years of schooling, which makes it comparable across countries. In order to isolate the effect of age and education from other sources of variation in cognitive skills, we first obtain elasticities of memory with respect to age and education from a regression of individual memory test score on person's age and years of schooling.[35] We then use these elasticities, estimated from micro data, along with the information on average age and years of schooling of population in different countries to construct in-sample predicted memory endowment at the country level. The obtained measure of memory endowment captures the variation in memory test scores across countries which is due to demographics and educational attainment only. The results, presented in column (4), are very similar to the benchmark. Next, we use the elasticities estimated in column (4) to construct the out-of-sample predicted value of the test score for all countries in our trade data sample. Interacting this measure of skill endowment with memory intensity in column (5) leaves the main result unchanged. Finally, in column (6) we construct a measure of skill endowment for senior workers only. At the first stage, we estimate the effect of age and education level for every 5-year cohort group among people aged 50–65, and construct a country-level measure of effective memory endowment using the data on educational attainment reported in Barro and Lee (2013) for every country and 5-year age group. The results are robust.

Overall, Table 6 shows that no matter which measure of skill endowment we use, the coefficient on its interaction with sectorial memory intensity is always of the expected sign and statistically significant, with the magnitude of the coefficient being remarkably stable across specification.

4.4. Extensions

4.4.1. The role of education and health care in age-related cognitive development

The use of a country's demographic composition as a proxy for unobserved endowment of age-dependent skills in Eq. (10) relies on the assumption that the stock of each age-dependent skill is a linear function of the median age only. However, age-related decrements in cognition may not be entirely due to biological aging process. The presence of other factors that affect cognitive functioning at different ages may result in biased estimates of β_k coefficients if the cross-country variation in those factors is correlated with demographics. In this subsection we consider two additional factors of cognitive development and demonstrate that our main findings remain quantitatively and statistically robust to alternative definitions of the proxy variables for the age-dependent skills.

The first such factor is the quality of the health care system. Results of numerous medical studies reveal a strong effect of psychological and systemic diseases on cognitive functioning for individuals of all ages,[36] but the effect is particularly pertinent to older individuals, who are subject to increased incidence and prevalence of such diseases. Thus, insofar as the age-related cognitive and physical decline is driven by deteriorating health conditions, it may, to some extent, be reversible with appropriate medical treatment. In this way, an efficient health care system could remediate the effect of population aging on the effective stock of cognitive skills and physical abilities.

The second factor which may affect the relationship between aging and cognitive functioning is education and cognitive training. A large body of literature documents a positive relationship between education and old age cognitive functioning, and several recent studies have identified a causal effect of childhood schooling on cognitive abilities (primarily on memory) at older ages by exploiting exogenous variation in education policies (e.g. Glymour et. al., 2008; Banks and Mazzonna, 2012). Moreover, it has also been established that education and training can moderate the course of intellectual decline as individuals get older (Schaie, 1986 and Schaie, 2005). Thus, we may expect that increasing rates of educational attainment, especially among older workers, can increase the effective stock of age-dependent cognitive skills.

Based on the above evidence, we extend Eq. (10) by allowing for country c's endowment of age-dependent skill k to be a function of the median age (Age_c), the quality of the health care system ($Health_c$), and education level ($Educ_c$)

$$\ln F_c^k = \sigma_0^k + \sigma_1^k Age_c + \sigma_2^k Health_c + \sigma_3^k Educ_c, \tag{4}$$

[34] Note that since the test score measures skill endowment, while the median age measures the depreciation of skill endowment, the expected sign of the interaction is positive with the former measure and negative with the latter.

[35] These elasticities are estimated at −0.005 and 0.011, respectively (column 2 of Table 9A in the online Appendix). In this regression we also control for country fixed effects. The main result is unchanged when age enters non-linearly.

[36] See Stern and Carstensen (2000) for a survey of the literature. In Subsection 4.3.3 we also provide some evidence of the relationship between health and cognition.

Table 6
Alternative measure of the stock of cognitive skills.

	(1)	(2)	(3)	(4)	(5)	(6)
$Memory\_I_i \times$	−0.022**		−0.019*			
$(Median\ age)_c$	(−4.55)		(−2.08)			
$Memory\_I_i \times$		0.020*		0.020*	0.027**	0.019**
$Score_c$		(2.45)		(2.49)	(5.90)	(3.69)
$(Capital\ int.)_i \times$	0.038**	0.057**	0.054**	0.049**	0.036**	0.036**
$(Capital\ abund.)_c$	(7.46)	(4.75)	(4.45)	(4.01)	(7.10)	(7.06)
$(Skill\ int.)_i \times$	0.043**	0.032**	0.033**	0.052**	0.048**	0.048**
$(Skill\ abund.)_c$	(8.81)	(4.14)	(4.36)	(6.72)	(9.96)	(10.15)
Importer-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Trade costs controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.552	0.669	0.640	0.666	0.552	0.552
N	413,466	160,945	160,945	150,178	413,466	413,466

Notes: The dependent variable is the normalized natural logarithm of exports from country c to country p in industry i in year 2000. Standardized beta coefficients are reported, with t-statistics in parentheses. Robust standard errors are clustered by exporter-industry.
* Significant at 5%.
** Significant at 1%.

where we expect $\sigma_1^k < 0$ for age-depreciating skills, $\sigma_1^k > 0$ for age-appreciating skills, and $\sigma_2^k > 0$ and $\sigma_3^k > 0$ for any k. Then Eq. (1) becomes

$$\ln X_{cpi} = \sum_{k \in K} \left(\beta_1^k I_i^k \times Age_c + \beta_2^k I_i^k \times Health_c + \beta_3^k I_i^k \times Educ_c \right) + \sum_n \phi_n I_i^n \times F_c^n + \delta'_{cp} \lambda + \gamma_c + \gamma_{pi} + \varepsilon_{cpi}, \quad (5)$$

where $\beta_j^i = \left(\rho_j^* + \phi_j^* \sigma_i^j \right)$. Estimation results for Eq. (5) are presented in Table 7. Education is measured with the share of population with secondary and post-secondary education, although the results do not change when we use alternative measures of education or when the measures of educational attainment are constructed only for senior workers. In column (1), the efficiency of the health care system is measured with the share of total health expenditure in GDP, obtained from the World Bank for the year 2000. All interactions of education variables and skill intensities in column (1) are insignificant, suggesting that education does not affect accumulation of age-dependent skills. This result, however, may be driven by poor quality of educational data, which does not take into account differences in the quality of education across countries. As for the effect of the share of health expenditure in GDP, only the interaction with the intensity in age-appreciating skills is statistically significant and positive, as expected. However, insignificant coefficients for age-depreciating skills provide no evidence that increase in health expenditure at the national level can remediate the effect of cognitive decline in aging population on comparative advantage. The estimated coefficients on the interactions of median age with intensities in age-dependent skills remain statistically significant and similar in magnitude to the benchmark values.

4.4.2. Population aging and changes in preferences

Our theoretical model focuses on the effect of population aging on trade flows through the effect on supply and thus suggests that demographics can be an important factor in a country's comparative advantage. However, the demographic composition can also affect trade through the effect on demand. In particular, it is possible that preferences and demand for different manufacturing products may change with age. In this case, our $I_i^k \times Age_c$ variables may capture changes in preferences rather than in specialization if aging is associated with a reduction in demand for products which use age-appreciating skills intensively and/or an increase in demand for products which are intensive in age-depreciating skills.

To explore this possibility, we use the Canadian Survey of Household Spending for the year 2000 kept by Statistics Canada. These data are representative of an open market economy, a context which is applicable to other developed countries that account for around half of exporter-industry observations in our sample. The survey includes complete information on household expenditure during the whole calendar year for over 14,000 households in Canada. Fig. 4 shows the variation in the share of different consumer goods in

Table 7
Extensions.

	(1)	(2)
$Cog\_app_i \times$	0.021**	0.031**
$(Median\ age)_c$	(3.48)	(5.69)
$Cog\_dep_i \times$	−0.045**	−0.047**
$(Median\ age)_c$	(−6.77)	(−7.69)
$Physical_i \times$	−0.016	−0.018
$(Median\ age)_c$	(−0.75)	(−0.97)
$Cog\_app_i \times Health_c$	0.031**	
	(5.02)	
$Cog\_dep_i \times Health_c$	−0.034	
	(−1.93)	
$Physical_i \times Health_c$	0.033	
	(1.73)	
$Cog\_app_i \times Educ_c$	0.003	
	(0.48)	
$Cog\_dep_i \times Educ_c$	0.016	
	(0.84)	
$Physical_i \times Educ_c$	−0.055*	
	(−2.45)	
$(Capital\ int.)_i \times$	0.023**	0.020**
$(Capital\ abund.)_c$	(4.67)	(3.39)
$(Skill\ int.)_i \times$	−0.006	0.018**
$(Skill\ abund.)_c$	(−0.65)	(2.68)
R-squared	0.559	0.562
N	401,851	257,866

Notes: The dependent variable is the normalized natural logarithm of export from country c to country p in industry i in year 2000. Standardized beta coefficients are reported, with t-statistics in parentheses. Robust standard errors are clustered by exporter-industry. All specifications include exporter fixed effects, importer-industry fixed effects, and controls for bilateral trade costs. Column (2) is estimated on a sample of industries that produce consumption goods.
* Significant at 5%.
** Significant at 1%.

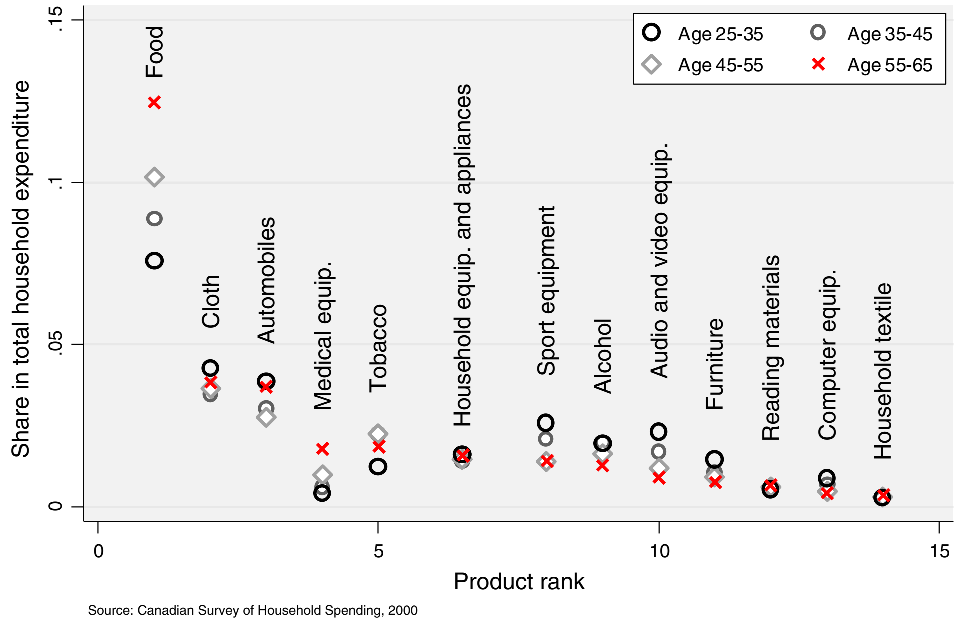

Fig. 4. Variation in consumer goods expenditure shares among different age cohorts.

total household expenditure across four cohorts.[37] The figure reveals that, while for most products there are no substantial differences in expenditure shares among different cohorts, older individuals tend to spend more on food and medical equipment and less on sports, audio, and video equipment. Hence, not controlling for differences in consumption patterns between older and younger individuals can result in omitted variable bias in β_k coefficients in Eq. (1) if those differences are systematically related to variation in skill intensities across industries. Yet, in the Canadian data this relationship is weak: the Spearman rank correlation between skill intensities and the gap in expenditure shares of 55–65 and 25–35 age cohorts is only around 0.1, while the same correlations with physical and human capital intensities are 0.23 and −0.34, respectively.[38]

As an additional robustness test, we estimate Eq. (1) on a subset of industries which produce consumer goods. We classify industry as producing consumer goods if at least one of the following two conditions is satisfied. First, the share of final consumption in total industry output, calculated from the US input–output tables for 2007, is at least 50%. Second, industry's share in total consumer expenditure on manufacturing goods exceeds the sample median of 0.8%. Because many industries that produce consumer goods also produce intermediate products, in this exercise we mostly remove industries that produce little consumer goods, such as fabricated metals or industrial machinery. If our results are mainly driven by the relationship between age and consumption behavior, we would expect the effect to be more pronounced for final goods. The results in pgtagcolumn (2) of Table 7 show that the magnitudes of β_k coefficients on the sample of consumption goods are similar to our baseline estimates for the entire sample, suggesting that age-dependent preferences are unlikely to play a major role in our results.

[37] We keep only households with either one person or married couples from the same cohort.

[38] These results are presented in Table 10A in the online Appendix.

5. The effect of population aging on comparative advantage

We have shown in the previous section that a country's age structure is a source of comparative advantage. In Section 2 we also argue that population aging at a rate faster than in other countries should alter a country's export structure via a decrease in relative productivity and increase in relative costs in industries which use age-depreciating skills intensively. To test this prediction of the model, we estimate Eq. (3) and relate changes in exports to the interaction of industry factor intensities and changes in population age structure between 1962 and 2000.

Estimation results are reported in columns (1)–(5) of Table 8. The results are based on the sample of 82 exporters, 135 importers, and 76 industries. Insignificant coefficients on capital and skilled labor in the first column reveal that, contrary to our expectations, accumulation of physical and human capitals is not associated with a shift in the export structure towards capital- or skill-intensive industries.[39] Both results are in contrast to Romalis (2004), who shows that changes in capital and, in some specification, skilled labor stocks imply changes in countries' structure of exports to the US. We find that the difference between our results and those by Romalis is primarily driven by the choice of the US as a single importing country. When we restrict our sample of importers to the US only, we obtain large and positive coefficients on both capital and skilled labor, with the latter also being statistically significant.[40]

Turning to the estimates with age-dependent skills in columns (2)–(4), we see that the coefficients on all skills are

[39] Using data on factor inputs and output for 28 manufacturing industries and 27 countries, Blum (2010) also finds that changes in capital and skilled labor endowment between 1973 and 1990 did not affect a country's output mix, but did affect its relative factor prices and factor intensities at the industry level.

[40] It is also important to note that lack of evidence for the Rybczynski effect for capital may be caused by changes in capital intensities over time. As column (9) of Table 4 shows, interactions of capital intensities, constructed with 2000 data, are insignificant determinants of trade flows in 1970. Poor measurement of effective capital stock and human capital can also be a problem as it is notoriously difficult to measure both types of capital in a consistent way across countries.

Table 8
Estimates for the effect of population aging on comparative advantage.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Cog\_app_i \times$		0.035**			0.027*	−0.027*	0.037**	0.034**	0.002
$(\Delta\,Age)_c$		(3.18)			(2.34)	(−2.05)	(3.84)	(3.71)	(0.25)
$Cog\_dep_i \times$			−0.037**		−0.029*	0.027*	−0.039**	−0.030**	−0.008
$(\Delta\,Age)_c$			(−3.19)		(−2.47)	(2.05)	(−4.00)	(−2.76)	(−0.90)
$Physical_i \times$				−0.039**					
$(\Delta\,Age)_c$				(−3.29)					
$(Capital\ int.)_i \times$	0.010	0.012	0.019	0.014	0.012	0.003	0.005	0.017*	0.018*
$(\Delta\,Age)_c$	(0.83)	(0.90)	(1.39)	(1.03)	(0.91)	(0.21)	(0.55)	(2.03)	(2.47)
$(Skill\ int.)_i \times$	−0.002	−0.004	−0.004	−0.004	−0.005	−0.003	−0.010	−0.002	0.007
$(\Delta\,Age)_c$	(−0.23)	(−0.39)	(−0.40)	(−0.45)	(−0.47)	(−0.32)	(−1.38)	(−0.31)	(1.39)
Measure for Age_c	Median age	Median age	Median age	Median age	Median age	Young worker share	Median age	Median age	Median age
End year	2000	2000	2000	2000	2000	2000	2000	2000	2000
Start year	1962	1962	1962	1962	1962	1962	1970	1980	1990
R-squared	0.476	0.477	0.477	0.477	0.478	0.477	0.444	0.425	0.324
N	62,488	61,835	61,835	61,835	61,835	62,488	83,976	101,977	93,352

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

significant and have expected signs. These results imply that rapid population aging, on one hand, increases a country's specialization in industries which use age-appreciating cognitive skills intensively, and on the other hand, erodes competitive advantage in industries which rely on age-depreciating cognitive skills and physical abilities. When both age-dependent cognitive skills are estimated in one regression in column (5), the magnitudes become smaller but the coefficients remain significant. We do not include physical skills in column (5) because it is highly collinear to age-depreciating cognitive skills and the two coefficients cannot be jointly identified. For this reason, in the specifications that follow we do not include physical ability in the list of covariates.

To illustrate the magnitude of the implied estimates, consider two countries, US and Argentina, and two industries, motor vehicles and meat products. Between 1968 and 2000 the median age in the US increased by one standard deviation relative to Argentina, or by 4.7 years. Also, the intensity of motor vehicles in age-appreciating cognitive skills is approximately one standard deviation higher than in meat products. Given that the standard deviation of change in log exports is 2.4, the estimates in column (5) imply that the increase in the relative stock of age-appreciating cognitive skills in the US caused by demographic changes induced exports of motor vehicles relative to meat products to increase by $e^{2.4\times0.027}=6.7\%$ more in the US than in Argentina. Similarly, Argentinian exports of textile products relative to household appliances, the two industries with one standard deviation difference in the intensity in age-depreciating cognitive skills, increased by $e^{2.4\times0.029}\ =\ 6.7\%$ more than in the US.

In columns (6)–(9) of Table 8 we report several robustness tests for the effect of demographic changes on comparative advantage. Column (6) presents the results with the share of young workers (aged 20–40) in the labor force as a measure of abundance in age-dependent skills. The results are fully consistent with the previous findings that population aging and the reduction in the share of young workers are associated with an increase in exports of products that use age-appreciating cognitive skills intensively, and decrease in exports of products which are intensive in age-depreciating cognitive skills.

In columns (7), (8), and (9) we report results using the base year of 1970, 1980, and 1990, respectively, to construct the differences in trade flows and factor endowments. The shorter span for time-differencing increases the number of exporting countries and observations, since many countries, especially less developed ones with younger populations, do not report trade data for 1960s and 70s. With the more representative sample of exporting countries in column (2), the effect of population aging becomes even more pronounced for age-dependent skills — the coefficients on both skills have expected signs and are statistically significant. However, with differencing over progressively shorter periods, the effect becomes weaker in column (3) and disappears entirely in column (4), where 1990 is used as the base date. That the results change substantially with shorter-span time differencing may indicate that the general-equilibrium effects due to resource relocation between industries are less visible in higher-frequency data if it takes more than ten years for the economy to adjust to changes in the supply of factor inputs. Yet the weak results in column (4) may also be due to low variation in population aging over shorter periods of time, which would make the identification of the effect of our interest more difficult.

The findings of this section provide new insights for evaluation of economic consequences of population aging and carry important public policy implications. The results imply that demographic changes affect a country's comparative advantage and the structure of output across industries. In particular, rapidly aging countries lose comparative advantage in industries which are intensive in age-depreciating cognitive and physical skills but gain comparative advantage in industries that utilize age-appreciating cognitive skills. As a result, population aging changes the relative supply of age-dependent skills, and international trade acts as the adjustment mechanism that works through increase in relative demand for more abundant factors by employing them in export-oriented sectors. Therefore, as long as the rates of population aging differ across countries, the effect of demographic changes on skill premia for age-dependent skills and relative income levels of senior and junior workers will be muted by changes in output and exports composition.

6. Conclusions

Variations in relative productivities and factor endowments across countries are the sources of comparative advantage. This paper contributes to the comparative advantage literature by analyzing the effect of cross-country differences in demographic composition and endowments of age-dependent skills on the structure of commodity trade. We incorporate age-dependent skills into the

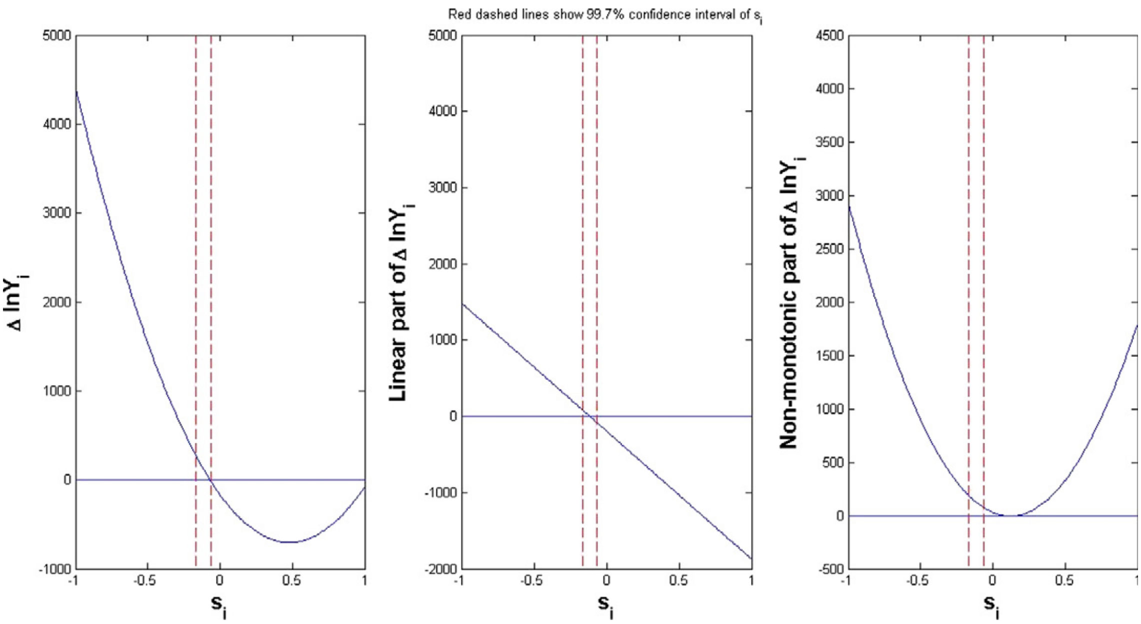

Fig. 5. The effect of population aging on output by industry.

extension of the Eaton–Kortum model by Chor (2010) to show that cross-country differences in demographic structure determine the pattern of trade. The model also predicts that population aging results in a reduction in productivity and an increase in unit output costs in industries that utilize age-depreciating skills intensively.

We apply the two main predictions of the model to bilateral trade data for a large panel of countries and 86 industries over the time period from 1962 to 2010, and confirm that population age structure is an important factor in a country's comparative advantage. First, we show that countries with a younger labor force tend to specialize in industries which are intensive in age-depreciating skills, and the result is remarkably robust to the inclusion of controls for alternative sources of comparative advantage and is not confined to a particular time period. Furthermore, the effect of a country's age structure on trade is economically sizable and explains more of the variation in trade flows than physical and human capital endowments combined.

Second, we establish that population aging results in a shift in a country's export structure towards industries which intensively use age-appreciating skills and away from industries which rely heavily on age-depreciating skills. Population aging could therefore play an important role in the structure of economic activity within and between countries. Nevertheless, our findings point to an optimistic perspective for the long-run impact of population aging on relative wages of older and younger workers. The results demonstrate that rapidly aging countries can adjust to demographic changes by utilizing the growing share of older workers in industries that intensively utilize age-appreciating skills. Thus, free trade and imports of products that embody age-depreciating skills can alleviate the effect of a reduction in supply of skills of younger workers in fast-aging countries on relative income levels.

Appendix A. Theoretical framework

A.1. Heckscher–Ohlin and Ricardian models with age-dependent skills

We illustrate the role of population age structure on a country's comparative advantage through the two main models of comparative advantage – the Heckscher–Ohlin and the Ricardian – using the extension of the Eaton and Kortum (2002) model by Chor (2010). The model accommodates both productivity and factor endowment differences in a setting with multiple countries, industries, and factors of production. In this setup, for any pair of countries $c1$ and $c2$, their relative exports of product i to country p is given by

$$\frac{X_{c1pi}}{X_{c2pi}} = \frac{\left(\varphi^i_{c1}/mc^i_{c1}d^i_{c1p}\right)^{\theta}}{\left(\varphi^i_{c2}/mc^i_{c2}d^i_{c2p}\right)^{\theta}}, \tag{6}$$

where X_{c1pi} is the value of exports of good i from $c1$ to country p, d^i_{cp} is the iceberg trade cost for shipping one unit of i from c to p, and θ is the inverse of productivity shock variance. The term mc^i_c is the unit production costs of country c in industry i which captures the Heckscher–Ohlin forces and φ^i_c is the Ricardian productivity of country c in industry i. Following Chor (2010), we parametrize the productivity term and the unit cost function as follows, distinguishing coefficients that relate to demographics with stars:

$$\ln\varphi^i_c = \mu_c + \mu_i + \sum_{k\in K}\rho^*_k I^k_i \times Age_c + \sum_{\{n,m\}}\rho_{nm}L^n_i \times M^m_c \tag{7}$$

$$mc^i_c = \prod_{k\in K}(w_{ck})^{s_{ki}}\prod_{f\in F}(w_{cf})^{s_{fi}}$$

μ_c and μ_i are country and industry productivity parameters, L^n_i and M^m_c are country and industry characteristics, such as institutional factors, which determine country's productivity edge in that industry, and coefficients ρ_{nm} reflect the strength of the effect of interactions $L^n_i \times M^m_c$ on productivity. If senior workers become less productive in tasks that require age-depreciating skills, productivity will also depend on the interaction of industry's intensity in age-dependent skill k, I^k_i, and a measure of a country's demographic composition, Age_c, which we assume is increasing as a country's population becomes older. To the extent that industries inherit age distribution of a country, older population would imply productivity advantage for industries which require age-appreciating skills ($\rho^*_k > 0$) and disadvantage for industries which use age-depreciating skills intensively ($\rho^*_k < 0$).

The unit cost function is a Cobb–Douglas aggregator of factor prices in country c, where K is a set of age-dependent skills, F is a set of other factors of production, such as human and physical capital, and s_{ji} is the share of factor $j \in \{K, F\}$ in total costs of industry i. If the Heckscher–Ohlin channel plays a role, then, as in , relative factor prices are inversely related to relative factor endowments, and the log unit costs becomes

$$\ln mc_c^i = -\sum_{k \in K} \phi_k^* s_{ki} \ln\left(F_c^k\right) - \sum_{f \in F} \phi_f s_{fi} \ln\left(F_c^f\right) \tag{8}$$

where F_c^j is the endowment of factor $j \in \{K, F\}$ in country c measured relative to some reference factor, and $\phi_k^* > 0$, $\phi_f > 0$. Substituting Eqs. (7) and (8) into Eq. (6) we obtain

$$\begin{aligned}\frac{1}{\theta}\ln\left(\frac{X_{c1pi}}{X_{c2pi}}\right) = & \sum_{k \in K} \rho_k^* I_i^k \times (Age_{c1} - Age_{c2}) + \sum_{k \in K} \phi_k^* s_{ki} \ln\left(\frac{F_{c1}^k}{F_{c2}^k}\right) \\ & + \sum_{\{n,m\}} \rho_{nm} L_i^n \times (M_{c1}^{nm} - M_{c2}^{nm}) + \sum_{f \in F} \phi_f s_{fi} \ln\left(\frac{F_{c1}^f}{F_{c2}^f}\right) \\ & + (\mu_{c1} - \mu_{c2}) - \left(d_{c1p}^i - d_{c2p}^i\right)\end{aligned} \tag{9}$$

The relative exports are determined by combination of six factors: Ricardian forces, as captured by the differential effect of age composition and institutional factors on productivity (the first and the third terms); the Heckscher–Ohlin forces, operating through the difference in factor endowments (the second and the fourth terms); productivity shifters (fifth term) and trade costs (sixth term). On one hand, if there are no Ricardian forces in the model and population aging affects only the stock of age-dependent skills but not the quality, then the first and the third terms disappear from Eq. (9), which becomes similar to the prediction of the Heckscher–Ohlin model by Romalis (2004). On the other hand, if population aging does not affect relative premia of different age-dependent skills, then the second term vanishes and demographic composition would affect trade only through variation in labor productivity across industries.

Specification (9) also allows analyzing the effect of changes in demographic composition over time on comparative advantage. It is easy to see that different rates of population aging in countries $c1$ and $c2$ will affect their relative exports through two complementary channels. First, more rapidly aging countries should observe a decrease in endowments of age-depreciating skills and increase in their premia. This, in turn, will shift a country's export structure away from industries which use age-depreciating skills intensively through the Rybczynski effect. Second, different aging rates affect relative exports of two countries directly through the effect on age composition of workers and labor productivity across industries (Ricardian effect).

Eq. (9) demonstrates both channels, Heckscher–Ohlin and Ricardian, through which age composition can affect comparative advantage. However, separating one channel from the other empirically would require data on either the endowments or relative prices of age-dependent skills, which are not available. In the absence of such data, we proxy the stock of age-dependent skills in Eq. (9) with the country's median age Age_c:

$$\ln F_c^k = \sigma_0^k + \sigma_1^k Age_c \tag{10}$$

so that for age-appreciating skills the stock of skills increases with population age ($\sigma_1^k > 0$) and for age-depreciating skills the stock decreases with age ($\sigma_1^k < 0$). This transformation results in an empirical specification which is similar to Chor (2010) and Bombardini et al. (2012):[41]

$$\begin{aligned}\ln X_{cpi} &= \sum_{k \in K} \beta_k I_i^k \times Age_c + \sum_{f \in F} \phi_f I_i^f \times F_c^f + \delta_{cp}'\lambda + \gamma_c + \gamma_{pi} + \varepsilon_{cpi} \\ \beta_k &= \left(\rho_k^* + \phi_k^* \sigma_1^k\right)\end{aligned} \tag{11}$$

In Eq. (11), β_k combines both ρ_k^* and ϕ_k^*, and the interactions $I_i^k \times Age_c$ capture both the Ricardian and the Heckscher–Ohlin channels. The model predicts that $\beta_k < 0$ for skills which worsen with age and $\beta_k > 0$ for skills that improve with age. This follows from the fact that for age-depreciating skills $\rho_k^* < 0$ and $\sigma_1^k < 0$, which implies that $\beta_k < 0$ since ϕ_k^* is positive for all k. For age-appreciating skills both ρ_k^* and σ_1^k are positive, and so is β_k.

A.2. The role of worker heterogeneity in age-dependent skills

An important feature of the above setup is that both age-appreciating and age-depreciating skills are bundled in workers. Although workers are perfectly mobile across industries, how skills are bundled across workers may also matter for aggregate productivity. Ohnsorge and Trefler (2007) demonstrate that in a setting with multiple skills embedded in workers, international comparative advantage is determined not only by the relative skill endowments across countries but also by the second moments of skill distributions. In what follows, we use the Ohnsorge and Trefler (2007) framework to analyze how the presence of multiple skills affects theoretical predictions and empirical methodology of the current study.

Each worker is endowed with two skills — age-appreciating skill L and age-depreciating skill H. Type (H, L) worker in industry i produces task $T(H, L, i)$, and the aggregate industry output is the sum of tasks of all employed workers. Workers are paid the value of their marginal product $W(H, L, i) = P(i)T(H, L, i)$, where $P(i)$ is the price of output produced by industry i. Assuming that the task function is constant return to scale in H and L, the log of worker's earnings can be expressed as $w(H, L, i) = p(i) + t(s, i) + l$, where lower-case letters are in logs, $l = ln(L)$, and $s = ln(H/L)$ is the log of worker's relative endowment of age-depreciating skills. Ohnsorge and Trefler (2007) show that when workers choose industries where their earnings are the largest, s determines worker's comparative advantage across industries so that high-s workers will sort into s-intensive industries. However, the international comparative advantage of an industry depends not only on s but also on the amount of the other factor l that workers bring in. Under the assumption that the distribution of skills across workers is bivariate normal

$$\begin{bmatrix} s \\ l \end{bmatrix} \sim N\left(\begin{bmatrix} \mu \\ 0 \end{bmatrix} \begin{bmatrix} \sigma_s^2 & \rho\sigma_s\sigma_l \\ \rho\sigma_s\sigma_l & \sigma_l^2 \end{bmatrix}\right) \tag{12}$$

the log output of industry i is

$$\ln Y(i) = \left[\sigma_l \rho \frac{s_i - \mu}{\sigma_s} + \frac{1}{2}\sigma_l^2\left(1 - \rho^2\right)\right] + t(s_i, i) - \frac{1}{2}\ln\left(2\pi\sigma_s^2\right) - \frac{1}{2}\left(\frac{s_i - \mu}{\sigma_s}\right)^2 \tag{13}$$

and country's comparative advantage is completely characterized by the parameters of the distribution function μ, ρ, σ_s, and σ_l.

[41] Note that both I_i^k and s_{ki} measure intensity of industry i in skill k and we assume that $I_i^k = s_{ki}$. In this specification we also do not consider the role of institutional factors of production but introduce some of them in extensions.

Our analysis proceeds in two steps. We first look at the comparative statics for output when the parameters of skill distribution change. Then, by introducing additional assumption on the dynamics of skill distribution, we predict the effect of population aging on distributional parameters and, hence, on the pattern of comparative advantage.

We begin by analyzing the response of log output to changes in skill endowments and correlation in worker's absolute and comparative advantage. Differentiate Eq. (13) with respect to μ and ρ:

$$\frac{\partial \ln(Y_i)}{\partial \mu} = -\frac{\sigma_l \rho}{\sigma_s} + \frac{s_i - \mu}{\sigma_s^2} = \frac{1}{\sigma_s^2}(s_i - \mu - \sigma_s \sigma_l \rho) \tag{14}$$

$$\frac{\partial \ln(Y_i)}{\partial \rho} = \frac{\sigma_l (s_i - \mu)}{\sigma_s} - \sigma_l^2 \rho = \frac{\sigma_l}{\sigma_s}(s_i - \mu - \sigma_s \sigma_l \rho) \tag{15}$$

One can see that the two derivatives have the same sign on the entire domain of industry's factor intensity s_i. When both μ and ρ decrease due to population aging, Y_i decreases in industries that are intensive in age-depreciating skills (when $s_i > \mu + \sigma_s \sigma_l \rho$) and increases in industries that are intensive in age-appreciating skills (when $s_i < \mu + \sigma_s \sigma_l \rho$).[42] Hence, for given σ_s and σ_l, the standard Heckscher–Ohlin prediction regarding the effect of population aging on comparative advantage continue to hold in the presence of multiple age-dependent skills per worker. In such case, changes in both the means of age-dependent skill endowments and their covariances, caused by demographic transformations, have the same effect on comparative advantage. As a result, a country's median age used in the empirical analysis will pick up both channels through which demographic changes affect comparative advantage in industries with different intensities in age-dependent skills.

To analyze of the effect of variances in skill distributions on output, differentiate Eq. (13) with respect to σ_s and σ_l to obtain:

$$\frac{\partial \ln(Y_i)}{\partial \sigma_l} = \sigma_l \left(1 - \rho^2\right) \tag{16}$$

$$\frac{\partial \ln(Y_i)}{\partial \sigma_s} = \frac{\sigma_l (\mu - s_i)}{\sigma_s^2} - \frac{1}{\sigma_s} + \frac{(\mu - s_i)^2}{\sigma_s^3} \tag{17}$$

It is easy to see that $\frac{\partial \ln(Y_i)}{\partial \sigma_l}$ is always positive and independent of s_i, hence, changes in σ_l do not affect sectorial comparative advantage. In contrast, $\frac{\partial \ln(Y_i)}{\partial \sigma_s}$ is non-monotone in s_i. If σ_s is not independent of demographic changes, the exact effect of population aging on output depends on the effect of aging on σ_s.

Using Eqs. (14)–(17), the total impact of population aging on output can be summarized as follows:

$$\begin{aligned}\Delta \ln(Y_i) &= \frac{\partial \ln(Y_i)}{\partial \mu}\Delta\mu + \frac{\partial \ln(Y_i)}{\partial \rho}\Delta\rho + \frac{\partial \ln(Y_i)}{\partial \sigma_s}\Delta\sigma_s + \sigma_l\left(1-\rho^2\right) \\ &= (s_i - \mu - \sigma_s\sigma_l\rho)\left(\frac{1}{\sigma_s^2}\Delta\mu + \frac{\sigma_l}{\sigma_s}\Delta\rho\right) + \sigma_l\left(1-\rho^2\right)\Delta\sigma_l \\ &\quad + \left(\frac{\sigma_l(\mu - s_i)}{\sigma_s^2} - \frac{1}{\sigma_s} + \frac{(\mu - s_i)^2}{\sigma_s^3}\right)\Delta\sigma_s \end{aligned} \tag{18}$$

We now turn to the analysis of the effect of population aging on distributional parameters in Eq. (12). To derive sharper predictions on the effect of aging on comparative advantage, we introduce more structure into the model and assume that joint normality of skill distribution is preserved with aging. Furthermore, suppose there are only two types of workers, senior and junior, with all variables that refer to the former group being distinguished with a star. These two assumptions imply that changes in skill endowments are log linear in aging:

$$\begin{aligned} h_i^* &= \gamma_H + \delta_H h_i \\ l_i^* &= \gamma_L + \delta_L l_i \end{aligned} \tag{19}$$

where h_i and l_i (h_i^* and l_i^*) denote logs of age-depreciating and age-appreciating skills of junior (senior) workers, and $\gamma_H < 0 < \gamma_L$. Under this assumption the joint normality of skill distribution is preserved for both young and old workers. Re-writing Eq. (19) in terms of relative endowments, we obtain

$$\begin{aligned} l_i^* &= \gamma_L + \delta_L l_i \\ s_i^* &= (\gamma_H - \gamma_L) + (\delta_H - \delta_L)\, l_i + \delta_H s_i \end{aligned}$$

and the parameters of the skill distribution of senior workers can be expressed in terms of the parameters of the skill distribution of junior workers as follows:

$$\begin{aligned} \mu^* &= (\gamma_H - \gamma_L) + (\delta_H - \delta_L)\,\mu_L + \delta_H \mu \\ \sigma_l^{2*} &= \delta_L^2 \sigma_l^2 \\ \sigma_s^{2*} &= (\delta_H - \delta_L)^2 \sigma_l^2 + \delta_H^2 \sigma_s^2 + 2\,(\delta_H - \delta_L)\,\delta_H \sigma_s \sigma_l \rho \\ \rho^* &= (\delta_H - \delta_L)\,\delta_L \frac{\sigma_l}{\sigma_s} + \delta_H \delta_L \rho \end{aligned} \tag{20}$$

If the effect of aging on log skill endowments is proportional, i.e. $\delta_H = 1 = \delta_L$, then $(\mu^* - \mu) < 0$, and $(\sigma_l^{2*} - \sigma_l^2) = (\sigma_s^{2*} - \sigma_s^2) = (\rho^* - \rho) = 0$. In such case, $\Delta \ln(Y_i) = \frac{(s_i - \mu - \sigma_s\sigma_l\rho)}{\sigma_s^2}\Delta\mu$, and the effect of population aging on comparative advantage operates entirely through the Heckscher–Ohlin channel.

To obtain more general predictions, we refer to neuroscience literature to impose additional restrictions on skill distribution parameters that govern dynamics of factor endowments. Ardila (2007) reports second moments of age-dependent skill distributions and find that aging not only decreases means of tests scores that reflect age-depreciating skills, but also increases dispersions. Moreover, for skills that depreciate with age faster, the increase in skill dispersion is greater. At the same time, there is little evidence on any substantial changes in the variance of age-appreciating skills with age.

In order to incorporate this evidence into the model, we need to map the parameters of log-normal distribution (12) to the mean and standard deviation of the test scores published in neuroscience literature. For a random variable with a log-normal distribution $\log(N(a, b))$, the mean and variance are $e^{a+b^2/2}$ and $\left(e^{b^2} - 1\right)\left(e^{2a+b^2}\right)$, respectively. Therefore, if the skill distribution follows Eq. (12), then the mean of the test scores associated with that skill is equal to $\gamma_H + \delta_H \mu_H + \frac{1}{2}\delta_H^2 \sigma_H^2$ for senior workers and $\mu_H + \frac{\sigma_H^2}{2}$ for junior. Since the mean of age-depreciating skill H_i decrease with age, it follows that

$$\gamma_H + \delta_H \mu_H + \frac{1}{2}\delta_H^2 \sigma_H^2 < \mu_H + \frac{\sigma_H^2}{2}, \tag{21}$$

where μ_H and σ_H^2 are the mean and variance of $\ln(H_i)$.

[42] The relative magnitude of these two effects depends on $\sigma_s \sigma_l$ and the relative change in μ and ρ :

$$\frac{\frac{\partial \ln(Y_i)}{\partial \mu}\Delta\mu}{\frac{\partial \ln(Y_i)}{\partial \rho}\Delta\rho} = \frac{\Delta\mu}{\sigma_s \sigma_l \Delta\rho}$$

When the joint skill distribution is more dispersed ($\Delta\rho/\Delta\mu$ is greater), changes in ρ, contribute relatively more to changes in production and trade pattern than μ.

The variance of the skill test score is $\left(e^{\delta_H^2\sigma_H^2}-1\right)\left(e^{2\left(\gamma_H+\delta_H^2\sigma_H^2\right)+\delta_H^2\sigma_H^2}\right)$ for senior workers and $\left(e^{\sigma_H^2}-1\right)\left(e^{2\mu_H+\sigma_H^2}\right)$ for junior. Increase in the variances of age-depreciating skill H_i with age requires that

$$\left(e^{\delta_H^2\sigma_H^2}-1\right)\left(e^{2\left(\gamma_H+\delta_H^2\sigma_H^2\right)+\delta_H^2\sigma_H^2}\right)>\left(e^{\sigma_H^2}-1\right)\left(e^{2\mu_H+\sigma_H^2}\right). \quad (22)$$

Conditions (21) and (22) together imply that $\delta_H>1$. Substituting $\delta_H>1$ back to Eq. (21), we have $\gamma_H<\mu_H(1-\delta_H)+\frac{\sigma_H^2}{2}(1-\delta_H^2)<0$.

The corresponding conditions for mean and variance for age-appreciating skills are

$$\gamma_L+\delta_L\mu_L+\frac{1}{2}\delta_L^2\sigma_L^2>\mu_L+\frac{\sigma_L^2}{2}, \quad (23)$$

and

$$\left(e^{\delta_L^2\sigma_L^2}-1\right)\left(e^{2\left(\gamma_L+\delta_L^2\sigma_L^2\right)+\delta_L^2\sigma_L^2}\right)\approx\left(e^{\sigma_L^2}-1\right)\left(e^{2\mu_L+\sigma_L^2}\right), \quad (24)$$

where μ_L and σ_L^2 are the mean and variance of $ln(L_i)$. It follows from conditions (23) and (24) that $\delta_L<1$, and substituting this result back into Eq. (23), we get $\gamma_L>\mu_L(1-\delta_L)+\frac{\sigma_L^2}{2}(1-\delta_L^2)>0$.

Overall, the evidence from the literature on the relationship between aging and dispersion in age-dependent skills suggests the following set of parameter restrictions for conditions (19):

$$\begin{aligned}\gamma_H &< 0<\gamma_L\\ \delta_L &< 1<\delta_H\end{aligned}$$

Along with Eq. (20), these parameter restrictions imply that population aging causes the skill distribution mean to decrease, $(\mu^*-\mu)<0$, and the Heckscher–Ohlin theorem still applies.[43] However, pinning down the signs of $\Delta\rho$ and $\Delta\sigma_s^2$ requires information on the parameter values in Eq. (20). We calibrate parameters of skill distribution using the information on $(\mu_H,\mu_L,\sigma_H,\sigma_L)$ reported by Ardila (2007), and show that the effect of variation in second moments of skill distribution on output is too small relative to the first moments to revert the predictions of the Heckscher–Ohlin theorem. For age-depreciating skill H, we choose matrix reasoning as the skill which demonstrates the strongest decline with advancing age. Comprehension was used for age-appreciating skill L. The mean and variance of original level skill scores are presented in the following tables.

Matrix reasoning	20–24	55–64	Comprehension	20–24	55–64
Mean	16.5	12.5	Mean	18.5	20.5
Variance	4.7	6.0	Variance	6.0	6.0

The implied means and variances of log-scaled skill scores are hence

Matrix reasoning	20–24	55–64	Comprehension	20–24	55–64
μ_H	2.79	2.51	μ_L	2.91	3.01
σ_H	0.13	0.19	σ_L	0.13	0.12

and we can back out all parameters of skill dynamic process (19):

$$\begin{aligned}\delta_H &= 1.48\,;\ \delta_L=0.9\\ \gamma_H &= -1.62\,;\ \gamma_L=0.39\end{aligned}$$

For these parameter values, we have

$$\begin{aligned}\Delta\mu=\mu^*-\mu &= \gamma_H-\gamma_L+\delta_H\mu_H-\delta_L\mu_L=-0.5\\ \Delta\sigma_s=\sigma_s^{2*}-\sigma_s^2 &= \sigma_H^{*2}+\sigma_L^{*2}-\sigma_H^2-\sigma_L^2-2\rho_{HL}\left(\sigma_H^*\sigma_L^*-\sigma_H\sigma_L\right)\\ &= 0.0056+0.0188\rho_{HL}\\ \Delta\rho=\rho^*-\rho &= \delta_L\left(\delta_H-\delta_L\right)\sigma_L+\left(\delta_H\delta_L-1\right)\rho\\ &= 0.4092+0.3401\rho\end{aligned}$$

If ρ_{HL} is positive as found in Ohnsorge and Trefler (2007), then $\Delta\sigma_s^2$ is also positive and lies within the range $0.0056\le\Delta\sigma_s^2\le0.0174$, where the bounds of the possible parameter range are determined by $\rho_{HL}\in[0,1]$ condition. For $\rho\in[-1,0]$ also found in Ohnsorge and Trefler (2007), $(\rho^*-\rho)\in[0.0691,0.4092]$ and is always positive. To quantify the effect of population aging on output, we assume $\rho_{HL}=0.5$, so that $\Delta\sigma_s=0.015$ and $\Delta\rho=0.24$. The following table summarizes the parameter values of skill distribution for young and senior workers, and the difference between the two

	Young	Senior(*)	Δ
μ	−0.12	−0.62	−0.50
ρ	−0.5	−0.26	0.24
σ_s	0.017	0.032	0.015
σ_l	0.13	0.12	−0.01

For this parametrization of the model, we rely on Eq. (18) to analyze the effect of population aging on comparative advantage. Fig. 5 plots changes in output by industry, triggered by population aging and associate change in skill distribution. The left panel of the figure shows the overall effect of demographic changes on output, and the middle and right panels decompose the overall effect into the components of $\Delta\ln(Y_i)$ that are linear (the first term in Eq. (18)) and non-linear (the third term in Eq. (18)) in s_i, respectively. Red dashed lined identify the range of industries with skill intensity $s_i\in[-3\sigma_s+\mu,3\sigma_s+\mu]$. Since s_i is distributed log-normally, this range covers 99.7% of the industries. One can see that for the plausible range of skill intensities, the effect of population aging of output is monotone and, hence, the Heckscher–Ohlin prediction continues to hold. It is only for the extreme values of skill intensities (33 standard deviations away from the mean of s_i) that the non-monotonic component of output growth start to dominate the linear component. It is also important to note that the effects of linear and non-monotone components on $\Delta\ln(Y_i)$ are comparable in magnitudes for the plausible range of s_i.

Overall, the above simulation analysis points to two main results. First, the effect of population aging on comparative advantage through the effect on second moments of skill distribution could be quantitatively strong. This results further emphasize the importance of studying the effect of variances and covariances in skill distributions on comparative advantage. Second, while changes in variances of skill endowments due to population aging can undo the effect of changes in means on comparative advantage, the two effects are complements for the plausible range of parameter values of our model. Therefore, the Heckscher–Ohlin model still applies and we expect export of age-depreciating skills intensive industries to decline with population aging.

[43] From Eqs. (21) and (23), we have $\gamma_H+\delta_H\mu_H-\mu_H<\frac{1}{2}\sigma_H^2(1-\delta_H^2)<0$ and $\gamma_L+\delta_L\mu_L-\mu_L>\frac{1}{2}\sigma_L^2(1-\delta_L^2)>0$. These two conditions imply that the difference in means $\mu^*-\mu=\gamma_H+\delta_H\mu_H-\mu_H-(\gamma_L+\delta_L\mu_L-\mu_L)$ is negative.

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jinteco.2016.04.006.

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