

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 relative supply and increases 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 younger labor force. At the same time, countries with older populations will have a comparative advantage in industries which use age-appreciating skills intensively. Building upon the neuroscience and economics literature, we construct industry-level measures of intensities in various age-dependent skills and show that countries with higher median age specialize in production of goods which use age-appreciating skills intensively and import goods for which age-depreciating skills are more important. We also demonstrate that fast-aging countries experience a shift in their production and export structure towards industries which use age-appreciating skills intensively and away from industries which rely more on age-depreciating skills.

JEL Classification codes: F14, F16, J1

Key words: trade patterns; comparative advantage, cognitive skills, population aging

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1 Introduction

Many countries observe major changes in demographics of their populations as aging leads to a shift in the age structure of labour force in most countries towards older workers. These changes are likely to have 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 at the age of 25. This implies that aging societies experience more rapid decline in the stock of certain cognitive skills and may thus lose competitive advantage in industries which use those skills intensively. In this paper, we empirically study how differences in age structure of populations across countries affect global trade flows. Specifically, we find a novel and empirically sizeable source of comparative advantage: the relative supply of age-dependent skills that vary with population age.

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. 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. A related stream of literature demonstrates that the ability to learn new skills and adaptability to changes in working environment are impaired in older individuals. Finally, 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 skills are many 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 workers in occupations which require good written and/or oral communications skills (e.g. *technical writers* or *sales representatives*) and use age-appreciating skills intensively.

To explore the impact of age composition of population on trade, we incorporate age-dependent skills into the extension of the classical Heckscher-Ohlin-Samuelson model by Romalis (2004). The model is a combination of the Dornbusch, Fischer, and Samuelson (1977) model with a continuum of goods and the Krugman (1980) model of monopolistic competition with transportation costs. The main prediction that emerges from this extension is that countries with older labor force, all else being equal, have lower endowments in age-depreciating skills and thus specialize on production of goods which utilize age-appreciating skills intensively. Figures 1 to 4 illustrate this prediction for countries with median age below 20 (young) and above 35 (old) in the year 2000. Older countries export more in industries which use age-appreciating cognitive skills intensively, and less in industries which depend more on age-depreciating cognitive, physical, and learning skills. The opposite pattern is observed among younger countries, which specialize more on commodities that rely on age-depreciating skills.

The central prediction of the model is that countries with younger populations specialize on goods which are intensive in age-depreciating skills. In this way, 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 a 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 a 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 use Principal Component Analysis to construct three age-dependent skills indicators: physical skills, age-appreciating cognitive skills, and age-depreciating cognitive skills.

We confirm the main prediction of the model using rich bilateral trade data which include 86 industries and cover the time period between 1962 and 2010. We find that older (younger) countries 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.¹ The results are robust to the inclusion of the standard determinants of comparative advantage such as endowments of physical and human capitals. Furthermore, age-appreciating and age-depreciating cognitive skills explain more variation in trade flows than physical and human capital combined. A possible explanation could be that our measures industry-level intensities and country-level abundance in age-dependent skills are more accurate than similar measures for physical and human capitals. Furthermore, the magnitude of the impact of age differences on trade flows, estimated in this study, is greater than other determinants of comparative advantage identified in recent literatures, such as institution quality (Nunn, 2007) and skill dispersion (Bombardini, Gallipoli, and Pupato, 2012).² The main finding of this paper is robust to the definition of human capital and holds in different time periods. We also show that cognitive skills which do not change with age have little explanatory power for trade flows, providing further support to our interpretation of the results.

Another prediction of the model by Romalis (2004) is the quasi-Rybczynski effect. In our context, it implies that fast(slow)-aging countries should observe an increase in relative supply and decrease in relative price of age-appreciating (age-depreciating) skills, thus making industries which use those skills intensively more competitive in the global market. We find substantial support for this prediction in the data. We demonstrate that 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 learning 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

¹Similar results are obtain 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.

²Although the main predictions of our model are not supported once we control for the role of institutional quality and skill dispersion, the reason is that the data from these two studies are available only for a small set of relatively rich countries. To make things worse, these countries are exclusively concentrated in the right tale of the median age distribution across countries and thus feature similar pattern of comparative advantage in age-appreciating skills. It makes identification of our coefficients of interest problematic on those samples.

the production and exports of goods which use them intensively.

Our research relates to the literature on macroeconomic impacts of population aging. Holzmann (2002), Boersch-Supan, Ludwig, and Winter (2001), Boersch-Supan, Ludwig, and Winter (2006), Domeij and Floden (2006), Attanasio, Kitao, and Violante (2007), Ludwig, Krueger, and Boersch-Supan (2007), among others, study the role of aging in international capital and immigration flows using overlapping generations framework. Overall, these studies 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.³ 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) show 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.

This paper also contributes to the fast-growing literature that formally test the relationship between factor proportions and trade flows. Specifically, it is related to the classical works emphasizing the important role of physical and human capital endowments in comparative advantage.⁴ 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; Cuñat and Melitz, 2012; Tang, 2012), skill dispersion (Bombardini, Gallipoli and Pupato, 2012), and water resources (Debeare, 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 coun-

³Ludwig and Vogel (2010) and Ludwig, Schelkle, and Vogel (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.

⁴See Treffer (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.

tries. Using the variation in demographic composition across countries and the variation in age-dependence of different cognitive skills, we are able to construct a good proxy for a country's endowment in unobservable cognitive and physical skills. This paper is thus the first one to show that cross-country differences in endowments of cognitive and physical skills are as important determinants of comparative advantage as the differences in physical and human capitals.

The paper is organized as follows. Section 2 presents a theoretical model of comparative advantage with age-dependent factors of production. Section 3 discusses the empirical strategy for testing the main predictions of the theoretical model. Section 4 describes the data and Sections 5 presents the baseline empirical results and several robustness checks. Section 6 concludes.

2 Theory and testable predictions

In the presence of age-dependent skills, the stocks of those skills will vary across countries with the age structure of their populations. The Heckscher-Ohlin model then implies that with cross-industry variation in skill intensity, the age structure of a country becomes a source of comparative advantage. For example, a country with low median age will have a comparative advantage in products which intensively use age-declining skills. However, in the traditional multi-country version of the Heckscher-Ohlin model, factor price equalization and free trade result in commodity price equalization, which makes the pattern of production and commodity trade for a given country indeterminate.

The theoretical foundation for our empirical strategy is based on the extension of the Heckscher-Ohlin model by Romalis (2004),⁵ who introduced monopolistic competition and trade frictions in the Heckscher-Ohlin model with multiple countries, goods, and factors of production. Transportation costs generate a departure from the factor price equalization and thus introduce a variation in production costs across countries. Romalis show that in the presence

⁵The empirical specification derived from this model is identical to the one obtained by Chor (2010) from the modification of the Eaton and Kortum (2002) model.

of trade frictions locally abundant factors are cheaper, so that a country enjoys a cost advantage in industries which utilize those factors intensively. Since countries specialize in different varieties, consumers in all countries spend more on varieties produced in countries with lower costs. Therefore, the combination of trade costs and product differentiation pins down the volume of trade for every good between any pair of countries.

The model predicts that every country exports all commodities it produces, but the total value of exports is increasing with the industry's intensity in the abundant factor. Therefore, for any pair of countries H and F , if H is relatively more endowed in some skill S than country F , it will have a productivity advantage in commodities that use skill S intensively. As a result, H will export more of those commodities than F to all other countries, all else being equal. Furthermore, relative exports of country H is increasing in the skill intensity of an exported product and in the difference in relative endowments of skill S between the two countries. In our context, if country H has younger labour force than country F , it will be relatively abundant in skills that depreciate with age, and thus export more to third countries of all products which use those skills intensively. In Appendix A we formally derive the relationship between relative age of a pair of countries and their relative endowments of age-dependent skills.

Another prediction of the model by Romalis is the quasi-Rybczynski effect, which states that accumulation of a certain factor of production at a rate faster than the world average will shift a country's export structure towards industries which use that factor intensively. In our setting, this predictions translates into the relationship between population aging and a country's export structure in different industries. More rapidly aging countries should observe their export structure shifting towards industries which use age-appreciating skills intensively.

3 Empirical model

To test the main prediction of the theoretical model, we adopt the empirical specification which follows Chor (2010) and Bombardini, Gallipoli, and Pupato (2012):

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

where $\ln X_{cpi}$ is the log of exports from country c to country p in industry i , Age_c is the variable that measures age composition of labour force in country c relative to other countries, $Skill_i^k$ is the measure of industry i 's intensity in skill k , K is the set of age-dependent skills, and δ_{cp} is a vector of variables that captures bilateral trade frictions. Exporter fixed effects γ_c control for exporter's 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 for its size.

The interaction $Skill_i^k \times Age_c$ is the main variable of interest and the sign of β_k allows us to test the key theoretical prediction that younger countries export relatively more in industries which intensively use age-depreciating skills. For any pair of countries c_1 and c_2 exporting goods i and j to a third country p , equation (1) implies:

$$E \left[\ln \left(\frac{X_{c_1 p i}}{X_{c_2 p i}} \right) - \ln \left(\frac{X_{c_1 p j}}{X_{c_2 p j}} \right) \right] = \sum_{k \in K} \beta_k (Skill_i^k - Skill_j^k) \times (Age_{c_1} - Age_{c_2}) \quad (2)$$

If country c_1 has 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 , $(Skill_i^k - Skill_j^k) > 0$, then we would expect country c_1 to export relatively more (less) of good i than j if skill k depreciates (appreciates) with age. Therefore, we would expect $\beta_k < 0$ for skills that decline with age and $\beta_k > 0$ for skills that improve with age.

The extension of the Heckscher-Ohlin model, discussed in the previous section, predicts how differences in factor endowments across countries can generate comparative advantage. Yet, specification (1) contains only age-dependent skills and excludes other factors of production.

Since these factors may be important determinants of exporter’s comparative advantage and can be correlated with our main variables of interest, we extend the baseline specification to account for the role of other factors of production in trade:

$$\ln X_{cpi} = \sum_{k \in K} \beta_k Skill_i^k \times Age_c + \sum_n \phi_n I_i^n \times F_c^n + \delta'_{cp} \lambda + \gamma_c + \gamma_{pi} + \varepsilon_{cpi} \quad (3)$$

where F_c^n is the measure of country c ’s abundance in factor n , and I_i^n is the intensity of industry i in factor n . In our baseline specifications we control for two standard factors of comparative advantage in the Heckscher-Ohlin model – the cross-country differences in physical capital and skilled labor – and in the robustness section we control for other factors of production suggested by previous literature as important determinants of trade pattern. Given that countries export more in industries which use their abundant factors intensively, we expect $\phi_n > 0$ for all standard factors of production.

It is important to note that the endogeneity of $Skill_i^k \times Age_c$ variables in equation (3) is unlikely to be a serious concern. First, the demographic composition of a country’s population is predetermined relative to trade flows, and it is difficult to think of any reasons for why the median age of a country’s population could affect the export structure other than through the effect on output. Second, skill intensity measures, constructed from the occupational structures in the US industries, are also plausibly exogenous as long as the US employment structure is unaffected by bilateral trade flows between other countries.⁶

To test the Rybczynski prediction of the model, we estimate equation (3) in differences:

$$\Delta \ln X_{cpi} = \sum_{k \in K} \beta_k Skill_i^k \times \Delta Age_c + \sum_n \phi_n I_i^n \times \Delta F_c^n + \delta'_{cp} \lambda + \gamma_c + \gamma_{pi} + \varepsilon_{cpi} \quad (4)$$

where Δ is a time-difference indicator. Equation (4) thus assumes that while trade structure, age composition, and factor stocks can change within a country over time, industries’ factor

⁶In Section 5.2 we provide some evidence in support of this assumption. First, if there is a feedback from trade flows to employment structure, the simultaneity would be especially a problem for the US trade flows. However, removing the US from the set of importing and exporting countries does not affect our results. Second, 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.

intensities are constant. The model predicts that rapidly aging countries should lose competitive advantage in industries which rely on age-depreciating skills and specialize in industries which 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 labour the Rybczynski prediction implies $\phi_n > 0$.

4 Data

Estimation of the main model (3) requires four sets of data: industry-level data on bilateral trade flows; determinants of bilateral trade costs; industry's intensity in age-dependent skills and other factors of production; and country-level measures of abundance in those factors. Equation (3) is estimated with bilateral trade data for the year 2000. To estimate equation (4), 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.

Trade data. The data on industry-level bilateral trade flows for estimation of equation (3) are obtained from the UN-TRADES database at 6-digit Harmonized System classification and aggregated into 4-digit North American Industry Classification System (NAICS) using concordance from Feenstra, Romalis, and Schott (2002). The resulting data is an unbalanced panel of 235 exporters, 159 importers, and 85 industries for the year 2000. Changes in bilateral trade flows between 1962 and 2000, which we use to estimate the Rybczynski effect, are obtained from NBER-UN International Trade Database with the NBER concordance tables employed to convert 4-digit ISIC data into 4-digit NAICS. Equation (4) 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 equations (3) and (4) includes 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 one country.⁷ We also use two binary variables for the presence of a free trade agreement or a customs union between a pair of countries which we constructed from the WTO database on Regional Trade Agreements.

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.

Appendix B describes three categories of age-dependent skills – cognitive, physical, and learning – and reviews the literature that analyses the evolution of these skills over a course of an individual’s life. For cognitive skills, studies in neuropsychology literature provide convincing evidence that speech and language abilities improve with age, while memory, divided attention,⁸ and the speed of information processing deteriorate with age. The negative impact of aging on nearly all aspects of physical and psychomotoric skills – such as muscular strength, stamina, coordination, and dexterity – is well documented in the medical literature. Finally, there is considerable support for the age-associated decline in individual’s ability to learn and acquire new skills coming from the behavioral literature. Specifically, older people are slower in learning new tasks, worse in motor skill acquisition, and less efficient in developing career-relevant skills than younger people. As a result, older workers are likely to be less productive in occupations and industries where they have to adapt to frequent changes in the working environment.

To construct industry-level measures of intensity in cognitive skills and physical abilities,⁹ we use information on occupational composition for every industry, obtained from the US Bureau of Labor Statistics. Occupational employment shares were matched through 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,

⁷All of these variables were obtained from the Centre d’Etudes Prospectives et d’Informations Internationales (CEPII).

⁸Divided attention is the ability to process information from two or more sources at the same time or to switch from one task to another.

⁹Appendix C describes the construction of skill intensity variables in more details.

we construct industry-level measure of intensity in a particular skill as a weighted average of 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 variation 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 O*NET database. O*NET ranks all occupations in several dimensions which are closely related to age-depreciating skills described in the Appendix B. 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 high degree of correlation between cognitive skills indicators (see Tables 1A and 2A in the Appendix), it is difficult to separately identify the effect of each single one. For this reason, the four language indicators were grouped into a single indicator for age-appreciating cognitive skills, cog_app_i , using the principle component analysis (PCA). Similarly, the four indicators associated with age-declining skills were also grouped into one indicator for age-depreciating cognitive skills, cog_dep_i .

However, the two variables, cog_app_i and cog_dep_i , remain highly correlated, with the correlation coefficient of 0.84. The likely reason is a high degree of complementarity between all cognitive skills, so that the industries which use age-appreciating skills intensively are also intensive in age-depreciating skills. In this case, both cog_app_i and cog_dep_i will capture the intensity in cognitive skills in general. To deal with this problem, we choose a reference cognitive skill, not affected by aging, and measure industry-level intensities in age-dependent

skills relative to the reference skill. We choose inductive reasoning as a reference skill,¹⁰ and then perform the PCA on indicators demeaned by the O*NET score in the reference skill for each industry. This procedure generates measure of industry’s intensity in age-dependent relative to age-neutral cognitive skills. Constructed in this way, variables cog_app_i and cog_dep_i are negatively correlated with the correlation coefficient of -0.24 . Panels A and B of Table A3 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.

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 are highly correlated and were combined into a single indicator for physical abilities, $physical_i$, through the PCA.

Table 1 lists ten most and ten least intensive occupations for physical and both types of cognitive skills. Many of the occupations that are the most intensive in age-depreciating skills are related to sales for which oral and written communication skills are critical to excel. The top of the list for age-depreciating skills is dominated by various machine operators, where 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 intensities remains a problem and will be the concern in the following sections.

Intensity in the ability to learn. The ability of workers to learn and acquire new skills is considered to be an important element of their human capital, which can provide firms with greater adaptability to changes in market conditions and productivity advantage over

¹⁰This choice is justified by two considerations. First, there is no evidence in the literature that inductive reasoning is affected by age. Second, inductive reasoning has strong positive correlation with all age-dependent skills. Using other reference skills which satisfy these two conditions, such as deductive reasoning, information ordering, or fluency of ideas, does not qualitatively change our results.

competitors. In Appendix B we argue that as the ability to learn deteriorates with age, older countries have lower endowment of the “ability to learn” skill, all else being equal. In order to build an industry-level measure of intensity in the ability to learn, we rely on the US patent data to construct the rates of innovation and new product creation for each industry. In their recent study, Balasubramanian and Sivadasan (2011) established that patenting is primarily associated with new product innovations rather than improvements in existing products. Motivated by this insight, we cast the hypothesis that high patent intensity of a firm is associated with high rate of product turnover, which, in turn, requires workers to frequently update their knowledge stock and acquire new skills in order to perform tasks associated with new products. Hence, abundant young labor force will generate a comparative advantage for fast innovating industries.

Since industry-level intensities in the ability to learn are unobservable, we construct two proxy measures based on the above hypothesis. The first one is the rate of patent intensity in industry i , $pintensity_i$, calculated as the annual growth rate of the number of patents for 3-digit NAICS industries, averaged over the years 1976 to 2006.¹¹ The second measure, $pcreation_i$, is the rate of product creation, calculated as a ratio of patents in new product categories over the total number of patents and averaged over firms and years. Each patent is assigned one or more International Patent Classification (IPC) codes, which classify patents into different technology categories. Presumably, when a firm registers a patent in a new IPC category in which it had not innovated previously, such patent is likely to result in development of a new product which is technologically different from the existing line of products. Therefore, this type of product creation is more likely to require workers to upgrade their set of skills than product creation in the existing IPCs. To construct industry-level measure of product creation, we average the share of patents in new IPC categories over firms within each industry and year.

Table 4A in the Appendix provides a breakdown of the 4-digit NAICS manufacturing sectors by intensity in our four measures of age-dependent skills.

Other data. Our primary measure of a country’s age structure is the median age, obtained from the United Nations.¹² As an alternative, we also use the share of young workers in

¹¹Patents were assigned to 3-digit NAICS industries using the concordance from the US Patent and Trademark Office (USPTO).

¹²See Table 5A in the Appendix for information on median age in 2000 and change in median age between

the labour 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 1998.¹³ As in Romalis (2004), capital-intensity is constructed as the share of value added net of the labor costs in value added, and skill intensity as the share of non-production workers in total employment.

Data on country's stock of physical capital, measured in 2005 prices, is retrieved from the Penn World Table. Human capital stock is obtained from Barro and Lee (2013) and is measured as a share of population with secondary and tertiary education.¹⁴ The full sample includes 136 exporting countries, 155 importing countries, and 83 industries.

5 Results

5.1 Baseline results

Table 3 reports estimation results for equation (3) with the country's median age used as a proxy for the stocks of age-depreciating skills. All specifications include exporter fixed effect, importer-industry fixed effects, and controls for bilateral trade costs described in Section 4. Standard errors are clustered at exporter-industry level. The first column confirms the main prediction of the standard 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. Adding $Skill_i^k \times Age_c$ 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, thus supporting the hypothesis that age differences across countries are the source

1962 and 2000 of all exporting countries in our sample.

¹³Under the assumption of no factor intensity reversals, the ranking of factor intensities across industries does not vary by country.

¹⁴Our three alternative measures are the average years of schooling attained, the share of workers with at least primary education, and the share of workers completed tertiary schooling.

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 age-depreciating cognitive skills, physical skills, and learning.

Columns (6) and (7) of Table 3 report results for a complete specification with all skill measures included in the regression. This extension does not substantially affect the coefficient estimates for two types of cognitive skills, however, the coefficients on physical and learning skills become insignificant. The effect of learning skills on exports disappears once the effect of age-depreciating cognitive skills is controlled for, which suggests that the ability to learn can be impaired in older individuals because of the cognitive decline. Indeed, many studies on age and learning argue that the ability to learn is affected by memory and the speed of information processing, the two cognitive skills which are known to deteriorate with age. Furthermore, industry-level intensities in physical skills and age-depreciating cognitive skills are highly correlated (see Table 1), and the interaction ($cog_dep_i \times Age_c$) picks up the effect of physical skills.

Because the reported coefficients in Table 3 are standardized, we can directly compare the magnitudes of the effect of different factors of production on trade using the estimates for equation (2). Suppose industry i has one standard deviation higher intensity in all factors of production. Then, focusing on the most complete specification in column (7), a country which has one standard deviation higher median age than another one will export 10.2% more in industries which are intensive in age-appreciating skills, 23.2% less in industries which use age-depreciating skills intensively, and 7.7% and 5.9% more in capital and labor intensive industries, respectively.¹⁵

In Table 4 we report the estimates of equation (3) with the age composition being measured by the share of young workers in the labour 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

¹⁵With 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 $\exp(3.36 \cdot \beta_k)$.

we do not know the exact onset of the age-related cognitive decline, the age threshold of 40 in the definition of young workers is somewhat ad hoc.¹⁶ The estimates in Table 4 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 in Tables 3 and 4 are of opposite signs). In column (6) we include the interaction of industry’s skill intensity and country’s 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.

5.2 Robustness tests and extensions

In Table 5 we present several extension of the main specification and explore robustness of our results to changes in econometric specification and definitions of the key variables.

Alternative measures of human capital. In columns (1) and (2) of Table 5 we use two alternative definitions of human capital to better measure endowments in high and low skilled workers. In the first column we construct a country’s abundance in skilled labor as the average number of years of schooling, and in the second column as the share of population with completed tertiary education. These modifications leave the coefficients of interest nearly unchanged.

Alternative measure of learning intensity. Column (3) presents the estimation results for equation (3) when industry-level intensity in learning skills is measures with the growth rate of patents, $pintensity_i$. As it is discussed in Section 4, patent growth rate is associated with frequent changes in product line and production process. This, in turn, would require workers to adapt by learning new tasks and acquiring new skills, which younger workers can do relatively better. The coefficient on the interaction of patent intensity and median age is negative and statistically significant at 10% confidence level, so that countries with older populations export relatively less in industries with high patent growth rate. This result is consistent with the hypothesis that the age-related decline in learning ability is a source of comparative advantage, although alternative interpretations are also possible. For example, comparative advantage of

¹⁶Changing the threshold to 35 or 45 does not alter our main estimation results.

younger countries in industries with high patent growth rate may be related to lower productivity of older workers in R&D activities.

Controlling for bilateral trade costs. In column (4) we estimate equation (3) with importer-product and exporter-importer fixed effects. The former 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.

Results for other time periods. In columns (5) and (6) we demonstrate that the results are not confined to a particular time period by estimating equation (3) using trade and median country's age data for the years 2010 and 1970, respectively. The negative effect of the median age on exports in industries which rely on learning skills becomes more pronounced and statistically significant in these two samples, and the coefficients on other cognitive skills remain qualitatively unchanged. Another difference with the benchmark results is insignificant coefficient on physical capital in both time periods.¹⁷

Results without the USA. The above result that skill-intensities, constructed with the US data for 2010, can predict trade flows in 1970 and in more recent data equally well suggests that the reverse causality from bilateral trade to occupational composition across industries is unlikely to be a serious problem. Furthermore, if reverse causality were present, it would be stronger for the US trade data. However, excluding the US from the sample (column 7) produces virtually identical results to those in the benchmark specification, which corroborates the conjecture that our main results are not subject to simultaneity bias.

The role of other cognitive skills. The results presented to this point are based on two sets of cognitive skills which neuropsychology literature identifies as age-dependent. However, there is a large set of other cognitive skills for which there is either no consensus in the literature or which are known to be unaffected by aging. If our main interaction variables are really

¹⁷The cross-section regressions of equation (3) 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. The coefficient on $(mcreation_i \times Age_c)$ is always negative and significant for the years 1980 and 1990 at 5% confidence level.

picking up the effect of demographics on trade, we would expect the effect of age-neutral skills to be close to zero or at least be smaller than that for age-dependent skills. To conduct this robustness test, we build an industry-level measure of intensity in age-neutral cognitive skills, $cog_neutral_i$. This variable is constructed in the same way as the age-dependent skill intensities using O*NET indicators for all cognitive skills which were not used in the construction of cog_app_i and cog_dep_i variables.¹⁸ Results in column (8) confirm our expectation.¹⁹ Although the coefficient on age-neutral cognitive skills is significant, it is much smaller in magnitude than the coefficients on age-dependent skills. Furthermore, the negative coefficient on age-neutral skills suggests that some of those skills may actually depreciate with age.

Other determinants of comparative advantage. Recent studies on comparative advantage have identified a number of determinants of trade flows which may be correlated to our variables and cause a bias in the estimates if omitted from the regressions. One of such factors is the dispersion of human capital within a country in the presence of differences in skill complementarities across industries. In column (9) we introduce the interaction of a country's skill dispersion and the measure of sectorial skill complementarity obtained from Bombardini, Gallipoli, and Pupato (2012). Skill dispersion is measured with the standard deviation in the International Adult Literacy Survey scores within a country and skill complementarity with the average importance of teamwork for workers employed in an industry.²⁰ In column (10) we control for the role of institutional quality by including the interaction a country's ability to enforce contracts and industry-level measure of contract intensity from Nunn (2007).

With inclusion of these controls, both of which are statistically significant, the coefficients on the main variables of our interest change dramatically relative to the benchmark specification. However, this change is entirely driven by the change in the sample rather than by correlation between our key variables and the additional covariates. Since the data on country-level characteristics in the above studies is only available for a small number of countries, the

¹⁸The complete list of indicators for age-neutral cognitive skills and their description is provided in Appendix C.

¹⁹We do not include age-depreciating skills in column (8) because of high correlation between five variables. With only 85 industries in the sample it is difficult to separately identify the effect of five skills.

²⁰Other measures of skill dispersion and complementarity, used in Bombardini, Gallipoli, and Pupato (2012), yield similar results.

regression coefficients in columns (9) and (10) are identified from the variation in median age of only 19 exporting countries. Furthermore, these are primarily developed countries with older populations. Indeed, as Figure 5 shows, these are the countries with the smallest share of young workers in the labour force: 17 out of 19 countries in the sample fall in the bottom quintile of the young worker share distribution. As a result, the estimates in columns (9) and (10) are based on a subsample of countries with very similar distribution of age-dependent skills and similar patterns of comparative advantage. Therefore, we argue that insignificant estimates for age-dependent skills in columns (9) and (10) should not be treated as evidence against the importance of age structure for trade because they cannot be properly identified on the restricted subsample of exporting countries.

5.3 Estimation of the Rybczynski effect

We have shown in the previous section that a country's age structure is a source of comparative advantage. The Heckscher-Ohlin model then implies that population aging should alter a country's export structure via an increase in age-appreciating and a decrease in age-depreciating skill endowments. Thus, if a country's population is aging more (less) rapidly than other countries, then its output and exports of goods which use age-appreciating (-depreciating) factors of production intensively must raise. To test this Rybczynski prediction of the model, we estimate equation (4) 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 Table 6. 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 capital is not associated with a shift in the export structure towards capital- or skill-intensive industries.²¹ Both results are in contrast with Romalis (2004), who show that changes in capital and, in some specification, skilled labour stocks imply changes in countries'

²¹Using data on factor inputs and output for 28 manufacturing industries and 27 countries, Blum (2010) also find 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.

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.²²

Turning to the estimates with age-dependent skills in columns (2)-(5), we see that the coefficients on all skills are 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, but on the other hand, it erodes competitive advantage in industries which rely on age-depreciating cognitive skills, physical abilities, and learning skills. When all four skills are estimated in one regression in column (6), the coefficients on physical and age-depreciating skills become insignificant. Furthermore, as with the benchmark specification, the coefficient estimates for learning and age-appreciating skills become smaller as we control for the other two skills. The likely reason here is, as in Section 5.1, the high correlation between our four measures of intensity in age-dependent skills, especially between physical and age-depreciating cognitive skills. With only 76 industries in the sample, it is difficult to identify the effects of four skill measures together.²³ For this reason, in specifications that follow we do not include physical ability in the list of covariates.

In Table 7 we report several specification and robustness tests for the Rybczynski effect. Column (1) presents the results with the share of young workers (aged 20-40) in the labour 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 increase in exports of products that use age-appreciating cognitive skills intensively, and decrease in exports of products which are intensive in learning and age-depreciating cognitive skills, although the latter effect is not statistically significant.

In columns (2), (3), and (4) we report results using the base year of 1970, 1980, and 1990,

²²It 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 (6) of Table 5 shows, capital intensities, constructed with 2000 data, is an insignificant determinant of trade flows in 1970. Poor measurement of effective capital stock can also be a problem as capital is notoriously difficult to measure in a consistent way across countries.

²³When either $cog_dep_i \times (\Delta Median_age)_c$ or $physical_i \times (\Delta Median_age)_c$ is excluded from the regression, the remaining three coefficients become statistically significant with the same signs as in columns (2)-(5).

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 Rybczynski effect for age-dependent skills becomes even more pronounced – the coefficients on all three groups of skills have expected signs and are statistically significant. However, with differencing over progressively shorter periods, the effect becomes weaker in column (3) and almost disappears in column (4), where 1990 is used as the base date. That the results change substantially with shorter-span time differencing suggests that it takes more than ten years for the economy to adjust to changes in the supply of factor inputs. Hence, the general-equilibrium effects due to resource relocation between industries are less visible in higher-frequency data.

Our baseline specification (4) implies a linear relationship between population aging and trade flows for given factor intensities. However, it may be the case that increases and decreases in the median age of population may have different impact on the structure of trade. For example, we know that countries with rapidly aging population will experience an increase in the relative supply and decrease in the relative price of age-appreciating skills. Therefore, if relative goods' prices do not change much over time, aging countries may observe more substantial changes in the production structure as compared to countries with stable demographics and constant relative supply of age-dependent skills. In column (5) of Table 7 we present the results for specification (4) where the effect of $Skill_i^k \times \Delta Age_c$ interaction is estimated separately for slowly and rapidly aging countries:

$$\Delta \ln X_{cpi} = \sum_{k \in K} \sum_{j \in Y, O} \beta_k^j D_c^j Skill_i^k \times \Delta Age_c + \sum_n \phi_n I_i^n \times \Delta F_c^n + \delta'_{cp} \lambda + \gamma_c + \gamma_{pi} + \varepsilon_{cpi} \quad (5)$$

where D_c^Y and D_c^O are dummy variables which take the value of one if country c is below and above the median of ΔAge distribution, respectively. The results reveal that only coefficients β_k^O are statistically significant, implying the effect of age structure on trade is mainly driven by countries with fast population aging.

6 Conclusions

Variation in relative factor endowments across countries is the source of comparative advantage. This paper contributes to the comparative advantage literature by analyzing the effect of cross-country differences in endowments of age-dependent skills on the structure of commodity trade. We incorporate age-dependent skills into the extension of the Heckscher-Ohlin model by Romalis (2004) and show that population aging is associated with a reduction in the relative supply and increase in the relative price of age-depreciating skills, which in turn has negative impact on productivity of industries that utilize those skills intensively.

We apply 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 of a country's comparative advantage. First, we show that countries with younger labour 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. Yet, 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, the effect of a reduction in supply of skills of younger workers in fast-aging countries on relative income levels can be alleviated through free trade and imports of products that embody age-depreciating skills.

References

- ATTANASIO, O., S. KITAO, AND G. L. VIOLANTE (2007): “Global demographic trends and social security reform,” *Journal of Monetary Economics*, 54(1), 144–198.
- BALASUBRAMANIAN, N., AND J. SIVADASAN (2011): “What Happens When Firms Patent? New Evidence from U.S. Economic Census Data,” *The Review of Economics and Statistics*, 93(1), 126–146.
- BARRO, R. J., AND J. W. LEE (2013): “A new data set of educational attainment in the world, 1950-2010,” *Journal of Development Economics*, 104(C), 184–198.
- BECK, T. (2003): “Financial Dependence and International Trade,” *Review of International Economics*, 11(2), 296–316.
- BLUM, B. S. (2010): “Endowments, Output, and the Bias of Directed Innovation,” *Review of Economic Studies*, 77(2), 534–559.
- BOERSCH-SUPAN, A., A. LUDWIG, AND J. WINTER (2001): “Aging and International Capital Flows,” Working Paper 8553, National Bureau of Economic Research.
- (2006): “Ageing, Pension Reform and Capital Flows: A Multi-Country Simulation Model,” *Economica*, 73(292), 625–658.
- BOMBARDINI, M., G. GALLIPOLI, AND G. PUPATO (2012): “Skill Dispersion and Trade Flows,” *American Economic Review*, 102(5), 2327–48.
- BRADLEY R. KING, STUART M. FOGEL, G. A., AND J. DOYON (2013): “Neural correlates of the age-related changes in motor sequence learning and motor adaptation in older adults,” pp. 7–142.
- BROOKE, L., AND P. TAYLOR (2005): “Older Workers and Employment: Managing Age Relations,” *Ageing and Society*, 25, 415–429.
- CHARNESS, N. (2006): “Work, Older Worker and Technology,” pp. 25–30.

- CHARNESS, N., AND S. J. CZAJA (2006): “Older Worker Training: What We Know and Don’t Know,” Discussion paper, AARP.
- CHOR, D. (2010): “Unpacking sources of comparative advantage: A quantitative approach,” *Journal of International Economics*, 82(2), 152–167.
- CUNAT, A., AND M. J. MELITZ (2012): “Volatility, Labor Market Flexibility, And The Pattern Of Comparative Advantage,” *Journal of the European Economic Association*, 10(2), 225–254.
- DAVIS, D. R., AND D. E. WEINSTEIN (2001): “An Account of Global Factor Trade,” *American Economic Review*, 91(5), 1423–1453.
- DEBAERE, P. (2014): “The Global Economics of Water: Is Water A Source of Comparative Advantage?,” *American Economic Journal: Applied Economics*, 6(2), 32–48.
- DEBEARE, P. (2003): “Relative Factor Abundance and Trade,” *Journal of Political Economy*, 111(3), 589–610.
- DOMELJ, D., AND M. FLODEN (2006): “Population Ageing and International Capital Flows,” Discussion paper.
- DORNBUSCH, R., S. FISCHER, AND P. A. SAMUELSON (1977): “Comparative Advantage, Trade, and Payments in a Ricardian Model with a Continuum of Goods,” *American Economic Review*, 67(5), 823–39.
- EATON, J., AND S. KORTUM (2002): “Technology, Geography, and Trade,” *Econometrica*, 70(5), 1741–1779.
- ETHAN R. BUCH, S. Y., AND J. L. CONTRERAS-VIDAL (2003): “Visuomotor adaptation in normal aging,” pp. 55–63.
- FEENSTRA, R., J. ROMALIS, AND P. SCHOTT (2002): “U.S. Imports, Exports and Tariff Data, 1989-2001,” Discussion paper, NBER Working Paper 9387.
- GIST, M., B. ROSEN, AND C. SCHWOERER (1988): “The Influence of Training Method and Trainee Age on the Acquisition of Computer Skills,” *Personnel Psychology*, 41, 255–265.

- HARRIGAN, J. (1997): “Technology, Factor Supplies, and International Specialization: Estimating the Neoclassical Model,” *American Economic Review*, 87(4), 475–94.
- HARRINGTON, D. L., AND K. Y. HAALAND (1992): “Skill learning in the elderly: diminished implicit and explicit memory for a motor sequence,” pp. 425–434.
- HEDGE, JERRY; BORMAN, W. L. S. (2005): *The Aging Workforce: Realities, Myths, And Implications For Organizations*. American Psychological Association.
- HELLIWELL, J. F. (2004): “Demographic Changes and International Factor Mobility,” NBER Working Papers 10945, National Bureau of Economic Research, Inc.
- HELPMAN, E., AND O. ITSKHOKI (2010): “Labour Market Rigidities, Trade and Unemployment,” *Review of Economic Studies*, 77(3), 1100–1137.
- HIGGINS, M. (1997): “Demography, national savings and international capital flows,” Discussion paper.
- HOLZMANN, R. (2002): “Can Investments in Emerging Markets Help to Solve the Aging Problem?,” *Journal of Emerging Market Finance*, 1(2), 215–241.
- HOWARD, J. H., AND D. V. HOWARD (1997): “Age differences in implicit learning of higher order dependencies in serial patterns,” pp. 634–656.
- JAY PRATT, A. C., AND R. ABRAMS (1994): “Rapid aimed limb movements: age differences and practice effects in component submovements,” pp. 325–334.
- JOLLIFFE, I. (2002): *Principal Component Analysis*. Springer, Berlin.
- JULIE MESSIER, SERGEI ADAMOVICH, D. J. W. H. J. S., AND H. POIZNER (2006): “Visuomotor learning in immersive 3D virtual reality in Parkinson’s disease and in aging,” pp. 457–474.
- KRUGMAN, P. (1980): “Scale Economies, Product Differentiation, and the Pattern of Trade,” *American Economic Review*, 70(5), 950–59.

- LEVCHENKO, A. A. (2007): “Institutional Quality and International Trade,” *Review of Economic Studies*, 74(3), 791–819.
- LUDWIG, A., D. KRUEGER, AND A. H. BOERSCH-SUPAN (2007): “Demographic Change, Relative Factor Prices, International Capital Flows, and Their Differential Effects on the Welfare of Generations,” Working Paper 13185, National Bureau of Economic Research.
- LUDWIG, A., T. SCHELKLE, AND E. VOGEL (2012): “Demographic Change, Human Capital and Welfare,” *Review of Economic Dynamics*, 15(1), 94–107.
- LUDWIG, A., AND E. VOGEL (2010): “Mortality, fertility, education and capital accumulation in a simple OLG economy,” *Journal of Population Economics*, 23(2), 703–735.
- MANOVA, K. (2008): “Credit constraints, equity market liberalizations and international trade,” *Journal of International Economics*, 76(1), 33–47.
- MAURER, T. J. (2001): “Career-relevant Learning and Development, Worker Age, and Beliefs about Self-efficacy for Development,” *Journal of Management*, 27(2), 123–140.
- MCDOWD, J., AND F. CRAIK (1988): “Effects of aging and task difficulty on divided attention performance,” *Journal of Experimental Psychology: Human Perception and Performance*, 14, 267–280.
- MCDOWD, J., AND R. SHAW (2000): *Attention and aging: a functional perspective*. Erlbaum; Mahwah, NJ.
- MCNAY, E. C., AND D. B. WILLINGHAM (1998): “Deficit in learning of a motor skill requiring strategy, but not of perceptuomotor recalibration, with aging,” pp. 411–420.
- MORRIS, M. G., AND V. WENKATESH (2000): “Age differences in Technology Adoption Decisions: Implications for a Changing Work Force,” *Personnel Psychology*, 53, 375–403.
- NARCISO, A. (2013): “The impact of an ageing population on international capital flows,” MPRA Working Papers 26457, Copenhagen Business School.
- NUNN, N. (2007): “Relationship-Specificity, Incomplete Contracts, and the Pattern of Trade,” *The Quarterly Journal of Economics*, 122(2), 569–600.

- PRENDA, K. M., AND S. STAHL (2001): “The Truth about Older Workers,” pp. 30–37.
- ROMALIS, J. (2004): “Factor Proportions and the Structure of Commodity Trade,” *American Economic Review*, 94(1), 67–97.
- RUCH, F. L. (1934): “The differentiative effects of age upon human learning,” pp. 261–286.
- SALTHOUSE, T. (1998): “Independence of Age-Related Influences on Cognitive Abilities Across the Life Span,” *Developmental Psychology*, 34, 851–864.
- (2009): “When does age-related cognitive decline begin?,” *Neurobiology of Aging*, 30, 507–514.
- (2010): “Influence of Age on Practice Effects in Longitudinal Neurocognitive Change,” *Neuropsychology*, 24, 563–572.
- SCHAE, W. (1986): *Adult Development and Aging*. Boston: Little, Brown & Co.
- (1994): “The Course of Adult Intellectual Development,” *American Psychologist*, 49, 304–313.
- (2000): “The Impact of Longitudinal Studies on Understanding Development from Young Adulthood to Old Age,” *International Journal of Behavioral Development*, 24, 257–266.
- (2005): *Developmental influences on adult intelligence: The Seattle Longitudinal Study*. New York: Oxford University Press.
- SEIDLER, R. D. (2006): “Differential effects of age on sequence learning and sensorimotor adaptation,” pp. 337–346.
- SINGH-MANOUX, ARCHANA; KIVIMAKI, M. G. M. E. A. (2012): “Timing of Onset of Cognitive Decline: Results from Whitehall II Prospective Cohort Study,” *British Medical Journal*, 344, 18–26.
- SKIRBEKK, V. (2004): “Age and Individual Productivity: A Literature Survey, Vienna Yearbook of Population Research,” pp. 133–153.

- STERNBERG, R. J., AND C. A. BERG (1992): *Intellectual Development*. Cambridge University Press.
- TANG, H. (2012): “Labor market institutions, firm-specific skills, and trade patterns,” *Journal of International Economics*, 87(2), 337–351.
- TREFLER, D. (1993): “International Factor Price Differences: Leontief Was Right!,” *Journal of Political Economy*, 101(6), 961–87.
- TSANG, P. (1998): “Age, attention, expertise, and time-sharing performance,” *Psychology and Aging*, 13, 323–347.
- VERHAEGHEN, P., AND J. CERELLA (2002): “Aging, executive control, and attention: a review of meta-analyses,” *Neuroscience Biobehavioral Review*, 26, 849–57.

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 Pumps	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)	(6)
(1) <i>cog_app</i>	1					
(2) <i>cog_dep</i>	-0.24	1				
(3) <i>physical</i>	-0.32	0.89	1			
(4) <i>pcreation</i>	-0.10	0.36	0.30	1		
(5) <i>capital intensity</i>	0.48	-0.07	0.04	-0.09	1	
(6) <i>skill intensity</i>	0.56	-0.77	-0.78	-0.23	0.25	1

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

Table 3. Baseline specification with median age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Cog_app_i \times$ $(Median\ age)_c$		0.040** (8.17)				0.042** (9.07)	0.029** (5.78)
$Cog_dep_i \times$ $(Median\ age)_c$			-0.058** (-10.59)			-0.076** (-7.39)	-0.062** (-5.77)
$Physical_i \times$ $(Median\ age)_c$				-0.051** (-9.00)		0.020* (2.02)	0.011 (1.05)
$Pcreation_i \times$ $(Median\ age)_c$					-0.027** (-5.65)	-0.009 (-1.61)	-0.007 (-1.30)
$(Capital\ int.)_i \times$ $(Capital\ abund.)_c$	0.030** (6.23)	0.018** (3.60)	0.029** (5.83)	0.036** (7.18)	0.033** (6.26)		0.022** (3.79)
$(Skill\ int.)_i \times$ $(Skill\ abund.)_c$	0.049** (10.31)	0.038** (7.59)	0.023** (4.16)	0.025** (4.50)	0.045** (9.30)		0.017** (3.07)
Importer-industry FE	YES	YES	YES	YES	YES	YES	YES
Exporter FE	YES	YES	YES	YES	YES	YES	YES
Trade costs controls	YES	YES	YES	YES	YES	YES	YES
R-squared	0.551	0.553	0.554	0.554	0.554	0.556	0.556
N	414,918	413,466	413,466	413,466	410,486	410,486	410,486

Notes: The dependent variable is the normalized natural logarithm of export from country c to country p in industry i in year 2000. * significant at 5%, ** significant at 1%. Robust standard errors are clustered by exporter-industry.

Table 4. Baseline specification with the share of young workers

	(1)	(2)	(3)	(4)	(5)	(6)
$Cog_app_i \times$ $(share\ of\ young\ workers)_c$	-0.038** (-8.03)				-0.027** (-5.93)	-0.025** (-5.47)
$Cog_dep_i \times$ $(share\ of\ young\ workers)_c$		0.054** (10.58)			0.068** (6.65)	0.065** (6.38)
$Physical_i \times$ $(share\ of\ young\ workers)_c$			0.045** (8.41)		-0.023* (-2.25)	-0.025* (-2.44)
$Pcreation_i \times$ $(share\ of\ young\ workers)_c$				0.028** (5.79)	0.007 (1.40)	0.008 (1.51)
$(Capital\ int.)_i \times$ $(Capital\ abund.)_c$	0.020** (4.20)	0.029** (5.99)	0.034** (6.97)	0.032** (6.38)	0.023** (4.40)	0.023** (4.42)
$(Skill\ int.)_i \times$ $(Skill\ abund.)_c$	0.040** (8.03)	0.026** (4.91)	0.030** (5.51)	0.046** (9.62)	0.022** (3.98)	0.017** (3.33)
$(Skill\ int.)_i \times$ $(Skill\ abund.\ young)_c$						-0.023** (-4.86)
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	0.553	0.554	0.554	0.555	0.557	0.557
N	411,362	411,362	411,362	408,393	408,393	408,393

Notes: The dependent variable is the normalized natural logarithm of export from country c to country p in industry i in year 2000. * significant at 5%, ** significant at 1%. Robust standard errors are clustered by exporter-industry.

Table 5. Robustness tests.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Cog_app_i \times$ $(Median\ age)_c$	0.025** (5.00)	0.027** (5.50)	0.028** (5.61)	0.032** (6.07)	0.038** (7.18)	0.023** (2.96)	0.029** (5.90)		-0.034 (-1.06)	-0.042 (-1.31)
$Cog_dep_i \times$ $(Median\ age)_c$	-0.057** (-5.30)	-0.060** (-5.59)	-0.069** (-6.68)	-0.062** (-5.60)	-0.053** (-5.13)	-0.070** (-4.63)	-0.061** (-5.68)		0.091 (1.24)	0.052 (0.71)
$Physical_i \times$ $(Median\ age)_c$	0.016 (1.44)	0.014 (1.34)	0.007 (0.68)	0.012 (1.15)	0.002 (0.23)	-0.008 (-0.55)	0.010 (0.90)		-0.092 (-1.38)	-0.075 (-1.10)
$Pcreation_i \times$ $(Median\ age)_c$	-0.008 (-1.47)	-0.008 (-1.41)		-0.010+ (-1.72)	-0.014* (-2.40)	-0.020* (-2.40)	-0.007 (-1.22)		-0.072* (-2.05)	-0.060 (-1.62)
$(Capital\ int.)_i \times$ $(Capital\ abund.)_c$	0.020** (3.44)	0.020** (3.45)	0.023** (3.92)	0.023** (3.81)	0.010 (1.74)	0.010 (1.40)	0.023** (3.95)	0.028** (5.43)	0.016 (0.57)	0.046 (1.58)
$(Skill\ int.)_i \times$ $(Skill\ abund.)_c$	0.030** (4.85)	0.037** (7.03)	0.016** (2.90)	0.020** (3.32)	0.027** (4.99)	0.027** (2.72)	0.011+ (1.85)	0.046** (9.32)	0.010 (0.92)	0.015 (1.51)
$Pintensity_i \times$ $(Median\ age)_c$			-0.011+ (-1.71)							
$Cog_neutral_i \times$ $(Median\ age)_c$								-0.013** (-2.88)		
$(Skill\ substitutability)_i \times$ $(Skill\ dispersion)_c$									-0.028** (-3.11)	
$(Contract\ intensity)_i \times$ $(Judicial\ quality)_c$										0.025* (2.15)
Sample	benchmark	benchmark	benchmark	benchmark	2010	1970	no USA	benchmark	benchmark	benchmark
Importer-industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Exporter FE	YES	YES	YES	NO	YES	YES	YES	YES	YES	YES
Importer-exporter FE	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO
Trade costs controls	YES	YES	YES	NO	YES	YES	YES	YES	YES	YES
R-squared	0.557	0.557	0.556	0.736	0.586	0.536	0.542	0.552	0.697	0.705
N	410,486	410,486	410,486	416,371	450,067	158,545	392,861	413,466	80,243	76,789

Notes: The dependent variable is the normalized natural logarithm of export from country c to country p in industry i in year 2000. + significant at 10%, * significant at 5%, ** significant at 1%. Robust standard errors are clustered by exporter-industry. In columns (1) and (2) skill abundance is measured with the average years of schooling and the share of population with tertiary education, respectively. Specification (3) includes additional unreported controls for bilateral trade costs. Column (4) reports results for the baseline specification for year 2010.

Table 6. Estimates for the Rybczynski effect

	(1)	(2)	(3)	(4)	(5)	(6)
$Cog_app_i \times (\Delta Median\ age)_c$		0.035** (3.18)				0.023+ (1.70)
$Cog_dep_i \times (\Delta Median\ age)_c$			-0.037** (-3.19)			0.003 (0.09)
$Physical_i \times (\Delta Median\ age)_c$				-0.041** (-3.67)		-0.026 (-0.82)
$Pcreation_i \times (\Delta Median\ age)_c$					-0.037** (-3.40)	-0.026* (-2.19)
$(Capital\ int.)_i \times (\Delta Capital\ abund.)_c$	0.010 (0.83)	0.012 (0.90)	0.019 (1.39)	0.024+ (1.83)	0.013 (0.86)	0.009 (0.51)
$(Skill\ int.)_i \times (\Delta Skill\ abund.)_c$	-0.002 (-0.23)	-0.004 (-0.39)	-0.004 (-0.40)	-0.004 (-0.42)	-0.004 (-0.47)	-0.006 (-0.64)
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	0.476	0.477	0.477	0.477	0.481	0.482
N	62,488	61,835	61,835	61,835	61,007	61,007

Notes: The dependent variable is the change in the normalized natural logarithm of export from country c to country p in industry i between years 2000 and 1960. + significant at 10%, * significant at 5%, ** significant at 1%. Robust standard errors are clustered by exporter-industry.

Table 7. Robustness and extensions for the Rybczynski effect

	(1)	(2)	(3)	(4)	(5)	(6)	
					β^o	β^y	
$Cog_app_i \times (\Delta Age)_c$	-0.030* (-2.22)	0.035** (3.54)	0.033** (3.59)	-0.003 (-0.30)	0.049** (4.09)	-0.008 (-0.41)	0.117+ (1.96)
$Cog_dep_i \times (\Delta Age)_c$	0.015 (1.00)	-0.032** (-2.91)	-0.020 (-1.61)	-0.003 (-0.30)	-0.037** (-2.78)	-0.013 (-0.56)	0.062 (1.07)
$Pcreation_i \times (\Delta Age)_c$	0.027* (1.99)	-0.020+ (-1.93)	-0.027* (-2.45)	-0.020* (-2.04)	-0.030* (-2.30)	-0.022 (-0.93)	0.007 (0.32)
$(Capital\ int.)_i \times (\Delta Age)_c$	-0.005 (-0.35)	0.005 (0.48)	0.016+ (1.83)	0.020** (2.77)	0.001 -0.06		0.118 (1.65)
$(Skill\ int.)_i \times (\Delta Age)_c$	-0.005 (-0.48)	-0.011 (-1.50)	-0.002 (-0.35)	0.007 (1.43)	-0.008 (-1.14)		0.136** (3.57)
Dependent variable	$\ln(Exp_{cpi})$	$\ln(Exp_{cpi})$	$\ln(Exp_{cpi})$	$\ln(Exp_{cpi})$	$\ln(Exp_{cpi})$	$(Import\ share)_{pci}$	
Measure for Age_c	young worker share	median age	median age	median age	median age	median age	
End year	2000	2000	2000	2000	2000	2000	
Start year	1962	1970	1980	1990	1970	1970	
Importers	all	all	all	all	all	USA	
Importer-industry FE	YES	YES	YES	YES	YES	NO	
Exporter FE	YES	YES	YES	YES	YES	NO	
Trade costs controls	YES	YES	YES	YES	YES	YES	
R-squared	0.481	0.448	0.429	0.327	0.448	0.113	
N	61,651	82,885	100,676	92,166	82,885	2,691	

Notes: The dependent variable is the change in the normalized natural logarithm of exports from country c to country p in industry i between years 2000 and 1960. + significant at 10%, * significant at 5%, ** significant at 1%. Robust standard errors are clustered by exporter-industry. Column (6) includes exporter and industry fixed effects.

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

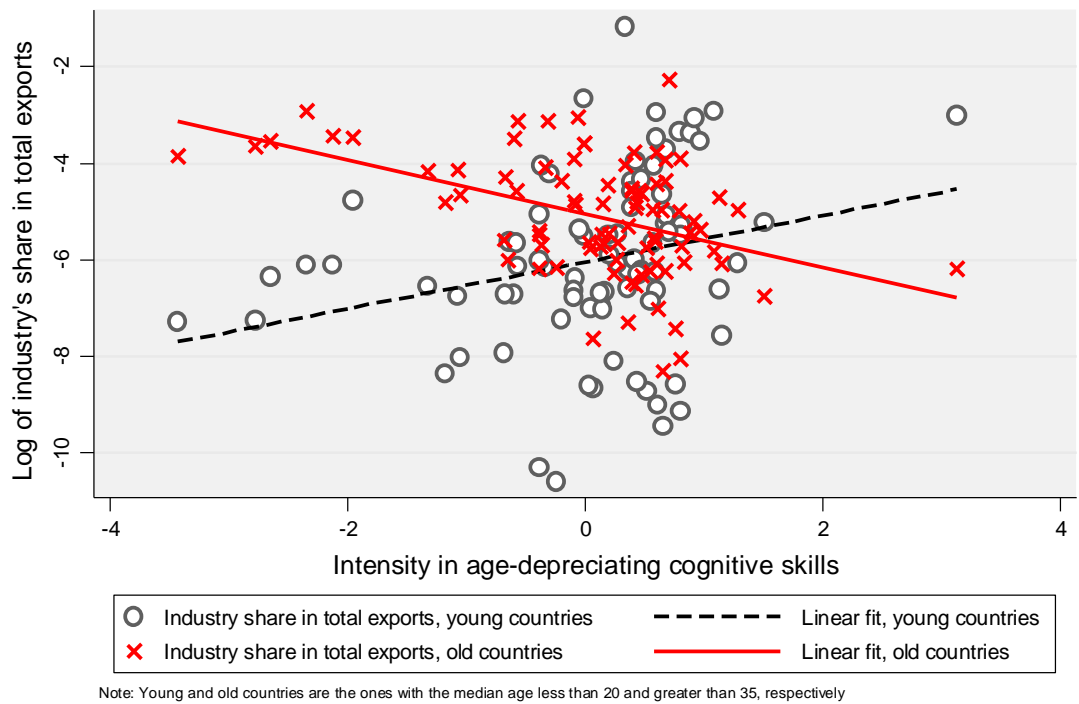


Figure 2. Correlation between intensity in age-appreciating cognitive skills and exports for old and young countries

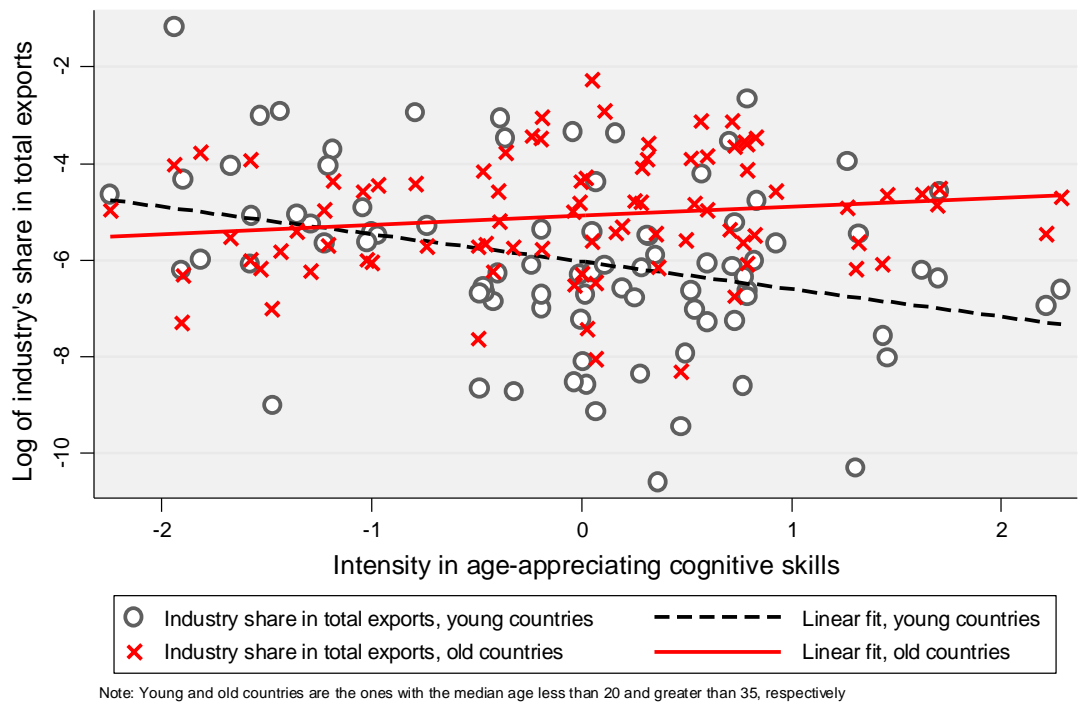


Figure 3. Correlation between intensity in physical abilities and exports for old and young countries

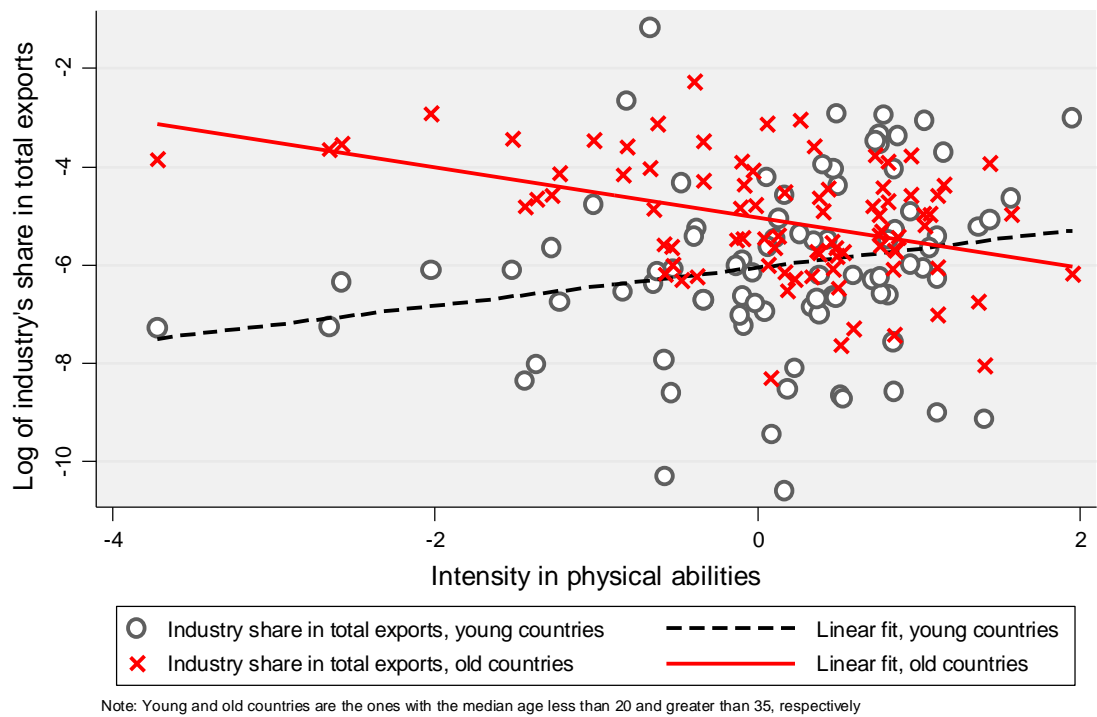


Figure 4. Correlation between intensity in learning skills and exports for old and young countries

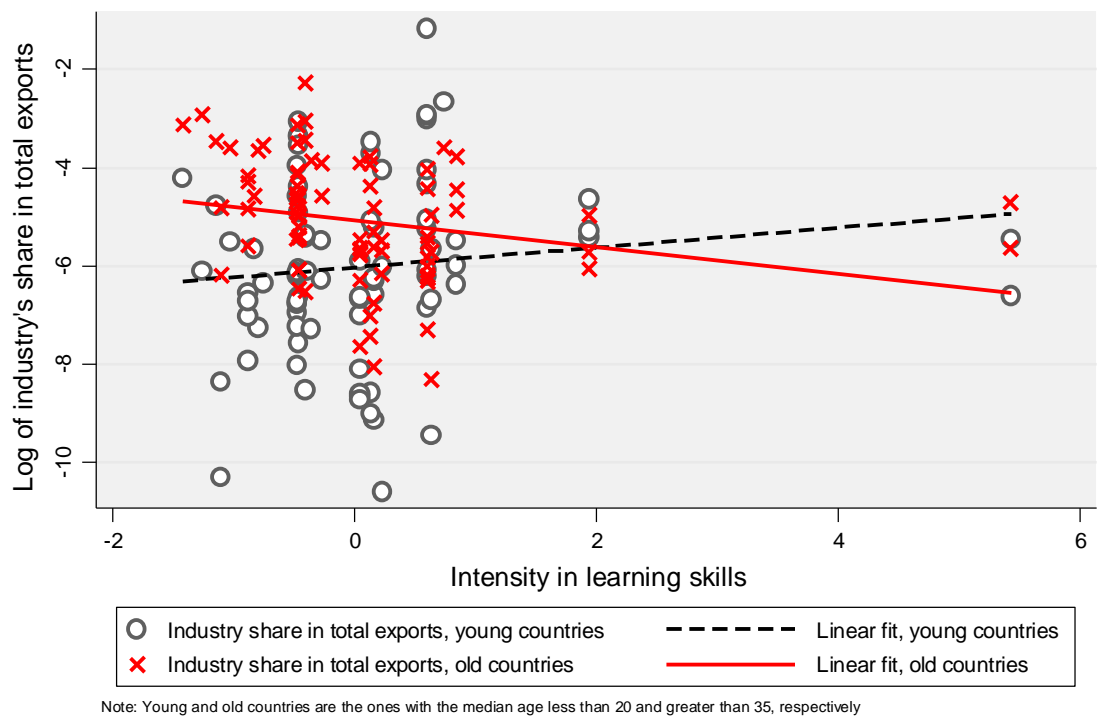


Figure 5. Kernel density for the distribution of the share of young workers among countries



Appendix A. Relationship between a country's average age and factor abundance.

In this appendix we prove that younger countries are abundant in skills that decline with age. Consider two countries, Home and Foreign, denoted by H and F . All measures that refer to the foreign country we label with a star superscript. Two countries are otherwise identical except for their population age structures. Let the number of young and old workers in Home country to be Y and O , respectively, and $(Y + O) = (Y^* + O^*)$. Suppose H is a younger country than F , that is $Y/O > Y^*/O^*$. One worker provides two types of age dependent skills: m (Memorization) and v (Vocabulary). We assume that m depreciates faster with age than v , so that $m_Y/v_Y > m_O/v_O$. Denote the total endowment of skills m and v at Home with M and V , and in Foreign with M^* and V^* . It is important to note that although we focus here on the example with two countries and two skills, the results below are valid for any number of counties and factors of production.

It is easy to prove that the younger country H is abundant in skill M relative to the older country F , or that $M/V > M^*/V^*$.

$$\frac{M}{V} = \frac{m_Y Y + m_O O}{v_Y Y + v_O O} = \frac{m_Y Y/O + m_O}{v_Y Y/O + v_O} = \frac{m_O}{v_O} \frac{m_Y/m_O Y/O + 1}{v_Y/v_O Y/O + 1}$$

$$\frac{M^*}{V^*} = \frac{m_Y Y^* + m_O O^*}{v_Y Y^* + v_O O^*} = \frac{m_O}{v_O} \frac{m_Y/m_O Y^*/O^* + 1}{v_Y/v_O Y^*/O^* + 1}$$

$$\begin{aligned} \frac{M}{V} - \frac{M^*}{V^*} &= \frac{m_O}{v_O} \left(\frac{m_Y/m_O Y/O + 1}{v_Y/v_O Y/O + 1} - \frac{m_Y/m_O Y^*/O^* + 1}{v_Y/v_O Y^*/O^* + 1} \right) \\ &= \frac{m_O}{v_O} \frac{(m_Y/m_O Y/O v_Y/v_O Y^*/O^* + v_Y/v_O Y^*/O^* + m_Y/m_O Y/O + 1) - (m_Y/m_O Y^*/O^* v_Y/v_O Y/O + v_Y/v_O Y/O + m_Y/m_O Y^*/O^* + 1)}{(v_Y/v_O Y/O + 1)(v_Y/v_O Y^*/O^* + 1)} \\ &= \frac{m_O}{v_O} \frac{(v_Y/v_O - m_Y/m_O)(Y^*/O^* - Y/O)}{(v_Y/v_O Y/O + 1)(v_Y/v_O Y^*/O^* + 1)} > 0, \end{aligned}$$

because $v_Y/v_O - m_Y/m_O < 0$ and $Y^*/O^* - Y/O < 0$.

Consider any pair of industries i and j and assume that i uses skill m more intensively than j . The Romalis' extension of the Heckscher-Ohlin model predicts that since H is abundant in m , the relative price of m will be lower at Home and it will export more of good i to country F than of good j . Furthermore, the larger is the difference in the average age of the two countries (the ratio of young to old workers), the larger is the asymmetry in skill endowments and in the relative factor prices. Therefore, exports of commodity i by country H to country F is increasing in the relative average age difference of the two countries. Overtime, if population is aging faster in F than in H , exports of good i from H to F will increase and exports of good j will contract.

Appendix B. Age-dependent skills

Age and cognitive skills

Of all studies on aging and cognition we primarily focus on those which utilize both cross-sectional and longitudinal analysis. Studies that derive their results from pure cross-sectional comparison of individuals of different age may not accurately distinguish the effect of chronological age on individual's performance from the effect of fundamental differences between age cohorts which may arise from changes in social or cultural environment. At the same time, longitudinal studies that test the same individuals multiple times are often argued to underestimate the effect of aging on cognitive skills due to positive effect of re-testing on test performance, even if the two tests are many years apart.

One of the first comprehensive research programs on cognitive abilities and aging has been conducted by Schaie (1986, 1994, 2000, 2005) in the Seattle Longitudinal Study (SLS). The SLS has followed several cohorts of adults aged 25 to 88, with more than 5,000 subjects in total. Participants were first tested in 1956 and then re-tested at every 7-year interval along with the new cohort added to the study in every cycle. The test battery included the measures of verbal comprehension, verbal memory, spatial orientation, inductive reasoning, numerical ability, and perceptual speed. The results of this program demonstrate that not all cognitive skills change uniformly through adulthood. Cross-sectional comparison of score means of individuals from different age groups shows that inductive reasoning and spatial orientation decrease monotonically with age starting at 25, whereas verbal and numerical abilities peak at mid-life and decline slowly afterwards. The longitudinal analysis reveals that all scores, except for perceptual speed, initially increase, and then level off for verbal ability and decrease for reasoning, spatial orientation, and numerical ability.

More recent work support the main message of the earlier studies that not all cognitive skills decline uniformly with age. Salthouse (1998, 2009, 2010) report results of another laboratory testing with over 2,000 participants tested twice in 1-7 years intervals. He confirmed that in the cross sectional comparison nearly all cognitive abilities are found to monotonically declining

with age, including memory, reasoning, and space orientation. Only vocabulary was found to be improving throughout the adulthood. Results from the longitudinal analysis, adjusted for prior testing experience, paint a different picture: only memory demonstrates considerable decline with age, while reasoning and vocabulary remain stable throughout lifecycle. In another study by Singh-Manoux (2012), 7,400 participants aged 45-70 were tested three times every five years beginning in 1997. The authors find, both in cross-sectional and longitudinal analysis, a significant decline in memory and reasoning between 45 and 55 years, and slight but statistically significant improvement in vocabulary.

Overall, the research on age and cognitive development seems to reach a consensus on a number cognitive abilities. First, nearly all studies that examine the effect of aging on speech and language abilities find that they improve with age. Older individuals usually have more extensive vocabularies and are more skilled conversationalists than younger adults, and older people out-perform younger people on tasks that involve language and writing skills. Second, there is a general consensus in the literature that there is a significant decline in memory with age. Older adults exhibit difficulties with activities that involve manipulations of the content of their working memory. Third, while older adults have been shown to experience no difficulties in maintaining selective attention on a particular activity without being distracted by others (McDowd and Shaw, 2000; Verhaeghen and Cerella, 2002), the divided attention is associated with significant age-related decline. When individuals are required to process information from two or more sources at the same time or to switch from one task to another, older adults are more affected by the cost of dividing attention into multiple tasks (McDowd and Craik, 1988; Tsang, 1998; McDowd and Shaw, 2000; Verhaeghen and Cerella, 2002).²⁴

Finally, there is little disagreement in the literature that the speed of information processing is falling with age. Schaie (1994, 2005) and Salthouse (2010) identify perceptual speed as one of the abilities associated with the most rapid age-related decline which begins between ages 25 and 32. In fact, many researchers argue that much of the evidence for age-related decline in some cognitive abilities can be explained by slowing of information processing. Salthouse has demonstrated in numerous works that an age-related decline in some cognitive tasks, such

²⁴McDowd and Shaw (2000) have demonstrated that divided attention impairment is a significant factor of higher car accidents among adults.

as reasoning, can be accounted for by falling speed of information processing. Moreover, some studies emphasize that older individuals may be worse on the measures of reasoning because the tests on those measures are administered with tight time limits and may thus pick up the speed of information processing. However, Salthouse suggests that the effect of aging on memory is independent of processing speed.

Therefore, in our empirical analysis we primarily focus memory, language skills, divided attention, and processing speed as the four cognitive skills that are known to change substantially with age.

Age and ability to learn

A related stream of literature demonstrates negative relationship between aging and learning. The ability to learn new skills matters more for industries with high rates of product creation and destruction because workers need to constantly update their skills and adapt to new tasks associated with the new products. If learning and adaptability are impaired in older adults, we would expect countries with older population to lose comparative advantage in industries with high rates of product creation and destruction. Therefore, we would expect aging countries to specialize in low product turnover industries.

Behavioral, neurological, and neuroimaging literature consistently reports negative relationship between aging and motor skill acquisition, whereby older adults learns slower, and in many cases, even when provided with extended practice, their performance levels do not reach those of younger adults.²⁵ In an updated review, Bradley R. King and Doyon (2013) summarized that older adults have deficits in motor skill learning in the following three occasions: the initial acquisition of movement sequences under conditions of increased task complexity, the consolidation of learned motor sequences, and during the exposure phase to various sensorimotor perturbations. Specifically, the behavioral results are, at least partially, manifestations of age-related dysfunctions in the structure and functioning of the fronto-striatal networks subserving

²⁵See, for example, Ethan R. Buch and Contreras-Vidal (2003), Harrington and Haaland (1992), Howard and Howard (1997), McNay and Willingham (1998), Julie Messier and Poizner (2006), Jay Pratt and Abrams (1994), Ruch (1934), and Seidler (2006).

the different phases of motor learning.

The other stream of literature focuses on age differences in the acquisition of new information and the attitude towards new technologies. For example, Gist, Rosen, and Schwoerer (1988), Sternberg and Berg (1992), Morris and Wenkatesh (2000), Maurer (2001), Prenda and Stahl (2001), Skirbekk (2004), Brooke and Taylor (2005), Charness (2006) find that older workers learn new skills at a slower pace than younger workers for various reasons. Sternberg and Berg (1992) speculate that the slow acquisition of new information may occur to older workers because of their large knowledge base. First, some experiences may be discounted to the new task. Second, those experiences might actually be handicap to their learning, which may occur from past habits or old ways of thinking, specially when the new information contradicts their existing belief. Maurer (2001) finds there is a decline in self-confidence (or self-efficacy) for career-relevant learning and skill development with age. Charness and Czaja (2006) shows that some of the slowing in learning new tasks may be attributable to older adults' preference for accuracy over speed, with the reverse holding true for younger adults.

Aging and physical abilities

A decline in physical strength with age is well documented in the literature (see Hedge (2005) for a survey). The loss of strength is a natural process caused by changes in body composition with a reduction in muscle mass being the main factor. Starting in late 20, the lean muscle mass start to decrease and the fat levels to increase. Moreover, the quality of muscle mass deteriorates: the decline in strength is more rapid than the reduction in muscle mass and the maintaining of muscle mass does not prevent from age-declining muscle strength.

Appendix C. Construction of industry-level measures of skill intensities

Industry-level measures of intensity in cognitive skills are constructed using two sources of data. First, from the O*NET database we retrieve measures importance of different cognitive skills for all occupational types, recorded at 7-digit Standard Occupational Classification (SOC). O*NET surveys workers and experts in different occupations and collects their response to questions about the importance of various skills and abilities for successful performance. The responses, ranked on a scale from 1 to 5, are averaged across respondents in each occupation.

Second, for every 4-digit NAICS industry, we obtain occupational composition using Occupational Employment Statistics (OES) Survey, maintained by the US Bureau of Labor Statistics. The OES database includes information on the number of workers in all 7-digit SOC occupational categories for the year 2012. This allows us to construct the share of each occupation in total employment in every industry, which we match to O*NET scores by SOC. Finally, using occupational employment shares as weights, we generate industry-level measure of skill intensity as the weighted average of importance of that skill across occupations within an industry. Therefore, the cross-industry variation in skill intensity is driven by the variation in occupational composition across industries.

We rely on O*NET database to construct measures of intensity in four age-dependent cognitive skills described in Appendix A. Below we explain which O*NET skill indicators were used to construct those measures.

Communication skills ranking across occupation is based on the following four O*NET indicators: oral comprehension - the ability to listen to and understand information and ideas presented through spoken words and sentences; oral expression - the ability to communicate information and ideas in speaking so others will understand; written comprehension - the ability to read and understand information and ideas presented in writing; and written expression - the ability to communicate information and ideas in writing so others will understand.

Memory: memorization - the ability to remember information such as words, numbers,

pictures, and procedures.

Divided attention: time sharing - the ability to shift back and forth between two or more activities or sources of information such as speech, sounds, touch, or other sources.

Speed of information processing: perceptual speed - the ability to quickly and accurately compare similarities and differences among sets of letters, numbers, objects, pictures, or patterns; and speed of closure - the ability to quickly make sense of, combine, and organize information into meaningful patterns.

Industry-level measures of intensity in physical skills are constructed in the same way as cognitive skills. The following questions about physical abilities were used from O*NET to generate nine measures of physical skill intensities: dynamic flexibility — the ability to quickly and repeatedly bend, stretch, twist, or reach out with your body, arms, and/or legs; dynamic strength — the ability to exert muscle force repeatedly or continuously over time (this involves muscular endurance and resistance to muscle fatigue); explosive strength — the ability to use short bursts of muscle force to propel oneself (as in jumping or sprinting), or to throw an object; extent flexibility — the ability to bend, stretch, twist, or reach with your body, arms, and/or legs; gross body coordination — the ability to coordinate the movement of your arms, legs, and torso together when the whole body is in motion; gross body equilibrium — the ability to keep or regain your body balance or stay upright when in an unstable position; stamina — the ability to exert yourself physically over long periods of time without getting winded or out of breath; static strength — the ability to exert maximum muscle force to lift, push, pull, or carry objects; trunk strength — the ability to use your abdominal and lower back muscles to support part of the body repeatedly or continuously over time without ‘giving out’ or fatiguing.

A measure of intensity in age-neutral cognitive skills was constructed based on the following O*NET indicators: category flexibility — the ability to generate or use different sets of rules for combining or grouping things in different ways; deductive reasoning — the ability to apply general rules to specific problems to produce answers that make sense; flexibility of closure — the ability to identify or detect a known pattern (a figure, object, word, or sound) that is hidden in other distracting material; fluency of ideas — the ability to come up with a number

of ideas about a topic (the number of ideas is important, not their quality, correctness, or creativity); information ordering — the ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations); mathematical reasoning — the ability to choose the right mathematical methods or formulas to solve a problem; number facility — the ability to add, subtract, multiply, or divide quickly and correctly; originality — the ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem; problem sensitivity — the ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing there is a problem; spatial orientation — the ability to know your location in relation to the environment or to know where other objects are in relation to you; visualization — the ability to imagine how something will look after it is moved around or when its parts are moved or rearranged.

Table 1A. Correlation between industry-level intensities in cognitive skills

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Oral comprehension	1							
(2) Oral expression	0.98	1						
(3) Written comprehension	0.93	0.91	1					
(4) Written expression	0.96	0.94	0.97	1				
(5) Memorization	0.91	0.92	0.87	0.91	1			
(6) Time sharing	0.55	0.57	0.61	0.61	0.66	1		
(7) Perceptual speed	0.43	0.49	0.44	0.43	0.57	0.80	1	
(8) Speed of closure	0.69	0.74	0.73	0.73	0.84	0.83	0.84	1

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

Table 2A. Correlation between industry-level intensities in physical abilities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Dynamic flexibility	1								
(2) Dynamic strength	0.73	1							
(3) Explosive strength	0.82	0.73	1						
(4) Extent flexibility	0.72	0.95	0.65	1					
(5) Gross body coordination	0.72	0.97	0.68	0.95	1				
(6) Gross body equilibrium	0.68	0.89	0.64	0.87	0.91	1			
(7) Stamina	0.74	0.97	0.70	0.96	0.98	0.91	1		
(8) Static strength	0.76	0.98	0.74	0.95	0.96	0.88	0.98	1	
(9) Trunk strength	0.74	0.97	0.73	0.95	0.96	0.84	0.98	0.98	1

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

Table 3A. Principle component analysis

	Variance	Proportion of explained variance		Factor 1 components
Panel A. Age-appreciating cognitive skills				
Factor1	2.26	0.57	Oral comprehension	0.482
Factor2	1.05	0.26	Oral expression	0.538
Factor3	0.49	0.12	Written comprehension	0.464
Factor4	0.19	0.05	Written expression	0.513
Panel B. Age-depreciating cognitive skills				
Factor1	3.04	0.76	Memorization	0.416
Factor2	0.59	0.15	Time sharing	0.525
Factor3	0.25	0.06	Perceptual speed	0.512
Factor4	0.13	0.03	Speed of closure	0.538
Panel C. Physical abilities				
Factor1	7.06	0.78	Dynamic flexibility	0.205
Factor2	1.46	0.16	Dynamic strength	0.366
Factor3	0.24	0.03	Explosive strength	0.194
Factor4	0.12	0.01	Extent flexibility	0.363
Factor5	0.05	0.01	Gross body coordination	0.367
Factor6	0.03	0.00	Gross body equilibrium	0.337
Factor7	0.02	0.00	Stamina	0.370
Factor8	0.01	0.00	Static strength	0.370
Factor9	0.01	0.00	Trunk strength	0.365

Table 4A. Intensity in age-dependent skills by 4-digit NAICS industries

Industry Name	NAICS code	Age-appreciating cognitive skills		Age-depreciating cognitive skills		Physical ability		Product creation	
		Value	Rank	Value	Rank	Value	Rank	Value	Rank
Animal food	3111	1.43	7	1.15	4	0.84	19	-0.47	14
Grain and oilseed milling	3112	-0.04	50	0.79	14	0.75	26	-0.47	14
Sugar and confectionery product	3113	0.16	38	0.88	9	0.87	15	-0.47	14
Fruit and vegetable preserving and specialty food manufacturing	3114	-0.39	57	0.92	8	1.04	11	-0.47	14
Dairy product	3115	0.60	23	1.29	3	1.03	12	-0.47	14
Meat product	3116	-1.04	69	0.39	39	0.95	14	-0.47	14
Seafood product preparation and packaging	3117	0.07	41	0.39	38	0.50	32	-0.47	14
Bakeries and tortilla	3118	0.79	15	0.60	23	0.47	35	-0.47	14
Other food	3119	0.70	22	0.97	7	0.76	25	-0.47	14
Beverage	3121	2.28	1	1.13	5	0.81	20	5.43	1
Tobacco	3122	1.32	8	0.27	44	0.11	50	5.43	1
Fibre, yarn and thread mills	3131	-1.53	77	3.13	1	1.96	1	0.60	6
Fabric mills	3132	-0.79	65	0.60	25	0.78	22	0.60	6
Textile and fabric finishing and fabric coating	3133	-0.42	59	0.55	29	0.34	43	0.60	6
Textile furnishings mills	3141	-1.43	75	1.08	6	0.49	33	0.60	6
Other textile product mills	3149	-1.29	73	0.67	19	-0.38	64	0.60	6
Clothing knitting mills	3151	-1.91	83	0.36	42	0.60	29	0.60	6
Cut and sew clothing	3152	-1.94	84	0.34	43	-0.67	73	0.60	6
Clothing accessories and other clothing	3159	-1.90	82	0.48	31	-0.47	66	0.60	6
Leather and hide tanning and finishing	3161	-1.67	80	0.58	27	0.47	36	0.60	6
Footwear	3162	-1.36	74	-0.39	69	0.13	49	0.60	6
Other leather and allied product	3169	-1.58	79	0.27	45	-0.53	67	0.60	6
Sawmills and wood preservation	3211	-2.24	85	0.64	21	1.58	2	1.94	2
Veneer, plywood and engineered wood product	3212	-1.00	67	0.83	10	1.12	9	1.94	2
Other wood product	3219	-0.74	64	0.81	11	0.86	16	1.94	2
Pulp, paper and paperboard mills	3221	-1.82	81	0.41	37	0.95	13	0.85	3
Converted paper product	3222	-0.97	66	0.19	48	0.44	37	0.85	3
Printing and related support activities	3231	1.70	4	-0.09	59	-0.64	72	0.85	3
Petroleum and coal product	3241	-1.02	68	-0.65	73	0.07	52		26
Basic chemical	3251	0.57	25	-0.31	64	0.06	53	-1.42	25
Resin, synthetic rubber, and artificial and synthetic fibres and filaments	3252	0.32	32	-0.01	57	0.35	42	-1.04	21
Pesticide, fertilizer and other agricultural chemical	3253	1.27	10	0.42	36	0.40	38	-0.48	16
Pharmaceutical and medicine	3254	0.83	12	-1.96	80	-1.02	76	-1.15	23
Paint, coating and adhesive	3255	2.21	2	0.14	51	0.05	54	-0.48	16

Soap, cleaning compound and toilet preparation	3256	1.71	3	0.39	40	0.17	47	-0.48	16
Other chemical product	3259	1.62	5	0.47	32	0.38	39	-0.48	16
Plastic product	3261	0.31	33	0.80	13	0.81	21	-0.27	11
Rubber product	3262	-0.40	58	0.45	33	1.12	8	-0.27	11
Clay product and refractory	3271	0.19	37	0.36	41	0.77	23	0.16	8
Glass and glass product	3272	-0.01	48	0.44	34	0.72	28	0.16	8
Cement and concrete product	3273	0.73	19	1.51	2	1.37	5	0.16	8
Lime and gypsum product	3274	0.07	40	0.80	12	1.41	4	0.16	8
Other non-metallic mineral product	3279	0.05	42	0.59	26	0.76	24	0.16	8
Iron and steel mills and ferro-alloy	3311	-1.57	78	0.68	17	1.44	3	0.13	9
Steel product manufacturing from purchased steel	3312	0.03	44	0.76	15	0.85	18	0.13	9
Alumina and aluminum production and processing	3313	-1.18	70	0.68	18	1.16	6	0.13	9
Non-ferrous metal (except aluminum) production and processing	3314	-0.36	56	0.60	24	0.73	27	0.13	9
Foundries	3315	-1.47	76	0.61	22	1.12	7	0.13	9
Forging and stamping	3321	-0.49	63	0.06	53	0.52	31	0.05	10
Cutlery and hand tool manufacturing	3322	0.35	31	0.20	47	-0.09	58	0.05	10
Architectural and structural metals	3323	-0.19	51	0.04	54	0.38	40	0.05	10
Boiler, tank and shipping container	3324	-0.46	60	0.16	49	0.48	34	0.05	10
Hardware	3325	0.77	18	0.03	55	-0.53	68	0.05	10
Spring and wire product	3326	0.00	46	0.24	46	0.24	45	0.05	10
Machine shops, turned product, and screw, nut and bolt	3327	-0.32	55	0.51	30	0.53	30	0.05	10
Other fabricated metal product manufacturing	3329	0.52	27	-0.10	60	-0.10	59	0.05	10
Agricultural, construction and mining machinery	3331	0.29	34	-0.33	65	-0.03	56	-0.48	15
Industrial machinery	3332	0.79	14	-1.07	77	-1.23	77	-0.48	15
Commercial and service industry machinery	3333	1.46	6	-1.06	76	-1.37	79	-0.48	15
Ventilation, heating, air-conditioning and commercial refrigeration equipment	3334	0.25	36	-0.10	61	-0.01	55	-0.48	15
Metalworking machinery	3335	0.00	47	-0.20	62	-0.08	57	-0.48	15
Engine, turbine and power transmission equipment	3336	-0.19	53	-0.60	72	-0.33	62	-0.48	15
Other general-purpose machinery	3339	0.72	21	-0.57	70	-0.62	71	-0.48	15
Computer and peripheral equipment	3341	0.60	24	-3.43	85	-3.73	85	-0.36	12
Communications equipment	3342	0.73	20	-2.78	84	-2.66	84	-0.80	18
Audio and video equipment	3343	0.28	35	-1.18	78	-1.44	80	-1.11	22
Semiconductor and other electronic component	3344	0.11	39	-2.35	82	-2.03	82	-1.27	24
Navigational, measuring, medical and control instruments	3345	0.78	17	-2.66	83	-2.58	83	-0.76	17
Manufacturing and reproducing magnetic and optical media	3346	1.31	9	-0.39	67	-0.57	69	-1.11	22
Electric lighting equipment	3351	0.50	28	-0.69	75	-0.58	70	-0.88	20

Household appliance	3352	0.54	26	0.15	50	-0.11	60	-0.88	20
Electrical equipment	3353	-0.47	61	-1.33	79	-0.83	75	-0.88	20
Other electrical equipment and component	3359	0.02	45	-0.68	74	-0.34	63	-0.88	20
Motor vehicle	3361	0.05	43	0.71	16	-0.39	65	-0.41	13
Motor vehicle body and trailer	3362	-0.04	49	0.43	35	0.18	46	-0.41	13
Motor vehicle parts	3363	-0.19	52	-0.06	58	0.26	44	-0.41	13
Aerospace product and parts	3364	-0.24	54	-2.13	81	-1.52	81	-0.41	13
Railroad rolling stock	3365	0.37	30	-0.24	63	0.17	48	0.23	7
Ship and boat building	3366	-1.21	71	-0.36	66	0.85	17	0.23	7
Other transportation equipment	3369	0.82	13	-0.39	68	-0.13	61	0.23	7
Household and institutional furniture and kitchen cabinet	3371	-1.23	72	0.57	28	1.07	10	0.63	5
Office furniture (including fixtures)	3372	-0.49	62	0.13	52	0.37	41	0.63	5
Other furniture-related product	3379	0.47	29	0.66	20	0.09	51	0.63	5
Medical equipment and supplies	3391	0.93	11	-0.58	71	-1.28	78	-0.83	19
Other miscellaneous	3399	0.79	16	-0.01	56	-0.81	74	0.74	4

Notes: For each skill, the first column reports the value of the standardized skill-intensity; the second column reports industry's rank in intensity of that skill. Ten most and ten least skill intensive industries are market with red and blue colors, respectively.

Table 5A. Median age in 1962 and 2000 for Countries

Country Name	Median age, 2000	Median age, 1962	Change 1962-2000	Country Name	Median age, 2000	Median age, 1962	Change 1962-2000
1 Japan	41.3	25.5	15.81	71 Malaysia	23.8	17.6	6.25
2 Italy	40.2	31.6	8.64	72 Venezuela	23.3	17.2	6.04
3 Bulgaria	39.7	30.4	9.27	73 Guyana	23.2	17.0	6.23
4 Sweden	39.4	36.0	3.37	74 South Africa	23.2	19.7	3.49
5 Finland	39.4	28.4	11.00	75 India	23.0	20.3	2.76
6 Belgium	39.1	35.0	4.09	76 Mexico	23.0	17.1	5.87
7 Croatia	39.0	29.2	9.79	77 Peru	22.9	18.4	4.45
8 Switzerland	38.6	32.7	5.90	78 Ecuador	22.9	18.6	4.33
9 Hungary	38.6	32.2	6.41	79 Kyrgyzstan	22.5	24.0	-1.51
10 Denmark	38.4	33.0	5.40	80 Morocco	22.3	18.1	4.20
11 Greece	38.3	29.1	9.22	81 Libya	22.2	19.5	2.72
12 Austria	38.2	35.6	2.59	82 Fiji	22.1	15.8	6.31
13 Slovenia	38.0	29.3	8.68	83 Mongolia	22.0	23.0	-1.04
14 Estonia	37.9	32.2	5.73	84 Egypt	22.0	19.8	2.15
15 Latvia	37.9	32.3	5.67	85 Algeria	21.6	17.6	4.01
16 Portugal	37.8	27.9	9.82	86 Saudi Arabia	21.1	18.5	2.54
17 United Kingdom	37.6	35.5	2.16	87 Bangladesh	21.0	18.6	2.38
18 Spain	37.6	29.4	8.24	88 Iran	20.9	19.5	1.45
19 Ukraine	37.6	28.9	8.73	89 El Salvador	20.7	17.5	3.23
20 Czech Republic	37.6	33.1	4.46	90 Philippines	20.5	16.5	3.95
21 France	37.6	33.0	4.54	91 Paraguay	20.4	16.1	4.36
22 Netherlands	37.3	28.7	8.60	92 Bolivia	20.0	18.7	1.27
23 Luxembourg	37.3	35.2	2.14	93 Tonga	19.9	17.3	2.63
24 Norway	36.9	34.3	2.53	94 Botswana	19.8	17.2	2.59
25 Canada	36.8	26.5	10.33	95 Papua New Guinea	19.6	18.8	0.80
26 Russia	36.5	27.2	9.34	96 Nepal	19.6	20.2	-0.62
27 Hong Kong	36.5	23.1	13.39	97 Jordan	19.5	18.0	1.51
28 Malta	35.9	21.5	14.44	98 Gabon	19.5	27.1	-7.53
29 Lithuania	35.9	28.5	7.39	99 Namibia	19.5	19.3	0.15
30 Australia	35.4	29.6	5.77	100 Belize	19.3	17.8	1.52
31 Poland	35.3	26.6	8.75	101 Haiti	19.1	19.8	-0.68
32 USA	35.3	29.6	5.72	102 Pakistan	18.9	19.8	-0.91
33 Romania	34.4	28.4	5.93	103 Ghana	18.9	17.7	1.25
34 New Zealand	34.3	27.4	6.89	104 Syria	18.8	17.1	1.74
35 Singapore	34.1	18.8	15.33	105 Nicaragua	18.8	16.3	2.51
36 Slovakia	33.9	27.7	6.27	106 Congo	18.8	19.5	-0.71
37 Barbados	33.5	22.4	11.17	107 Lesotho	18.7	18.3	0.38
38 Iceland	32.8	25.4	7.37	108 Côte d'Ivoire	18.7	19.2	-0.52
39 Cuba	32.8	22.9	9.89	109 Maldives	18.5	20.5	-1.97
40 Ireland	32.5	30.1	2.41	110 Central African	18.5	21.4	-2.90

					Rep.				
41	Korea, Rep. of	32.1	19.8	12.30	111	Cambodia	18.4	17.2	1.19
42	Cyprus	31.8	23.0	8.76	112	Honduras	18.4	17.1	1.31
43	Uruguay	31.6	28.9	2.69	113	Mauritania	18.4	17.7	0.69
44	Armenia	30.3	22.5	7.87	114	Iraq	18.3	19.6	-1.33
45	Qatar	30.3	19.4	10.92	115	Tajikistan	18.2	21.9	-3.75
46	Thailand	30.1	18.7	11.36	116	Sierra Leone	18.1	20.9	-2.79
47	China	29.6	21.3	8.27	117	Liberia	18.1	19.0	-0.92
48	Mauritius	29.0	16.7	12.31	118	Lao PDR	18.0	19.1	-1.05
49	Chile	28.7	20.6	8.12	119	Mozambique	17.9	18.8	-0.91
50	Kuwait	28.6	24.0	4.57	120	Sudan	17.9	17.6	0.36
51	United Arab Emirates	28.2	18.5	9.71	121	Guatemala	17.6	17.2	0.48
52	Israel	28.0	24.1	3.90	122	Togo	17.5	18.5	-0.96
53	Argentina	27.9	26.8	1.01	123	Kenya	17.4	17.2	0.26
54	Trinidad and Tobago	27.8	18.7	9.09	124	Tanzania	17.4	17.0	0.36
55	Kazakhstan	27.7	22.8	4.84	125	Swaziland	17.2	17.4	-0.21
56	Sri Lanka	27.5	19.2	8.33	126	Benin	17.2	20.9	-3.74
57	Bahrain	26.5	19.6	6.84	127	Senegal	17.2	18.4	-1.27
58	Albania	26.2	19.5	6.67	128	Cameroon	17.1	20.1	-2.94
59	Brunei	25.6	19.4	6.22	129	Malawi	17.0	17.0	0.08
60	Brazil	25.3	18.6	6.75	130	Zambia	16.9	17.4	-0.50
61	Costa Rica	24.8	18.0	6.76	131	Gambia	16.9	20.8	-3.92
62	Turkey	24.7	19.1	5.66	132	Mali	16.8	19.9	-3.19
63	Tunisia	24.6	18.3	6.28	133	Rwanda	16.4	16.3	0.15
64	Jamaica	24.5	19.6	4.87	134	Niger	16.1	16.2	-0.13
65	Indonesia	24.5	20.2	4.25	135	Yemen	15.6	19.4	-3.82
66	Panama	24.4	18.0	6.39	136	Burundi	15.4	18.4	-2.94
67	Vietnam	24.2	21.8	2.36	137	Uganda	15.3	17.1	-1.71
68	Colombia	23.8	16.9	6.95	138	Afghanistan	15.3	18.0	-2.77