Population Aging and Comparative Advantage

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Abstract

In this paper we show that demographic differences between countries are a source of comparative advantage in international trade. Since many skills are age-dependent, population aging decreases the relative supply and increases the relative price of skills which depreciate with age. Thus, industries relying on skills in which younger workers are relatively more efficient will be more productive in countries with younger labor force and less productive in countries with older populations. Building upon the behavioral 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, population aging, cognitive skills

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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 the labour force in most countries towards older workers. These changes are likely to have a profound influence on the structure of economic activity within countries and on the pattern of trade between them through a change in the relative supply of age-dependent skills. Recent research on aging suggests that there is a negative relationship between age and some cognitive abilities, with a number of studies showing that cognitive decline begins as early as at the age of 25. This implies that aging societies experience a more rapid decline in the quality and the stock of certain cognitive skills and may thus lose competitive advantage in industries which use those skills intensively. In this paper, we empirically study how differences in age structure of populations between countries affect global trade flows. Specifically, we find a novel and empirically sizeable source of comparative advantage: the relative supply and quality of age-dependent skills that vary across countries with 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. A series of studies on cognitive abilities and aging consistently report that speech and language abilities improve with age, while memory, multitasking, and the speed of information processing decline with age. A related stream of literature demonstrates that the ability to acquire new skills and adaptability to changes in working environment are also impaired in older individuals. Finally, a decline in physical strength with age is well documented in the medical literature. Knowing the importance of those three groups of 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 various types of machine operators, where coordination, divided attention, and perceptual speed are very important. As a result, in industries where most workers enter as *machine setters and operators*, such as yarn mills or wood product manufacturing, age-depreciating skills are used intensively. Other industries, such as printing or beverages and tobacco, employ many 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.

We provide two theoretical mechanisms for the effect of population aging on trade flows. One such mechanism operates through the effect of population aging on the stocks of age-dependent skills. To formalize this relationship, we incorporate age-dependent skills into the extension of the classical Hechscher-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 an older labor force, all else being equal, have lower endowments and higher relative prices of age-depreciating skills and thus specialize in the production of goods which utilize age-appreciating skills intensively. The second mechanism through which demographics operate is to influence labor productivity. We illustrate the working of this mechanism using the extension of the Eaton-Kortum model by Chor (2010) and Costinot, Donaldson, and Komunjer (2012). If aging affects the quality rather than the quantity of age-dependent skills, then the age composition of the labor force would determine relative productivity of an industry. In the presence of labor market frictions which prevent the sorting of workers to industries based on their age, industries would inherit national age distribution, in which case population aging will shift the age distribution of employees in all sectors and increase (decrease) labor productivity in industries which rely on age-appreciating (age-depreciating) skills.

Thus, both models predict that countries with older (younger) populations will specialize in industries which use age-appreciating (age-depreciating) 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 with a greater dependence 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 relationship between skill development and aging allows us to analyze the effect of unobservable endowments of cognitive skills on trade flows by using observable cross-country variation in demographic composition as a proxy. Surveying behavioral and neuroscience literature, we identify cognitive skills which are known to change over the course of an individual's life. To measure sectorial intensities in those skills, we retrieve the indicators of their importance for different worker occupations from the O*NET database. We then use occupational composition for each 4-digit NAICS industry, obtained from the US Bureau of Labor Statistics, to construct 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 four age-dependent indicators of industry-level skill intensities: physical abilities, age-appreciating cognitive skills, age-depreciating cognitive skills, and learning ability.

We confirm the main theoretical prediction using rich bilateral trade data which include 86 industries and cover the time period between 1962 and 2010. We find that countries with older (younger) populations capture larger shares of world trade in commodities that more intensively use age-appreciating (age-depreciating) skills. In the baseline regressions that include 136 exporting countries, we show that the interaction of a country's median age and the industry's intensity in age-dependent skills is an important determinant of bilateral trade flows, both statistically and economically.[1] This finding is robust to the inclusion of the standard determinants of comparative advantage such as endowments of physical and human capitals. Moreover, 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 of 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 different definitions of human capital and holds in different time

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

[2] Although 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 a similar pattern of comparative advantage in age-appreciating skills. It makes identification of our coefficients of interest problematic on those samples.

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) and Costinot, Donaldson, and Komunjer (2012) is the quasi-Rybczynski effect. In our context, it implies that fast(slow)-aging countries should observe a decrease in the relative price of age-appreciating (age-depreciating) skills and an increase in relative productivity of industries which use those skills intensively, thus making them more competitive in the global market. We find substantial support for this prediction in the data. We demonstrate that an increase in the median age between 1962 and 2000 is associated with a shift in a country's production and export structure towards commodities that more intensively use age-appreciating skills and away from commodities that rely more on age-depreciating 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 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 an 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) shows with a theoretical model that demographic changes are associated with intensified outsourcing of labor-intensive processes to countries with younger populations and thus affect a country's comparative advantage. Our theoretical framework is also based on the effect of aging on trade through changes in relative factor prices but goes beyond the two factor

[3] Ludwig 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.

model and introduces multiple age-dependent factors of production.

This paper also contributes to the fast-growing literature that formally tests the relationship between factor proportions and trade flows. Specifically, it is related to the classical works documenting the important role of physical and human capital endowments in comparative advantage.[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 countries. Using the variation in demographic composition across countries and the variation in age-dependence of different cognitive skills, we are able to construct a reliable 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 equally important as determinants of comparative advantage as are 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.

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

2 Theory and testable predictions

In the presence of age-dependent skills, demographic composition can affect a country's comparative advantage through two different channels. First, population aging can affect the effective stocks and relative supply of age-dependent skills. In this case, comparative advantage stems from differences in relative prices of skills across countries (Heckscher-Ohlin channel). Second, workers of different ages may not be equally productive in tasks which require age-dependent skills, thus affecting relative labor productivity across industries with different composition of tasks and across countries with different demographic structure (Ricardian channel). In this section we describe theoretical frameworks for both channels and show that they deliver the same empirical specification.

2.1 Heckscher-Ohlin model

When certain skills change over the course of an individual's life, 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-depreciating skills. We apply this logic to the extension of the Heckscher-Ohlin model by Romalis (2004), who introduced monopolistic competition and trade frictions in the Heckscher-Ohlin model with multiple countries, goods, and factors of production. In the model, transportation costs generate a departure from the factor price equalization and thus introduce a variation in production costs across countries. Romalis shows that in the presence 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 in industry's intensity in the abundant factor. Therefore, for any pair of countries H and F, if H is relatively richer in some skill S than country F, it will have a price advantage in commodities that use skill S intensively. As a result, H will export more of those commodities than F to other countries, all else being equal. Furthermore, relative exports of country H is increasing in the skill intensity of an industry and in the difference in relative endowments of skill S between the two countries. In our context, if country H has a younger labour force than country F, it will be abundant in skills that depreciate with age, and the low premium for those skills would thus allow H to export more 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 production factor at a rate faster than the world average will lead to a reduction in relative price of that factor and shift a country's export structure towards industries which use it intensively. In our setting, this prediction translates into the relationship between population aging and a country's export structure. More rapidly aging countries should observe an increase in premium for age-depreciating skills and hence their export structure should shift towards industries which use age-appreciating skills intensively and away from industries which use age-depreciating skills intensively.

2.2 Ricardian model

Another channel through which demographic composition can affect comparative advantage is domestic industry productivity. It is plausible to assume that with age workers become less productive in tasks which require age-depreciating skills. Then, in the presence of industry-specific skills or other labor market frictions which would prevent workers from moving freely from one industry to another, the workers' age distribution in every industry will resemble the country's distribution. In this case, population aging will shift the age distribution of employees in all sectors and increase (decrease) labor productivity in industries which rely on age-appreciating (age-depreciating) skills.

We illustrate the role of population age structure on Ricardian productivity using an extension of the Eaton-Kortum model by Chor (2010) and Costinot, Donaldson, and Komunjer (2012) that accommodates both productivity and factor endowment differences in a setting with multiple countries, industries and factors of production. In this setup, for any pair of countries $c1$ and $c2$, their relative exports of product i to country p is given by

$$\frac{X_{c1pi}}{X_{c2pi}} = \frac{\left(\varphi^i_{c1}/mc^i_{c1}d^i_{c1p}\right)^\theta}{\left(\varphi^i_{c1}/mc^i_{c2}d^i_{c2p}\right)^\theta}, \tag{1}$$

where mc^i_c is the unit production costs of country c in industry i, d^i_{cp} is the iceberg trade cost for shipping one unit of i from c to p, θ is the inverse of productivity shock variance, and φ^i_c is the systematic component of country c's productivity in industry i. Following Chor (2010), we assume the following parametrizations of the productivity term and the unit cost function:

$$\ln \varphi^i_c = \mu_c + \mu_i + \sum_{k \in K} \rho^*_k I^k_i \times Age_c + \sum_{\{n,m\}} \rho_{nm} L^n_i \times M^m_c \tag{2}$$

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

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

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

$$\ln mc_c^i = -\sum_{k \in K} \phi_k^* s_{ki} \ln\left(F_c^k\right) - \sum_{f \in F} \phi_f s_{fi} \ln\left(F_c^f\right) \tag{3}$$

where F_c^j is the endowment of factor $j \in \{K, F\}$ in country c measured relative to some reference factor, and $\phi_k^* > 0$, $\phi_j > 0$. Substituting (2) and (3) into (1) we obtain

$$\begin{aligned}\frac{1}{\theta} \ln\left(\frac{X_{c1pi}}{X_{c2pi}}\right) = & \sum_{k \in K} \rho_k^* I_i^k \times (Age_{c1} - Age_{c2}) + \sum_{k \in K} \phi_k^* s_{ki} \ln\left(\frac{F_{c1}^k}{F_{c2}^k}\right) + \\ & \sum_{\{n,m\}} \rho_{nm} L_i^n \times (M_{c1}^{nm} - M_{c2}^{nm}) + \sum_{f \in F} \phi_f s_{fi} \ln\left(\frac{F_{c1}^f}{F_{c2}^f}\right) + (\mu_{c1} - \mu_{c2}) - \left(d_{c1p}^i - d_{c2p}^i\right)\end{aligned} \tag{4}$$

The relative exports are determined by the combination of six factors: Ricardian forces, as captured by the differential effect of age composition and institutional factors on productivity (the first and the third terms); the Heckscher-Ohlin forces, operating through the difference in factor endowments (the second and the fourth terms); productivity shifters (fifth term) and trade costs (sixth term). On one hand, if there is no Ricardian channel and population aging affects only the stock of age-dependent skills but not the quality, then the first and the third terms in equation (4) disappear and we are back to the Heckscher-Ohlin model in Section 2.1. On the other hand, if there is no sorting of workers to sectors and firms do not age-discriminate when hiring, then the second and the third terms vanish and demographic composition would affect trade only through variation in labor productivity across industries.

It is easy to see from equation (4) that in presence of the Ricardian channel the quasi-Rybczynski effect still holds. Different rates of population aging in countries $c1$ and $c2$ will affect their relative exports through two complementary channels. First, there is an indirect effect through change in the endowments of age-dependent skills (Heckscher-Ohlin effect). Second, different aging rates affect relative exports of two countries directly through the effect on age composition of workers and labor productivity across industries (Ricardian effect).

3 Empirical model

The previous section demonstrates that age composition can affect comparative advantage through two channels - the Heckscher-Ohlin and the Ricardian. However, separating one channel from the other empirically would require data on either the endowments of or relative prices of age-dependent skills, which is not available. Instead, we proxy the stock of age-dependent skills equation (4) with the country's median age Age_c:

$$\ln F_c^k = \sigma_0^K + \sigma_1^k Age_c \tag{5}$$

where $\sigma_1^k > 0$ for age-appreciating skills and $\sigma_1^k > 0$ for age-depreciating skills.

This transformation results in an empirical specification which is similar to Chor (2010) and Bombardini, Gallipoli, and Pupato (2012):[5]

$$\ln X_{cpi} = \sum_{k \in K} \beta_k I_i^k \times Age_c + \sum_{f \in F} \phi_f I_i^f \times F_c^f + \delta_{cp}^{'} \lambda + \gamma_c + \gamma_{pi} + \varepsilon_{cpi} \tag{6}$$

where $\beta_k = \left(\rho_k^* + \phi_k^* \sigma_1^k\right)$ and the interaction $I_i^k \times Age_c$ captures both the Ricardian and the Heckscher-Ohlin channels. This interaction is the main variable of interest and the sign of β_k allows us to test the key theoretical prediction that younger countries have comparative advantage in industries which intensively use age-depreciating skills. The theoretical model predicts that $\beta_k < 0$ for skills which worsen with age and $\beta_k > 0$ for skills that improve with age.[6] Furthermore, equation (6) implies that for any pair of countries c_1 and c_2 exporting goods i and j to a third country p the following holds

$$E\left[\ln\left(\frac{X_{c_1pi}}{X_{c_2pi}}\right) - \ln\left(\frac{X_{c_1pj}}{X_{c_2pj}}\right)\right] = \sum_{k \in K} \beta_k \left(I_i^k - I_j^k\right) \times \left(Age_{c_1} - Age_{c_2}\right) \tag{7}$$

If country c_1 has younger population than country c_2, $(Age_{c_1} - Age_{c_2}) < 0$, and industry i

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

[6] This follows from the fact that for age-depreciating skills $\rho_k^* < 0$ and $\sigma_1^k < 0$, which implies that $\beta_k < 0$ since ϕ_k^* is positive for all k. For age-appreciating skills both ρ_k^* and σ_1^k are positive, and so does β_k.

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

In our baseline specifications we control for two standard Heckscher-Ohlin factors of comparative advantage – the cross-country differences in physical capital and skilled labor. Given that countries export more in industries which use their abundant factors intensively, we expect $\phi_f > 0$ for all standard factors of production. The vector δ_{cp} equation (6) captures bilateral trade frictions between countries c and p. Exporter fixed effects γ_c control for exporter's aggregate productivity level, size, remoteness from other countries, and other characteristics that do not vary across industries. Importer-industry fixed effects γ_{pi} control for product prices in the importing country and all other demand shifters, including those which may be driven by cross-country demographic differences.

It is important to note that the endogeneity of $Skill\_I_i^k \times Age_c$ variables in equation (6) is unlikely to be a serious concern. First, the demographic composition of a country's population is predetermined relative to industry level trade flows, and it is difficult to think of any reason why the median age of a country's population could affect the export structure other than through the effect on either supply or demand.[7] While our model focuses on the effect of population aging on supply, the demographic composition, in principle, can also affect trade through the effect on demand if consumer preferences change with age. We explore this possibility in Section 5.2 and find that although consumption behavior does change with age, little evidence of age-related changes in preferences being systematically related to production technology in manufacturing can be found.

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. In Section 5.2 we provide some evidence in support of this assumption. First, if there is a feedback from trade flows to employment

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

structure, the simultaneity would especially be a problem for the US trade flows. However, removing the US from the set of importing and exporting countries does not affect our results. 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.

To test the Rybczynski prediction of the model, we estimate equation (6) in differences:

$$\Delta \ln X_{cpi} = \sum_{k \in K} \beta_k I_i^k \times \Delta Age_c + \sum_{f \in F} \phi_f I_i^f \times \Delta F_c^f + \delta_{cp}^{'} \lambda + \gamma_c + \gamma_{pi} + \varepsilon_{cpi} \tag{8}$$

where Δ is a time-difference indicator. Equation (8) thus assumes that while trade structure, age composition, and factor stocks can change within a country over time, industries' factor 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 $\phi_f > 0$.

4 Data

Estimation of the main model (6) requires four sets of data: industry-level data on bilateral trade flows; determinants of bilateral trade costs; industries' intensities in age-dependent skills and other factors of production; and country-level measures of abundance in those factors. Equation (6) is estimated with bilateral trade data for the year 2000. To estimate equation (8), 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 (6) are obtained from the UN-TRAINS database at 6-digit Harmonized System classification and aggregated into 4-digit North American Industry Classification System (NAICS) using concordance from Feenstra, 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 (8) 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 (6) and (8) includes the log of distance, defined as the distance between the major cities of the two countries, common land border indicator, common official language binary variable, colonial ties binary variable (separately for before and after 1945), and a binary variable taking the value of one if importer and exporter were ever part of one country.[8] We also use two binary variables, which we constructed from the WTO database on Regional Trade Agreements, for the presence of a free trade agreement or a customs union between a pair of countries.

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 the 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,[9] and the speed of information processing deteriorate with age. The negative impact of aging on nearly all aspects of physical and pshychomotoric 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

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

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

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

At the same time, the within-industry variations in intensities of different skills comes from the variation in the importance of those skills between occupations. To quantify the importance of cognitive skills and physical abilities for different occupations, we use O*NET database. O*NET ranks all occupations in several dimensions which are closely related to the 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 the high degree of correlation between cognitive skills indicators (see Tables 1A and 2A in the Appendix), it is difficult to identify the effect of each single one. For this reason,

[10] Appendix C describes the construction of skill intensity variables in more details.

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, still 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,[11] 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 were combined into a single indicator for physical abilities, $physical_i$, through the PCA.

Table 1 lists the ten most and the ten least intensive occupations for physical and both types of cognitive skills. Many of the occupations that are the most intensive in age-appreciating skills are related to sales where oral and written communication skills are critical. The top of the list for age-depreciating skills is dominated by various machine setters and operators, for whom

[11] This 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.

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 a concern in the empirical analysis.

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, providing firms with greater adaptability to changes in market conditions and productivity advantage over competitors. In Appendix B we argue that the ability to learn deteriorates with age and is thus another factor of comparative advantage.

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, our first measure of intensity in the ability to learn 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.[12] The second and preferred 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. When a firm registers a patent in a new IPC category in which it had not innovated previously, such a 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

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

upgrade their set of skills than product creation in the existing IPCs.

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.[13] As an alternative, we also use the share of young workers in 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.[14] 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.[15] 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 (6) with the country's median age used as a proxy for the stocks of age-depreciating skills. The first column confirms the main prediction of

[13]See Table 5A in the Appendix for information on median age in 2000 and change in median age between 1962 and 2000 for all exporting countries in our sample.

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

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

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 $I_i^k \times Age_c$ 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 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 the 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 (7). 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[16] 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.[17]

[16] The standard deviation of the median age is equal to 7.4 in our sample.

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

In Table 4 we report the estimates of equation (6) 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 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.[18] 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 industries' skill intensity and countries' abundance in skilled young workers (the share of young workers with secondary and tertiary education) to control for the differences in human capital of young workers across countries. The coefficients of interest remain broadly the same as before.

5.2 Robustness tests

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

Alternative measures of human capital. In columns (1) and (2) of Table 5 we use two alternative definitions of human capital to 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 (6) when industry-level intensity in learning skills is measured with the growth rate of patents, $pintensity_i$. As 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.

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

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 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 (6) 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.

Zero trade flows. A potential problem with estimating equation (6) by OLS is that it discards observations with zero trade flows, which constitute about two-thirds of the data. Excluding those observations from the sample can result in systematically biased OLS coefficients (Santos-Silva, Tenreyro, 2006; Helpman et al, 2008). We address this problem by using a two-step procedure to correct for sample selection as in Helpman, Melitz, and Rubinstein (2008).[19] The second stage results, reported in Column (5) of Table 5, do not suggest that sample selection affects the OLS estimates as all coefficients remain unchanged.

Results for other time periods. In columns (6) and (7) we demonstrate that the results are not confined to a particular time period by estimating equation (6) using trade and median countries' 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.[20]

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

[20] The cross-section regressions of equation (6) for the years 1962, 1980, and 1990, not presented in

Results without the USA. The above result that skill-intensities, constructed with the US data for 2000, can equally well predict bilateral trade flows in 1970 and in 2010 suggests that the reverse causality from trade to occupational composition across industries is unlikely to be a problem. Furthermore, if reverse causality were present, it would be stronger for the US trade data. However, excluding the US from the sample (column 8) 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 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 to 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.[21] Results in column (9) confirm our expectation.[22] 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 these factors is the dispersion of human capital within a country in the presence of differences in skill com-

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.

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

[22] We do not include age-depreciating skills in column (9) 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.

plementarities across industries. In column (10) 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.[23] In column (11) 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 regression coefficients in columns (10) and (11) 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 (10) and (11) 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 (10) and (11) 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.

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

5.3 Extensions

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

The use of a country's demographic composition as a proxy for unobserved endowment of age-dependent skills in equation (5) relies on the assumption that the stock of each age-dependent skill is a linear function of the median age only. However, age-related decrements in cognition may not be entirely due to biological aging process. The presence of other factors that affect cognitive functioning at different ages may result in biased estimates of β_k coefficients if the cross-country variation in those factors is correlated with demographics. In this subsection we consider two additional factors of cognitive development and demonstrate that our main findings remain quantitatively and statistically robust to alternative definitions of the proxy variables for the age-dependent skills.

The first such factor is the quality of the health care system. Results of numerous medical studies reveal a strong effect of psychological and systemic diseases on cognitive functioning for individuals of all ages,[24] but the effect is particularly pertinent to older individuals who are subject to increased incidence and prevalence of such diseases. Thus, insofar as the age-related cognitive and physical decline is driven by deteriorating health condition, it may, to some extent, be reversible with appropriate medical treatment. In this way, an efficient health care system could remediate the effect of population aging on the effective stock of cognitive skills and physical abilities.

The second factor which may affect the relationship between aging and cognitive functioning is education and cognitive training. A large amount of literature documents a positive relationship between education and old age cognitive functioning, and several recent studies have been able to identify a causal effect of childhood schooling on cognitive abilities (primarily on memory) at older ages by exploiting exogenous variation in education policies (e.g. Glymour et al, 2008, Banks and Mazzonna, 2012). Moreover, it has also been established that education and training can moderate the course of intellectual decline as individuals get older

[24] See Stern and Carstensen (2000) for a survey of the literature. In subsection 5.3.3 we also provide some evidence on the relationship between health and cognition.

(Schaie, 1986, and Schaie, 2005). Thus, we may expect that increasing rates of educational attainment, especially among older workers, can increase the effective stock of age-dependent cognitive skills.

Based on the above evidence, we extend equation (5) and allow for country c's endowment of age-dependent skill k to be a function of the median age (Age_c), the quality of the health care system ($Health_c$), and education level ($Educ_c$)

$$\ln F_c^k = \sigma_0^k + \sigma_1^k Age_c + \sigma_2^k Health_c + \sigma_3^k Educ_c \tag{9}$$

where we expect $\sigma_1^k < 0$ for age-depreciating skills, $\sigma_1^k > 0$ for age-appreciating skills, and $\sigma_2^k > 0$ and $\sigma_3^k > 0$ for any k. Then equation (6) becomes

$$\begin{aligned} \ln X_{cpi} &= \sum_{k \in K} \left(\beta_1^k I_i^k \times Age_c + \beta_2^k I_i^k \times Health_c + \beta_3^k I_i^k \times Educ_c \right) + \\ &\quad + \sum_n \phi_n I_i^n \times F_c^n + \delta_{cp}^{'} \lambda + \gamma_c + \gamma_{pi} + \varepsilon_{cpi} \end{aligned} \tag{10}$$

where $\beta_k^i = \left(\rho_k^* + \phi_k^* \sigma_i^k \right)$. Estimation results for equation (10) are presented in Table 6. Education is measured with the share of population with secondary and post-secondary education, although results do not change when we use alternative measures of education or when the measures of educational attainment are constructed only for senior workers. In column (1), the efficiency of the health care system is measured with the share of total health expenditure in GDP, obtained from the World Bank for the year 2000. All interactions of education variables and skill intensities in column (1) are insignificant, suggesting that education does not affect accumulation of age-dependent skills. This result, however, may be driven by poor quality of educational data, which does not take into account differences in the quality of education across countries. As for the effect of the share of health expenditure in GDP, only the interaction with the intensity in age-appreciating skills statistically significant and positive, as expected. Yet, insignificant coefficients for age-depreciating skills provide no evidence that increase in health expenditure at the national level can remediate the effect of cognitive decline in aging population on comparative advantage. The estimated coefficients on the interactions of median age with intensities in age-dependent skills decrease in magnitude relative to the benchmark results but remain statistically significant.

In column (2) we measure the quality of health care system with life expectancy at birth in 1960. Although life expectancy depends on various socio-economic conditions as well, the advantage of this measure is that it reflects the quality of health care at childhood and early adulthood of workers aged 40 to 65 in our sample, and can thus inform us on the long-term effect of the health care on cognitive development.[25] The estimates are similar to those presented in column (1).

5.3.2 Population aging and changes in preferences

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

To explore this possibility, we use the Canadian Survey of Household Spending for the year 2000 kept by Statistics Canada. These data are representative of an open market economy, a context which is applicable to the other developed countries that account for around half of exporter-industry observations in our sample. The survey includes complete information on household expenditure during the whole calendar year for over 14,000 households in Canada. Figure 6 shows variation in the share of different consumer goods in total household expenditure across four cohorts.[26] The figure reveals that, while for most products there are no substantial differences in expenditure shares among different cohorts, older individuals tend to spend more on food and medical equipment and less on sports, audio, and video equipment. Hence, not controlling for differences in consumption patterns between older and younger individuals

[25] No data on health care expenditure is available prior to 1995.

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

can result in omitted variable bias in β_k coefficients in equation (6) if those differences are systematically related to variation in skill intensities across industries. Yet, in the Canadian data this relationship is weak: the Spearman rank correlation between skill intensities and the gap in expenditure shares of 55-65 and 25-35 age cohorts is only around 0.1, while the same correlations with physical and human capital intensities are 0.23 and -0.34, respectively.[27]

As an additional robustness test, we estimate equation (6) on a subset of industries which produce consumer goods. If our results are mainly driven by the relationship between age and consumption behavior, we would expect the effect to be more pronounced for final goods. Results in column (3) of Table 6 show that the magnitudes of β_k coefficients on the sample of consumption goods are similar to our baseline estimates for the entire sample, suggesting that age-dependent preferences are unlikely to play a major role in our results.

5.3.3 An alternative measure of the stock of age-depreciating cognitive skills

In every regression specification so far we have used a country's age structure to proxy for its endowment of age-dependent skills. We have demonstrated that in the absence of a reliable measure of the stock of cognitive skills, consistently measured across countries, demographic differences between countries can identify the effect of age-dependent cognitive skills on comparative advantage. In this section we propose an alternative proxy variable for one of the age-depreciating skills (memory) and show that trade data is still consistent with the theoretical model.

The proposed measure is based on a standardized memory test conducted in 27 different countries among seniors.[28] The test consists of verbal registration and recall of a list of ten words one minute after an interviewer read them to respondents. The test score is the fraction of the number of words that were recalled correctly. The survey questionnaire also contains information on a respondent's age, gender, the highest completed education, the number of years of schooling, and self-reported health status, where respondents rate their health on 1 to 5 scale. This test provides a comparable variation in one of the age-depreciating cognitive skills

[27] These results are presented in Table 6A in the Appendix.

[28] A detailed test description can be found in Appendix D.

across countries and allows us to construct an alternative measure of cross-country differences in effective memory stock to test the robustness of our results.

In Column (1) of Table 7 we present the results for specification (6) using memory as a single cognitive skill and median age as a proxy for skill endowment. As with the composite age-depreciating skills, the coefficient on memory intensity interacted with a country's median age is negative and statistically significant. Thus, younger countries capture larger market shares in industries where employees are required to have good memory. In column (2) we use the unconditional word recall test score as a measure of skill endowment, averaged among individuals of 50-55 years of age within each country in order to control for different age composition of respondents. The effect of the interaction remains large and statistically significant.[29]

In order to better isolate the effect of age and education from other sources of variation in cognitive skills, we first regress memory test scores on age, health status, and education level, and then use the predicted values as a measure of skill endowment.[30] Results, presented in column (3), are similar to the benchmark. Next, we estimate the elasticity of the test score with respect to age and the number of years of schooling from the first stage regression, which are -0.005 and 0.011, respectively (column 2 of Table 7A). Assuming that the latter elasticity is age-independent, we construct the predicted value of skill endowment using the information on the mean age and education for all countries in our trade data sample. Interacting this measure of skill endowment with memory intensity in column (4) leaves the main result unchanged. Finally, in column (5) we construct a measure of skill endowment for senior workers only. At the first stage, we estimate the effect of age and education level for every 5-year cohort group among people aged 50-65, and construct the country-level measure on skill endowment using the data on educational attainment reported in Barro and Lee (2000) for every country and 5-year age group. The results are robust.

Overall, Table 7 shows that no matter which measure of skill endowment we use, the coefficient on its interaction with sectorial memory intensity is always of the expected sign and

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

[30] In the first stage regression we also control for country fixed effects. The main result is unchanged when age enters it non-linearly. Column (4) of Table 7A in the Appendix reports the results for this first-stage regression.

statistically significant, with the magnitude of the coefficient being remarkably stable across specification.

5.4 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 model in Section 2 then implies that population aging at a rate greater than in other countries should alter a country's export structure via an decrease in relative productivity and increase in relative costs in industries which use age-depreciating skills intensively. To test this quasi-Rybczynski prediction of the model, we estimate equation (8) 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.[31] Both results are in contrast with Romalis (2004), who shows that changes in capital and, in some specification, skilled labour stocks imply changes in countries' structure of exports to the US. We find that the difference between our results and those by Romalis is primarily driven by the choice of the US as a single importing country. When we restrict our sample of importers to the US only, we obtain large and positive coefficients on both capital and skilled labor, with the latter also being statistically significant.[32]

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-

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

[32] It is also important to note that lack of evidence for the Rybczynski effect for capital may be caused by changes in capital intensities over time. As column (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.

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 specification in levels, 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.[33] 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, 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

[33] When either $cog\_dep_i \times (\Delta Age)_c$ or $physical_i \times (\Delta Age)_c$ is excluded from the regression, the remaining three coefficients become statistically significant with the same signs as in columns (2)-(5).

effects due to resource relocation between industries are less visible in higher-frequency data.

Our baseline specification (8) 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 differential impacts on the structure of trade. For example, we know that countries with rapidly aging populations will experience an increase in the relative supply and a 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 (8) where the effect of $I_i^k \times \Delta Age_c$ interaction is estimated separately for slowly and rapidly aging countries:

$$\Delta \ln X_{cpi} = \sum_{k \in K} \sum_{j \in Y,O} \beta_k^j D_c^j I_i^k \times \Delta Age_c + \sum_{f \in F} \phi_f I_i^f \times \Delta F_c^f + \delta_{cp}^{'} \lambda + \gamma_c + \gamma_{pi} + \varepsilon_{cpi} \tag{11}$$

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

Variations in relative productivities and factor endowments across countries are the sources of comparative advantage. This paper contributes to the comparative advantage literature by analyzing the effect of cross-country differences in demographic composition and endowments of age-dependent skills on the structure of commodity trade. We incorporate age-dependent skills into the extension of the Heckscher-Ohlin model by Romalis (2004) and Eaton-Kortum model by Chor (2010) to show that cross-country differences in demographic structure determine the pattern of trade. The model also predicts that population aging results in a reduction in productivity and increase in unit output costs in industries that utilize age-depreciating skills intensively.

We apply the two main predictions of the model to bilateral trade data for a large panel of countries and 86 industries over the time period from 1962 to 2010, and confirm that population age structure is an important factor 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.

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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 are labeled with a start superscript. The 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 $M/V > M^*/V^*$.

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

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

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

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. Over time, 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 a 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 arguably underestimate the effect of aging on cognitive skills due to selection and the 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 after 60-65.

More recent works support the main message of the earlier studies that not all cognitive skills decline uniformly with age. Salthouse (1998, 2009, 2010) reports 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 be 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 found, 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 memory declines significantly with age. Older adults exhibit difficulties with activities that involve manipulations of the content of their working memory. Third, while older adults experience no difficulties in maintaining selective attention on a particular activity without being distracted by others (McDowd and Shaw, 2000; Verhaeghen and Cerella, 2002), 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).[34]

Finally, there is little disagreement in the literature that the speed of information processing is decreasing 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 the slowing of information processing. Salthouse has demonstrated in numerous works that an age-related decline in some cognitive tasks, such

[34] McDowd and Shaw (2000) have demonstrated that devided attention impairment is a significant factor of higher car accidents among adults.

as reasoning, can be accounted for by decreasing speed of information processing. Moreover, some studies emphasize that older individuals may show poorer results 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 effect. However, Salthouse suggests that the effect of aging on memory is independent of processing speed.

Therefore, in our empirical analysis we primarily focus on 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 a 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 an 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.

Furthermore, behavioral, neurological, and neuroimaging literature consistently reports a negative relationship between aging and motor skill acquisition. Older adults learn more slowly and in many cases, even with extended practice do not show performance levels which reach those of younger adults.[35] In an updated review, Bradley R. King and Doyon (2013) summarized that older adults have deficits in motor skill learning on 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

[35] See, 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. In particular, past habits or old ways of thinking may be a handicap to learning when new information contradicts existing beliefs. 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) show 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 medical literature (see de Zwart and Frings-Dresen (1995) and 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. Beginning in the late 20s, the lean muscle mass start to decrease and the fat levels start 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 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 of the 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 responses 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 measures 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 the 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 the 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.

Appendix D. Measuring country-level endowment in memory using standardized memory tests

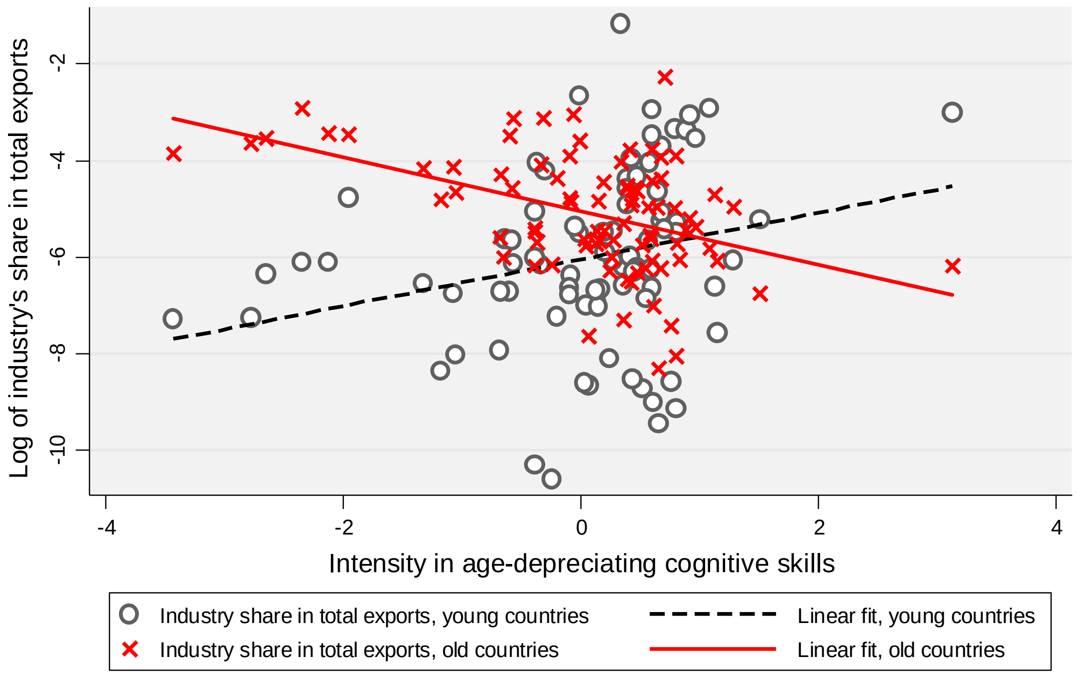
This appendix explains the details of construction of a proxy measure for a country's stock of cognitive skills which does not depend on the age structure. The measure that we propose relies on the variation in cognitive functioning across countries and is available from the international standardized tests of cognitive abilities. These tests are based on comparable cross-national household surveys conducted in different parts of the world and include Survey of Health, Aging and Retirement in Europe (SHARE), World Health Organization study on global aging and adult health (SAGE), English Longitudinal Study of Aging (ELSA), and Health and Retirement Study (HRS). These surveys cover 27 different countries: Austria, Belgium, Czech Republic, Denmark, Estonia, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Netherlands, Poland, Portugal, Slovenia, Spain, Sweeden, and Switzerland in the SHARE survey; China, Ghana, India, Mexico, Russia, and South Africa in the SAGE survey; UK in the ELSA survey; and USA in the HRS survey. Although the sample is overrepresented by countries from the top quartile of the median age distribution, four countries from the first and second quartiles (China, Ghana, India, and Mexico) are also present. In this study we use data from the last wave of surveys conducted in 2010-11.

The target population includes individual aged 50 years and over and their spouses. Participants of all four surveys take a standardized short-term memory test which consists of verbal registration and immediate recall of a list of ten simple words (e.g. sky, ocean, home, butter, child, etc). After one minute of asking other survey questions the respondents are asked to recall the nouns previously presented as part of the immediate recall task. The test score is the count of the number of words that were recalled correctly and ranges from zero to ten. Tests of other cognitive skills, such as numeracy or long-term memory test, are not covered in all surveys and are thus not included in our study. We standardized the memory test score to 0-1 interval.

Along with the tests, survey participants also fill out a questionnaire which provides detailed information on age, gender, household composition, health, social status, income and assets, employment, etc. Unfortunately, most of these questions are either not included in every survey or not measured in a comparable way. As a measure of individual's health we use a self-perceived health condition assessment, which is the only health-related indicator measured consistently across surveys. The respondents were asked to rank their health as excellent, very good, good, fair, or poor. For education, we use two outcome variables. The first one is the number of years of formal education. The second measure is based on the highest education level, which we categorized into four groups: less than primary, primary school completed, secondary school completed, post-secondary.

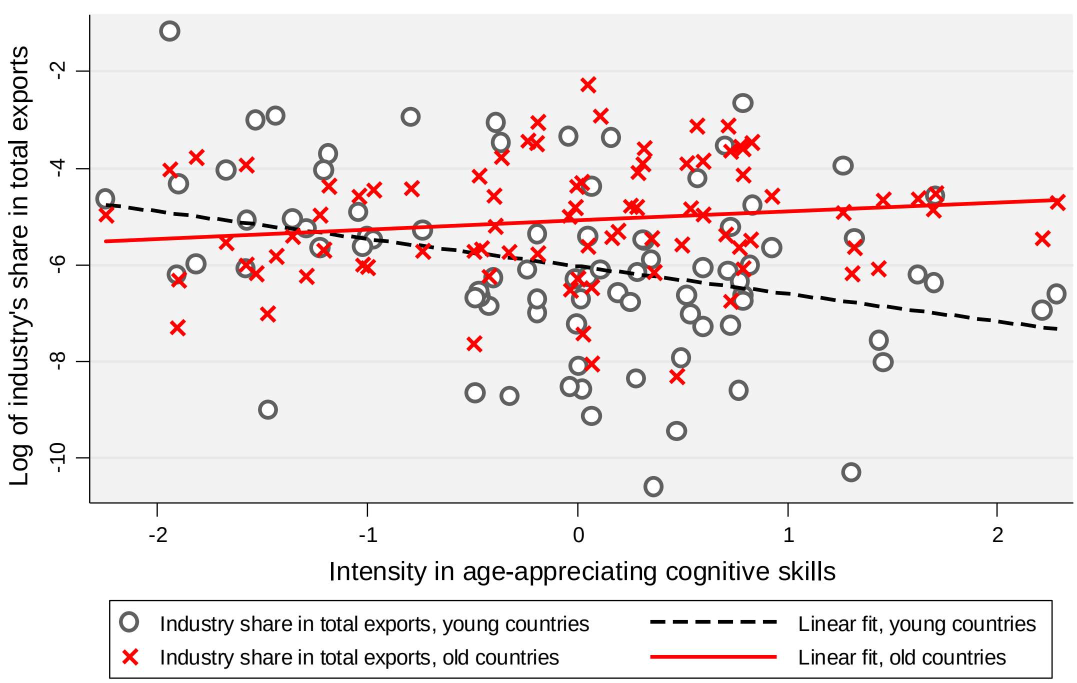
Figure 1A illustrates the relationship between the word recall test scores and age for selected countries. As expected, there is a strong age-related decline in short-term memory in all countries as measured by the proportion of words recalled correctly within 1 minute. Furthermore, this negative relationship is preserved when we control for the effect of gender, education, and self-reported health status on test outcomes in Figure 2A. Figure 2A also reveals substantial differences in the levels of test scores across countries even after controlling for cross-country differences in educational attainment, which suggests the presence of unobservable country-specific determinants of cognitive performance.

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



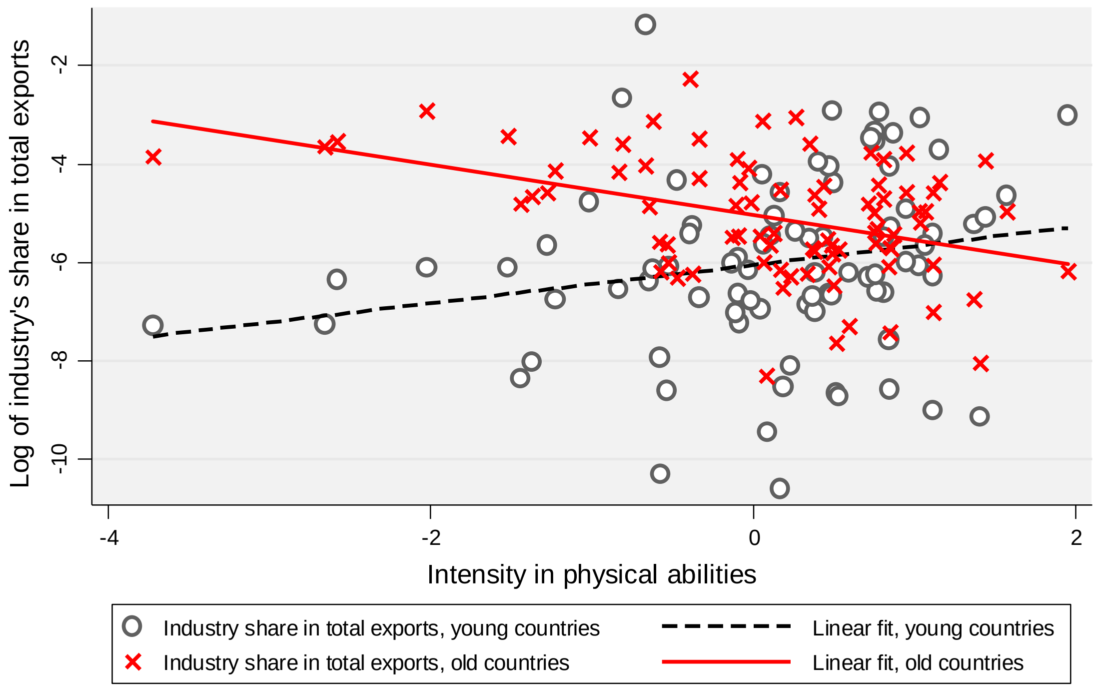
Note: Young and old countries are the ones with the median age less than 20 and greater than 35, respectively

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



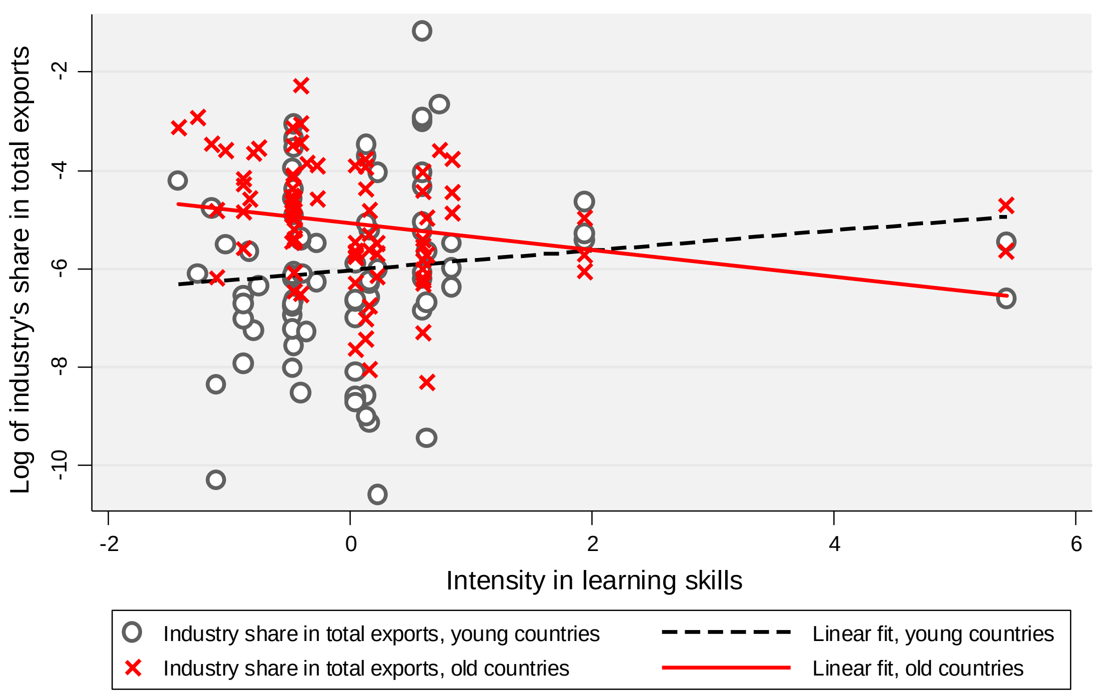
Note: Young and old countries are the ones with the median age less than 20 and greater than 35, respectively

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



Note: Young and old countries are the ones with the median age less than 20 and greater than 35, respectively

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



Note: Young and old countries are the ones with the median age less than 20 and greater than 35, respectively

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

Figure 6. Variation in consumer goods expenditure shares among different age cohorts

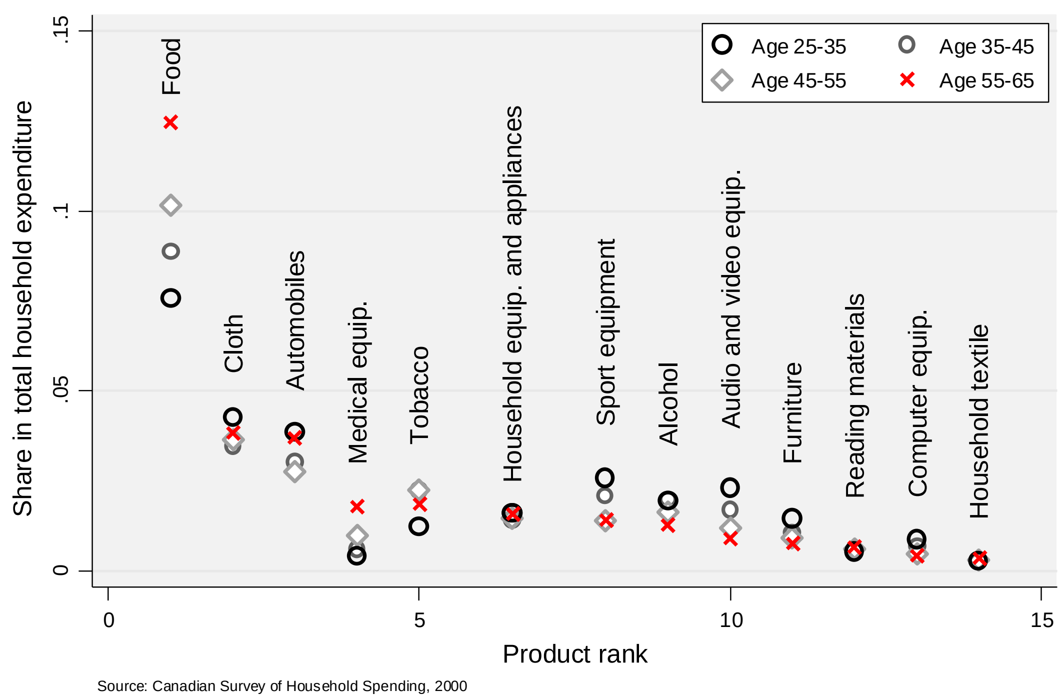


Table 1. Occupations with extreme skill intensities

10 Most skill intensive occupations			10 Least skill intensive occupations		
Rank	SOC	Occupation	Rank	SOC	Occupation
Age-appreciating cognitive skills					
1	273042	Technical Writers	1	516051	Sewers, Hand
2	113111	Compensation and Benefits Managers	2	191022	Microbiologists
3	434151	Order Clerks	3	517021	Furniture Finishers
4	414012	Sales Representatives, Except Technical and Scientific Products	4	499071	Maintenance and Repair Workers, General
5	414011	Sales Representatives, Technical and Scientific Products	5	514052	Pourers and Casters, Metal
6	519083	Ophthalmic Laboratory Technicians	6	519031	Cutters and Trimmers, Hand
7	113061	Purchasing Managers	7	517041	Sawing Machine Setters and Operators
8	113121	Human Resources Managers	8	519198	Helpers--Production Workers
9	439031	Desktop Publishers	9	519123	Painting, Coating, and Decorating Workers
10	433061	Procurement Clerks	10	518093	Petroleum Pump System Operators, Refinery Operators, and Gaugers
Age-depreciating cognitive skills					
1	514194	Tool Grinders, Filers, and Sharpeners	1	191022	Microbiologists
2	516064	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	2	172031	Biomedical Engineers
3	519041	Extruding, Forming, and Pressing Machine Setters, and Operators	3	452041	Graders and Sorters, Agricultural Products
4	519021	Crushing, Grinding, and Polishing Machine Setters, and Operators	4	191021	Biochemists and Biophysicists
5	537051	Industrial Truck and Tractor Operators	5	172131	Materials Engineers
6	519111	Packaging and Filling Machine Operators	6	111011	Chief Executives
7	434151	Order Clerks	7	172071	Electrical Engineers
8	537072	Pump Operators, Except Wellhead Pumpers	8	192031	Chemists
9	514021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	9	172041	Chemical Engineers
10	519121	Coating, Painting, and Spraying Machine Setters and Operators	10	172112	Industrial Engineers
Physical abilities					
1	475051	Rock Splitters, Quarry	1	131081	Logisticians
2	453011	Fishers and Related Fishing Workers	2	271024	Graphic Designers
3	499044	Millwrights	3	172131	Materials Engineers
4	537062	Laborers and Freight, Stock, and Material Movers, Hand	4	112021	Marketing Managers
5	472211	Sheet Metal Workers	5	271021	Commercial and Industrial Designers
6	472111	Electricians	6	173013	Mechanical Drafters
7	499096	Riggers	7	172141	Mechanical Engineers
8	519197	Tire Builders	8	172031	Biomedical Engineers
9	512011	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	9	173012	Electrical and Electronics Drafters
10	519012	Separating, Filtering, and Still Machine Setters, and Operators	10	273042	Technical Writers

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

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

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	*cog_app*	1					
(2)	*cog_dep*	-0.24	1				
(3)	*physical*	-0.32	0.89	1			
(4)	*pcreation*	-0.10	0.36	0.30	1		
(5)	*capital intensity*	0.48	-0.07	0.04	-0.09	1	
(6)	*skill intensity*	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 ×		0.040**				0.042**	0.029**
$(Median\ age)_c$		(8.17)				(9.07)	(5.78)
Cog_dep_i ×			-0.058**			-0.076**	-0.062**
$(Median\ age)_c$			(-10.59)			(-7.39)	(-5.77)
$Physical_i$ ×				-0.051**		0.020*	0.011
$(Median\ age)_c$				(-9.00)		(2.02)	(1.05)
$Pcreation_i$ ×					-0.027**	-0.009	-0.007
$(Median\ age)_c$					(-5.65)	(-1.61)	(-1.30)
$(Capital\ int.)_i$ ×	0.030**	0.018**	0.029**	0.036**	0.033**		0.022**
$(Capital\ abund.)_c$	(6.23)	(3.60)	(5.83)	(7.18)	(6.26)		(3.79)
$(Skill\ int.)_i$ ×	0.049**	0.038**	0.023**	0.025**	0.045**		0.017**
$(Skill\ abund.)_c$	(10.31)	(7.59)	(4.16)	(4.50)	(9.30)		(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 ×	-0.038**				-0.027**	-0.025**
(share of young workers)$_c$	(-8.03)				(-5.93)	(-5.47)
Cog_dep_i ×		0.054**			0.068**	0.065**
(share of young workers)$_c$		(10.58)			(6.65)	(6.38)
$Physical_i$ ×			0.045**		-0.023*	-0.025*
(share of young workers)$_c$			(8.41)		(-2.25)	(-2.44)
$Pcreation_i$ ×				0.028**	0.007	0.008
(share of young workers)$_c$				(5.79)	(1.40)	(1.51)
(Capital int.)$_i$ ×	0.020**	0.029**	0.034**	0.032**	0.023**	0.023**
(Capital abund.)$_c$	(4.20)	(5.99)	(6.97)	(6.38)	(4.40)	(4.42)
(Skill int.)$_i$ ×	0.040**	0.026**	0.030**	0.046**	0.022**	0.017**
(Skill abund.)$_c$	(8.03)	(4.91)	(5.51)	(9.62)	(3.98)	(3.33)
(Skill int.)$_i$ ×						-0.023**
(Skill abund. young)$_c$						(-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)	(11)
Cog_app$_i$ × *(Median age)$_c$*	0.025**	0.027**	0.028**	0.032**	0.032**	0.038**	0.023**	0.029**		-0.034	-0.042
	(5.00)	(5.50)	(5.61)	(6.07)	(5.69)	(7.18)	(2.96)	(5.90)		(-1.06)	(-1.31)
Cog_dep$_i$ × *(Median age)$_c$*	-0.057**	-0.060**	-0.069**	-0.062**	-0.070**	-0.053**	-0.070**	-0.061**		0.091	0.052
	(-5.30)	(-5.59)	(-6.68)	(-5.60)	(-5.96)	(-5.13)	(-4.63)	(-5.68)		(1.24)	(0.71)
Physical$_i$ × *(Median age)$_c$*	0.016	0.014	0.007	0.012	0.013	0.002	-0.008	0.010		-0.092	-0.075
	(1.44)	(1.34)	(0.68)	(1.15)	(1.11)	(0.23)	(-0.55)	(0.90)		(-1.38)	(-1.10)
Pcreation$_i$ × *(Median age)$_c$*	-0.008	-0.008		-0.010+	-0.012+	-0.014*	-0.020*	-0.007		-0.072*	-0.060
	(-1.47)	(-1.41)		(-1.72)	(-1.84)	(-2.40)	(-2.40)	(-1.22)		(-2.05)	(-1.62)
(Capital int.)$_i$ × *(Capital abund.)$_c$*	0.020**	0.020**	0.023**	0.023**	0.026**	0.010	0.010	0.023**	0.028**	0.016	0.046
	(3.44)	(3.45)	(3.92)	(3.81)	(3.47)	(1.74)	(1.40)	(3.95)	(5.43)	(0.57)	(1.58)
(Skill int.)$_i$ × *(Skill abund.)$_c$*	0.030**	0.037**	0.016**	0.020**	0.033**	0.027**	0.027**	0.011+	0.046**	0.010	0.015
	(4.85)	(7.03)	(2.90)	(3.32)	(5.53)	(4.99)	(2.72)	(1.85)	(9.32)	(0.92)	(1.51)
Pintensity$_i$ × *(Median age)$_c$*			-0.011+								
			(-1.71)								
Cog_neutral$_i$ × *(Median age)c*									-0.013**		
									(-2.88)		
(Skill substitutability)$_i$ × *(Skill dispersion)$_c$*										-0.028**	
										(-3.11)	
(Contract intensity)$_i$ × *(Judicial quality)$_c$*											0.025*
											(2.15)
Sample	benchmark	benchmark	benchmark	benchmark	benchmark	2010	1970	no USA	benchmark	benchmark	benchmark
Importer-industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Exporter FE	YES	YES	YES	NO	YES	YES	YES	YES	YES	YES	YES
Importer-exporter FE	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO	NO
Trade costs controls	YES	YES	YES	NO	YES	YES	YES	YES	YES	YES	YES
R-squared	0.557	0.557	0.556	0.736	0.566	0.586	0.536	0.542	0.552	0.697	0.705
N	410,486	410,486	410,486	416,371	295,272	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 (5) includes additional unreported probability of exports obtained from the first stage.

Table 6. Extensions.

	(1)	(2)	(3)
Cog_app_i ×	0.022**	0.018**	0.030**
$(Median\ age)_c$	(2.85)	(2.61)	(4.92)
Cog_dep_i ×	-0.045**	-0.059**	-0.029*
$(Median\ age)_c$	(-6.06)	(-4.60)	(-2.31)
$Pcreation_i$ ×	-0.006	-0.020+	-0.003
$(Median\ age)_c$	(-0.80)	(-1.78)	(-0.53)
$Cog\_app_i \times Health_c$	0.024**	0.048**	
	(4.62)	(4.30)	
$Cog\_dep_i \times Health_c$	-0.006	0.008	
	(-0.86)	(0.62)	
$Pcreation_i \times Health_c$	0.001	0.022	
	(0.20)	(1.75)	
$Cog\_app_i \times Educ_c$	0.005	0.003	
	(0.76)	(0.47)	
$Cog\_dep_i \times Educ_c$	-0.018	-0.016	
	(-1.93)	(-1.72)	
$Pcreation_i \times Educ_c$	-0.005	-0.009	
	(-0.71)	(-1.37)	
$(Capital\ int.)_i$ ×	0.029**	0.021**	0.027**
$(Capital\ abund.)_c$	(5.36)	(3.82)	(3.27)
$(Skill\ int.)_i$ ×	-0.002	-0.002	0.018*
$(Skill\ abund.)_c$	(-0.18)	(-0.27)	(2.26)
Importer-industry FE	YES	YES	YES
Exporter FE	YES	YES	YES
Trade costs controls	YES	YES	YES
R-squared	0.560	0.560	0.549
N	398,924	402,060	219,657

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 7. Alternative measure of the stock of cognitive skills

	(1)	(2)	(3)	(4)	(5)
$Memory\_I_i$ ×	-0.022**				
(Median age)$_c$	(-4.55)				
$Memory\_I_i$ ×		0.036**	0.027**	0.027**	0.019**
$Score_c$		(3.35)	(3.15)	(5.90)	(3.69)
(Capital int.)$_i$ ×	0.038**	0.048**	0.050**	0.036**	0.036**
(Capital abund.)$_c$	(7.46)	(4.14)	(4.22)	(7.10)	(7.06)
(Skill int.)$_i$ ×	0.043**	0.061**	0.060**	0.048**	0.048**
(Skill abund.)$_c$	(8.81)	(7.46)	(7.35)	(9.96)	(10.15)
Importer-industry FE	YES	YES	YES	YES	YES
Exporter FE	YES	YES	YES	YES	YES
Trade costs controls	YES	YES	YES	YES	YES
R-squared	0.552	0.667	0.668	0.552	0.552
N	413,466	151,637	151,637	413,466	413,466

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 8. Estimates for the Rybczynski effect

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

Table 9. Robustness and extensions for the Rybczynski effect

	(1)	(2)	(3)	(4)	(5)		(6)
					β^O	β^Y	
Cog_app_i × $(\Delta Age)_c$	-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 × $(\Delta Age)_c$	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)
$Pcreation_i$ × $(\Delta Age)_c$	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)
$(Capital\ int.)_i$ × $(\Delta Age)_c$	-0.005 (-0.35)	0.005 (0.48)	0.016+ (1.83)	0.020** (2.77)	0.001 -0.06		0.118 (1.65)
$(Skill\ int.)_i$ × $(\Delta Age)_c$	-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.

Appendix Tables and Figures

Figure 1A. The relationship between unconditional word recall test score and age.

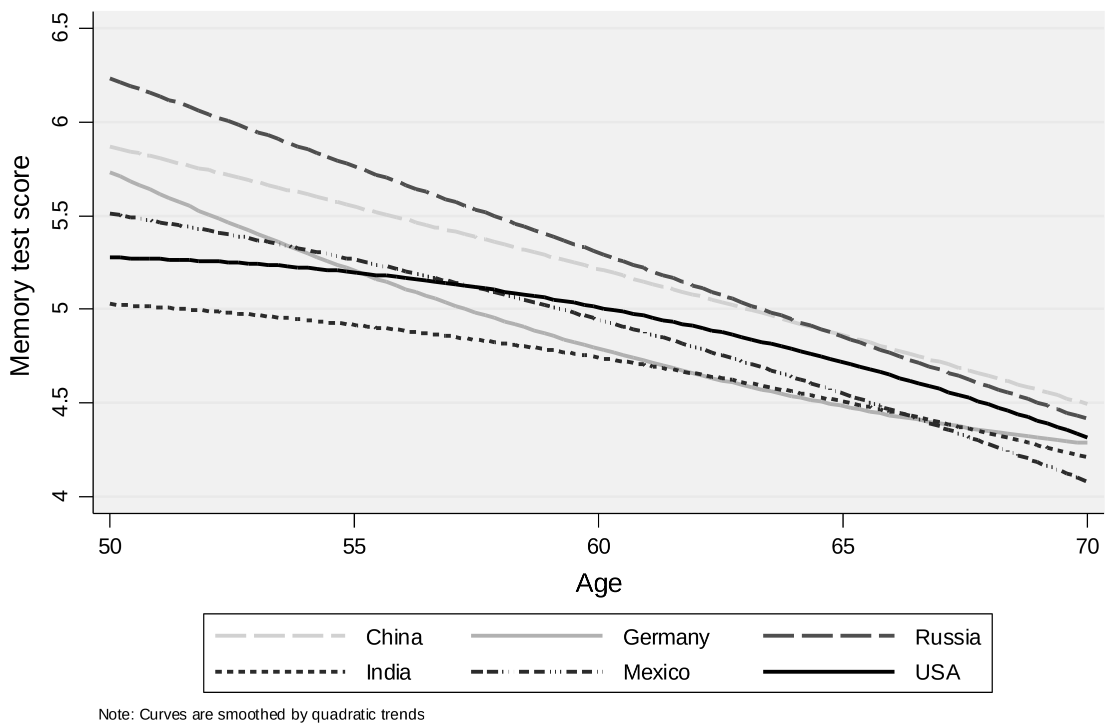


Figure 2A. The relationship between conditional word recall test score and age.

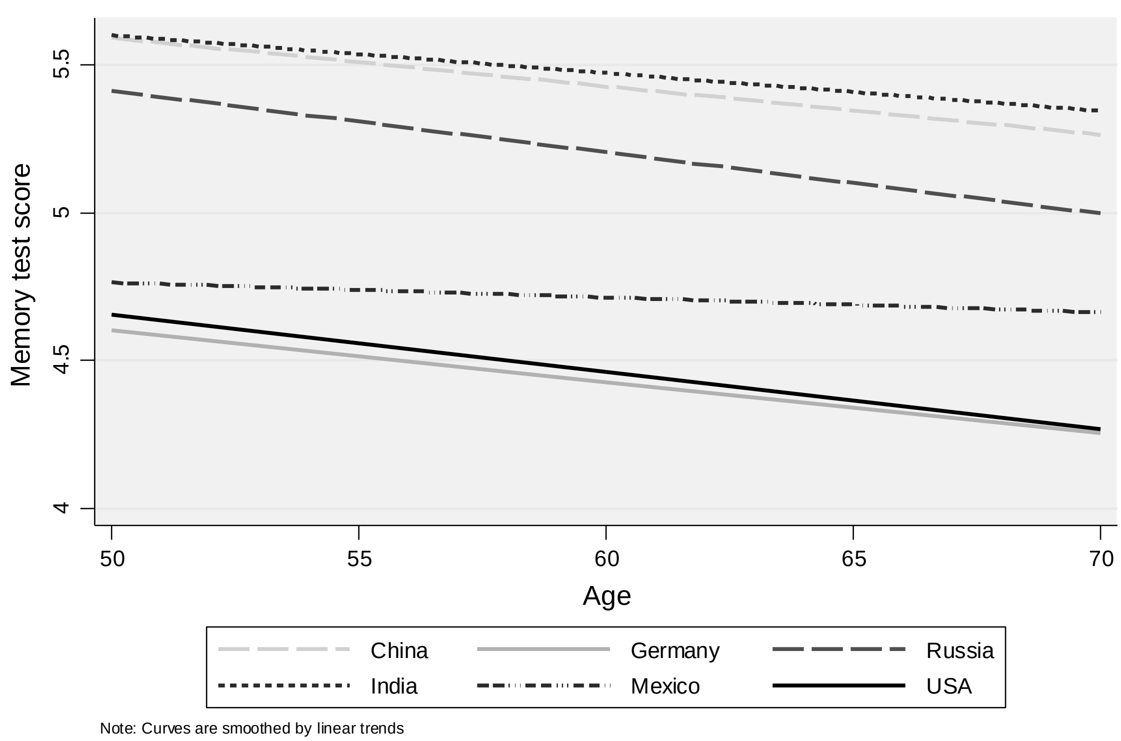


Table 1A. Correlation between industry-level intensities in cognitive skills

		(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	69	Malaysia	23.8	17.6	6.25
2	Italy	40.2	31.6	8.64	70	Venezuela	23.3	17.2	6.04
3	Bulgaria	39.7	30.4	9.27	71	Guyana	23.2	17.0	6.23
4	Sweden	39.4	36.0	3.37	72	South Africa	23.2	19.7	3.49
5	Finland	39.4	28.4	11.00	73	India	23.0	20.3	2.76
6	Belgium	39.1	35.0	4.09	74	Mexico	23.0	17.1	5.87
7	Croatia	39.0	29.2	9.79	75	Peru	22.9	18.4	4.45
8	Switzerland	38.6	32.7	5.90	76	Ecuador	22.9	18.6	4.33
9	Hungary	38.6	32.2	6.41	77	Kyrgyzstan	22.5	24.0	-1.51
10	Denmark	38.4	33.0	5.40	78	Morocco	22.3	18.1	4.20
11	Greece	38.3	29.1	9.22	79	Libya	22.2	19.5	2.72
12	Austria	38.2	35.6	2.59	80	Fiji	22.1	15.8	6.31
13	Slovenia	38.0	29.3	8.68	81	Mongolia	22.0	23.0	-1.04
14	Estonia	37.9	32.2	5.73	82	Egypt	22.0	19.8	2.15
15	Latvia	37.9	32.3	5.67	83	Algeria	21.6	17.6	4.01
16	Portugal	37.8	27.9	9.82	84	Saudi Arabia	21.1	18.5	2.54
17	United Kingdom	37.6	35.5	2.16	85	Bangladesh	21.0	18.6	2.38
18	Spain	37.6	29.4	8.24	86	Iran	20.9	19.5	1.45
19	Ukraine	37.6	28.9	8.73	87	El Salvador	20.7	17.5	3.23
20	Czech Republic	37.6	33.1	4.46	88	Philippines	20.5	16.5	3.95
21	France	37.6	33.0	4.54	89	Paraguay	20.4	16.1	4.36
22	Netherlands	37.3	28.7	8.60	90	Bolivia	20.0	18.7	1.27
23	Luxembourg	37.3	35.2	2.14	91	Tonga	19.9	17.3	2.63
24	Norway	36.9	34.3	2.53	92	Botswana	19.8	17.2	2.59
25	Canada	36.8	26.5	10.33	93	Papua New	19.6	18.8	0.80
26	Russia	36.5	27.2	9.34	94	Nepal	19.6	20.2	-0.62
27	Hong Kong	36.5	23.1	13.39	95	Jordan	19.5	18.0	1.51
28	Malta	35.9	21.5	14.44	96	Gabon	19.5	27.1	-7.53
29	Lithuania	35.9	28.5	7.39	97	Namibia	19.5	19.3	0.15
30	Australia	35.4	29.6	5.77	98	Belize	19.3	17.8	1.52
31	Poland	35.3	26.6	8.75	99	Haiti	19.1	19.8	-0.68
32	USA	35.3	29.6	5.72	100	Pakistan	18.9	19.8	-0.91
33	Romania	34.4	28.4	5.93	101	Ghana	18.9	17.7	1.25
34	New Zealand	34.3	27.4	6.89	102	Syria	18.8	17.1	1.74
35	Singapore	34.1	18.8	15.33	103	Nicaragua	18.8	16.3	2.51
36	Slovakia	33.9	27.7	6.27	104	Congo	18.8	19.5	-0.71
37	Barbados	33.5	22.4	11.17	105	Lesotho	18.7	18.3	0.38
38	Iceland	32.8	25.4	7.37	106	Côte d'Ivoire	18.7	19.2	-0.52
39	Cuba	32.8	22.9	9.89	107	Maldives	18.5	20.5	-1.97
40	Ireland	32.5	30.1	2.41	108	Central African	18.5	21.4	-2.90
41	Korea, Rep. of	32.1	19.8	12.30	109	Cambodia	18.4	17.2	1.19
42	Cyprus	31.8	23.0	8.76	110	Honduras	18.4	17.1	1.31

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

Table 6A. Correlation between factor intensities and the gap in expenditure shares of 55-65 and 25-35 age cohorts

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	*cog_app*	1						
(2)	*cog_dep*	-0.28	1					
(3)	*physical*	-0.18	0.93	1				
(4)	*pcreation*	0.37	0.46	0.39	1			
(5)	*capital intensity*	0.64	-0.02	0.11	0.22	1		
(6)	*skill intensity*	0.59	-0.49	-0.47	0.11	0.34	1	
(7)	*difference in consumption shares between 55-65 and 25-35 cohorts*	0.13	0.13	0.12	-0.04	0.23	-0.34	1

Note: Spearman rank correlation coefficients are calculated over 14 consumption product categories

Table 7A. The effect of age, education and health on memory test scores

	(1)	(2)	(3)	(4)
Age	-0.006** (-16.96)	-0.005** (-14.88)	-0.005** (-14.48)	-0.004** (-12.53)
Male	-0.028** (-3.59)	-0.038** (-6.36)	-0.035** (-5.11)	-0.040** (-6.66)
Education:				
Years of schooling		0.011** (10.86)		0.006** (5.78)
Primary			0.042* (2.77)	0.020 (1.41)
Secondary			0.101** (8.60)	0.055** (3.68)
Post-Secondary			0.171** (16.01)	0.094** (5.32)
Self-assessed health:				
Excellent				0.104** (17.57)
Very good				0.101** (20.70)
Good				0.075** (17.82)
Fair				0.046** (11.44)
Country FE	YES	YES	YES	YES
R-squared	0.101	0.161	0.144	0.187
N	80,673	65,296	80,673	65,296

Notes: The dependent variable is the memory test score, measured as the fraction of correctly recalled words by an individual. The sample is restricted to individuals of 50-70 years of age. The excluded education category is "less than primary" and the excluded health category is "poor". * significant at 5%, ** significant at 1%. Robust standard errors are clustered by country.