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Trade liberalization and relative employment: further evidence from Tunisia

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Abstract There are increasing studies that address the skill upgrading in developing countries. The theoretical analyses yield different results about which factors affect skill upgrading. The impact of trade openness and technology transfer on the relative demand for skilled labor remains a puzzle, the issue is mainly empirical questions. The empirical findings surrounding this question are in total contradiction with the prediction of traditional trade theory. This paper addresses this puzzle for the Tunisian economy by considering a database covering 12 Tunisian sectors for the period of 1983–2010. Empirical results indicate that trade openness positively affects relative demand of skilled labor. Empirical results also show that the effects of technological change induced by trade on relative demand of skilled labor are ambiguous. First, technology change has positive effects mediated via export channels, this is an evidence of the ''learning by exporting'' channel. Second, technology change has a negative effect mediated via imports. These empirical findings have important economic implications; for instance Tunisian economic policy should be oriented to improve a firm's competitiveness and labor market capacity to minimize the cost of trade liberalization in terms of employment losses mainly for unskilled workers.

Keywords Wages inequalities · Technology change · Skill upgrading · Dynamic panel data model

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1 Introduction

Since the beginning of the 1980s, several less developed countries (LDCs) have opened their economies to international trade. At the same time, considerable changes in the employment structure have been observed at the firm and sector levels in the form of skill upgrading (i.e., the relative demand for skilled labor compared to the demand for unskilled labor). Considerable interest has been emerged regarding the implications of trade liberalization and technological change on the labor market in DCs. As a small open developing country, Tunisia constitutes an interesting case for study. Tunisia has undergone significant changes in its economy over the last 30 years. These changes were designed in a general framework of structural adjustment program launched by the government at the end of the 1980s. The Tunisian government started by signing the GATT treaty in 1989, and after that in 1994, Tunisia finalized its entry into the World Trade Organization (WTO). In 1995, Tunisia's policy-makers signed a free trade agreement with the European Union. Together, these factors make Tunisia a suitable case study of the labor market adjustment associated with trade liberalization.

As a consequence of Tunisia's strategy of openness, its exports and imports volumes, have increased and made the economy more open to the world market. This increase in the volume of exports and imports has particularly been pronounced in the case of manufacturing industries. Moreover, import and export volume increases have facilitated the diffusion and transfer of technology between Tunisia and its trading partners. One of the most important issues related to the integration of the Tunisian economy into the world market may be its impact on labor demand, and, more specifically, its impact on the relative demand for skilled labor. The main evolutions observed over the period of trade liberalization are the substantial increases in the relative employment of skilled labor, and wage inequality (Ghazali 2011). This raises the question of whether these two simultaneously occurring phenomena are linked. Moreover, Ben Ayad Mouelhi (2007) documented that a skill upgrading behavior is taking place in the Tunisian economy, albeit without an econometric analysis.

The theoretical predictions regarding the links between trade liberalization and skill upgrading in developing countries are conflicting. The traditional Hecksher–Ohlin (H–O) theory is the main theoretical framework that is applied to international trade. According to this theory, since developing countries have an abundance of unskilled labor while skilled labor is scarce, trade openness should lead developing countries to specialize in unskilled labor intensive activities and raise the demand for labor in these sectors. A corollary of the H–O theory, the Stolper Samuelson (S–S) theorem suggests that trade should raise the relative price of the abundant factor (unskilled labor) in developing countries and reduce relative wage for skilled labor and, by extension, wage inequality. Recent data from developing countries show that the evolution of demand is biased toward skilled workers and away from unskilled workers. Moreover, most empirical research has found little evidence that trade reforms induce labor reallocation across sectors toward unskilled-labor-intensive sectors in developing countries (Goldberg and Pavcnik 2007). In general, the explanation of the observed trends remains puzzling, and is in contradiction with the prediction of the standard Heckscher–Ohlin–Samuelson (H–O–S) trade theory.

To explain this puzzle of increases in skill premiums in developing countries, several other directions have been followed (see Feenstra and Hanson 1997; Robbins 2003; Acemoglu 2003; Melitz 2003; Bustos (2011); Verhoogen 2008). According to these studies, trade liberalization may induce technological change in DCs. This can be possible, on the one hand, through goods imported from developed countries that may represent technology that is biased toward skilled workers (see Robbins 2003; Acemoglu 2003), and on the other hand, via export channel activities (see Pissarides 1997; Bustos 2011; Verhoogen 2008). Finally, others indicated that several stages of production are moving from industrialized countries to developing countries, which has a significant impact on relative employment (see Feenstra and Hanson 1997; Zhu and Trefler 2005).

The purpose of this paper is to investigate the impact of trade openness and trade induced technology change on the relative demand for skilled labor in 12 sectors of the Tunisian economy. We employ a dynamic panel data method to investigate this impact. To this end, we use an annual database constructed from data provided by the Tunisian National Institute (TNIS) and the Economic Quantitative Institute (EQI) for the period of 1983–2010.

The paper contributes to this debate in at least three ways. First, it provides new evidence on the increase in relative demand for skilled labor in Tunisia. We estimate the impact of trade liberalization and technological change induced by trade. Our strategy to deal with the luck of data directly measuring technological change consists of classifying sectors based on their technology intensity. Therefore, we distinguish between sectors that are intensive in technology and sectors that are not. For that purpose, we create an interaction proxy. Second, the paper also contributes to the empirical literature on Tunisia by including the service sector and other non-manufacturing sectors in the analysis. Focusing on the manufacturing sector only gives a partial picture of the impact of trade on labor market.

To our knowledge, no study on Tunisian case investigates all these sectors at the same time. Finally, our results differ from the existing results by showing that the increase in relative demand is mainly because of the increase in exports. This seems justified, on the one hand, by the policy of Tunisian government to promote export activities and encourage firms to compete nationally and internationally by allowing them to modernize their technology and learn a new way of production. On the other hand, despite the policy orientation towards liberalizing imports some facts show that Tunisia still protect some sectors from imports.

The remainder of this paper is organized as follow. The next section presents a survey of the theoretical and empirical literature which covers the impact of international trade on employment and wages inequalities. Section 3 presents the evolution of openness and the labor market in Tunisia. Section 4 presents the data, the econometric model and discusses the results. Finally, Sect. 5 concludes and discusses the economic implications of the empirical results.

2 The theoretical and empirical literature

2.1 Theoretical background

The Heckscher–Ohlin model (HO) and its Stolper–Samuelson (SS) corollary are still the main analytical tools used by researchers to analyze the impact of trade liberalization on labor markets. HOS model assumes a world with two countries, developed country (DC) and less developed country (LDC), two goods and two factors, i.e., skilled and unskilled labor. The DC has the comparative advantage of producing skilled-labor-intensive goods, and the LDC produces unskilled-labor-intensive goods. The Heckscher–Ohlin and Stolper–Samuelson (HOSS) model also assumes a world of homogenous firms and products, and inter-industry specialization. Under this set of assumptions HOSS model predicts that trade liberalization should raise the relative price of the abundant factor (unskilled labor) and reduce skilled wages and, by extension, wage inequality in developing countries.

Some of HOSS assumptions received a criticism from economists. The question is that what will happen if we neglect one or more assumptions of the HOSS? For example, the assumption that these countries have not the same level of technology. The answer of this question is complicated and remains ambiguous (Mrabet and Charfeddine 2012). Trefler (1995) and Meschi and Vivarelli (2009) concluded that the unpredictable results produced by the HOSS model can be attributed to the restrictive assumptions of this model. In fact, the assumptions that world is formed from only two countries, two goods and two factors of production are very restrictive. Thus, several researchers have tried to overcome this problem by extending the HOSS model. For example Dornbusch (1980) has extended this model to multiple goods. Wood (1994) added multiple skills, and Feenstra and Hanson (1996) extended the HOSS model to account trade in intermediary goods. Zhu and Trefler (2005) showed that, under some specific conditions, there is a shift in the production of the least skill-intensive Northern goods to Southern countries. Moreover, two more statements are vulnerable to criticism; the mobility of factors between sectors and the assumptions of homogenous firms and products. The assumption of homogeneity is often dropped, and neither technology (production functions) nor consumers' preferences (products) are identical and homogenous across developed and developing countries. Several authors have suggested that skill upgrading can be attributed to technology induced by trade liberalization (Robbins 2003; Lee and Vivarelli 2006). The inflow of technology is assumed to be skill-biased because it is mainly designed and developed in the industrialized world with skill-intensive technology (Berman et al. 1998). The trade inducing technology change will therefore be accompanied by a change in labor demand in favor of skilled workers. If this increase is large enough, it can outweigh the reduction in the demand for skilled labor that is predicted by the traditional trade theory. Furthermore, some other authors have explained that the increases of wage inequality and demand for highly skilled labor can emerge from the complementarities between capital inflow and skilled labor[1] (Robbins 1994; Berman et al. 1998; O'Connor and Lunati 1999).

Meschi and Vivarelli (2009) explained that the increase in relative demand for highly skilled labor in LDCs is related to the fact that the import of machines and equipment allows for simultaneous processes of technological modernization and deepening of capital. Robbins (2003) has called the effect of inflowing technology that results from trade liberalization the "skill-enhancing trade hypotheses". When the gap between existing and newly imported technology is large, trade reforms could have an even greater effect on skill demand in a developing country than it does in an industrialized country (O'Connor and Lunati 1999). Another mechanism developed by Feenstra and Hanson (1997) showed that transfer of some stages of production from developed to developing countries can lead to skill upgrading in both countries. These stages are unskilled-labor-intensive in the former first countries and skilled-labor-intensive in the later.

Another possible explanation is that firms operating in tradable sectors are pressed by international competition to adopt technologies that are more productive and more skill required. Moreover, western firms are interested in transferring some technologies to their partners in developing countries to produce high-quality products. (Verhoogen 2008; Matsuyama 2007; Stokey 1996). Revenues from export activities may increase after a reduction of tariff between trade partners, and incite firms to invest in more technologies (Bustos 2011).

2.2 The empirical literature

In the last two decades some of empirical studies investigated the relationship between trade liberalization and the labor markets of developing countries. Currently, it is widely maintained that trade openness increases skilled wage premiums and skill upgrading (Meschi and Vivarelli 2009; Cragg and Epelbaum 1996; Currie and Harrison 1997; Beyer et al. 1999; Harrison and Hanson 1999; Lee and Vivarelli 2006). Cragg and Epelbaum (1996) have used household-level data to examine how wage and employment changes differed across industries and occupations during the reform period in Mexico. Cragg and Epelbaum (1996) found that the return to occupation explained close to half of the growing wage dispersion. Workers in the highest paid occupations experienced the largest wage growth. Robbins (1996) examined the impact of real devaluation, trade liberalization and the relative growth of the skill supply on wage dispersion in Colombia's seven main cities over the period of 1976–1994. The author showed that there was no evidence supporting HOSS and that trade openness was negatively correlated with relative wages. Currie and Harrison (1997) examined the impact of trade reforms in Morocco on individual firms at micro-level detail. They traced the relationship between changes in trade policies and manufacturing employment at the firm level and showed that within a sector the effects of trade reform varied significantly

[1] Goldin and Katz (1998) propose the possibility that capital-skill complementarities exist in developing countries. Increased demand for capital will also increase demand for skilled labor, and if demand grows faster than supply, their wages will also increase.

depending on firm characteristics such as ownership (public versus private) and the degree of export orientation. Harrison and Hanson (1999) used data from 2354 Mexican manufacturing plants between 1984 and 1990 and the Mexican Industrial Census of 1965–1988 to investigate the reasons underlying the wideness of the wage gap between skilled and unskilled labor after trade liberalization. They found that relative wage changes occurred without large changes in relative employment. Arbache et al. (2004) investigated the effects of trade liberalization on wages in Brazil. They considered data provided by the Pesquisa Nacional por Amostra de Domicilios (PNAD) during the period 1981–1999. The authors concluded that wages fell substantially in the tradable sector and that trade liberalization increased marginally with the return to college education (skilled labor). Pavcnik (2003) investigated the causes of skill upgrading in Chilean plants during the 1980s using semi-parametric and parametric approaches. The empirical results of this study showed that the increase in the relative demand for skilled workers could be attributed to capital deepening and that the relationship between technology proxies and skill upgrading disappeared when unobserved plant characteristics were controlled for. Fuentes and Gilchrist (2005) extended their analysis to include an additional nine-year time span covered the period of 1979–1995. They found a significant positive correlation between the demand for skilled workers and the adoption of new foreign technologies. However, other papers have instead underlined the skill-enhancing effects of exporting, which make the adoption of new technologies profitable for more firms (Yeaple 2005), induces quality upgrading (Fajnzylber and Fernandes 2009; Verhoogen 2008) and produces opportunities to acquire knowledge about international best practices (Epifani 2003; Bigsten et al. 2004). Araujo et al. (2009) investigated the role of skill enhancing trade using micro data from several Brazilian manufacturing firms over the period of 1997–2005. They concluded that the increase in the relative demand for skilled labor was mainly driven by within-industry variation, which supports the idea that technology changes are the main determinant of skill upgrading. In addition, they show that domestic capital complements skilled labor. These results are in line with the view that importation of capital goods embodies a technological change that involves a clear skill-biased impact, (Conte and Vivarelli 2007; Meschi and Vivarelli 2009).

3 International trade and labor market evolution in Tunisia: descriptive analysis

3.1 Tunisian trade evolution

The Tunisian government has started the economic and financial reforms by the adoption of the Structural Adjustment Program implemented in the mid-1980s.[2] The main objectives of these reforms are to strengthen market mechanisms, making the

[2] Tunisia has signed the General Agreement on Terms of Trade (GATT), 1989 and the free-trade agreement with the European Union in 1995. The country has adhered the World Trade Organization (WTO) in 1994.

economy more open to trade and progressively reducing the intervention of the government in the economic activities. In terms of trade liberalization, these reforms have the objective to promote exports and imports. Consequently, several measures were undertaken to promote the exports such as the removal of licenses and corresponding taxes, the adoption of many bilateral and multilateral trade agreements and the creation of export processing zones.

In 1995 Tunisia has signed the free trade agreement (FTA) with European Union. This agreement stipulates that Tunisia gradually eliminates tariffs on imported goods from the European Union within 12 years. The measures related to the imports include the reduction of quantitative restrictions and reduce tariffs.[3]

The report of EQI (2003), reveal that the effective rate of protection for all the economy has increased from 48 % in 1995 to 88 % in 1997 and decreased to 62 % in 2001. This rate was estimated at 28 % in 2008. Ghazali (2012) suggests that before the episode of trade liberalization the unskilled intensive sectors are highly protected. After the trade liberalization some of these sectors, as the Food-processing and Textile industries, recorded a decrease of their protection rates by about 300 and 150 percentage points, respectively. However, skill intensive sectors underwent an increase and a decrease of their rate of protection. For instance, the protection rate has increased from 88 to 126 % in the electrical and mechanical industries between 1986 and 1997 and increased to 44 % in 2001. The protection rate in Chemical industries have decreased from 65 to 50 % between 1995 and 2001.

Figure 1 traces the evolution of the exports share in value added over time for the technology-intensive and technology-non-intensive sectors. We have classified the 12 sectors based on the OCDE classification (OCDE science, Technology and Industry scoreboard 2007). In our database, 5 of the 12 sectors were considered to have “high” or “medium–high” levels of technology intensity (the Chemical sector, Electrical & Mechanical sector, Mines sector, Hydrocarbon sector and Transport & telecommunication sector). The seven other sectors were considered to have “low” or “medium–low” technology intensities.

This figure shows a steady and progressive increase in both sectors of the exports share in value added. This ratio increased from 0.69 in 1983 to 1.38 in 2010 in the technology intensive sectors, and from 0.27 in 1983 to 0.87 in 2010 in the technology non-intensive sectors. The increase is more pronounced for sectors intensive in technology, mainly after 2003. It is worth noting in this respect that a technological upgrading may be occurred in Tunisian economy which explain the improvement in the production and/or management processes in the various economic sectors in Tunisia (Mrabet and Charfeddine 2013b).

[3] The reduction of restrictions and tariffs on imports concerns a list of products. The first list of products includes raw materials and capital goods not locally produced. In addition, the dismantling of tariffs on these products was immediate. The second list consists of finished products that are not locally manufactured, and a period of five years has been required for the complete elimination of the associated tariffs. The third list corresponds to the set of locally manufactured products that face foreign competition. The agreement entails a progressive dismantling of tariffs on these products over a period of 12 years. The fourth list includes the products that are vulnerable to competition and essentially consists of final consumer goods. Agricultural and fishing, imports from the EU are subject to a specific regime due to the specificity of these products in the Tunisian productive system.

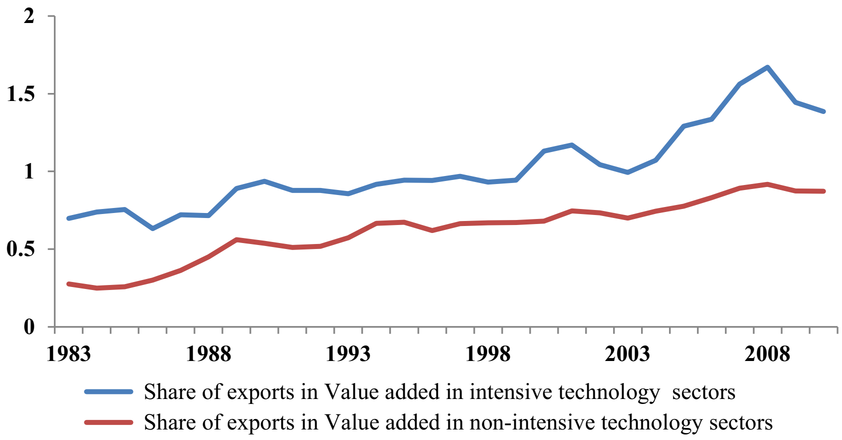

Fig. 1 Share of exports in value added

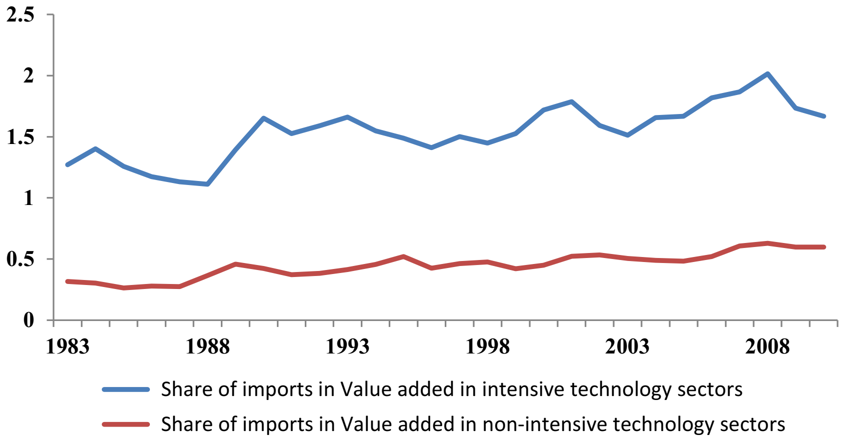

Fig. 2 Share of imports in value added

The Tunisian import liberalization process has been followed by two stages. The first phase was accomplished by the liberalization of import licensing and the reduction of tariff rates. This first stage was implemented at beginning of 1990s. The second phase of import liberalization was launched in 1995 and has taken the form of a new 5 year tariff reduction program. As a result of these two phases of tariff reduction, the competitive pressure on domestic industries has increased.

Figure 2 reports the evolution of the imports share in value added. This figure illustrates that technology intensive sectors have shown higher imports compared to sectors non-intensive in technology during the period 1983–2010. This evolution is much more apparent after 2003 in technology intensive sectors. In general, the evolution of imports in both sectors remains small if we consider the efforts took by

Tunisian government to liberalize the imports activities. This can be explained by the fact that the cuts of tariffs is not immediately but progressive.

The previous analysis gives us a clear idea about the desire and the efforts that have been made by the Tunisian authorities to open its economy to international trade. In addition to this later objective, the Tunisian government has as a second objective of resolving problems related to labor market.

3.2 Labor market evolution

This section reports the evolution of the Tunisian labor market over the period of 1983–2010. We discussed the evolution of relative employment of skilled to unskilled labor. The skilled labor and unskilled labor are defined basis on education level. See Sect. 4.1.1 for more explanation.

We also discussed the evolution of the relative wage between skilled and unskilled labor. To overcome the lack of data on wages by skill, we construct an indicator of relative wage between skills based on annual real wages. Bigsten and Durevall (2006) have created an intersectoral wage inequality indicator which is the ratio of the average annual wages in manufacturing over the average annual wages in agriculture. These authors argue that workers in manufacturing are generally more skilled than those working in agriculture. Therefore, the indicator used here is inspired from their method. The indicator consists to measure the evolution of the average relative wage between sectors intensive in technology and those non intensive in technology. The evolution of this ratio is supposed to capture changes in relative wage between skilled and unskilled labor.

Figure 3 reports the evolution of the ratio of skilled workers in total employment for technology-intensive sectors and technology non-intensive sectors. According to Ben Salha (2013) the job creation has been improved during 2000s. For example, in 2009 the manufacturing industries have generated employment for around 615,000

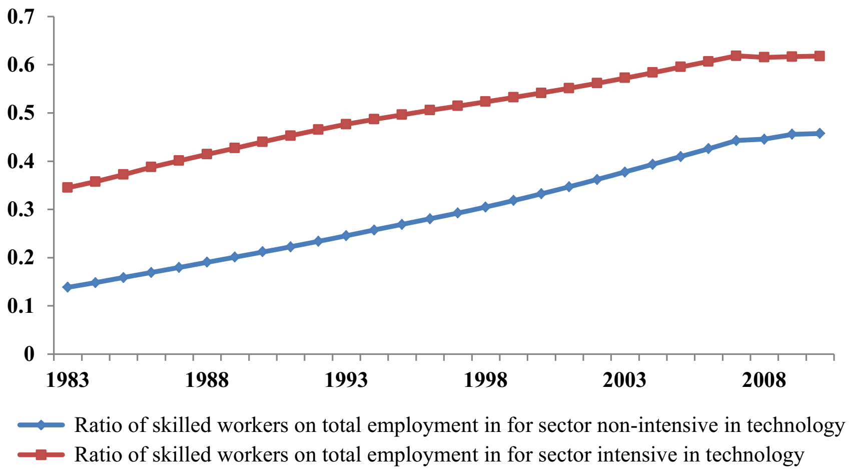

Fig. 3 The evolution of the ratio of skilled workers on total employment

people. He argues that the number of people with higher level of education working in manufacturing and non-manufacturing industries has increased by more than five times between 1989 and 2007.

This figure shows that, during the period of 1983–2010, the ratio of skilled labor in total employment increases for both sectors. Nevertheless, for technology intensive sectors the increase in skilled workers relative to total employment is much more apparent. This increase is from 0.13 to approximately 0.45 in technology-non-intensive sectors and from 0.34 to 0.61 for technology-intensive sectors. In general, the share of skilled labor in the total labor pool has become increasingly important. Therefore, the change in skilled share may be an indicator of the presence of skill bias within these sectors. However, this figure summarizes the common fear about the increases of competition in domestic markets and world markets rather well this fear is mainly the fear unskilled employment losses. This trend coincides with the evolution of trade indices reported in Sect. 3.1. The observation reinforces the argument that trade liberalization plays a vital role in increasing the share of skilled labor compared to the share of unskilled labor.

Figures 4 reports the evolution ratio of the skilled and unskilled labor in terms of technology-intensive sectors and technology non-intensive sectors, the figure illustrates trends toward an increase in the skilled/unskilled labor ratio. For example, this ratio grew from 0.16 in 1983 to 0.84 in 2010 for technology non-intensive sectors. For highly technology intensive sectors, the ratio of skilled labor to unskilled labor is more important and exceeds one. This ratio grew from 0.52 in 1983 to approximately 1.61 in 2010. In fact, despite its constant evolutionary behavior, the progress of the ratio of skilled labor differs respect to the technology intensity of sectors.

The second important element of Tunisian labor market is related to the evolution of relative wage. The Tunisian government revises regularly the minimum wage and wages after negotiation with trade unions. Figure 5 plots key evidences of the simultaneous trends in the average relative wages between sectors intensive in

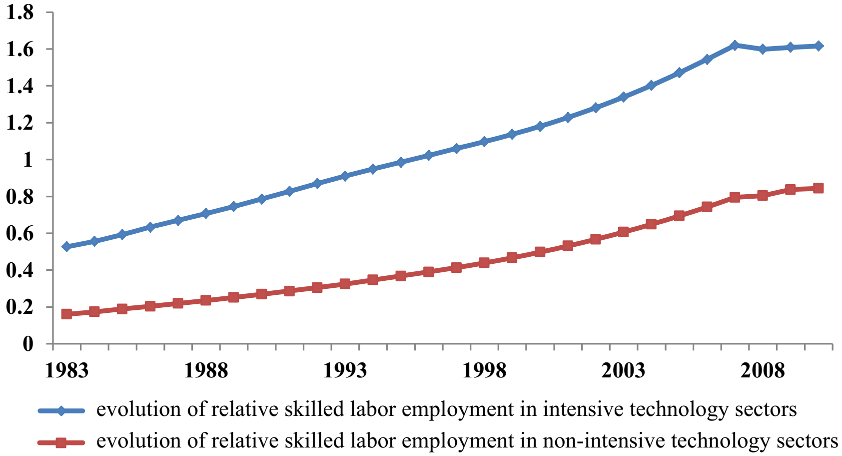

Fig. 4 Evolution of the relative skilled labor

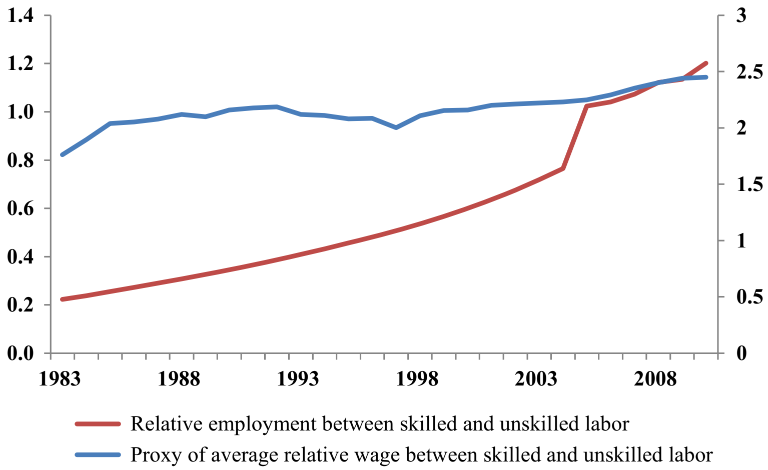

Fig. 5 Evolution of the relative employment and average relative wages

technology and sectors non-intensive in technology (right axis) and relative employment (left axis) over the 1983–2010 period. This figure shows that relative employment has moved toward skilled workers. In particular, the rise of relative employment becomes more significant since the beginning of 1990s and 2000s. In the other hand, the average relative wages also increased during the two periods of 1983–1992 and 1998–2010, and decreased during the period 1993–1997. Then, we can conclude that there is a simultaneous increase of relative employment and relative wage of skilled labor[4] which means an outward shift in relative demand curve implying an increase of relative demand of skilled labor (Berman et al. 2005). Two potential explanations of this shift: the existence of technical changes biased to skilled labor which leads to the replacement of unskilled workers with skilled one (Berman et al. 1994), and the trade openness.[5]

4 Data and econometric specification

4.1 Data and proxies

The dataset used in this paper was provided by two sources; the Tunisian National Institute of Statistics (TNIS) and the Economic Quantitative Institute (EQI).[6] These

[4] A same evolution of relative wage has been revealed by Ben Ayed Mouelhi and Ghazali (2012). They suggest that Tunisia has been subject to an increase, however relatively moderate, in wage inequality.

[5] The explanation of the increase in skilled workers share relative to unskilled workers can be explained also by other factors. The first one is related to an increase in relative costs for the unskilled workforce. In other words, skilled labor should have falling costs with respect to unskilled ones. The second one contemplates output elasticities. If elasticities differ according to worker types, output growth will lead to different increases in labor demand. The third one considers the complementarity or substitutability with capital. In the substitutability case, firms that invest reduce their relative number of unskilled workers.

[6] All data used in this study are free access from database in TNIS and EQI.

two sources allowed us to build a database at sector level of the labor market, trade liberalization and technological change. The database covers a panel of 12 sectors that were observed annually over the period of 1983–2010. The number of observations is equal to $N \times T = 336$, where N is the number of sectors and T is the number of years. We didn't include the years after 2010 because some data was missing; this is in part was caused by the revolution that occurred in Tunisia since 2011.

The dataset includes the following variables: product (Y), measured as the value of total products produced during a calendar year value-added (VA), the total products less materials and energy (Both the Y and VA variables were transformed to fixed 1990 prices using the product price index). It also includes the capital stock variable K, the exports(X), the imports (M), the skilled labor variable H, the unskilled labor variable L and the relative employment variable H/L. The exports, the imports, the value-added, and the product variables were provided by the TNIS. The number of workers by level of education variable was provided by the EQI.

The twelve sectors used in this paper are as follows: Foods, Construction and Glasses, Mechanics & Electronics, Chemical, Textile & Leather, Diverse Manufacturing industries, Mines, Hydrocarbon, Transport & Telecommunication, Agriculture & Fishing, Services and Other Services. The diverse manufacturing industries include a range of activities that are not classified as into the other manufacturing industries and include the Wood and Furniture, Paper, and Plastic industries.

4.1.1 Skilled and unskilled proxies

In this paper, we use education level rather than production and non-production classifications as proxies for skilled and unskilled labor.[7] We define skilled labor as all people of working age and secondary or tertiary education levels. Gonzaga et al. (2006) and Bustos (2011) suggested that skills are better described by classifications based on education characteristics. They argue that the change in skill premiums based on production/non-production classifications may be driven by compositional shifts in the education of workers within the occupation categories.

4.1.2 International trade proxies

Two proxies of trade liberalization are used in this paper. The first is the share of imports in value added (VA), which is calculated by dividing imports (M) (by sector and by year) by the value added (M/VA). The second proxy is the share of exports

[7] Economic literature often adopts two competing definitions to proxy skilled labor production/non-production classification and education level classification. Gonzaga et al. (2006) suggest that neither occupation nor educational measures provide exact measures of skill intensities. For instance, in countries like Tunisia, occupational proxy is problematic since there are a lot of non-skilled tasks that do not require particular skills. In the case of Tunisia, the distinction between skills by education is often the only available proxy in aggregated sector level data. Moreover, Berman et al. (1994) argue that identifying skilled and unskilled labor on the basis of job classifications and educational attainment leads to very similar results.

in value added, which is calculated by dividing the exports (X) by value added (X/VA). The choice of these proxies was made for at least two reasons. First, these variables reveal the real openness of a country and its actual capacity to increase its volume of trade flow. Second, changes in the volume of trade over time can capture the various phases of the liberalization process.

4.1.3 Trade inducing technological change:

A common problem faced by applied researchers when investigating the impact of trade openness and technology on the employment of skilled and unskilled labor in developing countries is related to the unavailability of exhaustive data that provides exact and direct measures of technology change induced by the trade variable. We faced this problem with Tunisian data.

Therefore, we built on some theoretical arguments which suggest that trade in goods and services and knowledge can acts as a channel of technology transmission (Grossman and Helpman 1991). The process of trade liberalization in the Tunisian economy has been characterized by a continued orientation toward the international market. As the large share of Tunisian trade is with the European Union, export activities as well as the imports activities may be potential channels of technological change.

The export-oriented technological change occurs when firms adjust their production process in response to an access to foreign markets through exports and the need to compete with more technologically advanced products. Export activity may lead to a learning process as described by Pissarides (1997), see also Hoekman and Javorcik (2006). Greater exposure to the world market should induce the use of more modern techniques and create more competitive pressure, which feeds back positively on productivity (Yeaple 2005; Melitz 2003; Fajnzylber and Fernandes 2009; Bustos 2011).

Import activity is also thought to induce technological change and have a positive impact on skill upgrading. This import activity can lead to productivity gains that accrue across the entire economy. Firms in different sectors are likely to increase their level of knowledge, especially when imports are sourced from technically advanced countries. Imports of new capital and intermediate goods are viewed as the main channels of international transfers of technology (Keller 2004). By importing, firms learn through imitation. These firms become innovative and, at the same time, are able to build the absorptive capacity necessary to further absorb spillovers. Some arguments stress that this type of importing will have greater benefits for skilled labor, as skilled labors are more able to learn and use the new technology. To overcome the absence of data concerning a direct measure of trade inducing technological change we have created interaction variables between trade variables and a dummy variable. These interaction variables are supposed to measure the technology intensities of different sectors. By this way we can assess the expected impact of technological change induced by trade on skill upgrading.

The dummy variable takes a value of 1 if the sector is "high" or "medium–high" intensive in technology and 0 if the sector is "low" or "medium–low" intensive in technology. The technique consists of classifying sectors with different levels of technology intensity. We have classified the 12 sectors according to the OCDE classification (OCDE science, Technology and Industry scoreboard, 2007).

$$\mathrm{TC\_DUM} = \begin{cases} 1 & \text{if the industry is high or medium} - \text{ high in technology intensity} \\ 0 & \text{if the industry is low or medium} - \text{low in technology intensity} \end{cases}$$

with respect to the share of imports and exports in the value-added variable, we are able to construct two interaction variables between the dummy variable and the shares of exports (or imports) by sector, (X/VA) × TC_Dum [(M/VA) × TC_-Dum]. We may expect that the effects of exports (imports) on skill upgrading vary across technology-intensive sectors. The [(X/VA) × TC_Dum] dummy variable is used to test the hypothesis that exportation induces technology change in sectors distinguished by technology intensity. Using the ((M/VA) × TC_Dum) variable, we tested whether imports significantly increased the employment of skilled labor compared to unskilled labor in sectors with high technology intensity. Therefore, imports in these industries consist mostly of capital goods characterized by high technology, which are biased toward skilled workers.

There are, of course, other forms of technological change, such as skill-biased technological change arising from, for example, the use of computers. While some of these effects are captured by the time trend, the lack of adequate data (computer usage, R&D expenditure and patents by industry) prevented a closer interrogation of these effects, and further exploration is left for a later study. We should note that it would be more relevant to use direct measures of transferred technology such as imported machinery, imported materials and investments sourced abroad (Harrison and Hanson 1999; Gorg and Strobl 2002). Indeed, such indicators produce more reliable assessments of the impact of "trade-induced" technological change on relative employment. Unfortunately, such data were not available from the current database. This limit may dismiss or mitigate the impact of this variable in this study of Tunisia.

4.2 Econometric specification

To identify how trade liberalization affects relative demand of skilled to unskilled employment within the 12 Tunisian sectors, we present a simple framework that allow us to derive an equation that can be estimated. We start from a constant elasticity of substitution production function (CES) that includes two factors of production, skilled and unskilled labor. This production function is given by:

$$\mathrm{Y}_t = \mathrm{A}\ [\gamma_1(\mathrm{L_t})^{\rho} + \gamma_2(\mathrm{H_t})^{\rho}]^{(1/\rho)} \quad (1)$$

where product (Y) is measured as the output produced during a calendar year. H is the skilled labor variable, and L is the unskilled labor variable. Education levels were used to define skilled and unskilled labor. γ_2 and γ_1 is a technology parameter that can be interpreted as the share of work activities allocated to unskilled and skilled labor, respectively. The parameter A is an efficiency parameter.

Assuming profit maximization under perfect competition, then the relative wage factors between skilled and unskilled labor can be given as (see Katz and Murphy 1992, and Acemoglu 2002):

$$\left(\frac{\mathrm{w_h}}{\mathrm{w_l}}\right)_{\mathrm{t}} = \left(\frac{\mathrm{H}}{\mathrm{L}}\right)_{\mathrm{t}}^{-\frac{1}{\sigma}} \left(\frac{\gamma_2}{\gamma_1}\right)^{\frac{\sigma-1}{\sigma}} \tag{2}$$

Using Eq. (2) is possible to derive an estimate of relative demand of skilled to unskilled employment (Haskel 2000; Gallego 2012)

$$\left(\frac{H}{L}\right)_t = \left(\frac{w_h}{w_l}\right)_t^{-\sigma} \left(\frac{\gamma_2}{\gamma_1}\right)_t^{\sigma} \tag{3}$$

where, $\sigma = \frac{1}{1-\rho}$. is the elasticity of substitution between factors. Relative employment $\left(\frac{H}{L}\right)$. is positively affected by a rise in $\left(\frac{\gamma_2}{\gamma_1}\right)$. and a decline in $\left(\frac{w_h}{w_l}\right)$.

By modeling $\left(\frac{\gamma_2}{\gamma_1}\right)$ as a function of openness and technology change we obtain the following form:

$$\left(\frac{\gamma_2}{\gamma_1}\right) = \exp(\lambda_0) TO^{\lambda_1} TC^{\lambda_2} \tag{4}$$

$$\ln\,(\mathrm{H/L})_{\mathrm{t}} = \alpha_0 + \alpha_1 \ln(\mathrm{T\ O})_{\mathrm{t}} + \alpha_2 \ln(\mathrm{T\ C})_{\mathrm{t}} + \alpha_3 \ln(\omega_{\mathrm{h}}/\omega_{\mathrm{l}})_{\mathrm{t}} \tag{5}$$

where TO and TC measure trade openness and technology change, respectively.

However, firm's decisions in different sectors can be influenced by the presence of adjustment costs. Hamermesh (1993) provides a thorough survey on dynamics of labor demand and adjustment cost. Some empirical studies indicate that the current employment level depends on past employment levels (Van Reenen 1997; Nickell 1981). The firms in different sectors facing many shocks, mainly trade liberalization, and do not necessarily immediately adjust their employment levels due to the presence of adjustment costs, namely firing and hiring costs. Therefore, it is important to take into account the speed at which employment is adjusted in response to many shocks.

Fm an econometric point of view, the use of that specification can be justified by the persistence of the relative employment variable. Consequently, the estimation of Eq. (5) using a dynamic model is more appropriate.

Our empirical strategy consists of estimating relative skilled labor employment, whereby the ratio of skilled to unskilled employment of a given sector is related to the observable measures of international openness and technology proxies. In particular, for sector i at time t this equation takes the following form:

$$\ln\left(\frac{H}{L}\right)_{i,t} = \alpha_0 + \alpha_1 \ln\left(\frac{H}{L}\right)_{i,t-1} + \alpha_2 \ln Y_{i,t} + \alpha_3 \ln K_{i,t} + \alpha_4 \ln TO_{i,t} + \alpha_5 \ln TC_{i,t} + D_t + \mu_i + \epsilon_{i,t} \tag{6}$$

where i and t denote sector and time period, respectively. H/L is the relative demand for skilled to unskilled employment variable and Y is a measure of total products. The product output was transformed to fixed 1990 prices using the product price index. K is the capital stock to value added ratio variable (K/VA). TO is the trade openness proxy and TC is the technology change proxy. D_t is the year dummy variables, μ_i is the sector fixed effect and $\varepsilon_{i,t}$ is the error term. The use of 1 year-lagged values for the *H/L* dependent variable as an independent variable in the right side of Eq. (6) provides us the delay in employment adjustments in response to the shocks of trade liberalization and technologies. The estimated value of α_1 measures the adjustment of relative employment $d = 1 - \alpha_1$ to its desired value, and the long run elasticity of labor demand with respect to trade openness is, for example, α_4/d. One problem that can arise when estimating such an equation is how to identify the links between technology adoption and the employment of skilled and unskilled workers. In some cases, an omitted characteristic of a sector could be correlated with technology variables. This would bias the results and lead overestimations of skill-biased technological changes. To overcome this issue, we introduced into our equation the industry fixed effect (μ) and time-specific effect (D) to control for omitted variables. The fixed effect controls, in general, for industry heterogeneity (time-fixed and immeasurable variables, such as industry-specific persistent technological differences or differences in average management quality). The time-specific effects were also introduced to control for any homogenous forms of technological change across industries that vary across and to capture other macroeconomic shocks.

The relative wages between skilled and unskilled labor are not included in the Eq. (6), because there is no data available for this variable by sector and by year.

4.3 The empirical methodology

To investigate the central question of this paper, our empirical methodology was based on the estimation of Eq. (6) using panel data methods. Our empirical analysis began by checking for the presence of endogeneity and autocorrelation in our sample before estimating the proposed econometric model.

4.3.1 Check for stationarity

An important issue that came up before estimating the dynamic panel data model for a long time series ($T > N$) is whether the variables in the model are stationary or not. To check for the stationarity condition, we conduct a series of unit root test, the Levin, Lin & Chu (LLC), the Im, Pesaran and Shin (IPS), the Augmented Dickey–Fuller (ADF-Fisher) and the Fisher–Phillips and Peron (PP-Fisher) tests. For all these panel unit Root tests the null hypothesis consists of the presence of unit root which means that the time series is non-stationary. Overall the empirical results of these tests, displayed in Table 1, indicate that we can indeed proceed with stationary panel data estimation techniques.

Table 1 Panel unit root tests results

	Levin et al. (2002)	Im et al. (2003) W-stat	Choi (2001) ADF-Fisher Chi square	PP Fisher Chi square
Log(LQ/LNQ)	−10.305 (0.000)	−6.552 (0.000)	96.515 (0.000)	55.786 (0.000)
Log(K)	−0.366 (0.357)	0.1280 (0.551)	44.040 (0.007)	19.870 (0.704)
Log(Y)	−5.208 (0.000)	0.149 (0.559)	34.574 (0.075)	39.376 (0.025)
Log(K/VA)	−4.095 (0.000)	−1.325 (0.0926)	51.498 (0.000)	60.475 (0.000)
Log(TAUX PEN)	−0.313 (0.377)	−1.270 (0.100)	37.305 (0.041)	58.405 (0.000)
Log(TAUX OUV)	−1.314 (0.094)	−0.551 (0.291)	28.052 (0.258)	27.346 (0.288)
Log(M/VA)	−0.109 (0.457)	−1.035 (0.150)	47.852 (0.003)	36.968 (0.044)
Log(X/VA)	−2.485 (0.006)	−0.571 (0.284)	37.917 (0.035)	25.418 (0.383)
(M/VA) × INT	0.441 (0.670)	−1.414 (0.078)	27.003 (0.003)	10.513 (0.397)
(X/VA) × INT	−1.864 (0.031)	−0.177 (0.429)	11.575 (0.315)	11.628 (0.310)

4.3.2 Endogeneity test

A potential problem in the estimation of Eq. (6) that can be addressed is the possible endogeneity of some variables that were considered to be independent. We suspected that the share of value-added exports (X/VA) and the share of value-added imports (M/VA) were endogenous. Consequently, interaction terms would also be endogenous. The intuition behind the possible emergence of this endogeneity problem is as follows. It is possible that some sectors employ more skilled workers and have greater shares of value-added exports (imports) due to trade openness. Additionally, a simultaneity bias may be observed, given that sectors that are more intensive in skilled workers are more likely to have a superior share of exports (imports). However, in our database, no exogenous variable can play the role of an instrument variable, neither for the share of value-added exports nor for the share of value-added imports. It is difficult to find a variable that can be a perfect instrument to endogenous variable. Usually, the possible solution to this problem is to use lagged endogenous variables as instrumental variables. For our case we will use the lagged of the shares of value-added exports and imports variables as instrumental variables.

4.3.3 Autocorrelation and multicollinearity test

As we examined a relatively long period of 28 years, we expected that innovation errors would be serially correlated. In general, the autocorrelation of errors leads to an underestimation of standard deviations and, therefore, an increased likelihood of inferring significant statistical effects in the absence of truly significant effects. We used the Wooldridge test (Wooldridge 2002) to examine whether errors were correlated.[8] The results of the Wooldridge test led us to reject the null hypothesis of no first order autocorrelation at the 1 % significance level. Thus, this error

[8] The results of the test are not reported in the table it can be obtained upon request from the authors.

autocorrelation problem has been corrected in our empirical investigation.[9] Moreover, to correct for the presence of heteroskedasticity in the residuals, we have used robust standard errors (White 1980). The second problem that may arise when estimating Eq. (6) is the possible presence of multicollinearity between explanatory variables, which would influence the magnitude and significance of the regression coefficients. To test for multicollinearity while estimating Eq. (6), we used the variance inflation factor (VIF). The empirical results of the applications of the variance inflation factor (VIF) tests revealed that the multicollinearity problem was not present in our sample.[10]

4.3.4 Methods of estimation

The inclusions of lag dependent variable as independent variables induce a number of econometric problems. One of the crucial problems is the presence of correlation between the lagged dependent variables and the error terms which imply an endogeneity issue. This will make the estimated results of OLS fixed effects techniques to be biased and inconsistent (Baltagi 2001; Harris and Mátyás 2004). To resolve this problem, we used two approaches the FE-IV and general moment method estimation (GMM). In our estimation, we used the lags of the endogenous variables as instruments. However, in recent studies, several researchers have used the generalized moment method of Arellano and Bond (1991) to estimate dynamic models (GMM-DIFF). However, the GMM-DIFF estimators have been found to be weaker than their true values if there is a strong persistence in the investigated time series and if cross-section variability dominates time variability (Bond et al. 2001). Blundell and Bond (1998) developed a new method that improves efficiency by also considering the original equation in levels instrumented according to their own differences (Blundell and Bond 1998) (GMM-SYS). The GMM-SYS estimator is more efficient in the presence of highly persistent dependent variables such as the employment indicators used in this empirical analysis. It is common that the GMM-SYS estimator of Blundell and Bond (1998) is more suitable for small-T and large-N panels. However, when T increases the number of instruments grows rapidly. This implies that in a typical macro panel data (larger T and smaller N) it is common for the second step variance covariance matrix to become singular if instruments are not restricted. As a practical rule of thumb in order to avoid these problems, the number of the instruments should not be more than the number of cross-section units (Roodman 2006). There are two options in trying to deal with this problem: limiting the lags used in the GMM-style instruments or using command for collapsing instruments available in *xtabond2*. In this analysis the second approach has been conducted. This could improve the consistency of the GMM estimator (Judson and Owen 1999).

[9] In STATA after xtivreg28 command the option bw (#) corrects this problem.

[10] This is based on auxiliary regressions of each explanatory variable included in the original regression on the remaining explanatory variables. The R-square from these regressions (R^2) is used to calculate the VIF for each regressor, defined as VIFj = 1/(1-Rj^2). A value of VIF greater than 10 may reflect the presence of multicollinearity.

One critical issue associated with the use of instrumental variables is whether those instruments are highly correlated with the endogenous variable. To select and test the suitability of the instruments in the FE-IV method, two criteria were employed, the relevance and the validity of the instrument. When these two criteria were not satisfied, the instrument was said to be weak, and the IV estimates were biased in the same direction as the OLS estimates (Staiger and Stock 1997). Instrument relevance requires that each instrument should be highly correlated with the endogenous regressor. The instrument relevance can be tested empirically using the test of Bound et al. (1995), which can be implemented in the presence of one endogenous regressor. This test is implemented as an F-test of the joint significance of the instruments in the first-stage regression. As a rule of thumb, these authors suggested that a value of the first-stage F-test less than 10 should raise concern about the relevance of the chosen instruments. In this paper, we respected this simple rule in our assessments of instrument relevance. The second criterion is the validity of instrument. This criterion requires the absence of correlation between each component of the instrument set and idiosyncratic error. In the case of an exact identification model, instrument validity is not testable. However, in the case of over identifying restrictions, which imply that the number of instruments exceeds that of endogenous regressors, instrument validity can be tested with the Sargan statistic or the Hansen J-statistic, if a robust option is considered. To simplify the evaluation of our estimation results, for each model and estimator, we explicitly state the assumptions that guarantee instrument validity and whether the model was fairly identified.

For the GMM method Arellano and Bond (1991) recommend two specification tests to address the GMM estimator's consistency, namely, a second-order serial correlation test for the first-differenced residual m_2 statistics and a Sargan/Hansen test for the over-identifying restrictions' validity. First, an Arellano–Bond test for autocorrelation should be used to confirm that the estimated results will not have autocorrelation. Second, the Sargan tests of over-identifying restrictions should also be reported to verify the overall validity of the GMM instruments. The null hypothesis suggests that the instruments are uncorrelated with some set of residuals.

4.4 Empirical results

The Tables 2 and 3 report the estimated results of different specifications from Eq. (6). Before examining and analyzing the impact of trade openness and technology change on the relative employment between skilled and unskilled workers, we first examined the results of the different tests reported in Tables 2 and 3.

The bottom panel of Table 2 reports the results of the different tests of the two-stage instrument strategy, the Anderson (1984) canonical correlations test,[11] the

[11] Is a likelihood-ratio test of whether the equation is identified, i.e., that the excluded instruments are "relevant", meaning correlated with the endogenous regressors.

Cragg–Donald test of weak instrument problems[12] and the endogeneity tests.[13] The Anderson test confirmed the relevance of the instrumental variables used. The Cragg–Donald tests verified the validity of our instruments. For all columns, we obtained F-statistics above the informal threshold of 10 suggested by Staiger and Stock (1997) for the assessment of the validities of instruments. Moreover, the empirical result confirmed that the null hypothesis of the endogeneity test could be rejected at the 5 % level. Therefore, our variables were endogenous.

The consistency of the GMM estimates (Table 2) was checked based on the two tests of Arelano and Bond (1991). The results of these tests are reported at the bottom of Table 3. Specifically, the results of the test of no-serial autocorrelation, which examine whether the residual of the regression in differences is second-order serially correlated, are reported. Therefore, the GMM estimator may use second and higher-order lags of the dependent variable as instruments. In all columns, the test detected only first-order serial correlations. The Sargan test of over-identifying restrictions did not reject the null hypothesis of exogeneity of instruments in all the specifications. We turn now to our main question, which deals with the impact of trade liberalization and technological change on the relative demand of skilled to unskilled employment in Tunisia.

The empirical results reported in Tables 2 and 3, show that the estimated coefficient on the one time lagged dependent variables were significantly different from zero, indicating that firms in all sectors adjust significantly their level of relative employment, which confirm the presence of important labor reallocation costs in Tunisia.

The coefficient of the output variable, which notably controls for business cycle fluctuations, was positive and statistically significant; indicating that the increase in the relative employment of skilled workers was compatible with the increase in output. From Tables 2 and 3 the coefficient estimated range between 0.01 and 0.043, indicating that an increase of 1 % in output causes an increase of 0.01–0.043 % in skilled labor employment. Capital stock ratio had a positive effect on the employment of skilled labor. The estimated coefficients were significant. In all columns, the regression coefficients of capital stock ratio were between 0.01 and 0.09, indicating that an increase of 1 % in capital stock generated an increase of between 0.01 and 0.09 % in skilled labor employment. This finding seems consistent with the idea that skilled worker intensity and capital move together. In other words, this result seems compatible with the presence of possible complementarities between skilled labor and capital. One possible explanation for

[12] The test for weak identification automatically reported by ivreg28 is based on the Cragg-Donald F statistic.

[13] Endogeneity tests of one or more endogenous regressors can be implemented using the endog option. Under the null hypothesis that the specified endogenous regressors may actually be treated as exogenous, the test statistic is distributed as a Chi square with degrees of freedom equal to the number of regressors tested. The endogeneity test implemented by ivreg28 is, like the C statistic, defined as the difference of two Sargan-Hansen statistics one for the equation with the smaller set of instruments, where the suspect regressor(s) are treated as endogenous, and one for the equation with the larger set of instruments, where the suspect regressors are treated as exogenous. Also like the C statistic, the estimated covariance matrix used guarantees a non-negative test statistic. Under conditional homoskedasticity, this endogeneity test statistic is numerically equal to a Hausman test statistic see Hayashi (2000, pp. 233-34).

Table 2 FE-IV estimation

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$(H/L)_{t-1}$	0.89*** (66.6)	0.89*** (52.4)	0.88*** (66.6)	0.89*** (67.8)	0.89*** (61.05)	0.87*** (60.2)
$Log(Y)_t$	0.011** (2.19)	0.033** (5.60)	0.028*** (4.98)	0.028*** (5,02)	0.036*** (6.7)	0.031*** (5.36)
$log(K/va)_t$	0.011* (1.69)	0.0101* (1.74)	0.013** (2.30)	0.0116** (2.04)	0.014*** (3.5)	0.012** (2.25)
$log(M/va)_t$	0.010* (1.86)	0.012* (1.86)	0.014** (2.39)	0.016*** (2.74)	–	0.011* (1.78)
$log(X/va)_t$	0.007* (1.68)	0.013*** (3.24)	0.014*** 3.45)	–	0.015*** (3.7)	0.0101** (2.10)
$log[(M/VA)*TC\_Dum]_t$	–	−0.021*** (-3.86)	–	−0.20*** (-3.89)	–	-0.026*** (-3.29)
$log[(X/VA)*TC\_Dum]_t$	–	–	0.010** (2.52)	–	0.0111*** (2.55)	0.012* (1.9)
Number of observation	300	300	300	300	300	300
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes
Anderson-Canon LR-statistic	211.6 $\chi^2 = 0.000$	205.7 $\chi^2 = 0.00$	197.4 $\chi^2 = 0.00$	199.1 $\chi^2 = 0.00$	201.7 $\chi^2 = 0.00$	199.2 Chi2 = 0.00
Cragg-Donald F-statistic	141.1	134.13	127.022	129.5	131.4	128.6
VIF test	1.24	1.40	1.29	1.28	1.19	1.62
Endogenous TEST	7.808 (0.0052)	8.36 (0.0036)	7.6 (0.0056)	8.85 (0.0029)	8.5 (0.003)	8.56 (0.0034)

t-students are in parentheses. *, **, *** indicate respectively 10, 5 and 1 % significance levels. The regressions include a constant term. Corresponding results are not reported for space reasons. The statistic of Anderso–Canon measured by the LM test ratio confirms that the equation is not under identified. The F statistics of Cragg–Donald test at 5 % are higher than the critical value at 10 % level; indicate that instrument is sufficiently strong

Table 3 GMM-SYS estimation

Independent variables	Dependent variable (H/L)					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Δ $\log(H/L)_{t-1}$	0.73*** (23.12)	0.80*** (26.4)	0.81*** (33.6)	0.81*** (28.3)	0.74*** (21.55)	0.84*** (31.2)
Δ $\log(y)_t$	0.025*** (2.99)	0.04*** (2.57)	0.043*** (2.65)	0.038** (2.36)	0.042*** (2.80)	0.04** (2.55)
Δ $\log(K/va)_t$	0.090*** (5.05)	0.039** (2.34)	0.08* (1.91)	0.057*** (3.65)	0.076*** (4.88)	0.035** (2.33)
Δ $\log(M/va)_t$	0.038* (1.75)	0.042 (1.41)	0.067*** (4.35)	0.076*** (5.08)	–	0.045 (1.00)
Δ $\log(X/va)_t$	0.048* (1.74)	0.07*** (4.44)	0.057** (3.24)	–	0.11*** (6.9)	0.063*** (3.95)
Δ $\log[(M/VA)*TC\_Dum]_t$	–	−0.071* (−1.67)	–	−0.052** (−3.49)	–	−0.063* (−1.71)
Δ $\log[(X/VA)*TC\_Dum]_t$	–	–	0.062** (2.06)	–	0.044* (1.88)	0.087* (1.74)
Number of observation	324	324	324	324	324	324
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes
Sargan Test	137.8 (0.46)	124.6 (0.16)	144.32 (0.31)	128.4 (0.110	138.8 (0.44)	120.5 (0.12)
AR(1)	−8.03 (0.000)	−8.21 (0.000)	−7.6 (0.000)	−7.9 (0.000)	−8.01 (0.000)	−7.67 (0.000)
AR(2)	0.25 (0.78)	−0.2 (0.7)	0.09 (0.94)	−0.10 (0.9)	0.11 (0.91)	0.08 (0.93)

t-students are in parentheses. *, **, *** indicate respectively 10, 5 and 1 % significance levels. The regressions include a constant term. Corresponding results are not reported for space reasons. The estimated standard errors are heteroskedasticity and autocorrelation robust.

the Tunisian case is that the reduction of inputs and capital barriers has encouraged firms to use more capital and other intermediate inputs at low prices after trade liberalization. Tunisian industries, particularly the textile industry, rely heavily on importation of raw materials to satisfy production needs.

Turning our attention to the role of trade liberalization, we tested the impact of two variables that reflect a sector's openness; the share of imports in value added and the share of exports in value added. The estimated coefficients of these two trade openness proxies showed the same results. In all columns, the coefficients were positive and statistically significant, emphasizing the importance of increasing globalization in fostering skill upgrading within sectors engaged in international markets. The positive effect of the share of exports in value added can be explained by the fact that the production processes of some Tunisian market-oriented sectors have begun to use new production methods that require skilled workers. Domestic firms in these sectors respond to competition by foreign firms by increasing the employment of skilled workers. In fact, when the market became highly competitive, the firms that employ more skilled workers are relatively more productive (Anwar and Sun 2012).

The estimated impact of the share of imports in value added shows a significant positive coefficient. Therefore, we can interpret this result by the fact that an increase of imports causes a skill upgrading in Tunisia, in which most imports come from developed countries. The possible explanations for these results are the abilities of skilled workers to capture available rent during trade protection, which allows them to buffer employment variation due to a liberalization shock by accepting wage reductions after quasi-rent dissipation. Ghazali (2011) suggests that unskilled-labor-intensive sectors adjust their employment using two different mechanisms. First, these sectors increase skilled labor demand and decrease quasi-rent per worker. Second, this effect can be explained by relatively lower speeds of adjustment, which suggests that adjustment costs are a significant impediment to the mobility of these sectors (Mrabet and Charfeddine 2013a).

The estimation of the coefficients related to the technological change variables shows opposite results. The coefficients of the interaction term *log[(M/VA)∗TC_-Dum]* were negative and statistically significant. This finding can be explained by the fact that technology transferred through imports could decrease the demand for skilled labor. This result contrasts the theoretical prediction that skill-biased technological change mediated by imports increases the demand for skilled labor. It seems that imports imply a transfer of new technologies that are not more skill-intensive than those previously in use in the production process. Within a sector, the production processes of different importing firms generally comply with the comparative advantage of the country. For example, in the case of Tunisia, to produce unskilled-labor-intensive goods, some export-oriented firms need to import skilled labor-intensive intermediate inputs. In sum, the effects of the use of imported inputs on the demand for skilled labor depend on the importance of technology diffusion relative to specialization according to comparative advantage. This result shows that an increase of the share of imports in value-added decreases the relative employment of skilled workers mostly in sectors with relatively high levels of technology intensity. These results are in line with those of Ben Ayed Mouelhi

(2007) which demonstrate that unskilled intensive sectors in Tunisia, which generally employ less sophisticated production technology, use means of adjustment other than cutting employment in response to the import of technology. Moreover, this behavior can be explained by the fact that a greater total factor productivity occurs in unskilled-labor-intensive sectors than in skilled-labor-intensive sectors. This form of technological change may reduce the demand for skilled labor (Krugman 2000).

The coefficient of the interaction term *log*[(X/VA)*TC_Dum] was positive and significant, which suggests that an increase in export share increases the relative employment of skilled workers in technology-intensive sectors. These findings provide some evidence supporting the role of exports in transmitting skill-biased technology, which supports the suggestion that export shares in these sectors (i.e., electronic and mechanical sectors and mine and hydrocarbon sectors) increase and become more important with time.

Through easier and greater penetration of new markets and enhanced competitive pressure, trade integration has led to a gradual structural transformation of Tunisia's production and exports as evidenced by the growing share of medium-technology exports relative to total exports. Thus, exports may act as a channel for international technology diffusion. In this manner, exports may increase the demand for skilled labor among firms in developing countries, like Tunisia, through two effects. First, exporters are faced with product quality requirements that are set by the world market. Second, exporters have the opportunity to learn more production techniques and innovations from the international market. Through the first effect, exporters are pressured by foreign clients to enforce quality standards that are higher than those that prevail in the domestic market. This process may also provide the exporters with tacit information or proprietary knowledge that is provided to them by foreign clients to help them meet those standards (Clerides et al. 1998; Keller 2004). Through the second effect, firms exporting to the world market learn new processes of production and management from other firms operating in the world market. These results may be explained by the argument of learning by exporting developed by Pissarides (1997). In this learning context, export openness potentially increases innovation, knowledge and productivity by encouraging firms to find new ways to compete. The shares of medium and high-technology exports have been increasing, while low-tech exports have been significantly declining (World Bank report 2010).

Table 4 adds an estimation of the impact of trade liberalization on total employment. The results show that the share of exports and the share of imports in value added are positively connected to changes in total employment. We can suggest that this positive effect on total employment is mainly originated from higher demand of skilled labor. However, the technological change induced by trade has two opposite impacts. The technology change induced by exports seems to be positively affecting total employment, but the technology change induced by imports seems to be negatively affecting it.

It appears that in accounting for the sector employment changes, it is technology that matters more than trade. This finding is very important in terms of its policy implications. First, trade appears to be a tool to stimulate employment. Second, technological change induced by imports may destroy employment. In this case

Table 4 Estimation of total employment (TE) using FE-IV and GMM-SYS

Independent variables	Dependent variable $(TE)_t$							
	FE-IV				GMM-SYS			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
$(TE)_{t-1}$	0.82*** (67.07)	0.83*** (67.4)	0.86*** (64.8)	0.82*** (61.9)	0.87*** (63.4)	0.86*** (52.3)	0.9*** (53.2)	0.88*** (45.4)
$\log(Y)_t$	0.058*** (6.88)	0.042*** (5.53)	0.057*** (6.7)	0.053*** (6.14)	0.050*** (4,58)	0.06*** (5.92)	0.039** (2.29)	0.042*** (3.26)
$\log(K/va)_t$	0.014** (2.16)	0.010* (1.82)	0.015** (2.19)	0.013* (1.87)	0.020*** (4.11)	0.036*** (6.12)	0.016*** (4.5)	0.023*** (3.76)
$\log(M/va)_t$	0.021*** (3.17)	0.026*** (3.52)	0.22*** (3.06)	0.014* (1.69)	0.023*** (3.16)	0.019*** (3.66)	0.006 (1.5)	0.034*** (3.82)
$\log(X/va)_t$	0.022*** (4.75)	0.024** (2.25)	0.021*** (4.11)	0.018*** (3.42)	0.029*** (2.77)	0.03** (2.3)	0.009* (1.7)	0.0209** (1.99)
$\log[(M/VA)*TC\_Dum]_t$	–	−0.032*** (−3.66)	–	−0.017* (−1.70)	–	−0.011*** (−2.79)		−0.020* (−1.8)
$\log[(X/VA)*TC\_Dum]_t$	–	–	0.0015 (0.26)	0.012* (1.73)	–	–	0.02** (2.4)	0.015** (2.1)
Number of observation	300	300	300	300	324	324	324	324
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Anderson–Canon LR-statistic	148.6 $\chi^2 = 0.000$	133.4.7 $\chi^2 = 0.00$	141.1 $\chi^2 = 0.00$	135.8 $\chi^2 = 0.000$	–	–	–	–
Cragg–Donald F-statistic	173.6	152.13	161.3	153.3	–	–	–	–
Sargan test	–	–		–	43.3 (0.9)	61.13 (0.39)	49.8 (0.7)	60.8 (0.32)
AR(1)	–	–		–	−2.33 (0.002)	−4.66 (0.000)	−4.5 (0.000)	−4.52 (0.000)
AR(2)	–	–		–	−1.39 (0.16)	−0.99 (0.32)	−1.5 (0.13)	−0.9 (0.32)

t-students are in parentheses. *, **, *** indicate respectively 10, 5 and 1 % significance levels. The regressions include a constant term. Corresponding results are not reported for space reasons. The estimated standard errors are heteroskedasticity and autocorrelation robust appropriate policies are needed to stimulate firms to invest and import new technology without reducing employment.

5 Conclusion and economic implications

In this paper, we have investigated the impact of trade openness and technological change on the relative employment of skilled labor in Tunisia. Using a database including information from 12 sectors over the period 1983–2010, we observe that, in the aftermath of trade liberalization, the relative employment of skilled workers has significantly increased. Based on this result, a dynamic panel data equation at the sector level was estimated. We estimated a relative skilled employment equation derived from the CES production function where the relative employment of skilled workers in a given sector was related to observable measures of international exposure and technology change.

Two main results follow from our empirical analysis of using Tunisian data. On the one hand, trade openness positively affects the employment of skilled labor in relative terms. On the other hand, the changes in technology induced by exports seem relatively more favorable to skilled workers and were involved in skill upgrading across sectors. This finding seems to confirm the complementarity between capital and skilled labor.

Together, our empirical findings show that the two forces, trade openness and technology change, play key roles in shifting labor demand towards more skilled workers. This result may be explained by the decisions taken by the Tunisian government to prepare the domestic economy for international competition through the “adjustment program”. The policies included in this program have led to increases in foreign and national investments that are favorable to the creation of skilled employment. This paper contributes to the existing literature by joining the conclusions that trade and technology may be considered as complementary vehicles for increasing the number of skilled workers (Meschi et al. 2011).

The overall results of this paper have important policy implications. The new government of Tunisia is facing additional external and internal challenges. The latter challenges include the extreme social pressures that have arisen after the January 14th, 2011 revolution, increases in unemployment and prices and uneven regional economic development. Moreover, the development of programs that increase spending on improving the quality of infrastructure in poor regions may also reduce pressure and stimulate investment and employment. However, to attract increased foreign investment, the government should also improve human capital by investing more on education and training, mainly for less-skilled workers. Thus, favoring policies that increase the supply of educated workers may help to correct the adverse effects of technology transfer on inequality. More generally, the improvement of intellectual property rights in developing countries could create incentives for the development of technologies that better suited to the labor force available in these countries (Acemoglu 2003).

Finally, we should note that the relationships between trade, technology and labor markets in developing countries deserve advanced research. Indeed, future research on other DCs should enable us to confirm or disprove the results presented in this paper. Similarly, in Tunisia, the collapse of the dictatorial regime should allow further studies based on data sets that were not previously published due to political decisions that are necessary to further clarify the effects of trade and technology on employment. However, aggregation problems remain among the most vexing in all of applied economics. In general, aggregation of data may cause a loss of information and also an aggregation bias, Garrett (2003). Barker and Pesaran (1990) suggest that the suitable level of aggregation is an empirical question that needs to be answered in the context of particular applications. This point is considered to be a limit of this paper, as an extension in the future empirical studies we will try to include more sub-sectors when disaggregated data become available.

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