Rev World Econ (2016) 152:655–680
DOI 10.1007/s10290-016-0256-y

ORIGINAL PAPER

Globalization, technological change and labor demand: a firm-level analysis for Turkey

Elena Meschi[1] · Erol Taymaz[2] · Marco Vivarelli[3,4]

Published online: 4 June 2016

Abstract This paper studies the interlinked relationship between globalization and technological upgrading in affecting employment and wages of skilled and unskilled workers in a middle income developing country. It exploits a unique longitudinal firm-level database that covers all manufacturing firms in Turkey over the 1992–2001 period. Turkey is taken as an example of a developing economy that, in that period, had been technologically advancing and becoming increasingly integrated with the world market. The empirical analysis is performed at firm level within a dynamic framework using a model that depicts the employment and wage trends for skilled and unskilled workers separately. In particular, the System Generalized Method of Moments (GMM-SYS) procedure is applied to a panel dataset of about 15,000 firms. Our results confirm the theoretical expectation that developing countries face the phenomena of skill-biased technological change and skill-enhancing trade, both leading to increasing the employment and wage gap between skilled and unskilled workers. In particular, a strong evidence of a *relative* skill bias emerges: both domestic and imported technologies increase the relative demand for skilled workers more than the demand for the unskilled. "Learning by exporting" also appears to have a relative skill- biased impact, while FDI imply an *absolute* skill bias.

✉ Marco Vivarelli
marco.vivarelli@unicatt.it

1 Department of Economics, Ca Foscari University of Venice, Venice, Italy

2 Department of Economics, Middle East Technical University, Ankara, Turkey

3 Istituto di Politica Economica, Università Cattolica del Sacro Cuore, Largo Gemelli 1, 20123 Milan, Italy

4 Institute for the Study of Labor (IZA), Bonn, Germany

Keywords Skill-biased technological change · International technology transfer · GMM-SYS

JEL Classification O33

1 Introduction

Many developing countries (DCs) in the 1980 s underwent structural changes, where they moved from import substitution to liberalization and export-oriented strategies. Opening their doors to international trade, DCs were faced with two major growth effects. On the one hand, liberalization has involved a static effect pertaining to inter-sectoral transfer of resources, mainly due to changes in the relative price structure. On the other hand, trade openness has fostered a dynamic effect emerging from the productivity growth due to increased exposure of local firms to competition (both foreign and domestic), increased technological imports embodied in capital and intermediate goods, and to the transfer of knowledge through licensing, patents and other rights (see Rodrik 1995). The integration in the global market thus created new opportunities for developing countries that are now able to attract foreign investors, foreign capital and foreign technology.

However, globalization and technological upgrading have also implied important challenges for DCs' labor markets (see Stiglitz 2002). On the one hand, new technologies were often characterized by a labor-saving nature, involving increasing unemployment, at least in some sectors such as traditional manufacturing. On the other hand, the productivity gains brought about by globalization and technological upgrading were often coupled with a growing gap between the employment and the wages of skilled and unskilled workers. Indeed, the standard Heckscher–Ohlin and Stolper–Samuelson predictions that trade liberalization would reduce the skill premium in developing countries have not been supported by empirical evidence. In this respect, the skill-biased technological change (SBTC) hypothesis is better able to describe the reality of shifting relative employment demand towards more skilled labor.

This paper investigates these issues, using detailed firm-level data on Turkish manufacturing sector over the period 1992–2001 (Annual Manufacturing Industry Statistics by the Turkish Statistical Institute, TurkStat). In particular, we test how international openness and technological change (both domestic and imported) affected the Turkish labor market from both a quantitative and a qualitative point of view. Moreover, we investigate the impact of globalization and technology on the wage gap between skilled and unskilled labor.

Turkey—over the investigated period—presents itself as a suitable candidate for testing the interlinked relationship between globalization and technology adoption in affecting the labor demand. First, trade openness has increased substantially in Turkey over the period analyzed, due to a trade liberalization process initiated in the 1980 s and intensified during the 1990 s. Second, Turkey is a country with significant trade flows with developed countries, especially the EU, which make it a net technology importer that relies on technology import as a main source for technological upgrading. Moreover, being a rather developed middle-income country, it possesses sufficient capacity both to develop domestic innovations and to absorb new technologies (see Cohen and Levinthal 1990).

The novelty of this study in comparison with previous empirical literature (including our previous study: Meschi et al. 2011) on the subject is that it is performed at firm level within a dynamic framework using a model that depicts the employment and wages trends for skilled and unskilled workers separately. More specifically, it allows understanding the forces driving the movements in employment and wages of both types of workers. In fact, a positive shift of the skill-ratio could be the result of the reduction of unskilled workers only, the increase of skilled workers only, a faster increase in the numbers of skilled workers, or a combination of these movements. In other words, we are able to investigate the *relative* versus the *absolute* skill bias of trade and technology. A change in technology (or trade) would be *absolutely biased* toward skilled labor if it increases the number of skilled workers, while decreasing that of unskilled ones. A *relative* skill bias would instead appear when the coefficients for both skilled and unskilled workers are positive and significant but differ in their magnitude, with the coefficients for the unskilled workers being significantly lower. A single equation framework cannot capture these different dynamics; therefore, having two equations for both employment and wages can provide a more thorough understanding of the nature of the possible labor-saving and skill-biased nature of the impact of globalization and technological upgrading. Moreover, separately analyzing the effect of trade and technology on *employment* and *wages* of skilled and unskilled workers, we are able to distinguish between *quantity* and *price* effect. Finally, an important novelty of this paper is the availability for a middle-income country of a rich firm-level dataset that contains detailed information on firms' technological upgrading and trade openness. In particular, our data allow distinguishing between *disembodied* and *embodied* technological change and between domestic innovation capacity and technological transfer from abroad.

To the best of our knowledge, this is thus the first paper able to consider simultaneously the impacts of: (1) local and foreign investments in equipment; (2) research and development; (3) acquisition of patents from abroad; (4) exports and (5) foreign ownership, using longitudinal firm-level data. This allows studying the effect of various measures of internalization and technology adoption, while controlling for unobserved plant characteristics, thus following the literature that emphasizes the key role of firms' heterogeneity in international trade (see for example Roberts and Tybout 1996; Melitz and Redding 2014).

The remainder of the paper is organized as follows: Sect. 2 surveys existing literature on the quantitative and qualitative employment impact of technology and analyses the role of trade induced technological change on the relative demand for skilled labor developing countries. Section 3 describes the data and provides some descriptive statistics. Section 4 presents the empirical model and the econometric specification, while in Sect. 5 we present and discuss the results obtained. Section 6 concludes with some final remarks.

2 The impact of technology and trade on employment and skills

In this section, we start discussing the relevant literature devoted to study the impact of technology on employment and skills (Sect. 2.1). Then, we relate technological upgrading with globalization, focusing on their overall effects on the labor markets of the DCs (Sect. 2.2).

2.1 Quantitative and qualitative employment impact of technology

By definition, technological progress implies the possibility to produce the same amount of output with less workers. However, the conventional wisdom in economic theory states that technological unemployment is a temporary circumstance, which can be automatically compensated by market force mechanisms that work to reintegrate the employees who had lost their jobs. These mechanisms came to be known as the "compensation theory", using the terminology presented by Karl Marx in his discussions on large-scale industry and the introduction of machinery (see Marx 1961: Chap. 15). Six compensation mechanisms work to offset technology's labor-saving effects through: (1) additional employment in the capital goods sector where new machines are being produced, (2) decreases in prices resulting from lower production costs on account of technological innovations, (3) new investments made using extra profits due to technological change, (4) decreases in wages resulting from price adjustment mechanisms and leading to higher levels of employment, (5) increases in income resulting from redistribution of gains from innovation, and (6) new products created using new technologies (for a detailed analysis see Vivarelli 1995; Pianta 2005).

However, measuring the extent and actual effectiveness of these compensation mechanisms and assessing the final quantitative impact of technology on overall employment is not a straightforward exercise and has long been a subject of a controversial debate among economists (see Vivarelli 2013, 2014). In particular, low demand and capital/labor substitution elasticities, attrition, pessimistic expectations and delays in investment decisions may involve that compensation can only be partial.

The discourse on compensation mechanisms and their functioning has often taken place within the context of developed countries. Overall, the empirical literature on the subject has pointed out that product innovation tends to be labor friendly, while process innovation reveals to be labor-saving; moreover, the job-creating effect of innovation is far more obvious in high-tech sectors and new services rather than in low-tech manufacturing and traditional services (for recent studies see Bogliacino and Pianta 2010; Lachenmaier and Rottman 2011; Bogliacino and Vivarelli 2012; Bogliacino et al. 2012; Feldmann 2013). Therefore, the validity of the compensation theory becomes even more questionable in DCs, where process innovations dominate product innovations and where mature manufacturing sectors and traditional services represent the bulk of their economic structure.[1]

[1] However, product innovations may reveal their labor-friendly nature in DCs, as well (see Mitra and Jha 2015).

Another important stream of literature has shown that the relationship between technology and employment has a qualitative aspect as well, giving rise to the notion of Skill-Biased Technological Change (SBTC). The concept of SBTC, first developed by Griliches (1969) and Welch (1970), is based on the hypothesis of capital-skill complementarity, and suggests that employers' increased demand for skilled workers is driven by new technologies that are penetrating into modernized industries, and which only workers with a higher level of skill can operate (see Machin 2003; Piva and Vivarelli 2009).

The literature on SBTC remains mainly empirical, where many studies indicate that SBTC has gained momentum during the past three decades due to the surge in information technology and spread in computers (Pianta 2005). The first to explore SBTC empirically were Berman et al. (1994) who provided evidence for the existence of strong correlations between within industry skill upgrading and increased investment in both computer technology and R&D in the U.S. manufacturing sector between 1979 and 1989. Autor et al. (1998) also show that the spread of computer technology in the US since 1970 can in fact explain as much as 30–50 % of the increase in the growth rate of relative demand for skilled labor. Empirical studies supporting SBTC were conducted for several other OECD countries, such as, for example, UK (see Machin 1996; Haskel and Heden 1999), France (see Mairesse et al. 2001; Goux and Maurin 2000), Italy (see Piva and Vivarelli 2004), and Spain (see Aguirregabiria and Alonso-Borrego 2001). Additionally, Machin and Van Reenen (1998) provide evidence of SBTC in a cross-country study on seven OECD countries and again assert a positive relation between R&D expenditure and relative demand for skilled workers.

2.2 Trade and technological change in developing countries

Turning our attention to the impact of trade over labor demand in a DC, the recent literature has recognized the failure of the traditional trade theory [expressed in the Heckscher–Ohlin (HO) and the Stolper–Samuelson (SS) theorems] in explaining the increase in income inequality experienced by many DCs as a consequence of trade openness.[2]

In particular, these new approaches relax the fundamental HO–SS assumption of technological homogeneity among countries and consider instead that technological levels differ substantially between developed and developing countries and argue that trade openness facilitates technology diffusion from North to South.[3] Even though developed countries do not usually transfer their best state-of-the-art technologies, it remains safe to assume that they do bring about significant relative upgrading to the traditional modes of production of local industries in DCs. Therefore, the final impact of trade on employment and skill premium is highly dependent on the skill-intensity embodied in the transferred technology. Since R&D

[2] HO–SS theory in fact predicts that trade liberalization would *reduce* inequality in DCs, since they would specialize in the production and export of unskilled-labor-intensive goods, given that unskilled-labor is the abundant factor in those countries. This will in turn raise the real income of the unskilled labor and thus decrease the wage gap between skilled and unskilled labor (see Wood 1994, 1995).

[3] For a thorough survey on the literature on international diffusion of technology, see Keller (2004).

activities are generally quite limited in DCs, trade liberalization plays a crucial role in opening the door to various channels of technology transfer, which act as the primary means of technological upgrading (see Dosi and Nelson 2013).

The idea that DCs, through trade, import technologies that are relatively more skill-intensive than those in use domestically, was first proposed by Robbins (1996, 2003) that called this hypothesis "skill-enhancing trade (SET)". In particular, Robbins argues that DCs' imports mainly consist of capital goods, which embody technologies that are surely more advanced and skill-biased than those originally used in the local economies. Moreover, in those DCs that are shifting from import-substitution economic systems to trade liberalization systems, strategies that hampered the adoption of foreign technologies no longer exist, and increased market competition leads to an increased adoption of modern, skill-intensive technologies. Consequently, the liberalized DCs appear to follow a skill-intensive biased trend similar to that observed in developed countries (see Robbins 1996; Berman and Machin 2000, 2004).

There are additional channels through which trade liberalization favors technological upgrading. The first one is by increasing the international flows of capital goods that provide local firms access to new embodied technologies and create opportunities for reverse engineering (Acemoglu 2003; Coe and Helpman 1995). A second mechanism acts through the export channel. The idea is that exporting (especially to high-income countries) requires quality upgrades that are skill-intensive (Verhoogen 2008) and thus requires adopting newer and better technologies (Bustos 2011; Gkypali et al. 2015). Yeaple (2005) also showed that increased export opportunities make the adoption of new technologies profitable for more firms, thus increasing the aggregate demand for the skilled labor and the skill premium. Overall, the revealed skill-biased impact of exporting may be related to the so-called "learning by exporting" effect: engaging in export activities encourages hiring more skilled than unskilled workers as a response to a more sophisticated foreign demand and a tougher international competition. Finally, Maurin et al. (2002) study another channel through which exports may affect employment composition; in fact, the authors show that export activity demands more skilled labor in specialized service activities, such as sales persons, lawyers, marketing personnel, etc.

Other channels are the direct trade in knowledge through technology purchase or licensing and the FDI. Obviously enough, FDI can be an important conduit for the transfer of technology (see, for example, Blomström and Kokko 1998), which in turns requires an upgrading of the skills of the local labor force.

Empirically, the evidence on the impact of trade-induced technological change on employment and the relative demand for skills tends to support the hypotheses discussed above.[4] First, several studies[5] documented an increase in the share of skilled workers and their relative wage within fairly narrowly defined industry

[4] For theoretical and empirical analyses investigating the role of globalization and technology in affecting employment in the DCs (see also Lee and Vivarelli 2004, 2006a, b; Vivarelli 2004).

[5] See, for example, Robbins (1996), Sanchez-Paramo and Schady (2003), Attanasio et al. (2004) for Argentina, Brazil, Mexico, Chile, and Colombia, and Kijama (2006) for India.

categories also in DCs, which can be interpreted as an evidence in favor of skilled-biased technological change. Similarly, Berman and Machin (2000, 2004) observed that the industries that upgraded their technologies and increased their demand for skilled labor in the DCs during the 1980 s are the same industries that underwent this process in the US during the ‘60 s and ‘70 s. They conclude that technologies are transferred from developed to developing countries where they are having the same skill-upgrading effect. In a similar vein, Gallego (2012) shows that the patterns of skill upgrading in Chile and the US are significantly correlated and his findings suggest that the increase in the relative demand for skilled workers in Chile is a consequence of international transmission of skill-upgrading technologies from developed countries, in particular the US.

Other papers have studied more explicitly the link between imported technology and the relative demand for skilled labor and have generally confirmed the skill-biased nature of technological upgrading in DCs. For example, adopting a cross-country perspective, Meschi and Vivarelli (2009) found that trade flows with more technologically advanced countries worsen income distribution by increasing wage differentials between skilled and unskilled workers. Similarly, Conte and Vivarelli (2011) report evidence of a positive relationship between the imports of industrial machinery, equipment, and ICT capital goods and the demand for skilled labor in low and middle-income countries. Almeida (2009) reaches similar conclusions when studying eight East-Asian middle-income countries, but does not find evidence supporting SBTC in low income countries. Raveh and Reshef (2016) study how the composition of capital imports affects relative demand for skill and the skill premium in a sample of DCs and find that, while capital imports per se do not influence the skill premium, their composition does. Their results in fact indicate that imports of R&D-intensive capital equipment raise the skill premium, while imports of less innovative equipment lower it.

Turning to country specific studies, based on micro-data, Hanson and Harrison (1999) found that within each Mexican industry, firms that import machinery and materials are more likely to employ a higher share of white-collar workers than firms that do not import these inputs. Fuentes and Gilchrist (2005) using micro-data for Chilean firms, found a significant relation between the adoption of foreign technology, as measured by patent usage, and increased relative demand for skilled labor. On the other hand, Pavcnik (2003), finds that the increased relative demand for white-collar workers by Chilean plants in early 1980 s cannot be attributed to the use of imported materials, once she controls for time-invariant plant characteristics. More recently, Fajnzylber and Fernandes (2009) study the effects of international integration on a cross-section of manufacturing plants in Brazil and China. They find that the use of imported inputs, exports and FDI are associated with higher demand for skilled workers in Brazil; however, the same is not true for China, where specialization in unskilled labor-intensive productions turns out to compensate for the access to skill-biased technologies. A more recent paper that also takes the case of Brazil using a panel of manufacturing firms over the period 1997–2005, reaches similar conclusions that support the hypothesis of skill-enhancing trade and the fact that technology has played a significant role in up-skilling manufacturing labor in Brazil (Araújo et al. 2011). Birchenall (2001) also attributes increased inequality in

Colombia to SBTC resulting from trade liberalization and increased openness of the economy. Similar results are found for African countries, where Görg and Strobl (2002) show that the use of technologically advanced foreign machinery in Ghana has led to an increase in the demand for skilled labor. Edwards (2004), analyzing firm-level data in South Africa, finds convincing evidence that skill-enhancing trade (as reflected in diffusion of computers, FDI and import of intermediate inputs) has raised the skill intensity ratio in South-African manufacturing.

Finally, Meschi et al. (2011)—using a cost-share single equation framework over the period 1980–2001—study the effect of trade openness on inequality in Turkey. They conclude that both imports and exports contribute to raising inequality between skilled and unskilled workers due to the skill-biased nature of the technologies that are being imported and used in industries with export orientations.

In this paper, we build upon the analysis in Meschi et al. (2011), using a different time-span and introducing three important novelties. Firstly, we study the effect of technology adoption not only on the wage bill share of skilled worker, but estimating separate equations that allow to evaluate the *absolute* vs *relative* nature of SBTC (see Sect. 1). Secondly, in this paper we distinguish between *quantity* and *price* effect, in the sense that we analyze separately the effect of trade and technology on employment and wages of skilled and unskilled workers. Thirdly, in this study we rely on new data that allow identifying the possible labor-saving and skill-biased effect of firm-level investments in foreign machinery and contrast it with the impact of domestically produced machinery investments.

3 Data and descriptive statistics

This study uses data from the Turkish "Annual Manufacturing Industry Survey" conducted by the Turkish Statistical Institute, TurkStat. The survey covers 17,462 firms for the period between 1992 and 2001. The survey includes private firms having at least 10 employees as well as public ones, representing around 90 % of the Turkish manufacturing output, within the formal sector.

The database provides a wide range of information on each firm including economic activity, size and composition of workforce, wages, purchases of input, volume of sales and output, investment activities, and the status of assets and capital. All monetary variables are expressed in 1994 Turkish Lira, using sector-specific deflators.

Interestingly, the dataset provides different firm-level measures to indicate technology adoption, which make the data particularly suitable for our analysis. In particular, we construct the following indicators: R&D indicates the presence of internal R&D expenditures to proxy domestic innovation capacity. Disembodied technology transfer from abroad is measured through a variable indicating whether the firm obtained royalties, patents, know-how and other property rights from abroad (PAT). Embodied technological change is captured by two variables that describe respectively the cumulative investment in *domestically produced* (INV_D) and *foreign* (imported) (INV_FOR) machinery and equipment per worker. The data also provide information on firms' international involvement, and we have information on whether firms export (EXP) and whether are foreign owned (FOR).

Table 1 Variables in the analysis and their definitions *Source* Annual Manufacturing Industry Survey for the Republic of Turkey: TurkStat

Variable	Definition
BC	Number of "blue-collar" employees engaged in production activities
WC	Number of "white-collar" employees engaged in non-production activities
BCW	Real wages of blue-collar employees (total labor cost per worker)
WCW	Real wages of white-collar employees (total labor cost per worker)
VA	Real value added of the firm
R&D	Dummy variable for existence of R&D activities
PAT	Dummy variable for obtaining foreign royalties, patents, know–how and other property rights from abroad
EXP	Dummy variable for export activities
FOR	Dummy for firms in which 10 % or more of capital is owned by foreigners
INV_D	Investment in domestically produced machinery and equipment per worker
INV_FOR	Investment in imported machinery and equipment per worker

Annual observations for the period 1992–2001; all variables—apart from dummies—have been transformed into natural logarithms

Employment is measured as the number of workers per year. Workers are divided into two broad categories: (1) production workers, including technical personnel, foremen, supervisors and unskilled workers, and (2) administrative workers, including management and administration employees, and office personnel. This categorization is used in the empirical analysis to distinguish between white-collar (skilled) workers proxied by the administrative workers, and blue-collar (unskilled) workers proxied by the production workers.[6]

Table 1 summarizes and defines all the variables included in the analysis.

Table 2 reports the mean value of number of white- and blue-collars, their average wages and other relevant variables by types of firms, distinguishing by their exposure to domestic and foreign technology. The table shows that only a small proportion of firms are active in foreign markets and technology transfer from abroad. However, the table also highlights that these firms (last three columns in Table 2) tend to have a higher share of white-collars workers; a higher wage gap between white- and blue-collars, and also tend to be more productive (*i.e.:* they have higher value added per employee). This is consistent with the growing body of literature that demonstrated that trading firms differ substantially from firms that solely serve the domestic market (see for example, Bernard and Jensen 1997). Across a wide range of countries and industries, in fact, exporters have been shown to be larger, more productive, more skill- and capital-intensive, and to pay higher

[6] The decision to categorize skilled and unskilled labor based on this division stems from the fact that this approach has been widely used in the relevant literature, showing satisfactory results and a very strong correlation with the alternative classification based on educational attainments (see for example, Berman et al. 1994; Leamer 1998). Moreover, Meschi et al. (2011), using data from the Turkish Labor Force Survey on the composition and educational level of the Turkish manufacturing workforce, show that administrative employees are on average significantly more educated than production workers. In addition, the substantial wage differential between WC and BC workers is a further indication for skill differences.

Table 2 Descriptive statistics (mean), by types of firms

Variables	All firms	R&D performer (R&D = 1)	Technology transfer (PAT = 1)	Exporter (EXP = 1)	Foreign (FOR = 1)
Blue-collar workers	32	53	143	73	98
White-collar workers	7	15	58	17	39
White-collar/blue-collar	0.224	0.281	0.406	0.229	0.402
Wage rate, blue-collar	72	94	190	93	182
Wage rate, white-collar	97	135	339	136	335
White-collar/blue-collar	1.35	1.44	1.78	1.46	1.84
Real value added	11,379	33,649	232,806	47,946	154,250
Value added per employee	289	469	1083	508	1039
R&D performer	0.122	1.000	0.453	0.220	0.338
Technology transfer	0.018	0.068	1.000	0.055	0.266
Foreign	0.032	0.088	0.459	0.082	1.000
Foreign machinery share	0.174	0.171	0.189	0.172	0.197
Number of observations	114,577	14,002	2109	20,356	3639
	(100 %)	(12.2)	(1.8)	(17.8)	(3.2)

Level variables are calculated as firm-level geometric averages, proportions as firm-level simple averages. Non-missing number of observations vary by variable because of differences in item non-response rates

wages than non-exporting firms (see Bernard et al. 2007). This evidence may of course suggest self-selection: only more productive and more skill-intensive firms are able to overcome the costs of entering export market. This is why we need an appropriate econometric strategy to study the causal effect of firms' involvement in international market on labor demand.

Interestingly, we also note that exporters and foreign firms are more likely to adopt new technologies (i.e.: they transfer more technology from abroad, through patents, and are more likely to invest in R&D). This suggests a complementarity between trade and technology and is consistent with recent theoretical models that have put forward the idea that firms jointly make decisions about innovation and export market participation (Bustos 2011; Trefler 2004; Verhoogen 2008). The idea is that firms are more likely to decide to invest in productivity-enhancing activities such as R&D (Melitz and Costantini 2007) when entering international markets.

3.1 Trends in employment, wages and technological upgrading

Our data show that during the sample period, overall employment has been increasing for both production and administrative workers (Fig. 1), although production workers (plotted on the left axis) are about three time as numerous compared to administrative workers (right axis) However, over the same period, the wage gap between skilled and unskilled workers has increased substantially (see Fig. 2), which suggests an upward shift in the relative demand for skilled labor. In fact, an increase in relative wages in a period in which relative employment

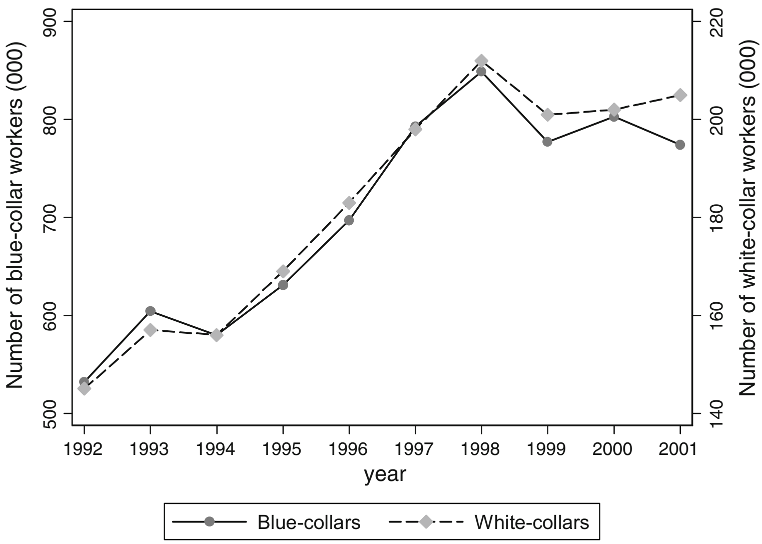

Fig. 1 Evolution of employment of white and blue-collar workers. *Source* own elaborations from *Annual Manufacturing Industry Survey*, TurkStat

remained nearly stable implies an increase in the wage bill share of skilled workers and thus an increase in the demand for skilled workers.[7]

As documented in Meschi et al. (2011) such an increase was mainly driven by skill upgrading within industry (more than 88 % of the overall change) rather than between industries, which points at the relevance of the SBTC hypothesis.

Indeed—over the period analyzed—the Turkish manufacturing sector was exposed to growing international competition and to a significant increase in trade flows,[8] which has favored technology adoption from abroad. Table 3 reports the evolution of the share of firms in the Turkish manufacturing sector performing R&D

[7] Under the hypothesis of elasticity of substitution between skilled and unskilled labor equal to one, an increase in the wage bill share can be interpreted as an upward shift of relative labor demand for skilled workers (see Berman and Machin 2000). The wage bill share of skilled workers can be expressed as: $WBSH = \frac{w_s S}{w_s S + w_l L} = \frac{w_s S}{wE}$ where w is wages, s subscript denotes skilled labor, l subscript denotes low-skilled labor, S and L are respectively the number of skilled and low-skilled workers and E is total employment. Taking the logarithm, the formula can be decomposed as follows: $\log(WBSH) = \log(w_s/w) + \log(S/E)$. If the elasticity of substitution between S and L is one, $WBSH$ is constant along a relative demand curve, so that the log change in relative wages and that of relative employment sum to zero: $\Delta\log(WBSH) = \Delta\log(w_s/w) + \Delta\log(S/E) = 0$.

[8] Until 1980, Turkish economic and trade policies were characterised by import-substituting industrialisation under heavy state protection. In January 1980, a comprehensive structural adjustment reform programme was launched and a major component of the reform package consisted in trade liberalisation policies. In 1989, the country opened up its domestic and asset markets to international competition with the declaration of the convertibility of the Turkish Lira in 1989 and the elimination of controls on foreign capital transactions. In 1996, Turkey signed the Custom Union agreement with the European Union and Free Trade Agreements with the European Free Trade countries, such as Central and Eastern European countries, and Israel. These policy changes led to significant increases in both imports and exports. For example, the import penetration ratio for manufacturing increased from 15 % in 1980 to 30 % in 2000 (Taymaz and Yilmaz 2007).

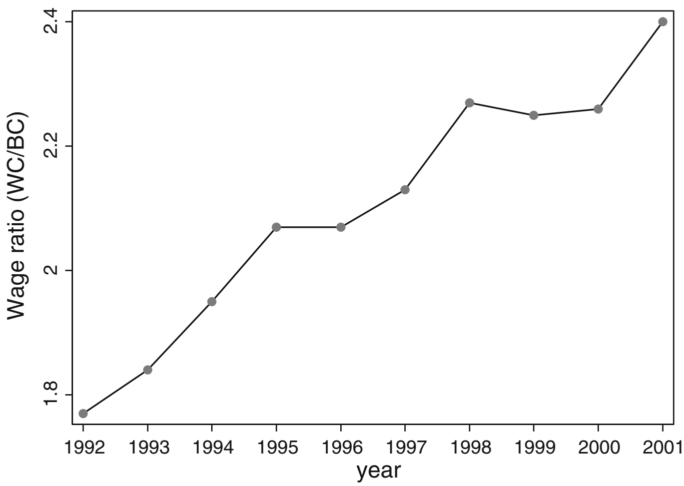

Fig. 2 Evolution of wage gap between white and blue-collar workers. *Source* own elaborations from *Annual Manufacturing Industry Survey*, TurkStat

Table 3 Descriptive statistics on the Turkish manufacturing sector *Source* own elaborations from *Annual Manufacturing Industry Survey*, TurkStat

	% of total firms			
	R&D performer (%)	Technology transfer (%)	Foreign-owned (%)	Exporter (%)
1992	8.1	1.5	2.4	13.8
1993	12.4	1.6	2.8	17.7
1994	14.7	1.7	3.0	19.5
1995	15.8	1.8	3.1	21.0
1996	13.8	1.9	3.1	16.6
1997	13.1	2.0	3.2	12.6
1998	13.3	1.8	3.3	17.9
1999	14.1	1.7	3.6	19.2
2000	14.6	2.0	3.7	20.6
2001	11.7	2.3	3.7	19.5

(col. 1), receiving technological transfer (patents, royalties) from abroad (col. 2), and the share of foreign-owned (col. 3) and exporter (col. 4) firms. The table highlights that during the trade liberalization phase, Turkish manufacturing sector has been increasingly exposed to international technology that contributed to technological upgrading possibly more than domestic investment in R&D.[9]

Overall, we have seen that during the 1992–2001 period, Turkish manufacturing firms have experienced a phase of technological upgrading, mainly due to

[9] From a macroeconomic point of view, the Turkish gross domestic expenditure on R&D (public and private) to GDP ratio has in fact increased over the investigated decade (from 0.49 in 1992 to 0.72 in 2001), but still falling much lower than the OECD average (see Elci 2003).

technology transfer from abroad and to the new technologies embodied in imported capital goods. Over the same period, the wage gap between skilled and unskilled workers has increased, suggesting a rising demand for skilled labor in the manufacturing sector. While these descriptive evidences are not in contrast with our interpretative hypotheses (see Sect. 2), we need to develop a micro-econometric approach to properly test them.

Indeed, the aim of the following empirical analysis is to investigate and quantify the role of *domestic* and *trade-induced* technological upgrading in explaining trends in labor demand, separately studying the effect on employment trends (*quantity effect*) and relative wages (*price effect*). Our empirical strategy and identification issues are discussed in the next section.

4 The empirical model: specification and econometric issues

Consistently with previous empirical literature, our estimating equation derives from a standard labor demand equation. In particular, following Van Reenen (1997), we consider a model in which firms operate under a constant elasticity of substitution production function (CES) of the form:

$$Y = T\left[(AL)^{\frac{\sigma-1}{\sigma}} + (BK)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where Y is the output, L and K represent conventional inputs such as labor and capital; T, A and B are a Hicks-neutral, a labor-augmenting and a capital-augmenting technology respectively; the first-order profit-maximization condition for labor yields to:

$$\log(L) = \ln(Y) - \sigma \log(W) + (\sigma - 1)\log(A) \tag{2}$$

We start from this standard framework and augment this equation replacing the unobserved technology variable A with proxies for innovation and technology adoption, and including variables describing firms' involvement in the international market (see Sect. 2).

If we consider two types of labor inputs, namely skilled (white-collars WC) and unskilled (blue-collars BC) and adopt a dynamic specification in order to account for adjustment costs that determine serial correlation in the employment series (see Van Reenen 1997; Lachenmaier and Rottman 2011; Conte and Vivarelli 2011), our estimating equations of the *quantity effect* are the following:

$$\begin{aligned} BC_{\mathrm{it}} = \rho\, BC_{\mathrm{it}-1} + \delta_1 BCW_{\mathrm{it}} + \delta_2 WCW_{it} + \gamma\, Y_{\mathrm{it}} + \eta \mathbf{TECH}_{\mathrm{it}} \\ + \mu \mathbf{OPEN}_{\mathrm{it}} + \lambda_1 INV\_D_{\mathrm{it}} + \lambda_2 INV\_F_{\mathrm{it}} + \tau_{\mathrm{t}} + (\mathrm{u}_{\mathrm{it}} + \varepsilon_{\mathrm{i}}) \end{aligned} \tag{3}$$

$$\begin{aligned} WC_{\mathrm{it}} = \rho\, WC_{\mathrm{it}-1} + \delta_1 WCW_{\mathrm{it}} + \delta_2 BCW_{\mathrm{it}} + \gamma\, Y_{\mathrm{it}} + \eta \mathbf{TECH}_{\mathrm{it}} \\ + \mu \mathbf{OPEN}_{\mathrm{it}} + \lambda_1 INV\_D_{\mathrm{it}} + \lambda_2 INV\_F_{\mathrm{it}} + \tau_{\mathrm{t}} + (\mathrm{u}_{\mathrm{it}} + \varepsilon_{\mathrm{i}}) \end{aligned} \tag{4}$$

All variables—apart from dummies—are expressed in natural logarithms. *BC* and *WC* are respectively the numbers of blue-collar and white-collar workers of firm *i* at time *t*. *BCW* and *WCW* are the wages of each labor category. Each equation contains wages for both the categories of workers, since the price of both types of labor are likely to affect firms' hiring decisions. *Y* is firms' value added that reflects the impact of firms' sales and controls for possible business cycle fluctuations that can affect demand for the different types of labor. **TECH** is a vector composed of two dummy variables representing domestic and imported technology: namely, the presence of internal R&D expenditures (*R&D*) and the obtained availability of a foreign patent or other appropriability devices developed abroad (*PAT*). **OPEN** is a vector of two dummy describing firms' international involvement: in particular, *EXP* is a dummy that takes the value of one when the firm is an exporter and zero if it does not export, while *FOR* is a dummy equal to 1 if 10 % or more of a firm's capital is owned by foreigners. To test the role of embodied technological change, we use two investment variables (*INV_D* and *INV_F*) which are respectively the cumulative investment in *domestically produced* machinery and equipment per worker and the cumulative investment in *foreign* (imported) machinery and equipment per worker. τ_t are time dummy to control for unobserved common macroeconomic and cyclical shocks that may affect the demand for labor. Finally, standard to panel data analysis, the error term is composed by the idiosyncratic error component (u_{it}) and the time invariant firm fixed effect component (ε_i).

Equations (3) and (4) can be seen as a twofold dynamic labor demand, where employment depends on output, investment and wages as traditionally assumed, but also on additional drivers such as domestic technology, imported technology, FDI and "learning by exporting" (see Sect. 2).

In order to test whether the coefficients of the variables of interest are significantly different for white- and blue-collars, we jointly estimate Eqs. (3) and (4), through a fully interacted model. This yields the same results as in (3) and (4), but allows computing the variance and covariance matrix between all the estimated coefficients, which in turn allows testing the difference in their magnitudes, through a battery of Wald tests.

Therefore, estimating Eqs. (3) and (4) and testing the differences in coefficient magnitudes allow to assess the impact of technology and trade variables on relative employment, and permit to investigate the *relative* versus *absolute* skill bias (see Sect. 1). Moreover, the estimation of two separate equations for white- and blue-collars (as opposed to the alternative strategy on estimating a single equation on the employment ratio) allows exploring the autoregressive dynamics of blue-collars and white-collars workers separately.

In estimating Eqs. (3) and (4), we can study the *quantitative* impact of trade and technology on employment. In order to test their impacts on wage differentials, thus studying the *price effect*, we also estimate two wage equations of the following form [where the variables are defined as in (3) and (4), *FS* stands for female share][10]:

[10] Assuming that markets are competitive, then the wage of each factor is given by the derivative of Y with respect to each factor BC and WC. As can be seen, Eqs. (5) and (6) include the female share (FS) as an additional control that may affect wage evolution (see, for example, Ilmakunnas and Maliranta 2005; Heyman et al. 2007). Finally, since wage can be seen as a component of firm's value added, Y has been lagged one period in the two wage equations to avoid endogeneity.

$$BCW_{it} = \rho\, BCW_{it-1} + \beta\, WCW_{it-1} + \gamma\, Y_{it-1} + \delta\, FS_{it} + \eta \mathbf{TECH}_{it} + \mu \mathbf{OPEN}_{it} + \lambda_1 INV\_D_{it} + \lambda_2 INV\_F_{it} + \tau_t + (u_{it} + \varepsilon_i) \quad (5)$$

$$WCW_{it} = \rho\, WCW_{it-1} + \beta\, BCW_{it-1} + \gamma\, Y_{it-1} + \delta\, FS_{it} + \eta \mathbf{TECH}_{it} + \mu \mathbf{OPEN}_{it} + \lambda_1 INV\_D_{it} + \lambda_2 INV\_F_{it} + \tau_t + (u_{it} + \varepsilon_i) \quad (6)$$

For both Eqs. (3) and (4) and Eqs. (5) and (6), the presence of firm-specific effects creates a correlation between the lagged dependent variable BC_{it-1} (and WC_{it-1}) and the individual fixed effect u_i. Therefore, the dynamic specification implies a violation of the assumption of strict exogeneity of the estimators. In this context, the use of least squares will lead to inconsistent and upwardly biased estimates for the coefficient of the lagged dependent variable (Hsiao 1986). The firm effects can be eliminated through the within-group estimator (or fixed effects estimator, FE). However, this leads to a downward bias of the estimated parameter of the lagged dependent variable (Nickell 1981).

Extensive econometric research has been done in order to obtain consistent and efficient estimators of the parameters in dynamic panel models. Almost all approaches include first transforming the original equations to eliminate the fixed effects and then applying instrumental variables estimations for the lagged endogenous variable. Anderson and Hsiao (1982) developed a formulation for obtaining consistent fixed effects-instrumental variables (FE-IV) estimators by resorting to first differencing in order to eliminate the unobserved fixed effects, and then using two lags and beyond to instrument the lagged dependent variable.

Efficiency improvements have been made to the Andersen and Hsiao model through the utilization of the GMM (Generalized Method of Moments) technique. Arellano and Bond (1991) first resorted to GMM by using an instrument matrix that includes all previous values of the lagged dependent variable, so obtaining the GMM-DIFF estimator. However, The GMM-DIFF estimator was found to be weak when (a) there is strong persistence in the time series, and/or (b) the time dimension and time variability of the panel is small compared with its cross-section dimension and variability (Bond et al. 2001). Blundell and Bond (1998) have performed an efficiency improvement to the GMM-DIFF by using additional level moment conditions and obtaining the system GMM or GMM-SYS model. Through these added moment conditions, the GMM-SYS uses all the information available in the data based on the assumption that $E(\Delta u_{it}\varepsilon_i) = 0$ (Blundell and Bond 1998; Bond 2002). Since our panel dataset is characterized by both the above conditions (a) and (b), we adopted a GMM-SYS model.

5 Results and discussion

Before looking into the results of the regression estimations, some results from tests and complementary regressions deserve a brief discussion.

First, we test autocorrelation in our panel using the test proposed by Wooldridge (2002) and the F-test statistic always rejected the null hypothesis of no autocorrelation at 1 % level, which calls for a dynamic specification.

Secondly, the presence of a lagged dependent variable required running an OLS regression to determine the upper bound for the value of the coefficient obtained in the GMM-SYS. The OLS outcomes reported in Table 6 in Appendix indeed show that the values of the coefficients of the lagged dependent variables from GMM-SYS (Table 4) are lower than those obtained from OLS. Similarly, the Fixed Effects (FE) methodology was applied to provide a lower bound for the value of the estimated coefficient of the lagged dependent variable in the GMM-SYS estimates, since the fixed effects lead to downward biased results. Also in this case, GMM-SYS results are consistent with the expectations. Overall, the comparison between GMM-SYS on the one hand and OLS and FE on the other hand is supporting the adequacy of the chosen GMM-SYS methodology. Results are discussed with reference to the preferred GMM-SYS specification proposed in Table 4, although they are generally consistent across the three methodologies (see Table 6 in Appendix).

A number of further tests were performed to test the validity of the estimated model and the robustness of the corresponding results. A Wald test[11] was run to test for the overall joint significance of the independent variables: it always rejects the null hypothesis of insignificant coefficients. The Hansen test for over-identifying restrictions was also performed: the null of adequate instruments was actually rejected in both the employment and wage equations, only for blue-collar workers. However, since it has been demonstrated that the Hansen test over-rejects the null in case of very large samples (see Blundell and Bond 1999; Roodman 2006), the same model was run and the Hansen test performed on a random sub-sample comprising 20 % of the original data. The outcome was that the Hansen tests never rejected the null, so reassuring on the validity of the chosen instruments.[12] Finally, the standard Arellano and Bond (AR) tests for autocorrelation support the consistency of the adopted GMM estimators, however only after using t-3 instruments.

Looking at employment equations (cols. 1 and 2, Table 4), the positive and highly significant values of the lagged coefficients for both types of workers confirm the persistence of the employment time-series. Also consistent with our expectations, the wage coefficients are in line with the standard requirement for the relationship between wages and labor demand. In particular, the labor demand for a specific category of workers turns out to be negatively correlated with the wage rate of the corresponding category, while positively correlated with the wage rate of the alternative category.

As expected, firms' value added has a positive impact on both blue-collar and white-collar workers, indicating that expansion of production requires higher demand for both types of labor.

By contrast, investment in domestic machinery implies a labor saving effect, especially for blue-collar workers. In particular, the estimates show that a 10 %

[11] It is distributed as a χ^2 where the degrees of freedom equate the number of restricted coefficients.

[12] Results available from the authors upon request.

Table 4 Employment and wage equations for unskilled and skilled workers; GMM-SYS estimates

	(1) Employment equations	(2)	(3) Wage equations	(4)
	BC	WC	BC	WC
Lagged employment	0.784***	0.762***		
	(0.0170)	(0.0241)		
Lagged wage BC			0.582***	0.0970**
			(0.0646)	(0.0377)
Lagged wage WC			0.0434*	0.551***
			(0.0249)	(0.0536)
Wage WC	0.0662***	−0.217***		
	(0.00350)	(0.00618)		
Wage BC	−0.182***	0.186***		
	(0.00570)	(0.00714)		
VA	0.127***	0.136***		
	(0.00652)	(0.00954)		
Lagged VA			0.0167*	0.0299***
			(0.00887)	(0.00517)
INV_D	−0.0184***	−0.000232	0.0139***	0.0148***
	(0.000975)	(0.00120)	(0.00102)	(0.00130)
INV_FOR	0.0102***	0.00898***	0.0183***	0.0229***
	(0.00130)	(0.00147)	(0.00149)	(0.00186)
R&D	0.00730*	0.0497***	0.0309***	0.0400***
	(0.00423)	(0.00667)	(0.00572)	(0.00787)
EXP	0.0331***	0.0532***	0.0378***	0.0530***
	(0.00498)	(0.00635)	(0.00457)	(0.00717)
PAT	0.0321***	0.0784***	0.104***	0.165***
	(0.0124)	(0.0170)	(0.0163)	(0.0198)
FOR	−0.0118	0.110***	0.198***	0.298***
	(0.0100)	(0.0122)	(0.0168)	(0.0244)
FS			−0.130***	0.00111
			(0.0160)	(0.0110)
Observations	73934	71329	73381	71072
Number of firms	14916	14358	14886	14316
Wald test	193572***	176447***	55533***	48401***
Hansen	60.56***	1.985	25.52***	4.341
Sargan	105.9***	2.884	31.17***	5.274
AR(1)	−26.14***	−26.51***	−13.82***	−15.7***
AR(2)	2.056**	6.025***	5.06***	5.239***
AR(3)	0.0947	1.415	1.895*	0.679

The number of firms reported in the table refers to firms whose data are used in estimating the model. Since all models include the lagged value of the dependent variable and take the difference of variables to run GMM estimates, a firm is included if it has at least three consecutive observations. This has implied the drop from 17,462 companies to less than 15,000

Robust standard errors in parentheses; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 5 Wald test statistics for the null hypothesis of equal coefficients for BC and WC

Variable	Labor demand equation	Wage equation
Local investment	145.61***	0.08
Foreign investment	0.56	5.27**
R&D performer	27.35***	0.76
Exporter	5.54**	4.69**
Technology transfer	4.44**	5.85**
Foreign	59.62***	12.56***

The significance of the difference in the coefficients for white- and blue-collar was tested jointly estimating Eqs. (3) and (4), and (5) and (6) through a fully interacted model

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

increase in domestic investment would lead to a 0.18 % reduction of blue-collar workers. This result is in line with the view according to which the introduction of new machines (that is a way to introduce process innovation) may cause job losses (see Sect. 2.1). Interestingly enough, blue-collar workers, directly involved in factory production, are those that are more likely to be displaced by new machinery.

However, this labor-saving effect appears to be confined to domestic investment. In fact, we get different results when we turn our attention to investment in foreign machinery, which tends to stimulate employment of both white- and blue-collar workers. This finding may also indicate that firms' access to new imported inputs increased their ability to manufacture new products (see for example Goldberg et al. 2010), thus increasing total labor demand. While the employment effect is not significantly different between white- and blue-collar (see Table 5, first column), we find that foreign technology embodied in capital goods leads to a widening of wage differentials between skilled and unskilled workers. Columns 3 and 4 of Table 4 in fact report that investment in foreign machinery tends to increase the wages of white-collar more than those of blue-collar workers (and the difference is statistically significant, as shown in Table 5, second column). Since the technological content of imported capital is likely more advanced than that embodied in domestic capital, we interpret this finding as a support of the SET hypothesis (see Sect. 2.2). The magnitude of this effect is such that a 10 % increase in investment in foreign machinery increases wages of white-collar workers by 0.23 %, while those of blue-collar workers by 0.18 %.

Turning our attention to the variables describing disembodied technological change (R&D and patents) and international openness (*EXP* and *FOR*), they all seem to have an employment enhancing effect. This means that no negative employment quantitative impacts emerge because of technological change, which implies that labor-friendly product innovation (captured by *R&D* and *PAT*) and compensation mechanisms have been effective in Turkish manufacturing, at least over the investigated period (see Sect. 2.1). In terms of the relative magnitudes of the observed effects, we note that the *FOR* dummy has the strongest effect, followed by technology transfer through patents and other property rights.[13]

However, for both the technological variables (*R&D* and *PAT*), we detect a *relative skill bias*, since they favour more the skilled workers rather than the low skilled ones: indeed, the coefficients for white-collar are significantly higher than those for blue-collar in both the employment and wage equation (the relevant four tests are displayed in Table 5 and are all significant at the 95 % level of confidence;). These results are fully consistent with those obtained in our previous study (see Meschi et al. 2011; Table 3).

Focusing on the variables describing firms' involvement in international markets, the results concerning *EXP* (pointing to a significant—see Table 5—relative skill bias in both the employment and wage equations) are supporting the "*learning by exporting*" hypothesis (see Sect. 2.2).[14] Looking at the variable *FOR*, which identifies firms partially foreign-owned, we see that receiving FDI increases the demand for skilled labor, and implies an *absolute* skill bias. FDI in fact increase the employment of white-collar workers, while do not significantly affect the employment of blue-collar workers. In the wage equations, we also see that FDI amplify the wage gap between skilled and unskilled workers. In particular, when the *FOR* dummy turns to 1, wages of white-collar workers increase by almost 30 %, and those of blue-collar workers by almost 20 % and this gap is highly significant (see Table 5). This is consistent with the idea that FDI can be an important conduit for the transfer of skill-biased technologies and increase the relative wages of skilled workers, thus widening wage inequality (Feenstra and Hanson 1997).

Overall, our results strongly support both the SBTC and the SET hypotheses in an emerging country, such as Turkey, thus confirming the view according to which firms in emergent markets are inclined to search for technology and high quality inputs when crossing the national borders (see Lo Turco and Maggioni 2013). This is likely to imply productivity improvements driven by technology transfers embodied in trade flows, which may in turn affect employment's level and composition (more than in developed countries whose import activity is often driven by labour cost saving reasons). Indeed our estimates show that both domestic and foreign technologies have fostered the demand for skilled workers in Turkish manufacturing. This means that opening up to international trade and the resulting technological upgrading, while increasing employment and possibly productivity, may also have a worrying effect on skill dispersion and wage inequality.

Since wages are the most important (often the sole) source of income for Turkish poor families, the trends we observe may cause a worsening in the conditions of living of the poor and so a deterioration in terms of the overall social cohesion of the country. In this context, the education of the youth and the life-long learning for the

[13] In particular, firms whose share of foreign ownership rises above 10 %, increase the employment of white-collar workers by 11 %, while does not affect BC's employment. Acquiring patents from abroad in fact leads to a 7.8 % growth in WC employment and 3.2 % growth in BC employment.

[14] This outcome is also consistent with that obtained by Meschi et al. (2011), although the role of exports turns out to be even more statistically significant in the present study. The results are also in line with Lo Turco and Maggioni (2013) who support the positive internationalization effects on the firm employment growth in Turkish manufacturing sector.

adults (including vocational training and on-the-job training) are extremely important for Turkey in order to mitigate the increase in inequality due to skill-biased technological change and skill-enhancing globalization and so to achieve inclusive growth.

6 Concluding remarks

This paper has empirically explored the possible roles of trade and technology in affecting employment, skills and wages within the Turkish manufacturing sector over the two decades of the '80 s and '90 s, a period of increasing globalization for the Turkish economy.

The first result of this study is that the interlinked relationship between technology and trade positively contributed to employment creation in Turkish manufacturing (this means that compensation did work, at least in Turkish manufacturing over the investigated period, see Sect. 2.1). A notable exception is the domestic investment in new machineries that exhibits an obvious labor-saving impact, although limited to the blue-collar workers.

A second important outcome of our research is that a strong evidence of a *relative skill bias* emerges: indeed, domestic R&D activities, imported technologies, and export increase the demand for skilled labor significantly more than the demand for the unskilled. Finally, FDI imply an *absolute skill bias*.

On the whole, these findings offer a strong support to the Skill-Biased-Technological-Change (SBTC) hypothesis and points out the key roles that the skill-enhancing-trade (SET), "learning by exporting" and FDI may play in shaping the demand for labor in a developing country (see Sect. 2.2).

The fact that technology and globalization imply an obvious skill-bias calls for economic policies in DCs able to couple trade liberalization with education and training policies targeted to increase and to better shape the local supply of skilled labor.

Acknowledgments We wish to thank Ilina Srour (American University of Beirut) for her impeccable research assistance.

Appendix

See Appendix Table 6.

Table 6 Employment and wage equations for unskilled and skilled workers; OLS and FE estimates

	Employment equations				Wage equations			
	BC		WC		BC		WC	
	OLS	*FE*	*OLS*	*FE*	*OLS*	*FE*	*OLS*	*FE*
Lagged employment	0.843***	0.467***	0.790***	0.362***				
	(0.00174)	(0.00331)	(0.00209)	(0.00363)				
Lagged wage rate BC					0.614***	0.153***	0.278***	0.115***
					(0.00334)	(0.00430)	(0.00463)	(0.00616)
Lagged wage rate WC					0.117***	0.0439***	0.509***	0.104***
					(0.00255)	(0.00301)	(0.00358)	(0.00433)
Wage rate WC	0.0423***	0.0710***	−0.151***	−0.234***				
	(0.00231)	(0.00274)	(0.00326)	(0.00391)				
Wage rate BC	−0.154***	−0.158***	0.125***	0.146***				
	(0.00295)	(0.00388)	(0.00412)	(0.00553)				
VA	0.109***	0.132***	0.136***	0.115***				
	(0.00130)	(0.00180)	(0.00176)	(0.00253)				
Lagged VA					0.0363***	0.0174***	0.0400***	0.0147***
					(0.00167)	(0.00216)	(0.00237)	(0.00312)
INV_D	−0.0104***	−0.0436***	0.00137	−0.0211***	0.00626***	0.0111***	0.00832***	0.00698***
	(0.000609)	(0.00141)	(0.000861)	(0.00202)	(0.000684)	(0.00158)	(0.000967)	(0.00228)
INV_FOR	0.00665***	0.00263**	0.00363***	0.0105***	0.00951***	0.00556***	0.0145***	0.0136***
	(0.000612)	(0.00130)	(0.000857)	(0.00185)	(0.000659)	(0.00146)	(0.000921)	(0.00209)
R&D	0.00353	0.0147***	0.0487***	0.0323***	0.0297***	0.0109**	0.0408***	0.00758
	(0.00337)	(0.00390)	(0.00476)	(0.00554)	(0.00379)	(0.00438)	(0.00531)	(0.00627)
EXP	0.0193***	0.0262***	0.0397***	0.0516***	0.0230***	0.0295***	0.0556***	0.0219***
	(0.00308)	(0.00409)	(0.00432)	(0.00580)	(0.00341)	(0.00458)	(0.00472)	(0.00654)

Table 6 continued

	Employment equations				Wage equations			
	BC		WC		BC		WC	
	OLS	*FE*	*OLS*	*FE*	*OLS*	*FE*	*OLS*	*FE*
PAT	0.0103	0.0301**	0.0513***	0.0414**	0.0579***	−0.00402	0.123***	0.00464
	(0.00838)	(0.0136)	(0.0117)	(0.0191)	(0.00939)	(0.0152)	(0.0130)	(0.0215)
FOR	−0.0209***	0.0542***	0.0634***	0.0724***	0.121***	0.0229	0.232***	0.140***
	(0.00664)	(0.0147)	(0.00927)	(0.0207)	(0.00745)	(0.0165)	(0.0103)	(0.0234)
FS					−0.116***	−0.0465***	−0.0161**	0.0386***
					(0.00552)	(0.0122)	(0.00697)	(0.00968)
Observations	73934	73934	71329	71329	73381	73381	71072	71072
R-squared	0.91	0.388	0.878	0.248	0.706	0.308	0.641	0.22
Number of firms	14916	14916	14358	14358	14886	14886	14316	14316

Robust standard errors in parentheses; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

References

Acemoglu, D. (2003). Patterns of skill premia. *Review of Economic Studies, 70*, 199–230.

Aguirregabiria, V., & Alonso-Borrego, C. (2001). Occupational structure, technological innovation, and reorganization of production. *Labor Economics, 8*(1), 43–73.

Almeida, R. (2009). *Openness and technological innovation in East Asia: have they increased the demand for skills?* (IZA Discussion Papers No. 4474). Bonn: Institute for the Study of Labor (IZA).

Anderson, T. W., & Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. *Journal of Econometrics, 18*, 47–82.

Araújo, B. C., Bogliacino, F., & Vivarelli, M. (2011). Technology, trade and skills in Brazil: Some evidence from microdata. *CEPAL Review, 105*, 157–171.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*, 277–297.

Attanasio, O., Goldberg, P., & Pavcnik, N. (2004). Trade reforms and wage inequality in Colombia. *Journal of Development Economics, 74*, 331–366.

Autor, D., Katz, L., & Krueger, A. (1998). Computing inequality: Have computers changed the labor market? *Quarterly Journal of Economics, 113*, 1169–1214.

Berman, E., Bound, J., & Griliches, Z. (1994). Changes in the demand for skilled labor within U.S. manufacturing industries. *Quarterly Journal of Economics, 109*, 367–398.

Berman, E., & Machin, S. (2000). Skill-Biased technology transfer around the World. *Oxford Review of Economic Policy, 16*, 12–22.

Berman, E., & Machin, S. (2004). Globalization, skill-biased technological change and labor demand. In E. Lee & M. Vivarelli (Eds.), *Understanding globalization, employment and poverty reduction* (pp. 39–66). New York: Palgrave Macmillan.

Bernard, A. B., & Jensen, J. B. (1997). Exporters, skill upgrading and the wage gap. *Journal of International Economics, 42*(1-2), 3–31.

Bernard, A. B., Jensen, J. B., Redding, S. J., & Schott, P. K. (2007). Firms in international trade. *Journal of Economic Perspectives, 21*(3), 105–130.

Birchenall, J. A. (2001). Income distribution, human capital and economic growth in Colombia. *Journal of Development Economics, 66*, 271–287.

Blomström, M., & Kokko, A. (1998). Multinational corporations and spillovers. *Journal of Economic Surveys, 12*, 247–277.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*, 115–143.

Blundell, R., & Bond, S. (1999). *GMM Estimation with persistent panel data: An application to production functions*. (IFS Working Papers no. 99/04). London: Institute for Fiscal Studies.

Bogliacino, F., & Pianta, M. (2010). Innovation and employment. A reinvestigation using revised Pavitt classes. *Research Policy, 39*, 799–809.

Bogliacino, F., Piva, M., & Vivarelli, M. (2012). R&D and employment: An application of the LSDVC estimator using European data. *Economics Letters, 116*, 56–59.

Bogliacino, F., & Vivarelli, M. (2012). The job creation effect of R&D expenditures. *Australian Economic Papers, 51*, 96–113.

Bond, S. (2002). *Dynamic panel data models: A guide to micro data methods and practice*. (CEMMAP Working Paper no. CWP09/02). London: Centre for Microdata Methods and Practice.

Bond, S., Hoeffler, A., & Temple, J. (2001). *GMM estimation of empirical growth models*. (CEPR Discussion Paper no. 3048). London: Centre for Economic Policy Research.

Bustos, P. (2011). Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on Argentinian firms. *American Economic Review, 101*(1), 304–340.

Coe, D. T., & Helpman, E. (1995). International R&D spillovers. *European Economic Review, 39*, 859–888.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*, 128–152.

Conte, A., & Vivarelli, M. (2011). Globalization and employment: Imported skill biased technological change in developing countries. *The Developing Economies, 49*, 36–65.

Dosi, G., & Nelson, R. R. (2013). The evolution of technologies: An assessment of the state-of-the art. *Eurasian Business Review, 3*, 3–46.

Edwards, L. (2004). A firm level analysis of trade, technology and employment in South Africa. *Journal of International Development, 16*, 45–61.

Elci, S. (2003). *Innovation policy profile: Turkey*. Enterprise Directorate-General Contract N°INNO-02-06. Study coordinated by ADE.

Fajnzylber, P., & Fernandes, A. (2009). International economic activities and skilled demand: Evidence from Brazil and China. *Applied Economics, 41*, 563–577.

Feenstra, R. C., & Hanson, G. H. (1997). Foreign direct investment and relative wages: Evidence from Mexico's maquiladoras. *Journal of International Economics, 42*(3), 371–393.

Feldmann, H. (2013). Technological unemployment in industrial countries. *Journal of Evolutionary Economics, 23*, 1099–1126.

Fuentes, O., & Gilchrist, S. (2005). Trade orientation and labor market evolution: Evidence from Chilean plant-level data. In J. Restrepo & A. Tokman (Eds.), *Labor markets and institutions*. Santiago: Central Bank of Chile.

Gallego, F. A. (2012). Skill premium in Chile: Studying skill upgrading in the South. *World Development, 40*(3), 594–609.

Gkypali, A., Rafailidis, A., & Tsekouras, K. (2015). Innovation and export performance: Do young and mature innovative firms differ? *Eurasian Business Review, 5*, 397–415.

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., & Topalova, P. (2010). Imported intermediate inputs and domestic product growth: Evidence from India. *Quarterly Journal of Economics, 125*(4), 1727–1767.

Görg, H., & Strobl, E. (2002). *Relative wages, openness and skill-biased technological change*. (IZA Discussion Papers No. 596). Institute for the Study of Labor (IZA).

Goux, D., & Maurin, E. (2000). The decline in demand for unskilled labor: An empirical analysis methods and its application to France. *The Review of Economics and Statistics, 82*(2), 596–607.

Griliches, Z. (1969). Capital-skill complementarity. *Review of Economics and Statistics, 51*, 465–468.

Hanson, G., & Harrison, A. (1999). Trade and wage inequality in Mexico. *Industrial and Labor Relations Review, 52*, 271–288.

Haskel, J., & Heden, Y. (1999). Computers and the demand for skilled labor: Industry and establishment-level panel evidence from the United Kingdom. *Economic Journal, 109*(454), C68–C79.

Heyman, F., Sjöholm, F., & Tingvall, P. G. (2007). Is there really a foreign ownership wage premium? Evidence from matched employer–employee data. *Journal of International Economics, 73*(2), 355–376.

Hsiao, C. (1986). *Analysis of panel data*. New York: Cambridge University Press.

Ilmakunnas, P., & Maliranta, M. (2005). Technology, labour characteristics and wage-productivity gaps. *Oxford Bulletin of Economics and Statistics, 67*(5), 623–645.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature, 42*(3), 752–782.

Kijama, Y. (2006). Why did wage inequality increase? Evidence from urban India 1983–99. *Journal of Development Economics, 81*, 97–117.

Lachenmaier, S., & Rottman, H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization, 29*, 210–220.

Leamer, E. (1998). In search of Stolper-Samuelson effects on US wages. In S. Collins (Ed.), *Imports, exports and the American worker* (pp. 141–214). Washington, D.C.: Brookings Institution Press.

Lee, E., & Vivarelli, M. (Eds.). (2004). *Understanding globalization, employment and poverty reduction*. New York: Palgrave Macmillan.

Lee, E., & Vivarelli, M. (Eds.). (2006a). *Globalization, employment and income distribution in developing countries*. New York: Palgrave Macmillan.

Lee, E., & Vivarelli, M. (2006b). The social impact of globalization in the developing countries. *International Labor Review, 145*, 167–184.

Lo Turco, A., & Maggioni, D. (2013). Does trade foster employment growth in emerging markets? Evidence from Turkey. *World Development, 52*, 1–18.

Machin, S. (1996). Wage inequality in the UK. *Oxford Review of Economic Policy, 12*(1), 47–64.

Machin, D. (2003). The changing nature of labor demand in the new economy and skill-biased technology change. *Oxford Bulletin of Economics and Statistics, 63*(S1), 753–776.

Machin, S., & Van Reenen, J. (1998). Technology and changes in skill structure: Evidence from seven OECD countries. *Quarterly Journal of Economics, 113*, 1215–1244.

Mairesse, J., Greenan, N., & Topiol-Bensaid, A. (2001). *Information technology and research and development impact on productivity and skills: Looking for correlations on French firm level data.* (NBER Working Paper No. 8075). Cambridge, MA: National Bureau of Economic Research.

Marx, K. (1961). *Capital*. Moscow: Foreign Languages Publishing House. (First edition 1867).
Maurin, E., Thesmar, D., & Thoenig, M. (2002). *Globalization and the demand for skill: An export based channel*. (CEPR Discussion Papers 3406).
Melitz, M., & Costantini, J. (2007). The dynamics of firm-level adjustment to trade liberalization. In E. Helpman, D. Marin, & T. Verdier (Eds.), *The organization of firms in a global economy*. Cambridge: Harvard University Press.
Melitz, M. J., & Redding, S. J. (2014). Heterogeneous firms and trade. In G. Gita, E. Helpman & K. Rogoff (Eds.) *Handbook of international economics* (4th ed., Vol. 4, pp. 1–54). Amsterdam: Elsevier.
Meschi, E., Taymaz, E., & Vivarelli, M. (2011). Trade, technology and skills: Evidence from Turkish microdata. *Labour Economics, 18*, S60–S70.
Meschi, E., & Vivarelli, M. (2009). Trade and income inequality in developing countries. *World Development, 37*, 287–302.
Mitra, A., & Jha, A. K. (2015). Innovation and employment: A firm level study of Indian industries. *Eurasian Business Review, 5*, 45–71.
Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica, 49*, 1417–1426.
Pavcnik, N. (2003). What explains skill upgrading in less developed countries? *Journal of Development Economics, 71*, 311–328.
Pianta, M. (2005). Innovation and employment. In J. Fagerberg, D. Mowery, & R. Nelson (Eds.), *Handbook of innovation (Chapter 22)*. Oxford: Oxford University Press.
Piva, M., & Vivarelli, M. (2004). Technological change and employment: Some micro evidence from Italy. *Applied Economic Letters, 11*, 373–376.
Piva, M., & Vivarelli, M. (2009). The role of skills as a major driver of corporate R&D. *International Journal of Manpower, 30*, 835–852.
Raveh, O., & Reshef, A. (2016). Capital imports composition, complementarities, and the skill premium in developing countries. *Journal of Development Economics, 118*, 183–206.
Robbins, D. (1996). *HOS hits facts: Facts win; evidence on trade and wages in the developing World*. (OECD Technical Paper No. 119). Paris: OECD.
Robbins, D. (2003). *The impact of trade liberalization upon inequality in developing countries: A review of theory and evidence*. (Working Paper No. 13). Geneva: International Labour Organization.
Roberts, M., & Tybout, J. (1996). *Industrial evolution in developing countries: Micro patterns of turnover, productivity, and market structure*. Oxford: Oxford University Press.
Rodrik, D. (1995). *Trade strategy, investment and exports: Another look at East Asia*. (NBER Working Paper No. 5339). Cambridge, MA.
Roodman, D. (2006). *How to do xtabond2: An introduction to "difference" and "system" GMM in Stata*. (Working Papers 103). Center for Global Development.
Sanchez-Paramo, C., & Schady, N. (2003). *Off and running? Technology, trade, and the rising demand for skilled workers in Latin America*. (World Bank Policy Research Working Paper 3015).Washington, DC: World Bank.
Stiglitz, J. (2002). *Globalisation and its discontents*. Oxford: Oxford University Press.
Taymaz, E., & Yilmaz, K. (2007). Productivity and trade orientation: Turkish manufacturing industry before and after the customs union. *The Journal of International Trade and Diplomacy, 1*, 127–154.
Trefler, D. (2004). The long and short of the Canada–U.S. free trade agreement. *The American Economic Review, 94*(4), 870–895.
Van Reenen, J. (1997). Employment and technological innovation: Evidence from UK manufacturing firms. *Journal of Labor Economics, 15*, 255–284.
Verhoogen, E. A. (2008). Trade, quality upgrading, and wage inequality in the Mexican manufacturing sector. *Quarterly Journal of Economics, 123*, 489–530.
Vivarelli, M. (1995). *The economics of technology and employment: Theory and empirical evidence*. Aldershot: Elgar.
Vivarelli, M. (2004). Globalization, skills and within-country income inequality in developing countries. In E. Lee & M. Vivarelli (Eds.), *Understanding globalization, employment and poverty reduction* (pp. 211–243). New York: Palgrave Macmillan.
Vivarelli, M. (2013). Technology, employment and skills: An interpretative framework. *Eurasian Business Review, 3*, 66–89.
Vivarelli, M. (2014). Innovation, Employment, and skills in advanced and developing countries: A survey of the economic literature. *Journal of Economic Issues, 48*, 123–154.
Welch, F. (1970). Education in production. *Journal of Political Economy, 78*, 35–59.

Wood, A. (1994). *North-South trade, employment, and inequality: Changing fortunes in a skill-driven World*. Oxford: Clarendon Press.

Wood, A. (1995). How trade hurt unskilled workers. *Journal of Economic Perspectives, 9*, 57–80.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.

Yeaple, S. R. (2005). A simple model of firm heterogeneity, international trade, and wages. *Journal of International Economics, 65*, 1–20.