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QUANTILE ESTIMATES FOR SOCIAL RETURNS TO EDUCATION IN TURKEY: 2006–2009*

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Augmenting a Mincerian earnings function with regional data we estimate both private and external returns to education in Turkey using Instrumental Variables, Ordinary Least Squares, Quantile Regression and Instrumental Variables Quantile Regression methods. Our results indicate a median external return between 1.5% and 2.3% for 2006–2009. There is some evidence supporting the skill-biased technical change hypothesis. External returns are uniformly higher for women. We point out some policy implications.

Keywords: Human capital; externalities; returns to education; instrumental quantile regression; growth.

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1. Introduction

In contrast to traditional growth theory where the source of growth, technical change, is exogenous, new growth theory endogenizes the source(s) involved. It posits that knowledge augmented accumulation of productive factors obviates diminishing returns thereby enabling sustained output increases. This allows room for policy intervention since increased investment in human capital would accelerate growth. Acemoglu (2009) provides a thorough treatment. Endogenous growth theorists differ in the precise mechanisms connecting knowledge to growth, but external benefits to

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education-knowledge spillovers — is the common theme. For Lucas (1988) such externalities constitute the foundation of economic development.

Early empirical work on external returns has relied on cross-country growth regressions and macroeconomic time series data (Barro 1997). These studies have been criticized on grounds of data and identification problems (e.g. Krueger and Lindahl 2001). A more recent body of literature investigates these issues at a more disaggregated level. The common approach is to estimate education's external benefits by augmenting an individual earnings model with aggregate measures of schooling. One strand pioneered by Winter-Ebmer (1994) focuses on spillovers occurring within industry sectors (Sakellariou 2001, Sakellariou and Maysami 2004, Kirby and Riley 2008). Starting with Rauch (1993), the other strand assesses knowledge spillovers occurring within sub-national geographic jurisdictions (e.g. Acemoglu and Angrist 2001, Moretti 2004, Filiztekin 2011a).

Previous papers studying external effects have all used ordinary least squares (OLS) based methods. The coefficient for such effects (if positive and significant) is an average pertaining to the whole wage distribution. It does not provide specific information about the impact of external effects for a worker, say, at the 10th or 90th percentiles of the wage distribution. This is a direct outcome of least squares estimation. It is also an important shortcoming when the conditional distribution of the dependent variable is skewed or fat-tailed and thus the median instead of the average is the better measure of central tendency. For such data, we can resort to quantile regression (QR) to get a fuller description and characterize the *entire* conditional distribution of wages. We contribute to this growing literature by presenting quantile estimates on external returns to regional level schooling in Turkey. Since wage data tend to be skewed and fat-tailed, we use the QR method based on least absolute *deviations* — rather than least *squares*. We estimate the education-earnings nexus at different points of the wage distribution — rather than only at the *mean* which allows for a richer interpretation.

With the emergence of endogenous growth theory there is some consensus that spillover effects of human capital and learning from others may benefit individual workers and increase their productivity. If this is the case regions with more human capital would display higher labor productivity and thus have higher wages. To estimate this effect we measure regional human capital by the share of college graduates in a region's workforce. As the best available safeguard against endogeneity, we use two years lagged values of college share. It may well be possible that not every worker gets the same benefit from these external effects due to the accumulation of skills in her region. If the external effects associated with human capital (or more generally, technological improvements) are biased towards more skilled and/or educated workers we expect the gains for these workers to be higher. This is the case we call "skill-biased technical change" (SBTC). If it is valid, external effects and/or technological improvements are expected to increase wage inequality. Using the share of college educated workers as human capital proxy in each region, we

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examine these two theoretical predictions for Turkey by performing quantile and OLS regressions.

To test the first prediction regarding the presence of external effects we use four cross-sections of Household Labor Force Surveys (HLS) between 2006 and 2009, and provide evidence on the existence of external returns to education. Our instrumental variable quantile regression (IVQR) median estimate indicates a 1% point increase in the ratio of college educated workers in a region raises the typical worker's wages by about 1.8% (2.3% females, 1.7% males). For comparison the corresponding IVQR private returns are almost thrice larger: 5.5%, 5.1%, 5.2% for all, females and males respectively. As expected the comparable IVOLS estimates are, in every instance, slightly higher: by about 1.2% for private and one fifth of 1% for external returns. Given concerns about the identification of external returns in cross-section data such as ours, we also discuss the likelihood of endogeneity problems due to sample selection and omitted variables.

The QR methodology allows us to test the second prediction about SBTC, i.e. how technological improvements and/or external effects affect wage inequality. There is an expanding literature claiming that increasing wage inequality can be explained by returns to education differing across skill levels (e.g. Lemieux 2006a). Supporting evidence is reported for the US, European as well as Latin American and East Asian wage distributions since the 1990s (e.g. Patrinos *et al.* 2009, Autor *et al.* 2008, Acemoglu 2002, Martins and Pereira 2004). We contribute to this literature by providing evidence pertaining to private and external returns to education. Our quantile estimates show, during any given year, that private returns to schooling are more spread out at higher educational levels — implying greater wage inequality as educational achievement rises. In addition this Q90–Q10 spread tends to increase over time, meaning for each educational stratum within group wage inequality grows from one year to the next. Although the length of our sample (four years) is too short for such an increase to be informative by itself, in conjunction with similar findings for other countries, it becomes, in our view, worth mentioning.

Our paper is organized as follows. In Sec. 2, we present briefly the theoretical background of our econometric model and describe our identification strategy. In Sec. 3, we present our data and estimation methods. Section 4 presents our results along with some discussion. Section 5 concludes.

2. Modeling and Identification

2.1. *Human capital externalities*

One can divide the literature on human capital externalities into two major groups: cross-country studies (e.g. Benhabib and Spiegel 1994, Vandenbussche *et al.* 2006) versus within country studies involving only one country. This second group has several sub-groups as well. Some papers focus on human capital externalities occurring

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within regions (e.g. Rauch 1993, Moretti 2004) while some others study externalities occurring within sectors or industries (e.g. Kirby and Riley 2008). Rauch (1993) is the first paper estimating human capital externalities using differences in regional mean schooling years. He interprets regional human capital as a local public good as in Roback (1982). In this setup, labor's marginal product includes an external return element due to average years of schooling in the region. Moretti (2004) and Acemoglu and Angrist (2001) are other well-known papers estimating human capital externalities in USA adopting the regional approach initiated by Rauch (1993). The underlying theoretical framework for local human capital externalities is discussed in detail by Moretti (2004) and Acemoglu and Angrist (2001). All these regional approach studies are based on the seminal work of Lucas (1988), where a region's aggregate human capital is also a productive factor. Lucas distinguishes explicitly between the effect of an individual's own human capital on her/his own productivity (internal or private effect) and the effect of average level of local skill or human capital (external effect) on that same productivity. Lucas argues that the natural scope for such external effects should be determined by ways various groups interact and learn from each other. He believes the environment shaping these social interactions is not as big as the national economy, but surely larger than family and firm. Lucas proposes cities as the natural setting for external effects. This viewpoint opened the door to the subsequent literature based on regional data (Rauch 1993, Acemoglu and Angrist 2001, Moretti 2004, Filiztekin 2011a).

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Following the above discussion of literature on local human capital externalities, our model assumes that the natural logarithm of individual wage (w_{ijt}) depends on observed individual characteristics (indexed by i), regional factors (indexed by j) and time-varying factors (indexed by t) as well as unobserved heterogeneity. Special attention is paid to the coefficients of individual human capital and regional human capital:

$$w_{ijt} = \beta_{0t} + \beta_t X_{it} + \lambda_t R_{jt} + \gamma_t D_j + \alpha_t H_{jt} + u_{ijt}. \tag{1}$$

Subscripts i and j track individuals and the 26 NUTS[a] regions comprising Turkey. X holds all individual and workplace attributes including completed years of schooling, experience, experience squared tenure, tenure squared, gender, workplace size, sectoral dummies, and social security status.[b] H is regional human capital proxied by NUTS2-level college share in ***total***-namely private plus public- employment, R stands for NUTS2-level unemployment rates by education level,[c] NUTS2-level log trade volume per capita as an openness indicator and finally D represents NUTS1-level region dummies and a dummy for urban residence (population over 20,000). We also discuss the implications for each gender separately.

[a]NUTS stands for Nomenclature of Territorial Units for Statistics.

[b]The extent of informality in Turkey is considerable. Informal workers lack social protection which is reflected in their wages. See Davutyan (2008).

[c]We have three strata: less than HS, HS, college and above.

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2.2. *Identification*

When utilizing OLS, our main identification strategy is to compare the wages of otherwise similar workers who live in regions with different human capital levels (college share). OLS estimation assumes the error term is uncorrelated with regional human capital, i.e. $\mathrm{Cov}(H_{jt}, u_{ijt}) = 0$. The presence of regional external effects would be reflected in a positive and significant coefficient for H. However, the possibility of omitted variable bias ($\mathrm{Cov}(H_{jt}, u_{ijt}) \neq 0$) has to be addressed. Wages may be higher in some regions due to unobservable region-specific characteristics or unobservable ability. Both individual and regional unobserved factors may be correlated with the college share so that the observed positive correlation between average wages and college share in a region may not show a causal link from human capital to wages, but reflect such unobservable characteristics. We rely on instrumental variables (IV) strategy for the omitted variable bias. Instrument reliability is hotly debated. This is due to the impossibility of demonstrating independence between the instrument and unobservable factors. Given the absence of commonly agreed upon instruments and following Vandenbussche *et al.* (2006), we use the two-years lag of the regional college share (H_{jt-2}) as an instrument for the current regional college share (H_{jt}). We expect a positive correlation between H_{jt-2} and H_{jt} so that $\mathrm{Cov}(H_{jt-2}, H_{jt}) > 0$ since it is not likely for college share to vary randomly in a given region in such a short time period. Admittedly, this is not an ideal instrument. The factors that lead to a correlation between (H_{jt}, u_{ijt}) may still be operative after lagging. Although weaker than the contemporaneous one, H_{jt-2} may still be correlated with the error term in a given year. However given the constraints imposed by data availability, this is the best we can do.

Table 1 presents summary information about regional unemployment rates by educational status in the 26 NUTS2 regions over the sample period. The high unemployment among HS graduates and the strong correlation between the unemployment rates of the two less-than-college groups are noteworthy. As expected, the smallest correlation occurs between college and less-than-HS graduates. This table clearly shows the need to take into account imperfect substitutability between workers from different educational strata. At least part of the observed changes in average wages may be due to a change in labor force composition in the region. As stressed by Moretti (2004), the external return to education may be decomposed into two separate effects: the standard imperfect substitution effect associated with

Table 1. Regional unemployment by education.

	Summary statistics				Correlation coefficients		
	Mean (%)	SD (%)	Min (%)	Max (%)	Less than HS	HS	College
Less than HS	10.3	4.6	3	20.9	1		
HS	14.1	3.8	7.3	26.6	0.645	1	
College	10.2	3.3	3.7	20.9	0.369	0.542	1

changes in labor force composition and the spillover effects underlined by endogenous growth models. A standard model with imperfect substitution among workers with different education levels is able to explain a positive correlation between college share and average wages even without any spillover effect under certain conditions.[d] Thus, a positive correlation between college share and average wages does not prove the existence of spillover effects. In order to distinguish between external effects and such compositional effects, we utilize two data sets: full and restricted versions. The restricted version keeps out college graduates whereas the full one keeps them in. This distinction allows us to treat the imperfect substitutability between workers from different educational levels and eventually identify spillover effects associated with college graduate workers. This is achieved by comparing the estimated external effects across education strata (two data sets). The effect of an increase in college share is to raise the wages of low education workers because both spillover and imperfect substitution have a positive impact. But, in the case of college graduates, substitution will have a negative effect on their wages while spillover has a positive one. The net outcome depends on the size of the spillover.

Further, to minimize unobserved regional heterogeneity we use available regional information (unemployment rate for each educational stratum, and per capita openness to foreign trade index). Figure 1 shows the variation of regional unemployment by educational stratum during our sample period. This allows us to deal with labor demand shocks that are potentially correlated with college share. By controlling for the unemployment rate at the regional level we strip out an important source of heterogeneity: regional labor demand effects on wages. Since the

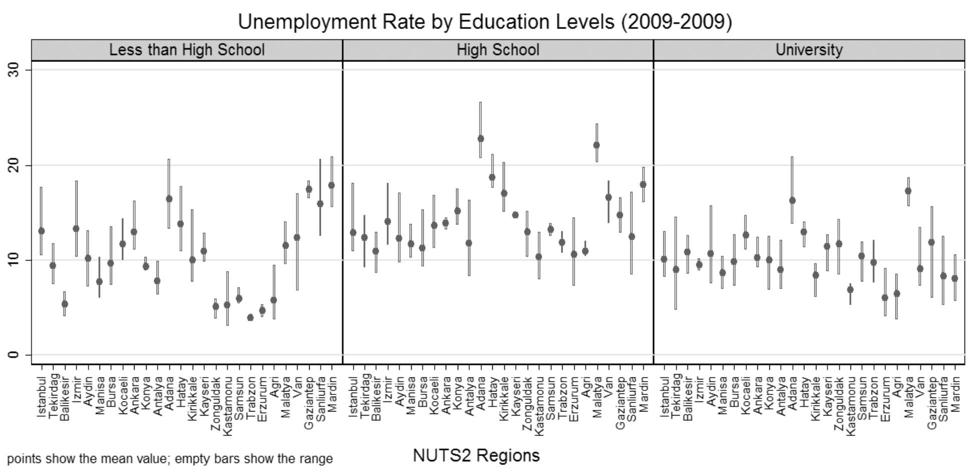

Fig. 1. Unemployment rates by NUTS2 regions.

[d]These conditions are about the share of college graduate workers and their income share in the total output. See Moretti (2004, Sec. 2) for details.

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unemployment rate varies on a regional as well as educational stratum basis, we think it can capture the impact of unemployment on wages. Per capita openness to foreign trade index is likely to capture the wage impact of technological sophistication, and at least to some extent, general attractiveness of regions.

3. Data and Estimation

We used the updated release of HLS (2004–2009) reweighted according to the census of 2008–2009. The data set consists of observations on individuals from the 26 statistical regions comprising Turkey.[e] Log-hourly real wages are calculated as follows. First, we divide nominal monthly wages by 4.3 to get weekly wages. Division by weekly hours of work converts weekly wages into hourly ones. In their turn hourly wages are divided by a regional consumer price index to derive the real hourly wage rates, expressed in 2004 prices. The regional consumer price index is obtained from TurkStat.[f] We measure individual human capital by completed years of schooling. HLS reports education information at seven levels: illiterate, literate but not graduate of any school, junior primary school graduate, primary school graduate, high school (HS) graduate, vocational high school (VHS) graduate and college and plus. A peculiarity of Turkish HLS data — age is grouped at five-year intervals — impairs our experience measure slightly since we cannot distinguish between, say, 40 and 44 years old individuals. To compute experience we assumed schooling starts at age six and assigned expected years of schooling for each level of education.[g] We approximate a region's average human capital, by its college share in employment. Our control variables are: worker experience and its square, four dummies for marital status, length of service in current job and its square, a dummy for urban residence (population over 20,000), a dummy indicating social security status and six indicators of workplace size. Nine sectoral dummies are: agriculture, construction, finance, manufacture, mining, social services, utilities, trade, and transport. Log unemployment rate (defined at the NUTS2 level) is computed for each educational stratum: less-than-HS, HS, college and above. Openness is measured as the logarithm of regional import plus export per capita (1.000$). Finally, our data considers only *private sector* wage earners above 15 years-old, who have positive wages and positive

[e] *Source*: TurkStat. Turkey is divided into 12 NUTS1/26 NUTS2 regions.

[f] By using regional consumer price index for all workers within a region, we implicitly assume that every worker within a region face the same vector of prices. This is an approximation which is not true in real life. To the extent that regions differ with respect to skill composition of workers, the measured regional price will be less representative and "real" wage will contain a measurement error.

[g] To calculate potential experience we use the standard "midpoint of age interval — years of schooling — 6" formula. Potential experience computed by the formula above assigns very high values to workers with low levels of education. Since potential experience is assumed to be a proxy for "on-the-job training", the standard formula probably implies too much training for low educated workers given that not we do not have the information on the age of having the first job. This is especially important for women in Turkish case, since they work less than men on average and they are likley to get their first job relatively late in comparison with men. We follow the standard approach to comply with the litertaure. We thank anonymous referee for raising this issue.

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Table 2. Public employment share.

	PES in paid jobs (total)	Less than HS		HS		College	
		Share in paid jobs	PES in paid jobs	Share in paid jobs	PES in paid jobs	Share in paid jobs	PES in paid jobs
2006	0.237	0.537	0.105	0.273	0.263	0.190	0.573
2007	0.224	0.527	0.095	0.275	0.234	0.198	0.549
2008	0.212	0.515	0.088	0.274	0.208	0.211	0.522
2009	0.213	0.506	0.082	0.267	0.196	0.227	0.524

Note: PES: Public employment share.

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working hours. The reason we focus on private sector workers is that the wage determination in the private sector is more likely to be based on performance, thus market-oriented, compared to public sector employment.

Table 2 provides summary information on the public/private dichotomy among employed wage and salary earners according to educational status across our sample period. Clearly, the public sector employs more than half of college graduates in paid jobs.

In addition to OLS, we use QR since it allows for a richer interpretation and is more in tune with the particularities of our data set. For instance, LS regression focuses on the mean. Thus, it only provides a partial view of the relationship between the explanatory and the dependent variables. QR gives a more complete picture since it provides information about the linkage between the outcome variable (in our case wages) and the covariates at different points of the conditional wage distribution.

Other advantages of quantile or least absolute deviations regression include robustness to outliers and avoidance of distributional assumptions regarding regression errors. As pointed out by Cameron and Trivedi (2009), these features make QR especially suitable for heteroskedastic data. We performed the available tests (Breusch–Pagan/Cook–Weisberg) to check for heteroskedasticity. The null hypothesis of constant variance was decisively rejected in every case.

The standard quantile method, just like OLS, assumes all covariates are exogenous. But if as is the case here, regional human capital H is endogenous, then using conventional QR to infer its impact over the entire wage distribution will yield biased results. Chernozhukov and Hansen (2006, 2008) develop an IVQR model that eliminates this source of bias.

Chernozhukov and Hansen (2008) provide two detailed examples of how their method works in practice; Hansen's website contains the required MATLAB programs. The present study was implemented both on STATA 10 and MATLAB. The two routines gave essentially the same results. Convergence was achieved with some difficulty in every case. However under STATA 10, the estimation of the variance-covariance matrix required the use of bootstrap methods, which increased running time very substantially. Other studies using this same approach include Eren (2009) and Galvao and Rojas (2009).

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4. Regression Results

4.1. *OLS and QR estimates*

Tables 3 and 4 exhibit our mean/median estimates of returns to education. We measure each worker's individual human capital by her/his years of schooling (Edu). Thus in each regression **Edu**'s coefficient is our measure of **private** or **internal** return to education. The share of college graduates in each region's workforce (College) is our proxy for the regional human capital stock. Therefore, **College**'s coefficient measures the **external** return to education.[h] We present our findings for both sexes as well as for each gender separately.

Table 3. OLS versus QR.

	External returns (College)			Private returns (Edu)		
	All	Female	Male	ALL	Female	Male
2006 Mean/OLS	0.018	0.027	0.016	0.063	0.057	0.064
2006 Median/QR	0.016	0.023	0.014	0.051	0.048	0.051
2007 Mean/OLS	0.017	0.028	0.015	0.065	0.061	0.064
2007 Median/QR	0.015	0.022	0.014	0.055	0.051	0.053
2008 Mean/OLS	0.019	0.022	0.019	0.068	0.067	0.067
2008 Median/QR	0.017	0.018	0.018	0.056	0.054	0.055
2009 Mean/OLS	0.017	0.020	0.016	0.063	0.062	0.062
2009 Median/QR	0.016	0.018	0.014	0.053	0.052	0.052

Note: Mean versus median log wages and OLS versus QR estimates of educational returns. In every case, mean/OLS estimate exceeds the median/QR estimate. All estimates have p values <0.001 (full sample).

Table 4. IVOLS versus IVQR.

	External returns (College)			Private returns (Edu)		
	All	Female	Male	ALL	Female	Male
2006 Mean/IVOLS	0.026	0.034	0.024	0.063	0.057	0.064
2006 Median/IVQR	0.023	0.029	0.021	0.050	0.047	0.050
2007 Mean/IVOLS	0.018	0.029	0.016	0.065	0.061	0.064
2007 Median/IVQR	0.016	0.022	0.015	0.054	0.051	0.052
2008 Mean/IVOLS	0.018	0.023	0.017	0.068	0.067	0.067
2008 Median/IVQR	0.016	0.020	0.016	0.056	0.052	0.054
2009 Mean/IVOLS	0.018	0.023	0.017	0.063	0.062	0.062
2009 Median/IVQR	0.017	0.020	0.016	0.053	0.052	0.051

Note: Mean versus median log wages and instrumental variable (IV) OLS versus QR estimates of educational returns. In every case, mean/OLS estimate exceeds the median/QR estimate. All estimates have p values <0.001 (full sample).

[h]In terms of Eq. (1) of Sec. 2, College is H.

We would like to point out, as expected, our median (QR, IVQR) estimates are consistently below the corresponding mean (OLS, IVOLS) estimates. This holds for all our variables.[i] Full set of results are available upon request from the authors. All coefficients have the expected signs.

Focusing on returns to education estimates, Table 3 compares the OLS estimates with the corresponding QR or median ($Q = 0.5$) estimates while Table 4 does the same for IVOLS and IVQR estimates. In each case, the median estimates of educational returns are less than the corresponding mean estimates. For instance private return estimates obtained by IV and OLS exceed the more robust median estimates ($Q = 0.5$) during each year. The average differences equal 1.1% and (1.15%) respectively. For external returns, the OLS estimates are larger than median estimates (QR) by about 0.2%. Comparable differences occur when we look at each gender separately. This is a consequence of the skewed and leptokurtic nature of our wage distribution and thus justifies the use of quantile methods. As a result our discussion will mainly focus on our IVQR estimates.

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4.2. *IVOLS and IVQR estimates*

In view of these findings we conclude the median private return to education does not vary much by gender and is about 5.3%, as indicated by the Edu ALL column of Table 4. During the four years covered in our sample, private returns vary within a narrow range of 5% to 5.6%. On the other hand, the median external return to education is smaller but of substantial magnitude. It varies between 1.6% and 2.3% during our sample period. See the corresponding entries in Table 4 for the college ALL columns and IVQR rows.

We note that Strawinski (2009) using 1994–2001 data for 14 European countries[j] reports IVOLS estimates ranging between 6% to 10% for private returns and 1% to 2% for external returns. A recent paper by Filiztekin (2011a) finds similar results for Turkey, using HLS data, 2004–2009. His estimates are between 5% to 8% for private returns, and 3% to 6% for external returns.[k] Filiztekin's IV results are slightly higher external returns (4% to 7%) while private returns are similar to OLS ones (5%). Our IVOLS results are about 6.5% and 2% for private and external returns respectively. We find this broad similarity between our findings comforting.

We now turn to analyze the returns to education information provided by the quantile estimates at the 10th, 50th, and 90th percentiles of the wage distribution.

Table 5 lists IVQR estimates of private returns of education. During every year, the private return to education is larger for workers in the upper percentiles of the wage distribution. Thus the wage distribution gets more spread out as years of

[i] We note for right skewed data the median is below the mean.

[j] They are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Portugal, Spain, Sweden, and the UK.

[k] Filiztekin's (2011a) results are based on pooled OLS and IV regressions and his proxy for regional human capital is average years of schooling in the region. He uses demographic variables and past levels of schooling in the region as instruments.

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Table 5. Private returns.

	All			Female			Male		
	$Q = 0.1$	$Q = 0.5$	$Q = 0.9$	$Q = 0.1$	$Q = 0.5$	$Q = 0.9$	$Q = 0.1$	$Q = 0.5$	$Q = 0.9$
2006	0.041	0.050	0.081	0.041	0.047	0.072	0.038	0.050	0.083
2007	0.040	0.054	0.082	0.039	0.051	0.086	0.039	0.052	0.085
2008	0.043	0.056	0.089	0.045	0.052	0.092	0.040	0.054	0.088
2009	0.042	0.053	0.082	0.045	0.052	0.077	0.039	0.051	0.082

Note: All estimates have p values < 0.001 (full sample).

schooling increase. This pattern holds for the whole data set as well as female and male workers separately. For ordinary quantile estimates — not reported for brevity — F-tests for the equality of these coefficients were soundly rejected. Intuitively this pattern namely Q90 > Q50 > Q10 — corresponds to heteroskedasticity under OLS and implies wage inequality is larger among, say, college graduates as compared to primary school graduates. In other words the case of Q10 = Q50 = Q90 corresponds to homoskedasticity under OLS and means wage inequality is the same among individuals at different educational levels (Angrist and Pischke 2009, p. 273).

We note that excepting 2009, the gap between Q90 and Q10 estimates tends to increase over time. It means for each educational stratum, within group wage inequality is growing across years. This points to skill biased technical change, an issue we'll deal with subsequently.[1]

Table 6 lists our IVQR estimates for external returns to education. Unlike private returns, there is no pattern of increased earnings due to externality when moving up the wage distribution for a given college share level. On the contrary and focusing on

Table 6. Exteral returns.

	All			Female			Male		
	$Q = 0.1$	$Q = 0.5$	$Q = 0.9$	$Q = 0.1$	$Q = 0.5$	$Q = 0.9$	$Q = 0.1$	$Q = 0.5$	$Q = 0.9$
2006	0.026	0.023	0.021	***0.051***	0.029	0.035	0.023	0.021	0.018
2007	0.019	0.016	0.016	0.035	0.022	0.025	0.017	0.015	0.016
2008	0.020	0.016	0.015	0.024	0.020	0.020	0.018	0.016	0.016
2009	0.017	0.017	0.019	0.024	0.020	0.020	0.016	0.016	0.018

Note: All estimates have p values < 0.001, except bold-italicized ones indicating insignificance (full sample).

[1]There may, certainly, be other explanations compatible with this finding. For instance, Card and DiNardo (2002) invoke instutional changes such as share of unionization and minimum wages to explain the rise in wage inequality in USA. However, we present another piece of supporting evidence: college premium has an upward trend between 2004–2010.

"**ALL**", there is a tendency for such externalities to fall across quantiles during each year, with the exception of 2009.

External returns for women are considerably above those for men. This pattern holds for each quantile level and for every year. For instance the median external return for women is about half as much larger than the corresponding return for men during 2007—2.2% versus 1.5%. For other years the differential is somewhat smaller, between 2% versus 1.6% and 2.9% versus 2.1%. Since we lack a joint covariance matrix, a formal significance test could not be performed. However, keeping in mind the miniscule size of the standard errors involved — about 0.001 — the extent of the difference in favor of women is noteworthy.

One can think of at least two complementary explanations for this phenomenon. Turkish women being relative newcomers to the labor market may have a greater zeal to learn, perhaps as a compensatory mechanism. Or social filtering may be at work whereby only more capable women are able to join the workforce. Lazear (1998, pp. 93, 94) contains an intuitively appealing analytic illustration of this point. Noting that we lack an individual capability variable, this explanation is consistent with an "ability bias" interpretation. Second, men might display a greater willingness to engage in informationally meaningful interactions with female — as compared with male-colleagues. Enterprise level data could shed more light on this point. However the policy implication of this finding is clear. Except for the 9th decile — covering relatively few workers and a single year — 2009 — social i.e. private plus external returns to education are higher for women. This finding points out to an additional reason towards encouraging female labor force participation. It can also have implications for promotion and other organizational practices within firms.

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4.3. *Separate estimates for non-college graduates*

The results presented in Tables 5 and 6 rely on samples that include college graduates in private employment. Since we measure a region's social capital by the share of college graduates in its workforce, the external returns we presented thus far combine "within college graduates" spillovers with "trickle down" spillovers to lower educational strata. In order to capture spillovers effects to HS graduates and below, we re-estimated our models excluding college graduates from our samples. We present our full IVQR educational return estimates for both types of samples in Tables 7(a) and 7(b).

Comparing *full* versus restricted sample results, we see in every instance that private returns are lower for the restricted group (see Table 7(a)). This reflects the large college premium found by other researchers studying Turkish and international data.[m] The magnitude of this difference increases as we move up the wage curve. It is

[m] There is an emerging literature on nonlinear returns to education. It seems that returns are increasing in years of schooling. See Tansel and Bircan (2011) and Filiztekin (2011b) for the Turkish case, Psacharopoulos and Patrinos (2004) for an international survey and Salehi-Isfahani *et al.* (2009) for a comparative study on Turkey, Iran, and Egypt.

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Table 7. (a) Private returns, (b) external returns.

	$Q = 0.1$		$Q = 0.5$		$Q = 0.9$	
IVQR estimates	Full	Restricted	Full	Restricted	Full	Restricted
(a)						
ALL						
2006	0.041	0.028	0.050	0.032	0.081	0.047
2007	0.040	0.028	0.054	0.030	0.082	0.046
2008	0.043	0.027	0.056	0.032	0.089	0.048
2009	0.042	0.029	0.053	0.031	0.082	0.044
Female						
2006	0.041	0.025	0.047	0.024	0.072	0.036
2007	0.039	0.021	0.051	0.022	0.086	0.040
2008	0.045	0.024	0.052	0.026	0.092	0.043
2009	0.045	0.026	0.052	0.025	0.077	0.037
Male						
2006	0.038	0.028	0.050	0.032	0.083	0.049
2007	0.039	0.029	0.052	0.029	0.085	0.046
2008	0.040	0.027	0.054	0.032	0.088	0.048
2009	0.039	0.028	0.051	0.032	0.082	0.044
(b)						
All						
2006	0.026	0.032	0.023	0.027	0.021	0.031
2007	0.019	0.021	0.016	0.020	0.016	0.023
2008	0.020	0.019	0.016	0.014	0.015	0.014
2009	0.017	0.015	0.017	0.012	0.019	0.010
Female						
2006	***0.051***	***0.064***	0.029	0.037	0.035	0.063
2007	0.035	0.047	0.022	0.027	0.025	0.040
2008	0.024	0.033	0.020	0.016	0.020	0.022
2009	0.024	0.026	0.020	0.014	0.020	0.020
Male						
2006	0.023	0.029	0.021	0.025	0.018	0.026
2007	0.017	0.019	0.015	0.018	0.016	0.019
2008	0.018	0.016	0.016	0.014	0.016	0.013
2009	0.016	0.014	0.016	0.011	0.018	0.008

Note: All estimates have p values < 0.001, except bold-italicized ones indicating insignificance.

about 1% to 2% at the first decile ($Q = 0.1$), 2% to 3% around the median and 2.5% to 4% at the ninth decile $Q = 0.9$.

When we compare *external returns* across the full versus restricted samples (see Table 7(b)) we note several important points. First, external returns are higher for women in both samples and across years. The already noted external return excedent in favor of females persists for every year and quantile level. For instance, in the restricted sample, the median external return for women during 2006 is 3.7%, that for men is 2.5%. Bearing in mind labor force participation among lesser educated women is lower, in addition to learning spillovers, "ability bias" could also lead to such an outcome if individual unobserved ability is correlated with regional college share.[n]

[n]We will discuss this concern in Sec. 4.4.

Table 8. College share in employment.[o]

2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
8.8	9.1	10.0	11.0	11.3	12.4	13.2	13.9	14.8	15.6	16.0

Second, external returns are falling across years in the restricted sample. The speed of this fall is larger (i) for women at any given skill i.e. quantile-level and (ii) for both men and women, at higher skill levels, namely larger for $Q = 0.9$ compared to $Q = 0.1$. The female–male external return excedent tends to fall over the years but is still positive. For 2009, in the restricted sample, the excedent is only 0.3% (1.4% versus 1.1%, $Q = 0.5$) but considering the very small standard errors, it is still a respectable magnitude. Third, invariably for men during 2006 and 2007 external returns for the restricted sample, which excludes college graduates, are larger. Whereas the reverse holds true for 2008 and 2009 when external returns are lower for the restricted sample. For females the picture is less clear. With a few exceptions (2006 $Q = 0.1$, 2008 and 2009 $Q = 0.5$, 2009 $Q = 0.9$) external returns are always larger for the restricted sample. Fourth, in the full sample external returns are larger in 2006 for males while they are larger in 2006 and 2007 for females. External returns are almost constant in the full sample in 2008 and 2009 both for males and females.

These findings are not compatible with a standard demand and supply framework neglecting external effects. Accordingly, an increase in college share should raise the wages of less educated groups if workers with different education levels are imperfect substitutes and if there is no spillover effects associated with college share. Given that the share of college graduate workers in total employment has a secular upward trend in Turkey (see Table 8), one would expect higher increases in wages of less educated/unskilled workers through time. Nevertheless, Table 7(b) shows almost the opposite. Although the external effects in the restricted sample are high in 2006 they are falling more rapidly in the restricted sample than in the full sample during a period where college share is increasing.

A possible explanation involves SBTC namely spillover effects are biased towards more educated/skilled workers. Since the SBTC hypothesis posits technical change favors more skilled workers and thus implies that demand for high skills increases more than their supply in a given period, one explains how wages of more educated/skilled workers increase while their supply is also increasing (see, Acemoglu (2002) for a theoretical model of SBTC and Katz and Murphy (1992), Autor *et al.* (1998) and Autor *et al.* (2008) for empirical applications).[p]

Another piece of supporting evidence comes from looking at the college premium ratio for the top and bottom deciles. SBTC theories would predict an increase in this ratio over time — presumably college premium at the top decile will capture the wage

[o]Table 1 deals with wage earners in paid jobs. Whereas Table 8 (*Source*: TurkStat) gives college share in ***total*** employment, e.g. including the self employed, unpaid family workers etc. However the upward trend is discernible in both tables.

[p]Even if our results are compatible with the hypothesis, our findings do not prove it. For a deeper anaysis of the SBTC issue one needs a much longer time interval.

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Fig. 2. College premium Q90/college premium Q10.

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impact of skills that are in sync with technical change, whereas the bottom decile is not. In order to track this evolution, we re-estimated our Eq. (1) with the full set of explanatory variables, except openness (which is not available for 2010), for males and females separately by QR. The sample period extends from 2004 to 2010; we used a subsample formed by only HS and college graduates. This exercise yielded the college premiums for the top and bottom ($Q = 0.9$, $Q = 0.1$) deciles during 2004–2010. Appendix B provides the details of this estimation. The college premium ratios depicted in Fig. 2 show a clear upward trend. We suspect the typical Q90 college graduate to be an engineering major from a top notch university. In a similar vein the typical Q10 one would be a humanities major from a provincial institution. However our conjecture can not be tested with available data which does not draw such distinctions.

4.4. *Caveats and discussion*

We can decompose the error term into three components, $u_{ijt} = k_j\theta_i + \mu_j + \varepsilon_{ijt}$, so that it comprises a regional factor μ_j which is possibly correlated with regional human capital H_{jt}, an individual unobserved factor (ability, θ_i) that is rewarded differently in each region, and finally an independently and identically distributed (iid) error term, ε_{ijt}. Both individual and regional unobserved factors may be correlated with regional college share, i.e. we may have $\mathrm{Cov}(H_{jt}, \theta_i) \neq 0$, $\mathrm{Cov}(H_{jt}, \mu_j) \neq 0$. Moretti (2004) uses two separate datasets to deal with these two problems: the NLSY (panel) data for unobserved individual heterogeneity and the census data (cross-section) for the unobserved regional heterogeneity where the IV approach is used. We will discuss each issue separately.

Non-existence of NUTS2 level panel data in Turkey makes dealing with individual unobserved heterogeneity in a satisfactory manner next to impossible. Surely, individual variables (years of schooling, experience, experience squared tenure, tenure squared, gender, workplace size, sectoral dummies, and social security status) are added to control for unobserved heterogeneity. However, unobserved ability (or family background) still plays a role after controlling for such factors. If talented or capable workers move into regions with high levels of college share, then, the

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observed positive correlation between average wages and college share in a region may not show a causal link from human capital to wages, but reflect such unobservable characteristics. For instance, this would be the case if regions with an industrial structure that demands more educated workers reward unobserved ability more generously. Our estimates will be biased to the extent that Cov $(H_{jt}, \theta_{it}) \neq 0$. Unfortunately we have no direct measure for the size of this bias in Turkey. However, to get a rough idea about how unobservable individual factors are correlated with regional college share we follow two separate strategies. First, we use a self-selection test due to Borjas *et al.* (1992) and second, we repeat our analysis by excluding three mega cities (Ankara, Istanbul, Izmir).

For the self-selection test the idea is the following: given our error term decomposition, $u_{ijt} = k_j\theta_i + \mu_j + \varepsilon_{ijt}$, the unobserved factor (ability) is allowed to be rewarded differently in each region. If there is a selection bias so that high levels of unobserved ability sort in regions having higher college share, we expect k to be related with the college share in the region. And as a result we would expect a positive correlation between wage dispersion and college share in the data. Our wage dispersion measure is, following Borjas *et al.* (1992), the root mean square error of the region by year (NUTS2*year) wage regressions.[q] This is a measure for the standardized dispersion. We tested whether there is a positive and significant correlation between college share and wage dispersion. We found correlation coefficients of 0.0031, 0.0117, and 0.0039 for total, male and female sample respectively all not significant at 10% level. For the sample excluding Ankara, Istanbul, and Izmir, the corresponding coefficients are −0.0496, −0.0098, and −0.0987 for total, male and female sample respectively all negative and yet not significant at 10% level.

A second strategy to check for the self sorting of capable workers into metropolitan centers involves using a restricted sample that excludes large cities with high college share. One expects their exclusion removes (or at least mitigates) the selection bias (in case it is driven by selective migration). Figure 3 displays college shares as percentage of employment in our 26 NUTS2 regions during 2006–2009. Ankara has the largest concentration of college graduates followed by Izmir then Istanbul.[r] To test this hypothesis, we reestimate both private and external returns to schooling by excluding the regions including Ankara, Istanbul and Izmir. Tables 9(a) and 9(b) show that our OLS estimations for external returns are not dramatically different and there seems to be no regular pattern for the minor differences between the two data sets. However, private returns differ considerably across the two samples (very similar for both sexes). Private returns seem to be higher by 0.5% and 1% points in the full sample. These findings are compatible with

[q]Same set of controls is used in the wage regression except regional variables (college share, openness, unempoyment).

[r]We think Ankara's status as center of defense industries explains the preponderance of college graduates there. The defense sector has intimate ties with the military; however its workers are not government employees. Our sector and region dummies capture wage variation due to such sectoral and regional factors.

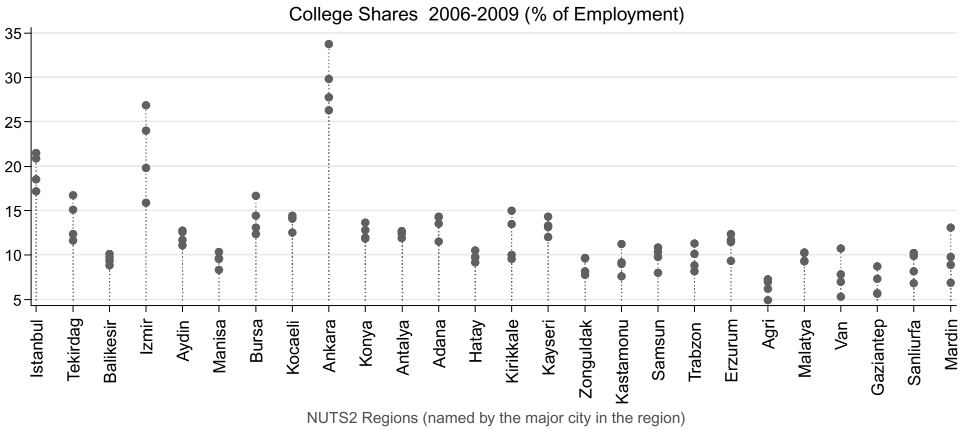

Fig. 3. College shares as % of employment.

the selection bias hypothesis, only for private returns. Consequently, even though we cannot exclude the possibility of selection bias, we are reassured the estimates for external returns are in general lower in the full sample. We do not have enough evidence to argue in favor of the reasonable intuition that the selection bias is greater for external returns in the full sample. Borjas *et al.*'s self-selection test also backs these OLS findings.

The second problem concerns regional unobserved heterogeneity, i.e. Cov$(H_{jt}, \mu_j) \neq 0$. By pooling multiple cross-sections, we can use region-fixed effects to control

Table 9. (a) Men, (b) women.

	2006	Rest. 2006	2007	Rest. 2007	2008	Rest. 2008	2009	Rest. 2009
(a)								
Years of schooling	0.064*** (0.001)	0.059*** (0.001)	0.064*** (0.001)	0.057*** (0.001)	0.067*** (0.001)	0.058*** (0.001)	0.062*** (0.001)	0.053*** (0.001)
Regional college share	0.016*** (0.001)	0.014*** (0.002)	0.015*** (0.001)	0.014*** (0.002)	0.019*** (0.001)	0.027*** (0.002)	0.016*** (0.001)	0.016*** (0.002)
Number of observations	42,737	28,796	43,367	28,934	44,858	30,184	44,729	30,588
R2	0.382	0.352	0.364	0.325	0.392	0.349	0.404	0.352
% of Excluded sample		32.60%		33.30%		32.70%		31.60%
(b)								
Years of schooling	0.057*** (0.002)	0.047*** (0.002)	0.061*** (0.002)	0.051*** (0.002)	0.067*** (0.002)	0.059*** (0.002)	0.062*** (0.002)	0.050*** (0.002)
Regional college share	0.027*** (0.003)	0.041*** (0.006)	0.028*** (0.002)	0.030*** (0.005)	0.022*** (0.002)	0.025*** (0.004)	0.020*** (0.001)	0.019*** (0.004)
Number of observations	11,742	7,169	12,016	7,232	12,692	7,607	12,622	7,675
R2	0.453	0.369	0.424	0.332	0.452	0.353	0.467	0.364
% of Excluded sample		38.90%		39.80%		40.10%		39.20%

Note: $^{***}p<0.001$, $^{**}p<0.01$, $^{*}p<0.05$; "Rest." refers to the restricted sample excluding Istanbul, Ankara, and Izmir.

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Table 10. Pooled cross sections (OLS).

	Models	m1	m2	m3	m4	m5	m6	m7
NUTS2	Regional college share	0.0035***	0.0046***	0.0052***	0.0056***	0.0039***	0.0028***	0.0033***
		(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0011)	(0.0005)	(0.0005)
	Female*regional college share							0.0077***
								(0.0004)
	Years of schooling	0.0774***	0.0624***	0.0615***	0.0605***	0.0593***	0.0366***	0.0584***
		(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0007)	(0.0004)	(0.0004)
	Female*years of schooling							0.0108***
								(0.0006)
	Adjusted R-squared	0.33	0.40	0.40	0.39	0.45	0.34	0.40
NUTS1	Regional college share	0.0151***	0.0140***	0.0131***	0.0125***	0.0159***	0.0117***	0.0114***
		(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0007)	(0.0003)	(0.0003)
	Female*regional college share							0.0073***
								(0.0004)
	Years of schooling	0.0779***	0.0623***	0.0615***	0.0605***	0.0591***	0.0366***	0.0584***
		(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0007)	(0.0004)	(0.0004)
	Female*years of schooling							0.0108***
								(0.0006)
	Adjusted R-squared	0.33	0.39	0.39	0.38	0.45	0.33	0.40
Controls	Gender dummy	Yes	Yes	Yes	Males	Females	Yes	Yes
	Sectoral effects		Yes	Yes	Yes	Yes	Yes	Yes
	Marital status dummies		Yes	Yes	Yes	Yes	Yes	Yes
	Firm size dummies		Yes	Yes	Yes	Yes	Yes	Yes
	Social security dummy		Yes	Yes	Yes	Yes	Yes	Yes
	Regional unemployment rate			Yes	Yes	Yes	Yes	Yes
	Openness			Yes	Yes	Yes	Yes	Yes
	Urban residence dummy			Yes	Yes	Yes	Yes	Yes
	Exclusion of college graduates						Yes	
	Observations	3,87,866	3,87,866	3,24,084	2,54,332	69,752	2,91,130	3,24,084

Note: Standard errors in parentheses; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; Models m3, m4, and m5 are very similar; m4 is estimated only for males whereas m5 for females.

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for the permanent regional effects that may be correlated with regional college share. Since this specification takes regional fixed effects out of the error term, the bias due to Cov $(H_{jt}, \mu_j) \neq 0$ is removed. However, there may be some time varying factors operating at the regional level that are correlated with college share which confound identification. The estimation bias will be proportional to the amount of this correlation.

Table 10 summarizes our findings with pooled cross sections. We estimate the same models using both NUTS1 and NUTS2 dummies. To avoid linear dependence we used NUTS1 dummies in estimating the independent cross sections. With pooled cross sections we are able to use NUTS2 dummies as well. We see that both private and external returns are significant and positive in all specifications. More interestingly, confirming our previous findings the interaction between female and regional college share is significant and positive (m7). Nevertheless, two points deserve to be underlined when NUTS2 dummies are used: first, the estimated coefficients for external returns are much smaller in pooled cross sections compared with independent ones. Second, with pooled data the external returns estimate is lower for women than men. Both of these differences arise from using NUTS2 instead of NUTS1 dummies. When we use NUTS1 dummies in the pooled sample, the picture becomes very similar to the independent cross sections' case: the magnitude of external returns increase, their range now goes from 0.114 to 0.159, and the estimate for external returns is higher for women than for men.

5. Conclusion

Endogenous growth theory emphasizes the role of knowledge spillovers in fostering economic growth. Given the econometric difficulties involved in quantifying such external effects using cross country data, recent work has focused on sub-national regions (e.g. Moretti 2004).

Using Household Labor Survey non-panel data for 2006–2009, covering 26 Turkish NUTS regions and each involving about 56,000 observations, we provide some mixed[s] evidence on the existence of external returns to education. Our median estimate (IVQR) indicates a 1% point increase in the ratio of college educated workers in a region, raises the "typical" worker's wages by 1.8% (2.3% females, 1.7% males). The comparable mean, namely IV, estimate is slightly larger (2.0%). However given the skewed and leptokurtic nature of our data, we believe mean estimates will tend to exagerate the typical impact, thus LAD estimation is likely to be more appropriate for such cases.

Our quantile estimates for external effects indicate knowledge spillovers in Turkey involving women are substantially larger than for men. Further research clarifying the validity of this pattern for comparable countries e.g. Balkan, Middle Eastern and Mediterranean ones, would have great practical significance.

[s]As discussed previously, since our instrument is weak, part of the wage rise may reflect "ability bias".

As another contribution, we show for each educational level, social returns (private + external) to be larger at higher echelons of the wage distribution. These findings imply as education levels increase the corresponding wage curve gets wider. The underlying reason is still debated.[t] Given Turkey's position in and integration with the world economy (its foreign trade grew from 31% of GNP in 2000 to 45% in 2008[u]), we think this phenomenon might be driven by SBTC associated with information and communication technologies and computer revolution. However, further research seems warranted since one needs a longer time interval to properly address this issue.

Appendix A. Summary Statistics

	2006		2007		2008		2009	
Independent variables	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
Gender Female = 1	0.216	0.411	0.218	0.413	0.221	0.415	0.221	0.415
Years of schooling	7.95	3.79	8.131	3.814	8.309	3.86	8.413	3.878
Potential experience	18.16	11.63	18.23	11.56	18.27	11.56	18.39	11.51
Tenure years	4.85	6.13	4.8	6.05	4.48	5.75	4.33	5.44
Social Security (sosec)	0.6	0.49	0.64	0.48	0.683	0.465	0.69	0.462
Urban	0.792	0.406	0.811	0.391	0.819	0.385	0.825	0.38
Never Married	0.332	0.471	0.324	0.468	0.313	0.464	0.312	0.463
Married	0.648	0.478	0.653	0.476	0.663	0.473	0.662	0.473
Divorced	0.014	0.118	0.017	0.128	0.018	0.131	0.02	0.141
Spouse Died	0.006	0.08	0.006	0.077	0.006	0.077	0.005	0.073
workplace Less than 10	0.447	0.497	0.432	0.495	0.407	0.491	0.418	0.493
workplace 10–24	0.121	0.326	0.116	0.32	0.12	0.325	0.121	0.327
workplace 25–49	0.139	0.346	0.157	0.364	0.166	0.372	0.162	0.368
workplace 50–249	0.181	0.385	0.189	0.391	0.192	0.393	0.194	0.396
workplace 250–499	0.049	0.217	0.048	0.213	0.055	0.227	0.049	0.215
workplace 500 and more	0.062	0.241	0.059	0.236	0.061	0.239	0.055	0.228
Nace 1 Agriculture	0.046	0.209	0.038	0.192	0.038	0.191	0.037	0.189
Nace 2 Mining and Quarrying	0.01	0.098	0.011	0.105	0.01	0.099	0.009	0.092
Nace 3 Manufacturing	0.36	0.48	0.35	0.477	0.352	0.477	0.327	0.469
Nace 4 Electricity	0.003	0.054	0.003	0.058	0.005	0.071	0.005	0.071
Nace 5 Construction	0.098	0.297	0.098	0.298	0.091	0.288	0.085	0.279
Nace 6 Wholesale and Trade	0.26	0.438	0.261	0.439	0.259	0.438	0.27	0.444
Nace 7 Transportation	0.062	0.24	0.064	0.245	0.063	0.242	0.067	0.25
Nace 8 Finance	0.068	0.251	0.077	0.267	0.087	0.281	0.105	0.307
Nace 9 Community, social service	0.095	0.293	0.096	0.295	0.096	0.295	0.095	0.293
Regional log unemployment rate by three education levels	2.302	0.372	2.291	0.346	2.375	0.303	2.618	0.362
Log trade volume per capita (1.000$)	0.589	1.483	0.791	1.417	0.96	1.413	0.64	1.334
Number of observations	54,479		55,583		57,550		57,351	

[t]See Autor *et al.* (2008) and Lemieux (2006b, 2008) for competing views.
[u]Undersecretariat for Foreign Trade. Available at http://www.dtm.gov.tr/dtmweb/

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Appendix B. QR Estimates (Q10 Versus Q90). Restricted Sample Incl. College and HS Graduates. Dep. Var.: Log Wages

	2004		2005		2006		2007		2008		2009		2010	
DV. inwage	Q10	Q90	Q10	Q90	Q10	Q90	Q10	Q90	Q10	Q90	Q10	Q90	Q10	Q90
lnwage							**Men**							
college gradute = 1	0.289	0.717	0.261	0.703	0.238	0.765	0.263	0.759	0.288	0.797	0.255	0.783	0.246	0.792
	(0.018)	(0.025)	(0.017)	(0.024)	(0.017)	(0.028)	(0.014)	(0.022)	(0.014)	(0.020)	(0.019)	(0.023)	(0.012)	(0.025)
Number of observations	10,715	10,715	12,690	12,690	13,908	13,908	14,721	14,721	15,955	15,955	16,240	16,240	17,859	17,859
							Women							
college gradute = 1	0.220	0.636	0.271	0.639	0.242	0.628	0.250	0.652	0.240	0.694	0.243	0.629	0.184	0.677
	(0.029)	(0.038)	(0.026)	(0.027)	(0.027)	(0.032)	(0.016)	(0.032)	(0.022)	(0.026)	(0.023)	(0.038)	(0.024)	(0.043)
Number of observations	3,958	3,958	4,621	4,621	5,318	5,318	5,841	5,841	6,452	6,452	6,509	6,509	6,919	6,919

Note: All estimates have p values < 0.001, except bold-italicized ones which are insignificant.

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