Brasch, T. (2016). Identifying the sector bias of technical change. Empirical Economics, 50(2), 595-621. http://doi.org/10.1007/s00181-015-0938-7

Identifying the Sector Bias of Technical Change

Thomas von Brasch

Abstract The empirical literature studying the sector bias of technical change has only focused on skill-biased technical change. In this paper, I analyse the sector bias of *both* factor-neutral and factor-biased technical change. In Norwegian data from 1972 to 2007 the empirical evidence is not clear on the impact of a sector bias of skill-biased technical change, but it points to a sector bias of factor-neutral technical change from the 1970s to the 1990s. That said, the impact of the sector bias seems to have reduced towards the latter part of the sample period. I also evaluate the cross-section model used in the literature and show the strong restrictions that must be placed on a vector equilibrium correction model to end up with the standard model. If these restrictions do not hold, the results reported in the literature may be biased. I show that the restrictions are strongly rejected, and that erroneously imposing them significantly changes the estimates of skill-biased technical change in many sectors. These results can, to some extent, be traced back to how the cross-section model ignores initial disequilibrium and imposes factors of production to be either complements or substitutes.

Keywords Econometric modeling · Technical change · Sector bias

JEL C5 · J3 · O3.

1 Introduction

In the past three decades, most OECD countries have experienced an increase in the wage premium and/or an increase in the relative unemployment rates between high- and low-skilled labour. The underlying reasons for this development are still debated (Acemoglu and Autor 2011). A growing body of research points to increased international trade, capital-skill complementarity or a shift in the production technology that favors skilled over unskilled workers.

Statistics Norway: Research Department, NO-0033 Oslo, Norway · NUPI: Department of International Economics, NO-0033 Oslo, Norway. E-mail: vonbrasch@gmail.com.

In the literature on skill-biased technical change (henceforth SBTC) there is an ongoing debate concerning the importance of a sector bias of SBTC. While the SBTC hypothesis is based on the relative profitability between factors of production, the sector bias hypothesis focuses on the relative profitability between sectors. For example, if the proportion of high-skilled labour varies across sectors, it is not clear that skill-biased technical change will lead to a higher wage premium. If technical change favours skilled labour in a sector where the proportion of skilled labour is low, this will increase the profitability of the sector where technical change takes place. Even if technical change were directed towards the high-skilled workers, this would lead to an increase in relative demand of low skilled labour and consequently a lowering of the wage premium, as technical change took place in a low-skilled labour intensive sector. In other words, the skill intensity of the sector where technical change occurs matters for the development of the wage premium. This theoretical result is well known and dates back to at least Findlay and Grubert (1959).

Econometric studies have found the sector bias hypothesis to be important in understanding the development of the wage premium. In line with the sector bias hypothesis, Haskel and Slaughter (2002) find that in a group of 10 OECD countries where the wage premia were rising (falling) during the 1970s and 80s, SBTC was generally concentrated in skill-intensive (unskill-intensive) sectors. Applying a similar econometric framework, Esposito and Stehrer (2009) also find the sector bias hypothesis to be important in explaining the rising wage premia in the Czech Republic, Hungary, and Poland during the late nineties. In contrast, Robertson (2004) finds that a weakly significant sector bias has worked in the opposite direction, as would be expected if it was to explain changes in wage inequality in Mexico during the period of trade liberalisation from 1986 to 1999.

The econometric framework typically used in the literature to identify SBTC is based on a panel version of the *growth rate econometric model* (Hendry 1995, Section 7.4), henceforth referred to as the cross-section model. This approach implicitly assumes that a number of restrictions are satisfied. For example, it is assumed that initial disequilibrium is irrelevant to the identification of structural parameters. The model also imposes factors of production to be either complements or substitutes. If these implicit restrictions do not hold, the estimates reported in the literature may be biased.

In this paper, I present a more general econometric framework. Using a vector equilibrium correction model (henceforth VEqCM), I show how to identify SBTC without imposing the strong restrictions implicitly used in the literature. To relate this framework to existing studies, I list a set of testable assumptions that must be imposed on the VEqCM in order to identify SBTC with the cross-section model. The restrictions that must be placed on the VEqCM to end up with the cross-section model are strongly rejected using Norwegian data from 1972 to 2007. Imposing them significantly changes the estimates of SBTC. This result can, to some extent, be traced back to how the cross-section model ignores initial disequilibrium and imposes the assumption that factors of production are either complements or substitutes.

The empirical literature analysing a sector bias of technical change has not, to my knowledge, analysed the impact from factor-neutral technical change or total factor productivity growth (TFP). A sector bias of TFP is present if there is a systematic relationship between TFP growth and skill intensity across sectors. From a theoretical standpoint, it should be easier to identify the sector bias of TFP than the sector bias of SBTC, since it is independent of the elasticity of substitution between the factors of production; see Stehrer (2010, p. 75). Although insignificant, the empirical evidence in this paper points to a sector bias of TFP in the 1970s, but that the impact of the sector bias gradually reduced towards the first decade in the current century.

The rest of the paper is organised as follows: Section 2 reviews the theoretical literature on the sector bias of technical change. Section 3 evaluates the empirical framework used in the literature and outlines how to identify the sector bias of both SBTC and TFP. Section 4 describes the data set used in the empirical analysis. Section 5 reports and discusses the empirical results. Section 6 concludes.

2 The sector bias of technical change

The sector bias hypothesis focuses on the relative profitability between sectors. For example, if technical change favours skilled labour in a sector where the proportion of skilled labour is low, this will increase the profitability of the sector where technical change takes place. Even if technical change were directed towards the high-skilled workers, this would lead to an increase in relative demand of low skilled labour and consequently a lowering of the wage premium, as technical change took place in a low-skilled labour intensive sector. This result, that the skill intensity of the sector where technical change occurs matters for the development of the wage premium, was the basis for the analysis by Haskel and Slaughter (2002).

The extent to which the sector bias impacts factor prices depends on the properties of the economy under consideration. Xu (2001) analysed how different forms of technical change impact relative factor prices in a two-country, two-good, two-factor Heckscher-Ohlin model. Some of the results were ambiguous. Stehrer (2010) shed light on this ambiguity. In a more detailed study, he analysed the effects of technical change on relative wages for various combinations of parameter values in an economy characterised by CES utility and production functions. Of particular importance is the elasticity of substitution in demand and in production. Since the model in Stehrer (2010) is built for a discrete number of sectors the elasticity of substitution in production can be assumed to be sector-specific. Stehrer (2010) assumes endogenous product prices both when considering a closed economy and when extending the framework to a discrete number of trading economies. Consequently, in the case of trading economies, the law of one price does not hold, since each good is considered a specific brand. Haskel and Slaughter (2002) also considers the case when product prices are endogenous, but in contrast to Stehrer (2010), the main assumption is not the specificity of brands, but rather that the country under consideration is sufficiently large in the world economy to affect product prices.

Stehrer (2010) showed that the size and the direction of sector bias technical change on relative wages depend on the size of the elasticity of substitution. When factors of production are substitutes, SBTC increases the wage premium if the innovating sector is not too skill intensive.[1] When SBTC occurs in a very skill-intensive sector, the demand for goods in the unskill-intensive sectors rises due to a dominating income effect which moreover causes a reduction in the relative wage rate. If, on the other hand, the factors of production are complements, the impact of SBTC on the wage premium becomes ambiguous (Stehrer 2010, p. 76, footnote 14.). The second case, when the elasticity of substitution in demand is high, is similar. If factors of production are substitutes but the elasticity of substitution in production is lower than the elasticity of substitution in demand, SBTC increases the wage premium for a large range of sectors, unless SBTC occurs in sectors with a very low skill level. In sum, the impact from the sector bias of SBTC depends on the skill intensities where SBTC occurs, whether factors of production are complements or substitutes, and on the elasticity of substitution in demand.

Although the empirical literature has focused on the sector bias of SBTC, Stehrer (2010) also analysed the sector bias of TFP. How TFP impacts the relative wage rate also depends on the elasticity of substitution of demand. If the elasticity of substitution of demand is lower than unity, the relative wage rate will rise if TFP occurs mostly in unskilled sectors. The rising wage premium is due to a dominating income effect which causes increased demand for all goods and in particular for goods produced with high skill intensities. On the other hand, if the elasticity of substitution of demand is greater than unity, the relative wage rate will rise if TFP occurs mostly in skilled sectors. In either case, it is the systematic relationship between TFP growth and skill intensity across sectors that give rise to the sector bias of technical change on relative wages.

3 Econometric Framework

Since Norway represents a very small open economy, and since the empirical analysis in this paper also includes services sectors where product prices typically are determined endogenously, the theoretical results from Stehrer (2010) are considered the most relevant for the econometric framework. In particular, the econometric framework takes into account both the skill intensity of sectors and, in the case of skill-biased technical change, the size of the elasticity of substitution between the factors of production. In the following, I first present the cross-section model adopted by Haskel and Slaughter (2002) to identify SBTC and then show how the vector equilibrium correction model encompasses this model. Thereafter,

[1] Note that I refer to SBTC only, i.e., skill-biased (skill-using) technical change, which is the Hicksian notion of technical change. Stehrer (2010, Section 2.2) discusses the different typologies of technical change and how they relate to the parameters in a CES production function more explicitly.

I show the index used to calculate TFP, and finally, I outline how to identify the sector bias of both SBTC and TFP.

3.1 Framework used in the literature

Haskel and Slaughter (2002) used a two-stage estimation procedure to identify the sector bias of SBTC. First they regressed the level change in the cost share of high-skilled (S) in sector i on changes in the wage premium, i.e., the ratio of the hourly wage of high-skilled (W_H) and the wage of low-skilled (W_L), and changes in capital intensity (K/Y)

$$\Delta S_i = b_1 + b_2 \Delta \ln(W_H/W_L)_i + b_3 \Delta \ln(K/Y)_i + u_i, \tag{1}$$

where K is capital and Y is real value-added output. The wage premium was modelled as the relative wage between production and non-production workers where non-production workers served as a proxy for high-skilled. The variation in the cost share that could not be explained by variation in neither the wage premium nor the capital intensity was attributed to SBTC, i.e., $(b_1 + u_i)$ was a measure of SBTC in sector i. In the second stage, the estimate of SBTC is regressed on the skill intensity

$$SBTC_i = \gamma_1 + \gamma_2 (H/L)_i + v_i, \tag{2}$$

where the skill intensity is the ratio of high- (H) to low (L) skilled workers. Haskel and Slaughter (2002) considered the coefficient γ_2 to represent the sector bias of SBTC. They state that if the sector-bias hypothesis is true, then a positive γ_2 is associated with rising skill premia and a negative γ_2 with falling skill premia (p. 1768). In the following two sections, I evaluate the suitability of this framework for analysing the sector bias hypothesis.

3.2 Identifying SBTC

Most econometric studies analysing SBTC and a potential sector bias use the translog cost function due to its flexibility and to the fact that it represents a second-order approximation of a general cost function; see for example Berman et al. (1994) and Binswanger (1974). The cost share of high-skilled labour in levels (S) is given by

$$S_{it} = b_{0,i} + b_{1,i} t + b_{2,i} \ln(W_H/W_L)_{it} + b_{3,i} \ln(K/Y)_{it}. \tag{3}$$

This framework is empirically convenient, since the cost share is a linear function of the wage premium, the capital intensity and a deterministic time trend (t).[2] A positive parameter $b_{3,i}$ indicates capital-skill

[2] Both constant returns to scale and price homogeneity have been imposed; see the appendix, Section 7.1.

complementarity. The parameter $b_{1,i}$ represents technical change. For example, if one empirically finds a significant positive value, it means that there has been an exogenous force increasing the relative demand for skilled labour and thus increasing the cost share of skilled labour. SBTC or skill using technical progress therefore occurs within the translog framework when there is a ceteris paribus deterministic increase in the cost share of high-skilled labour, i.e., $b_{1,i} > 0$. Conversely, a negative value ($b_{1,i} < 0$) implies that technical change has been biased towards unskilled labour. Note that even though this model is derived under cost minimisation, any trends in, for example, international product prices or general equilibrium effects that are not related to the wage premium, capital or value-added will empirically be interpreted as SBTC.

The parameter $b_{2,i}$ is closely related to the elasticity of substitution. As there are only two variable inputs, the expression for the elasticity of substitution between the two factors is defined by

$$\sigma_i \equiv \frac{\partial \ln(H_i/L_i)}{\partial \ln(W_{Li}/W_{Hi})} = 1 - \frac{b_{2,i}}{\hat{S}_i(1-\hat{S}_i)}, \tag{4}$$

where $\hat{S}_i$ is the predicted high-skilled cost share at some central point such as the mean.[3] Since there are only two variable factors of production, the elasticity of substitution is non-negative, i.e., an increase in $\ln(W_{Li}/W_{Hi})$ (a lowering of the wage premium) is met by either an increase in the skill ratio (H_i/L_i) or a constant skill ratio. Importantly, a positive estimate of $b_{2,i}$ implies an elasticity of substitution lower than unity, and a negative estimate of $b_{2,i}$ implies an elasticity of substitution greater than unity.

The vector equilibrium correction (VEqCM) model can be used to identify the parameters of the theoretical cost share equation (3). The point of departure is the general model

$$\text{(VEqCM)} \qquad \Delta \mathbf{x}_{i,t} = \tilde{\boldsymbol{\gamma}}_{\boldsymbol{i}} + \boldsymbol{\Gamma}_{1,i}\Delta \mathbf{x}_{i,t-1} + \cdots + \boldsymbol{\Gamma}_{k,i}\Delta \mathbf{x}_{i,t-k} + \boldsymbol{\Pi}_i \tilde{\mathbf{x}}_{i,t-1} + \boldsymbol{\epsilon}_{it},$$

where I allow for both a constant and a trend within the potential cointegrating relationships by defining the (3×1) vector $\mathbf{x}'_{it} = [S \;\; \ln(W_H/W_L) \;\; \ln(K/Y)]_{it}$ and the (5×1) vector $\tilde{\mathbf{x}}'_{it} = [\mathbf{x}'_{it} \; t \;\; 1]$. Although the model is specified with a stable deterministic trend, the methods outlined in Johansen et al. (2000) and Hungnes (2010) can be used to identify possible structural breaks. $\boldsymbol{\epsilon}_{it}$ is assumed multivariate normally distributed with covariance matrix $\boldsymbol{\Omega}$. The $(3{\times}5)$ matrix $\boldsymbol{\Pi}$ can be partitioned into $\boldsymbol{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$ where the $(3 \times r)$ matrix $\boldsymbol{\alpha}$ represents the speed of adjustment to disequilibrium, $\boldsymbol{\beta}'$ is the $(r \times 5)$ matrix of long-run coefficients and where r represents the number of cointegration relationships. If there is one cointegration relationship only ($r = 1$), the matrix $\boldsymbol{\Pi}$ can be partitioned to identify the long-run structure

[3] In contrast, several measures of the elasticity of substitution have been discussed in the literature when there are many inputs; see for example Blackorby and Russel (1989) and Thompson (1997).

in the translog model (3), that is

$$\mathbf{\Pi}_i = \boldsymbol{\alpha}_i \boldsymbol{\beta}_i' = \begin{bmatrix} \alpha_{1,i} \\ \alpha_{2,i} \\ \alpha_{3,i} \end{bmatrix} \begin{bmatrix} 1 & -b_2 & -b_3 & -b_1 & -b_0 \end{bmatrix}_i .$$

The VEqCM is somewhat different from the framework used in the literature, for example Haskel and Slaughter (2002). In particular, the VEqCM can be viewed as a more general model. In the following I list the set of testable assumptions that must be imposed on the VEqCM in order to end up with the framework used by Haskel and Slaughter (2002).

Assumption 1. *The wage premium and capital intensity are weakly exogenous, i.e.,* $\alpha_{2,i} = \alpha_{3,i} = 0$

The weak exogeneity assumption implies that it is the cost share variable alone that adjusts towards the equilibrium relationship. If true, this assumption allows for single equation modelling. More specifically, the conditional process for the cost share is then given by

$$\text{(A1)} \qquad \Delta S_{it} = \gamma_i + \omega_{1,i} \Delta \ln(W_H/W_L)_{it} + \omega_{2,i} \Delta \ln(K/Y)_{it} + \alpha_{1,i} \boldsymbol{\beta}_i' \tilde{\mathbf{x}}_{i,t-1} + \sum_{j=1}^{k} \tilde{\mathbf{\Gamma}}_{j,i} \Delta \mathbf{x}_{i,t-j} + \epsilon_{1,it},$$

where the subscript on the residual $\epsilon_{1,it}$ refers to the assumption under which it is constructed. The relationships between γ_i, $\omega_{1,i}$, $\omega_{2,i}$, $\tilde{\mathbf{\Gamma}}_{j,i}$ and $\epsilon_{1,it}$in model A1 and the parameters in the VEqCM model are shown in Johansen (1995, p. 122). If the weak exogeneity assumption is wrongly imposed, the estimate of the long-run parameter $\boldsymbol{\beta}_i$ will be inefficient (Johansen 1992).

Assumption 2. *There are no significant lags in the VEqCM, i.e.,* $\tilde{\mathbf{\Gamma}}_{j,i} = \mathbf{0} \;\; \forall \;\; i, j$

If there are no significant lags in A1, the model is reduced to the specification

$$\text{(A2)} \qquad \Delta S_{it} = \gamma_i + \omega_{1,i} \Delta \ln(W_H/W_L)_{it} + \omega_{2,i} \Delta \ln(K/Y)_{it} + \alpha_{1,i} \boldsymbol{\beta}_i' \tilde{\mathbf{x}}_{i,t-1} + \epsilon_{2,it}.$$

This model is more efficient than A1 if Assumption 2 holds, since no unnecessary coefficients are estimated. However, if Assumption 2 is wrongly imposed, the error term is serially dependant and the estimate of the long-run parameter $\boldsymbol{\beta}_i$ will be biased. Inference on skill-biased technical change is no longer valid.

Assumption 3. *There is no adjustment towards equilibrium, i.e.,* $\alpha_{1,i} = 0$.

Assumption 3 leads to the specification commonly referred to as a cross-section model

$$\text{(A3)} \qquad \Delta S_{it} = \gamma_i + \omega_{1,i} \Delta \ln(W_H/W_L)_{it} + \omega_{2,i} \Delta \ln(K/Y)_{it} + \epsilon_{3,it}.$$

In the models VEqCM, A1, and A2 the structural parameters of the translog framework have been a part of the vector $\boldsymbol{\beta}_i'$, but in Model A3 the vector $\boldsymbol{\beta}_i'$ is not included. In this model the structural parameters can be found by taking the first difference of the translog framework (3),

$$\Delta S_{it} = b_{1,i} + b_{2,i}\Delta \ln(W_H/W_L)_{it} + b_{3,i}\Delta \ln(K/Y)_{it} + \epsilon_{3,it}, \quad \text{(A3)}$$

which yield the relationships $b_{1,i} = \gamma_i$, $b_{2,i} = \omega_{1,i}$ and $b_{3,i} = \omega_{2i}$. Given that Assumptions 1-3 are all true, the OLS estimate of SBTC ($b_{1,i}$) is unbiased and efficient. However, for given time paths of $\Delta \ln(W_H/W_L)_{it}$ and $\Delta \ln(K/Y)_{it}$, the time path of ΔS_{it}, may depend on the relationship between the initial levels of the cost share (S_{0t}), the wage premium ($\ln(W_H/W_L)_{i0}$), and capital intensity ($\ln(K/Y)_{i0}$). There are no a priori grounds for assuming that such an initial disequilibrium is irrelevant. If the assumption of no equilibrium correction is false and - in particular - if there is a large deviation from equilibrium initially, estimates of SBTC will be biased.[4]

Assumption 4. *Homogeneous slope parameters across sectors, i.e., $b_{2,i} = b_2$ and $b_{3,i} = b_3$.*

The assumption that the slope parameters are homogeneous across sectors yields the *fixed effects* model

$$\Delta S_{it} = b_{1,i} + b_2\Delta \ln(W_H/W_L)_{it} + b_3\Delta \ln(K/Y)_{it} + \epsilon_{4,it}, \quad \text{(A4)}$$

In this framework, sector-specific SBTC is still identified by the sector-specific constant $b_{15,i}$. If Assumptions 2-4 are all true, the estimates of the slope parameters are more efficient than the OLS estimates of A3, since fewer parameters are estimated and information across sectors is also utilised. By denoting the estimators of SBTC in A3 and A4 by $\hat{b}^{A3}_{1,i}$ and $\hat{b}^{A4}_{1,i}$ respectively, the difference between these estimators can be decomposed into separate effects from the two explanatory variables as

$$\hat{b}^{A3}_{1,i} - \hat{b}^{A4}_{1,i} = (\hat{b}_2 - \hat{b}_{2,i})\overline{\Delta \ln(W_H/W_L)_i} + (\hat{b}_3 - \hat{b}_{3,i})\overline{\Delta \ln(K/Y)_i}. \quad (5)$$

If Assumption 4 is wrongly imposed, the estimates of the slope parameters in a given sector will be biased, and this bias leads to wrongful inference of SBTC unless the two effects precisely offset each other. Moreover, by imposing homogeneous slope parameters across sectors, one is restricting the elasticity of substitution between the factors of production to be of the same type. From equation (4) it follows that even though the elasticity of substitution can vary between sectors with a common slope parameter, $\sigma_i = 1 - \frac{b_2}{\hat{S}_i(1-\hat{S}_i)}$, the elasticity of substitution is either above or below unity depending on whether b_2 is positive or negative. Since unity marks a threshold for the elasticity of substitution in terms of how SBTC impacts the wage premium (Stehrer 2010), imposing that factors of production are *either* substitutes or complements can lead to wrongful inference about the sector bias.

Assumption 5. *No sector-specific heterogeneity, i.e., $b_{1,i} = b_1$.*

[4] See Hendry (1995, Section 7.4) for further discussion of the cross-section model.

Assumption 5 leads to a specification without sector-specific heterogeneity, i.e., where both the slope coefficients and the intercept are the same for all sectors

$$\text{(A5)} \qquad \Delta S_{it} = b_1 + b_2 \Delta \ln(W_H/W_L)_{it} + b_2 \Delta \ln(K/Y)_{it} + \epsilon_{5,it}.$$

The estimator for the slope coefficients is often referred to as a *global estimator* since it utilises both the variation within and between sectors. It is this framework Esposito and Stehrer (2009) used when identifying a sector bias in three central and eastern European transition economies. According to Esposito and Stehrer (2009), b_1 measures the cross-sector average of SBTC whereas $(b_1 + \epsilon_{5,it})$ reflects the sectoral distribution of SBTC (p. 358). But the reason why b_1 measures the cross-sector average of SBTC is due to Assumption 5 where it is explicitly stated that there is no cross-sector variation in SBTC. Defining a new variable $b_1 + \epsilon_{5,it}$ to capture cross-sectoral distribution of SBTC is inconsistent with the assumption that there is no heterogeneity in SBTC.

If one incorrectly imposes Assumption 5, there will be a double bias in the estimation of SBTC. To see this, rewrite the fixed-effects model A4 as

$$\Delta S_{it} = b_1 + b_2 \Delta \ln(W_H/W_L)_{it} + b_3 \Delta \ln(K/Y)_{it} + (b_{1,i} - b_1 + \epsilon_{4,it}),$$

where it follows from A5 that $\epsilon_{5,it} = b_{1,i} - b_1 + \epsilon_{4,it}$. The sectoral distribution of SBTC, as defined by Esposito and Stehrer (2009), is then given by $b_1 + \epsilon_{5,it} = b_{1,i} + \epsilon_{4,it}$. First, all of the random noise captured in the data that is included in the residual $\epsilon_{4,it}$ will in this model be interpreted as sector-specific SBTC. Second, unless there is no correlation between the regressors and the sector-specific means $(b_{1,i})$, the estimator for b_2, b_3 and most importantly b_1 will be biased. Consequently, the estimator for sector-specific SBTC is also biased. In other words, if one really believes that the intercepts vary across sectors, one should stick to modelling the fixed-effects equation (A4) where such heterogeneity is explicitly allowed for.

Assumption 6. *Estimating the multiperiod difference:*[5] $\Delta S_{iT} = S_{iT} - S_{i0}$

For the purpose of identifying sector-specific SBTC, Haskel and Slaughter (2002) and Robertson (2004) used the cross-sectoral model

$$\text{(A6)} \qquad \Delta S_{iT} = b_1 + b_2 \Delta \ln(W_H/W_L)_{iT} + b_3 \Delta \ln(K/Y)_{iT} + \epsilon_{6,iT}, \qquad (6)$$

where for example ΔS_{iT} represents the multiperiod difference $\Delta S_{iT} = S_{iT} - S_{i0}$. In this model, $T^{-1}(b_1 + \epsilon_{6,iT})$ is viewed as the sectoral distribution of SBTC. Identifying sectoral distribution of SBTC in this way was also done by, for example, Berman et al. (1994). However, the inconsistency of identifying

[5] Even though the multiperiod difference represents a new type of model, and not an assumption that can be tested empirically, I list it as an assumption since this framework is linked to the more general framework A4, as this section will show.

sector-specific parameters in a model where all parameters are homogeneous still applies to this model. The use of A6 in the literature is therefore probably due to lack of proper panel data and not because it is a preferred econometric model when panel data is readily available. This point becomes clearer when comparing the estimator for the slope coefficients in A4 with the estimator for the slope coefficients in A6. To this end, note that the multiperiod difference can be written

$$\Delta S_{iT} = S_{iT} - S_{i0} = (S_{iT} - S_{iT-1}) + (S_{iT-1} - S_{iT-2}) + \cdots + (S_{i1} - S_{i0}) = \sum_t \Delta S_{it}.$$

In other words, the model A6 is an equation in sector-specific means and the estimator of the slope coefficients is typically referred to as the *between estimator*. In contrast, the estimator for the slope coefficients in the fixed-effects model A4 is commonly referred to as the *within estimator*. Given that A4 is the preferred econometric model and that A6 is used due to lack of time series data, it would be favourable in terms of identification if there were a connection between the two estimators. However, there is no connection, as the two estimators are uncorrelated; see for example Arellano (2002, p.36). Even if Assumption 5 holds and there is no sector-specific heterogeneity, estimating the slope parameters with the between estimator in A6 instead of the global estimator in A5 is inefficient. The econometric model A6 should therefore not be used to identify sector-specific SBTC when panel data are available.

3.3 Identifying TFP growth

Total factor productivity growth is calculated using the Törnqvist productivity index

$$\Delta \ln TFP_{it} = \Delta \ln Y_{it} - \overline{s_{H,it}} \Delta \ln H_{it} - \overline{s_{L,it}} \Delta \ln L_{it} - \overline{s_{K,it}} \Delta \ln K_{it}, \tag{7}$$

where Y_{it} is value-added in sector i at time t, $s_{j,it}$ is the factor share of factor $j = H, L, K$ computed with regard to value-added in current prices. An overline above a variable indicates the moving average operator, in this case between two time periods, i.e., $\overline{s_{H,it}} = 1/2(s_{H,it} + s_{H,i,t-1})$. This index is exact for a Translog production function and is commonly used to identify TFP growth; see for example OECD (2001).

3.4 Identifying a sector bias of SBTC

The second stage of identifying a sector bias of SBTC is to regress the estimate of SBTC in the first stage on the level of skill intensity (2). In Stehrer (2010), it was shown that the impact of the sector bias depends on the type of substitution between high- and low-skilled labour in a sector. Since an elasticity of substitution equal to unity marks a threshold value for the sector bias, the second-stage regression is done separately in the case where factors of production are substitutes ($\sigma_i > 1$) and complements ($\sigma_i < 1$).

3.5 Identifying a sector bias of TFP

The results from Stehrer (2010) implied that there is a sector bias of TFP if there is a systematic relationship between TFP growth and skill intensity. To identify a sector bias of TFP, I apply a similar procedure as used in Haskel and Slaughter (2002) to identify the sector bias of SBTC and regress the mean growth in TFP on the skill intensity

$$\overline{\Delta \ln TFP_i} = \phi_1 + \phi_2 (H/L)_i + z_i, \tag{8}$$

where the overline represents the moving average operator $\overline{\Delta \ln TFP_i} = 1/T \sum \Delta \ln TFP_{it}$. As shown in Stehrer (2010), if the elasticity of substitution of demand is low, the relative wage rate will rise if TFP occurs mostly in unskilled sectors, which is consistent with a significant negative estimate of ϕ_2. On the other hand, if the elasticity of substitution of demand is high, the relative wage rate will rise if TFP occurs mostly in skilled sectors, which is consistent with a positive estimate of ϕ_2.

4 Data Description

In total, the dataset covers 12 private sectors over the period 1972-2007. Data on wages separated into high-skilled and low-skilled and data on employment classified by high-skilled and low-skilled are taken from the Labour Accounts classified by level of education. Low-skilled labour is defined as workers with primary, secondary and/or vocational education only, i.e., less than 13 years of schooling. Workers with 13 years of schooling or more are defined as skilled. The employment figures in the Labour Accounts classified by level of education are based on the Register of Employers and Employees (REE). All employers are obliged to report employment information to the Norwegian Labour and Welfare Administration (NAV) which administers the REE. The REE database, where each person is identified with his or her personal identification number, has been linked with information about educational levels from the Norwegian State Educational Loan Fund (Lnekassen) from 1986 onwards. Prior to 1986, register-based employment figures consistent with the National Accounts were not available. In order to extend the series prior to 1986, data from the Labour Force Survey between 1972 and 1986 are used. Details concerning the creation of employment statistics classified by level of education can be found in Skotner (1994). Wage data are retrieved from the survey-based Wage Statistics.[6] The population for the wage statistics is basically all active establishments in the Central Register of Establishments and Enterprises. All of the

[6] In 1997, Statistics Norway established a set of uniform and comprehensive wage statistics. The use of national and international standards makes the statistics accessible and comparable to other national and international statistics. Hytjan et al. (2005) and Lien et al. (2009) provide further details regarding the Wage Statistics.

largest enterprises are sampled. Among the small- and medium-sized enterprises, the sampling rates are about 40-50 and 10-20 per cent, respectively. In 2007, the Labour Accounts classified by the level of education covered about 60 per cent of all wage earners. In total, this new account system now holds information, consistent with the National Accounts at a two-digit level, concerning employment, hours worked, wages, and payroll costs across wage earners and self-employed, and educational levels.[7] Further information about the most recent Labour Accounts can be found in Gimming (2010).

Value-added and capital figures are taken from the National Accounts.[8] Capital may include objects such as buildings, oil and gas pipelines, boats, means of transport, machinery, software, valuables, oil platforms, airplanes and helicopters. The perpetual inventory method with geometric depreciation rate is used to construct capital series from observed levels of real investment,

$$K_{it+1} = (1 - \delta)K_{it} + I_{it},$$

where I_{it} represents real investment and δ represents the rate of depreciation. For example, the rate of depreciation is approximately 2 per cent for housing; 4 per cent for oil and gas pipelines; 5 per cent for trains; 10 per cent for helicopters, ships and airplanes; 20 per cent for cars, trucks, and buses; and 50 per cent for intangibles. Valuables do not depreciate. The choice of depreciation rates for capital objects in the Norwegian National Accounts corresponds to the levels chosen in Sweden, Germany, and Canada. Further details about the construction of capital levels can be found in Todsen (1997).

Table 1 shows how the wage premium, skill intensity, and cost share have developed between 1972 and 1986 and between 1987 and 2007. Between 1972 and 1986, the only sector that experienced an increase in the wage premium was Construction. In the time period 1987-2007, the Construction sector also experienced a decrease in the wage premium. In this latter time period, only the Financial intermediates sector experienced an increase in the wage premium.[9] The wage premium in this sector was the lowest of all sectors in 1987. A flexible labour market with mobility between sectors could cause the wage premium to converge across sectors. Note that the variation in wage premium decreased over the sample period in line with such convergence and that the wage of a high-skilled was roughly 1.4-1.5 that of an unskilled in most sectors in 2007.

[7] See Skoglund and Todsen (2007) for details regarding the definitions applied in the Labour Accounts. For example, wages refer to cash remuneration for services rendered, paid by the employer to the employee, while payroll costs include national insurance and pension premiums.

[8] http://statbank.ssb.no/statistikkbanken/default_fr.asp?PLanguage=1

[9] I refer to Hægeland and Kirkebøen (2007) and references therein for a detailed analysis of wage differentials across educational groups. Hægeland and Kirkebøen (2007) find an increasing wage premium during the nineties. The data used in Table 1 shows no such tendency. Note that Hægeland and Kirkebøen (2007) use a trimmed data set, i.e., only full-time workers (more than 30 hours per week) and exclude workers who were registered as unemployed or who left or started a new job during the year. They also exclude workers born outside Norway. Furthermore, they exclude workers with less than seven years of education as well as workers with particularly high or low income. In sum, they exclude up to 50 per cent of the data material within each category. In contrast, since the focus is on the macro economy, I do not exclude anything in my material. Also, since I aim for a measure of marginal cost (W), I use hourly wage costs while they analyse differences in full-time income. These differences should be taken into account when comparing Table 1 with the results from Hægeland and Kirkebøen (2007).

The lowering of the wage premium has occurred in tandem with an increase in skill intensity. This general increase in skill intensity more than offsets the lowering of the wage premium and has led to an overall increase in the cost share of high-skilled in both time periods. There are, however, variations in the development of the cost share between the two time periods. In particular, there was a surge in the cost share of high-skilled in the Oil and gas exploration sector from 0.06 in 1972 to 0.39 in 1986. This surge should be viewed in connection with the initial development of the Norwegian oil boom that began with the discovery of the Ekofisk oilfield. Production from the field started in June 1971, and several large discoveries such as Statfjord (1974), Gullfaks (1978), Oseberg (1979), and Troll (1983) were made during the following years (Ministry of Petroleum and Energy and Norwegian Petroleum Directorate 2013). Even though the increase in the cost share continued in the latter time period, the increase was modest and in line with development in other sectors, reaching a level of 0.43 in 2007. In the empirical section, I return to the particular development in the Oil and gas exploration sector.

Table 2 shows TFP growth across sectors in the time periods 1975-1986, 1987-1997, and 1998-2007. There was particularly high productivity growth between 1975 and 1986 in Energy intensive manufacturing and in Wholesale and retail trade, with an average growth of 3.57 and 4.03 per cent respectively. These two sectors experienced quite different productivity growth rates towards 2007. While productivity growth decreased to an average of 0.99 between 1998-2007 in Energy intensive manufacturing, the already high level of productivity growth between 1975-1986 in Wholesale and retail trade increased further, reaching an average of 6.72 between 1998 and 2007. From the 1990s, the Wholesale and retail trade industry has undertaken both horizontal and vertical integration. There has also been a surge in shopping malls since the late 1980s; see Rasmussen and Reidarson (2007). These developments are consistent with the efficiency gains illustrated in Table 2. There has also been an increase in productivity growth in Other private services, Domestic transportation, Electricity and Financial intermediates. Between 1998 and 2008, five sectors experienced average TFP growth higher than 3 per cent: Engineering products, Financial intermediates, Electricity, Domestic transportation and Wholesale and retail trade.

5 Econometric results

The econometric results are presented in three parts. In the first part, I discuss the estimates of SBTC based on the VEqCM and the simplified models from Assumptions 1 to 6. In the second part, the identification of a sector bias of SBTC is discussed, and in the third part, the identification of a sector bias of TFP is analysed.

5.1 Identifying SBTC

In Table 3, estimates of the cost share function (3) are reported together with the adjustment coefficients.[10] The lag structure was chosen so as to whiten the residuals, with particular focus on avoiding autocorrelation.[11]

There is wide variation in how the wage premium impacts the high-skilled cost share (b_2). In Energy intensive manufacturing, Oil and gas exploration and Other private services, an increase in the wage premium leads to a lowering of the cost share of high-skilled, indicating that these sectors are characterised by great substitutability between the high- and low-skilled labour, as shown in the last column. In contrast, the insignificant estimates in many of the other sectors could be interpreted by how price and quantity effects cancel out. When the wages of high-skilled increase, more unskilled workers are employed, but the change in employment is not large enough to significantly impact the cost share of high-skilled (ceteris paribus). An elasticity of substitution equal to unity is consistent with the Cobb-Douglas production function.

Capital is treated as a quasi-fixed factor of production. A significant positive estimate of capital intensity (b_3) implies that capital is complementary to skilled labour, that is, skilled workers are more efficient in utilising capital equipment than unskilled workers. Misc. manufacturing, Energy intensive manufacturing, Engineering products, Oil platforms and ships, Financial intermediates and Oil and gas exploration are characterised by significant complementarity towards the skilled while there is significant complementarity towards the unskilled in the Electricity sector only.

There is evidence of SBTC, i.e., a significant positive estimate of b_1, in most sectors. In Construction, Financial intermediates, Domestic transportation, Wholesale and retail trade and Other private services, the estimates of SBTC are positive but not significantly different from zero. Technical change has been particularly skill-biased in Energy intensive manufacturing and Electricity.

Table 4 shows the estimates of SBTC (b_1) in the models where Assumptions 1-6 have been imposed. This table should be analysed in conjunction with Table 5 where the imposed assumptions are empirically tested. Assumption 1 is empirically rejected in all sectors except for Consumption goods, Engineering products and Wholesale and retail trade. Imposing this restriction changes the estimate significantly in, for example, Energy intensive manufacturing and Domestic transportation. Given that Assumption 1 is already imposed, further restricting the model by imposing Assumption 2 is rejected in almost every sector.[12] Given that both Assumptions 1 and 2 have been imposed, the hypothesis that Assumption 3

[10] The results of the trace statistics used in testing for the cointegration rank can be found in the appendix; see Table 6. I assume that the cointegration rank is common across sectors, and I impose one cointegration relation in all sectors.

[11] Tests for autocorrelation are shown in the appendix; see Table 7.

[12] Given that the residuals from the VEqCM model are multivariate normal, the test for weak exogeneity of the wage premium and capital intensity (Assumption 1) is valid. However, the sequential testing procedure in Table 5 is not generally appropriate, and the test statistics should be interpreted with a grain of salt. For example, if test of Assumption 2 is rejected, as is the case in Misc. manufacturing, the consecutive test of Assumptions 3 is made with reference to a model with no empirical support. In order to reduce the magnitude of this problem, I have used robust standard errors that take both heteroskedasticity and autocorrelation into account. In the panel model, A4, I have imposed robust standard errors that

can also be imposed is rejected at the 5 per cent significance level in all sectors. Models A4, A5, and A6 are thus rejected in all sectors. The estimates of SBTC vary across models, particularly in Financial intermediates and Oil and gas exploration, where all assumptions were rejected at the 5 per cent level. Since both of these sectors experience a high level of skill intensity, this variation will impact the estimate of a sector bias.

5.2 Identifying a sector bias of SBTC

If the sector bias hypothesis is relevant, one should find a systematic relationship between the level of sector-specific technical change and skill intensity. The previous section discussed the sector-specific level of technical change and how it changed when imposing Assumptions 1-6. The purpose of Figure 1 is to illustrate how the conclusion regarding a sector bias can change when imposing Assumptions 1-6. Note that, in contrast to Haskel and Slaughter (2002) and Esposito and Stehrer (2009), which focused on manufacturing sectors only, both manufacturing and services sectors are included. Also, following Haskel and Slaughter (2002), all sectors are included irrespective of the size of the elasticity of substitution. The estimate of the parameter γ_2 from equation (2) is shown in all subfigures.

In Figure 1a, which is based on the most general VEqCM specification, there is a significant negative relationship between skill intensity and SBTC. The estimate of γ_2 is still negative when imposing Assumption 1, but it becomes insignificant. However, when also imposing Assumption 2, the insignificant negative estimate changes to an insignificant positive estimate. This change can mostly be traced back to the increased estimate of SBTC in Financial intermediates. Imposing Assumption 3 does not change the positive estimate of γ_2, but now the estimate is significantly different from zero at the 10 per cent significance level. The models used in the literature also impose Assumptions 4, 5 and 6. Imposing these assumptions in the case of Norway yields a higher estimate of γ_2. As a result, applying the framework used in the literature, which has been empirically rejected, significantly changes the conclusion regarding the sector bias.

Trying to pinpoint exactly why the estimates of γ_2 change when more assumptions are imposed can lead the discussion astray. However, the results from the Oil and gas exploration sector shed light on two general problems with the framework used in the literature. Figure 2 shows the cointegration relationship ($\boldsymbol{\beta}\tilde{\mathbf{x}}_{t-1}$) in this sector together with the cost share of high-skilled (S_t). Initially, the cost share of high-skilled is far from equilibrium, as shown by the cointegration relationship. It takes about seven years until the cointegration cost share schedule is in equilibrium. The general VEqCM specification allows for such initial disequilibrium. The rapid increase in the cost share of high-skilled in the 1970s, which occurred when the Norwegian oil boom began, is in this framework interpreted as a process of equilibrium

handle between-period correlation (cross-section clustering); see Beck and Katz (1995) and (Quantitative Micro Software 2010, p. 611).

correction. SBTC was estimated to be 3.4×10^{-3}. In contrast, in a pure difference approach, such as models A3-A6, there is no equilibrium correction. The rapid increase in the cost share of high-skilled in the 1970s will therefore be interpreted as SBTC. This explains the estimated level of SBTC in model A3 of 6.4×10^{-3}, which is significantly higher than the VEqCM estimate. To check that the initial disequilibrium is the cause of the bias, I re-estimate model A3 beginning in a year where the cost share schedule was roughly in equilibrium. It can be seen from the cointegration relationship in Figure 2 that the cost share schedule is roughly in equilibrium in 1982. Re-estimating model A3 starting in 1982 lowers the estimate of SBTC to 4.0×10^{-3}, which is not significantly different from the VEqCM estimate. Therefore, as the results from the Oil and gas exploration sector have shown, using an econometric framework that does not take initial disequilibrium into account can lead to biased estimates.

The second problem with the cross-section model is the assumed homogeneous slope parameters. In the Oil and gas exploration sector, the estimated level of SBTC was $\hat{b}_1^{A3} = 6.4 \times 10^{-3}$ in model A3 while the estimated level in model A4 was $\hat{b}_1^{A4} = 11.5 \times 10^{-3}$. Decomposing the difference between these estimates according to (5) yields

$$\begin{aligned}\hat{b}_1^{A3} - \hat{b}_1^{A4} &= (\hat{b}_2 - \hat{b}_{2,64})\overline{\Delta \ln(W_H/W_L)_{64}} + (\hat{b}_3 - \hat{b}_{3,64})\overline{\Delta \ln(K/Y)_{64}} \\ &= -5.2 \times 10^{-3} + 0.1 \times 10^{-3} = -5.1 \times 10^{-3},\end{aligned}$$

where the values $\hat{b}_2 = .0569$, $\hat{b}_{2,64} = -.4289$, $\hat{b}_3 = .0001$, $\hat{b}_{3,64} = .0045$, $\overline{\Delta \ln(W_H/W_L)_{64}} = -.0108$ and $\overline{\Delta \ln(K/Y)_{64}} = -.0290$ have been used and where 64 is the industry code for the Oil and gas exploration sector. The estimate $\hat{b}_{2,64} = -.4289$ indicates that the Oil and gas exploration sector is characterised by great substitutability between high- and low-skilled labour. Since the "average" sector in contrast is characterised by low substitutability, $\hat{b}_2 = .0569$, the error of assuming the same type of labour substitutability across sectors is significant in the Oil and gas exploration sector. As the decomposition shows, it is the impact of wrongly imposing a homogeneous effect from the wage premium that causes the increased estimate of SBTC. Moreover, if one has erroneously imposed homogeneous slope parameters in the first stage, the second stage of the estimation procedure (2) will wrongfully include all sectors, irrespective of the true size of the elasticity of substitution.

The impact of a sector bias of SBTC depends on whether a sector is characterised by elasticity of substitution in production higher or lower than unity. To identify the sector bias of SBTC, Figure 3 plots SBTC against the skill intensity separately for sectors where factors of production are complements (3a) and substitutes (3b). In neither of the two cases is the slope coefficient significantly different from zero. However, the negative relationship between SBTC and skill intensity in Figure 3b shows that SBTC has mainly occurred in sectors with a low skill intensity. This is consistent with a rising wage premium when the elasticity of substitution of demand is low, or with a decreasing wage premium if the elasticity of substitution of demand is high. The lack of a significant estimate of γ_2 should be viewed in conjunction with the sample size. As there are only six sectors in each subfigure, the empirical evidence presented provides neither clear support for a sector bias of SBTC nor clear rejection of a sector bias of SBTC.

5.3 Identifying a sector bias of TFP

Figure 4 plots the average TFP growth over the time periods 1975–1986 (4a), 1987–1997 (4b) and 1998–2007 (4c) against skill intensity evaluated in 1980, 1990, and 2000 respectively. The Oil and gas exploration sector has been excluded from the sample since increased extraction of oil and gas, which represents economic rent, ends up as TFP in the index formula (7). Further, to control for business cycles, the TFP indices have been chained and smoothed with the Hodrick-Prescott filter using a smoothing parameter $\lambda = 100$.

There is a clear shift in trend between the time periods. Between 1975 and 1997, TFP growth was highly concentrated in low-skilled sectors. This is consistent with the sector bias hypothesis, i.e., a rising relative wage rate if the elasticity of substitution in demand is low and a falling relative wage rate if the elasticity of substitution in demand is high. In the time period 1998–2007, this relationship changes. TFP growth becomes higher in high-skilled sectors and lower in low-skilled sectors. The negative relationship between TFP growth and skill intensity observed between 1975 and 1997 has disappeared. The empirical evidence points to a sector bias of TFP from the 1970s to the 1990s, but the impact of the sector bias reduced towards the latter part of the sample period.

6 Conclusion

The sector bias of technical change is a theoretical result, implying that the skill intensity of the sector where technical change occurs matters for the development of the wage premium. Identifying the importance of a sector bias is therefore crucial in understanding the development of the wage premium. The empirical literature studying a sector bias of technical change has only focused on skill-biased technical change. In this paper, I have analysed the sector bias of both factor-neutral and factor-biased technical change. In Norwegian data from 1972 to 2007, the empirical evidence is not clear on the impact of a sector bias of skill-biased technical change, but it points to a sector bias of factor-neutral technical change from the 1970s to the 1990s. That said, the impact of the sector bias seems to have gradually reduced towards the latter part of the sample period. I also evaluated the cross-section model used in the literature and showed that strong restrictions must be placed on a vector equilibrium correction model to end up with this model. If these restrictions do not hold, the results reported in the literature may be biased. I showed that the restrictions were strongly rejected, and erroneously imposing them significantly changed the estimates of skill-biased technical change in many sectors. The results from the Oil and gas exploration sector shed light on two general problems with the framework used in the literature. It was shown that what is interpreted as equilibrium correction in the VEqCM is wrongfully interpreted as SBTC in the cross-section model. Also, assuming high- and low-skilled labour to be either substitutes or complements leads to a large bias of SBTC. By using a VEqCM specification, the pitfalls of the cross-section model can be avoided.

Acknowledgements Thanks are due to Terje Skjerpen, Victoria Sparrman, Karen Helene Ulltveit-Moe, Pål Boug, Håvard Hungnes and Ådne Cappelen for useful comments. The usual disclaimer applies.

References

Acemoglu, D. and Autor, D.: 2011, Skills, Tasks and Technologies: Implications for Employment and Earnings, *Handbook of Labor Economics*, Elsevier Inc., chapter 12, pp. 1043–1171.

Arellano, M.: 2002, *Panel Data Econometrics*, Oxford University Press.

Bårdsen, G.: 1989, Estimation of long run coefficients in error correction models, *Oxford Bulletin of Economics and Statistics* **51**(2).

Beck, N. and Katz, J.: 1995, What to do (and not to do) with time-series cross-section data, *American Political Science Review* **89**(3), 634–647.

Berman, E., Bound, J. and Griliches, Z.: 1994, Changes in the demand for skilled labor within US manufacturing: Evidence from the annual survey of manufacturers, *Quarterly Journal of Economics* **109**(2), 367–397.

Binswanger, H. P.: 1974, The measurement of technical change biases with many factors of production, *American Economic Review* **64**(6), 964–976.

Blackorby, C. and Russel, R. R.: 1989, Will the real elasticity of substitution please stand up? (A comparison of the Allen/Uzawa and Morishima elasticities), *American Economic Review* **79**(4), 882–888.

Caves, D. W., Christensen, L. R. and Swanson, J. A.: 1981, Productivity Growth, Scale Economies, and Capacity Utilization in U.S. Railroads, 1955-74, *American Economic Review* **71**(5), 994–1002.

Esposito, P. and Stehrer, R.: 2009, The sector bias of skill-biased technical change and the rising skill premium in transition economies, *Empirica* **36**(3), 351–364.

Findlay, R. and Grubert, H.: 1959, Factor intensities, technological progress, and the terms of trade, *Oxford Economic Papers* **11**(1), 111–121.

Gimming, K.: 2010, Utdanningsfordelt arbeidskraftregnskap (Labour Accounts classified by level of education), Statistics Norway, Mimeo.

Greene, W. H.: 2003, *Econometric Analysis*, 5th edn, Prentice Hall.

Hægeland, T. and Kirkebøen, L. J.: 2007, Lønnsforskjeller mellom utdanningsgrupper (Income differences between educational groups), Statistics Norway, Documents (36).

Haskel, J. and Slaughter, M.: 2002, Does the sector bias of skill-biased technical change explain changing skill premia?, *European Economic Review* **46**(10), 1757–1783.

Hendry, D.: 1995, *Dynamic Econometrics*, Oxford University Press.

Hungnes, H.: 2010, Identifying Structural Breaks in Cointegrated Vector Autoregressive Models, *Oxford Bulletin of Economics and Statistics* **72**(4), 551–565.

Hytjan, L. T., Løvbak, T. and Tønder, A.: 2005, Lønnsstatistikk 2005 (Wage Statistics 2005), Statistics Norway, NOS (D 362).

Johansen, S.: 1992, Cointegration in partial systems and the efficiency of single-equation analysis, *Journal of Econometrics* **52**(3), 389–402.

Johansen, S.: 1995, *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*, Oxford University Press.

Johansen, S., Mosconi, R. and Nielsen, B.: 2000, Cointegration analysis in the presence of structural breaks in the deterministic trend, *The Econometrics Journal* **3**, 216–249.

Lien, H. H., Beyrer, S. and Lunde, H.: 2009, Quality Report on the Norwegian Structure of Earnings Survey 2006, Statistics Norway, Reports (20).

Ministry of Petroleum and Energy and Norwegian Petroleum Directorate: 2013, Facts 2013 - The Norwegian petroleum sector, Available at http://www.npd.no/en/Publications/Facts/Facts-2013/.

OECD: 2001, Measuring Productivity: Measurement of Aggregate and Industry-level Productivity Growth, OECD Manual.

Quantitative Micro Software: 2010, Eviews 7: User's Guide II, QMS, LLC, 4521 Campus Drive, 336, Irvine CA.

Rasmussen, P. G. and Reidarson, P.: 2007, *Handelstrender, kjedeutvikling og service*, Fagbokforlaget.

Robertson, R.: 2004, Relative prices and wage inequality: Evidence from Mexico, *Journal of International Economics* **64**(2), 387–409.

Skoglund, T. and Todsen, S.: 2007, Begreper og beregninger i nytt arbeidskraftsregnskap (Definitions and the computational framework in the Labour Accounts), Statistics Norway, Documents (6).

Skotner, K. R.: 1994, Sysselsetting og lønn etter utdanning i nasjonalregnskapet (Employment and wage classified by level of education in the National Accounts), Statistics Norway, Documents (10).

Stehrer, R.: 2010, The effects of factor and sector biased technical change revisited, *Economic Change and Restructuring* **43**(1), 65–94.

Thompson, H.: 1997, Substitution elasticities with many inputs, *Applied Mathematics Letters* **10**(3), 123–127.

Todsen, S.: 1997, Nasjonalregnskap: Beregning av realkapitalbeholdninger og kapitalslit (Calculating the level of capital and rate of depreciation in the National Accounts), Statistics Norway, Documents (61).

Xu, B.: 2001, Factor bias, sector bias, and the effects of technical progress on relative factor prices, *Journal of International Economics* **54**, 5–25.

7 Appendix

7.1 Translog Cost Function

Below I derive the econometric specification of the cost share and show the restrictions that follow from assuming constant returns to scale and price homogeneity. The translog cost function is given by

$$\ln C_{it} = \tilde{b}_{0,i} + \tilde{\mathbf{b}}_i' \ln(\mathbf{y}_{it}) + .5 \ \ln(\mathbf{y}_{it})' \tilde{\mathbf{B}}_i \ln(\mathbf{y}_{it}),$$

where the subscripts i and t denote sector and time respectively and $'$ is the transpose operator. The vector of right-hand-side variables ($\mathbf{y}$) include, for example the wage rate of skilled (W_H) and unskilled (W_L) labour, the level of production (Y), the volume of capital (K), and a deterministic time trend entering as an exponential function

$$\mathbf{y}_{it} = \begin{bmatrix} W_H & W_L & Y & K & e^t \end{bmatrix}'_{it}.$$

Before any restrictions are imposed on the cost function, it holds in total 21 parameters including the intercept. There are five parameters in the vector $\mathbf{b}$ where a typical element is denoted $\{b_k\}$, while there are 15 parameters in the symmetric matrix of the quadratic form $\tilde{\mathbf{B}}$ where a typical element is denoted

$\{\tilde{b}_{jk}\}$ for $j,k = 1,\ldots,5$. Expanding the expression for the translog Cost function yields

$$\begin{aligned}
\ln C_{it} &= \tilde{b}_{0,i} + \tilde{\mathbf{b}}_i' \ln(\mathbf{y}_{it}) + .5\ \ln(\mathbf{y}_{it})'\tilde{\mathbf{B}}_i \ln(\mathbf{y}_{it}) \\
&= \tilde{b}_{0,i} + \tilde{b}_{1,i}\ln W_{H,it} + \tilde{b}_{2,i}\ln W_{L,it} + \tilde{b}_{3,i}\ln Y_{it} + \tilde{b}_{4,i}\ln K_{it} + \tilde{b}_{5,i}t \\
&+ .5\tilde{b}_{11,i}(\ln W_{H,it})^2 + \tilde{b}_{12,i}\ln W_{H,it}\ln W_{L,it} + \tilde{b}_{13,i}\ln W_{H,it}\ln Y_{it} \\
&+ \tilde{b}_{14,i}\ln W_{H,it}\ln K_{it} + \tilde{b}_{15,i}(\ln W_{H,it})t + .5\tilde{b}_{22,i}(\ln W_{L,it})^2 \\
&+ \tilde{b}_{23,i}\ln W_{L,it}\ln Y_{it} + \tilde{b}_{24,i}\ln W_{L,it}\ln K_{it} + \tilde{b}_{25,i}(\ln W_{L,it})t \\
&+ .5\tilde{b}_{33,i}(\ln Y_{it})^2 + \tilde{b}_{34,i}\ln Y_{it}\ln K_{it} + \tilde{b}_{35,i}(\ln Y_{it})t + .5\tilde{b}_{44,i}(\ln K_{it})^2 \\
&+ \tilde{b}_{45,i}(\ln K_{it})t + .5\tilde{b}_{55,i}(t)^2,
\end{aligned}$$

where I have imposed the symmetry conditions $\tilde{b}_{ij} = \tilde{b}_{ji}$ for $j \neq i$. From the properties of the logarithmic function, it follows that logarithmic derivation with respect to the high-skilled wage rate yields the cost share equation of high-skilled labour

$$\begin{aligned}
\partial \ln C_{it}/\partial \ln W_{H,it} &= (\partial C_{it}/\partial W_{H,it})(W_{H,it}/C_{it}) \\
&= H_{it}W_{H,it}/C_{it} \equiv S_{it},
\end{aligned}$$

where the second equality follows from Shepard's Lemma. The cost share of high-skilled labour can thus be written

$$S_{it} = \tilde{b}_{1,i} + \tilde{b}_{11,i}\ln W_{H,it} + \tilde{b}_{12,i}\ln W_{L,it} + \tilde{b}_{13,i}\ln Y_{it} + \tilde{b}_{14,i}\ln K_{it} + \tilde{b}_{15,i}t. \tag{9}$$

Constant returns to scale (CRS) in a cost function with capital as a quasi-fixed factor of production is generally defined by (Caves et al. 1981)

$$CRS: \qquad 1 = \frac{1 - \partial \ln C_t/\partial \ln K_t}{\partial \ln C_t/\partial \ln Y_t}.$$

In terms of the translog cost function, this implies

$$1 = \frac{1 - \tilde{b}_{4,i} - \tilde{b}_{14,i}\ln W_{H,it} - \tilde{b}_{24,i}\ln W_{L,it} - \tilde{b}_{34,i}\ln Y_{it} - \tilde{b}_{44,i}\ln K_{it}}{\tilde{b}_{3,i} + \tilde{b}_{13,i}\ln W_{H,it} + \tilde{b}_{23,i}\ln W_{L,it} + \tilde{b}_{33,i}\ln Y_{it} + \tilde{b}_{43,i}\ln K_{it}},$$

which further yields the CRS restrictions

$$\tilde{b}_{3,i} + \tilde{b}_{4,i} = 1,\ \tilde{b}_{13,i} + \tilde{b}_{14,i} = 0,\ \tilde{b}_{23,i} + \tilde{b}_{24,i} = 0,\ \tilde{b}_{33,i} + \tilde{b}_{34,i} = 0,\ \tilde{b}_{43,i} + \tilde{b}_{44,i} = 0.$$

The restrictions implied by price homogeneity follow directly from the definition of price homogeneity: $C(\mu\mathbf{W}, K, Y, t) = \mu C(\mathbf{W}, K, Y, t)$. This condition ensures that the cost-minimising bundle does not change if all prices are multiplied by the same factor μ. In other words, it is only the ratio of input prices that affect the allocation of inputs. If $\ln C(\mu\mathbf{W}, K, Y, t) = \ln \mu + \ln C(\mathbf{W}, K, Y, t)$ is to hold for the translog cost function, the following restrictions must be imposed: $\tilde{b}_{1,i} + \tilde{b}_{2,i} = 1$, $\tilde{b}_{11,i} = -\tilde{b}_{12,i}$, $\tilde{b}_{13,i} = -\tilde{b}_{23,i}$, $\tilde{b}_{14,i} = -\tilde{b}_{24,i}$ and $\tilde{b}_{15,i} = -\tilde{b}_{25,i}$.

The elasticity of substitution evaluated at some central point of the cost share ($\hat{S}_i$) is given by (see for example Greene (2003, p. 368))

$$\sigma_i \equiv \frac{\partial \ln(H_i/L_i)}{\partial \ln(W_{Li}/W_{Hi})} = 1 + \frac{\tilde{b}_{12,i}}{\hat{S}_i(1-\hat{S}_i)}, \tag{10}$$

Imposing both price homogeneity ($\tilde{b}_{11,i} = -\tilde{b}_{12,i}$) and constant returns to scale ($-\tilde{b}_{13,i} = \tilde{b}_{14,i}$), and using the relationships $b_{0,i} = \tilde{b}_{1,i}$, $b_{1,i} = \tilde{b}_{15,i}$, $b_{2,i} = \tilde{b}_{11,i}$ and $b_{3,i} = \tilde{b}_{14,i}$ to the cost share equation (9) and the elasticity of substitution (10) yields the specifications used in the paper

$$\begin{aligned} S_{it} &= b_{0,i} + b_{1,i}t + b_{2,i}\ln(W_H/W_L)_{it} + b_{3,i}\ln(K/Y)_{it}, \\ \sigma_i &= 1 - \frac{b_{2,i}}{\hat{S}_i(1-\hat{S}_i)}. \end{aligned}$$

Table 1: Descriptive evidence

	Wage premium			Skill intensity			Cost share		
	1972	1986	Δ	1972	1986	Δ	1972	1986	Δ
15 Consumption goods	1.72	1.58	-0.13	0.03	0.05	0.03	0.05	0.08	0.03
25 Misc. manufacturing	1.68	1.49	-0.20	0.06	0.11	0.05	0.09	0.14	0.05
30 Energy intensive manufacturing	1.92	1.78	-0.14	0.08	0.15	0.07	0.13	0.21	0.08
45 Engineering products	1.74	1.61	-0.13	0.14	0.22	0.07	0.20	0.26	0.06
50 Oil platforms and ships	1.90	1.75	-0.15	0.10	0.17	0.07	0.16	0.23	0.07
55 Construction	1.63	1.77	0.14	0.03	0.07	0.04	0.05	0.11	0.06
63 Financial intermediates	1.32	1.31	-0.02	0.25	0.30	0.05	0.25	0.28	0.03
64 Oil and gas exploration	1.63	1.36	-0.28	0.04	0.47	0.43	0.06	0.39	0.33
71 Electricity	1.79	1.62	-0.16	0.16	0.21	0.05	0.23	0.26	0.03
74 Domestic transportation	1.79	1.63	-0.16	0.03	0.07	0.04	0.06	0.11	0.05
81 Wholesale and retail trade	1.94	1.61	-0.33	0.03	0.08	0.05	0.05	0.11	0.06
85 Other private services	1.45	1.37	-0.08	0.33	0.42	0.10	0.32	0.37	0.05
	1987	2007	Δ	1987	2007	Δ	1987	2007	Δ
15 Consumption goods	1.57	1.45	-0.13	0.05	0.11	0.05	0.08	0.14	0.06
25 Misc. manufacturing	1.44	1.39	-0.04	0.12	0.23	0.11	0.14	0.24	0.10
30 Energy intensive manufacturing	1.70	1.57	-0.13	0.16	0.22	0.06	0.21	0.26	0.04
45 Engineering products	1.57	1.48	-0.09	0.22	0.26	0.04	0.26	0.27	0.02
50 Oil platforms and ships	1.72	1.55	-0.17	0.18	0.23	0.04	0.24	0.26	0.02
55 Construction	1.70	1.58	-0.12	0.07	0.07	0.00	0.10	0.10	-0.00
63 Financial intermediates	1.27	1.40	0.13	0.32	0.83	0.51	0.29	0.54	0.25
64 Oil and gas exploration	1.32	1.25	-0.06	0.48	0.61	0.13	0.39	0.43	0.05
71 Electricity	1.63	1.50	-0.12	0.23	0.47	0.24	0.27	0.41	0.14
74 Domestic transportation	1.58	1.57	-0.02	0.07	0.17	0.10	0.10	0.21	0.11
81 Wholesale and retail trade	1.61	1.43	-0.18	0.08	0.16	0.08	0.12	0.19	0.07
85 Other private services	1.36	1.31	-0.05	0.42	0.58	0.15	0.37	0.43	0.06

Definitions: *Wage premium* $= W_H/W_L$, *Skill intensity* $= H/L$ and the high-skilled *Cost share* $(S) = W_H H/(W_H H + W_L L)$. Δ shows the difference in levels (in the top part of the table between 1986 and 1972 and in the lower part between 2007 and 1987).

Table 2: Total factor productivity growth

	1975 – 1986	1987 – 1997	1998 – 2007
15 Consumption goods	1.95	1.73	1.92
25 Misc. manufacturing	1.00	0.45	2.66
30 Energy intensive manufacturing	3.57	2.61	0.99
45 Engineering products	1.95	1.76	3.10
50 Oil platforms and ships	2.07	0.73	1.47
55 Construction	1.89	2.18	-2.17
63 Financial intermediates	-2.19	-1.94	3.80
64 Oil and gas exploration	4.03	4.45	-0.76
71 Electricity	0.68	1.29	4.09
74 Domestic transportation	1.69	3.58	3.37
81 Wholesale and retail trade	4.25	4.70	6.72
85 Other private services	1.21	1.22	1.33

The table shows the mean growth rates in per cent, i.e., $\frac{100}{T}\sum_t \Delta \ln TFP_t$, where the TFP_t series have been smoothed with the Hodrick-Prescott filter using the smoothing parameter $\lambda = 100$.

Table 3: VEqCM: estimates of the translog cost share function

	$\hat{b}_2$	$\hat{b}_3$	$\hat{b}_1$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_3$	Lags, k	σ
15 Consumption goods	-0.02	0.01	2.46**	-0.42**	0.08	2.51	1	1.3
	(0.04)	(0.01)	(0.21)	(0.12)	(0.55)	(2.50)		
25 Misc. manufacturing	0.08	0.07**	4.41**	-0.68**	-0.49	1.00	4	0.5
	(-)	(0.01)	(0.15)	(0.16)	(0.92)	(2.05)		
30 Energy intensive manufact.	-2.58**	1.21**	7.04**	-0.06**	-0.26**	0.37	4	16.1
	(0.42)	(0.20)	(2.56)	(0.03)	(0.04)	(0.39)		
45 Engineering products	-0.01	0.14**	2.41**	-0.32**	-0.10	0.25	1	1.1
	(0.11)	(0.02)	(0.51)	(0.07)	(0.23)	(0.99)		
50 Oil platforms and ships	0.13	0.10**	3.84**	-0.36**	-0.92**	1.59	2	0.2
	(-)	(0.01)	(0.23)	(0.16)	(0.20)	(2.53)		
55 Construction	0.05	-0.44	8.90	-0.04	-0.07	-0.52	1	0.4
	(-)	(0.16)	(3.68)	(0.02)	(0.08)	(0.29)		
63 Financial intermediates	0.19	0.07**	2.79	-0.12*	0.34*	-2.01**	3	0.2
	(-)	(0.03)	(1.72)	(0.10)	(0.25)	(0.66)		
64 Oil and gas exploration	-0.56**	0.10**	3.41**	-0.35**	0.30**	1.83**	1	3.4
	(0.09)	(0.03)	(0.80)	(0.04)	(0.06)	(0.57)		
71 Electricity	0.17	-0.15**	4.50**	-0.59**	-0.38*	-3.20	4	0.2
	(-)	(0.02)	(0.28)	(0.19)	(0.46)	(2.87)		
74 Domestic transportation	0.05	-0.08	4.44	-0.13	0.05	-0.58	1	0.5
	(-)	(0.04)	(0.66)	(0.05)	(0.21)	(0.97)		
81 Wholesale and retail trade	-0.06	0.02	4.33	-0.27*	-0.84	-3.14	1	1.5
	(0.05)	(0.01)	(0.76)	(0.09)	(0.57)	(1.77)		
85 Other private services	-2.42**	-0.15	0.13	-0.10**	-0.27**	0.06	1	11.2
	(0.40)	(0.11)	(1.80)	(0.02)	(0.06)	(0.17)		

The estimate of b_1 is multiplied with 10^3. k refers to the number of lags in the VEqCM model: $\Delta\mathbf{x}_{i,t} = \tilde{\boldsymbol{\gamma}}_{\boldsymbol{i}} + \boldsymbol{\Gamma}_{1,i}\Delta\mathbf{x}_{i,t-1} + \cdots + \boldsymbol{\Gamma}_{k,i}\Delta\mathbf{x}_{i,t-k} + \boldsymbol{\Pi}_i\tilde{\mathbf{x}}_{i,t-1} + \boldsymbol{\epsilon}_{it}$. The LR statistic have been applied to test if the coefficients are significantly different from zero. Rejection at the 10 per cent significance level is indicated with * and ** indicates rejection at the 5 per cent significance level. Asymptotic standard errors are reported in brackets. The last row shows the elasticity of substitution $\sigma = 1 - b_2/(\hat{S}(1-\hat{S}))$ where $\hat{S}$ is the mean cost share of high-skilled. In some sectors $\hat{b}_2$ have been restricted by $\hat{b}_2 = \min_t \ S_t(1-S_t)$ to ensure a positive elasticity of substitution, marked with $(-)$.

Table 4: Estimates of SBTC with different models

	VEqCM	A1	A2	A3	A4	A5	A6
15 Consumption goods	2.5**	2.5**	2.5**	2.7**	3.0	3.1	5.5
	(0.2)	(0.8)	(0.8)	(0.6)			
25 Misc. manufacturing	4.4**	4.7**	4.3	5.0**	5.0	5.0	7.5
	(0.2)	(1.8)	(1.8)	(0.6)			
30 Energy intensive manufact.	7.0**	2.1**	2.6	3.9**	4.1	4.1	6.0
	(2.6)	(0.9)	(1.3)	(1.2)			
45 Engineering products	2.4**	2.4**	2.4**	2.8**	2.6	2.5	3.4
	(0.5)	(1.0)	(0.4)	(1.1)			
50 Oil platforms and ships	3.8**	7.7**	7.6**	4.9**	3.5	3.4	4.4
	(0.2)	(2.0)	(1.7)	(1.6)			
55 Construction	8.9	3.1**	3.9**	1.8**	1.5	1.6	3.9
	(3.7)	(1.3)	(1.6)	(0.7)			
63 Financial intermediates	2.8	5.6**	17.3*	7.4**	8.2	8.3	9.4
	(1.7)	(2.4)	(6.2)	(1.9)			
64 Oil and gas exploration	3.4**	2.5**	-0.2	6.4*	11.5	11.5	12.6
	(0.8)	(0.9)	(0.0)	(3.4)			
71 Electricity	4.5**	6.4**	8.6*	6.4**	5.9	5.9	6.3
	(0.3)	(2.0)	(4.4)	(1.8)			
74 Domestic transportation	4.4	4.6*	1.2	5.0**	4.9	4.8	5.3
	(0.7)	(2.2)	(0.6)	(1.0)			
81 Wholesale and retail trade	4.3	7.0**	7.1**	4.4**	4.8	4.7	4.5
	(0.8)	(3.1)	(2.4)	(0.9)			
85 Other private services	0.1	2.0	0.3	3.5**	3.3	3.4	5.3
	(1.8)	(1.5)	(0.1)	(0.8)			

Standard errors are reported in parentheses. The estimate of SBTC (b_1) is multiplied with 10^3. The LR statistic have been applied to test if the coefficients are significantly different from zero in the VEqCM model. Rejection at the 10 per cent significance level is indicated with * and ** indicates rejection at the 5 per cent significance level. In models A1 and A2, the test of significance is made with respect to the short term parameter $\widehat{\alpha_1 b_1}$. Standard errors are computed by dividing the standard error of the short term parameter $\widehat{\alpha_1 b_1}$ with the estimate of the adjustment coefficient $\widehat{\alpha_1}$. Note that the method in Bårdsen (1989) can be applied to test if b_1 is significantly different from a value that is not equal to zero.

Table 5: Testing assumptions 1 to 5

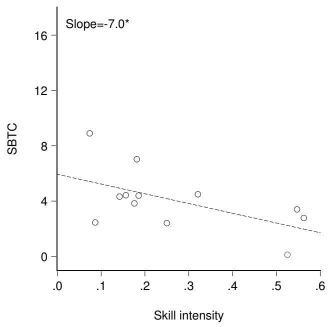
	Assumptions				
	1	2	3	4	5
15 Consumption goods	0.9	9.4**	-2.9**	1.8	-1.4
25 Misc. manufacturing	22.6**	3.7**	-2.8**	0.2	0.1
30 Energy intensive manufact.	31.2**	6.2**	-3.5**	0.5	-0.6
45 Engineering products	0.1	0.4	-9.9**	0.8	-1.7*
50 Oil platforms and ships	5.5*	2.3*	-5.2**	6.4**	-1.1
55 Construction	12.9**	1.0	-6.4**	31.0**	-2.5**
63 Financial intermediates	18.2**	15.7**	-3.9**	45.8**	2.5**
64 Oil and gas exploration	18.8**	4.4**	-5.8**	8.8**	5.2**
71 Electricity	8.4**	24.3**	-2.8**	0.8	0.8
74 Domestic transportation	5.5*	6.5**	-2.3**	1.4	0.0
81 Wholesale and retail trade	2.9	0.9	-4.7**	4.7**	-0.0
85 Other private services	14.5**	2.5*	-4.6**	1.6	-1.2
Model	VEqCM	A1	A2	A3	A4
Test	$\alpha_{2,i} = 0$ $\alpha_{3,i} = 0$	$\tilde{\mathbf{\Gamma}}_{j,i} = \mathbf{0}$ $\forall j$	$\alpha_{1,i} = 0$	$b_{2,i} = b_2$ $b_{3,i} = b_3$	$b_{1,i} = b_1$
Test statistic	χ^2	F-value	t-value	F-value	t-value

Robust standard errors that take both heteroskedasticity and autocorrelation into account (Newey and West) are used in models A1, A2 and A3. In the panel model, A4, robust standard errors that handle between-period correlation (cross-section clustering) have been imposed; see Beck and Katz (1995). Rejection at the 10 per cent significance level is indicated with * and ** indicates rejection at the 5 per cent significance level.

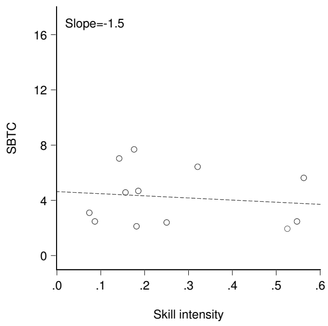
Table 6: VEqCM: test of the cointegration rank (Trace test).

H_0: No. of cointegrating equations	0	≤ 1	≤ 2
Sector, i	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$
15 Consumption goods	0.41	0.29	0.12
25 Misc. manufacturing	0.83**	0.62**	0.21
30 Energy intensive manufact.	0.80**	0.58**	0.17
45 Engineering products	0.45	0.28	0.20
50 Oil platforms and ships	0.57**	0.45**	0.35**
55 Construction	0.52*	0.28	0.21
63 Financial intermediates	0.74**	0.51**	0.13
64 Oil and gas exploration	0.85**	0.41**	0.30*
71 Electricity	0.70**	0.40	0.14
74 Domestic transportation	0.38	0.26	0.18
81 Wholesale and retail trade	0.36	0.30	0.24
85 Other private services	0.58**	0.41*	0.19

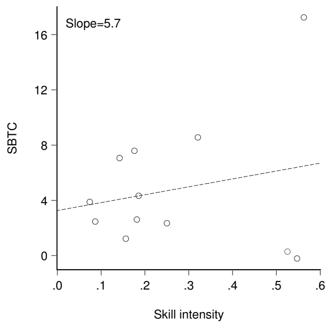
Rejection at the 10 per cent significance level is indicated with * and ** indicates rejection at the 5 per cent significance level using Mackinnon-Haug-Michelis p-values.



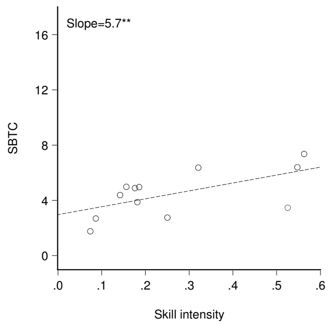
(a) VEqCM



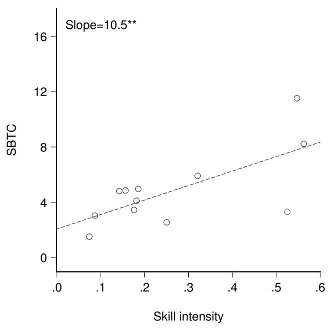
(b) A1



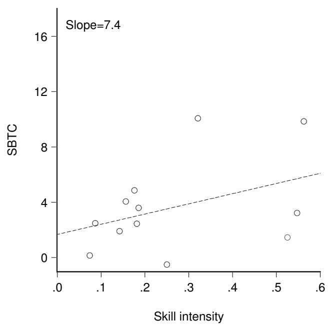
(c) A2



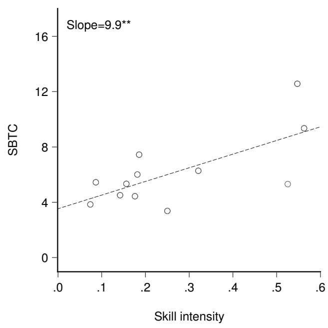
(d) A3



(e) A4



(f) A5



(g) A6

Fig. 1: The sensitivity of key assumptions. The y axis measures SBTC while the x axis measures skill intensity at the 1990 level, i.e., the relative number of man-hours of skilled and unskilled (H/L). The OLS regression line specified in equation (2) is included. Significance of the γ_2 slope coefficient is indicated by $*$ at the 10 per cent significance level and by $**$ at the 5 per cent significance level.

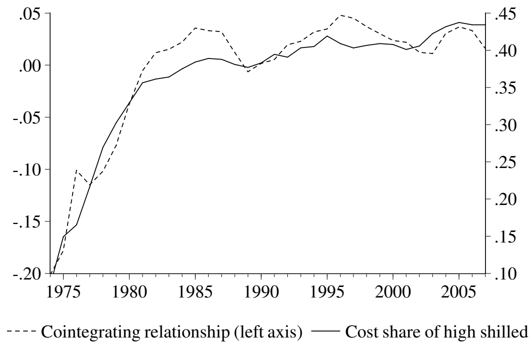
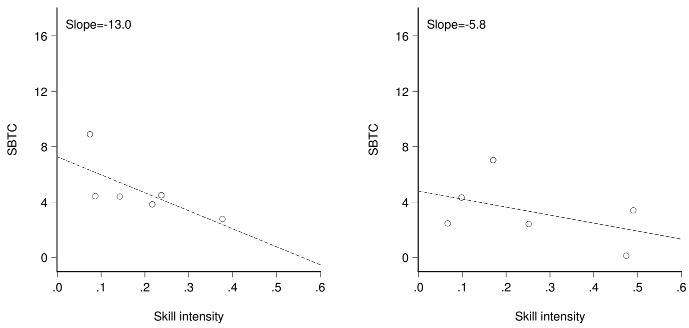
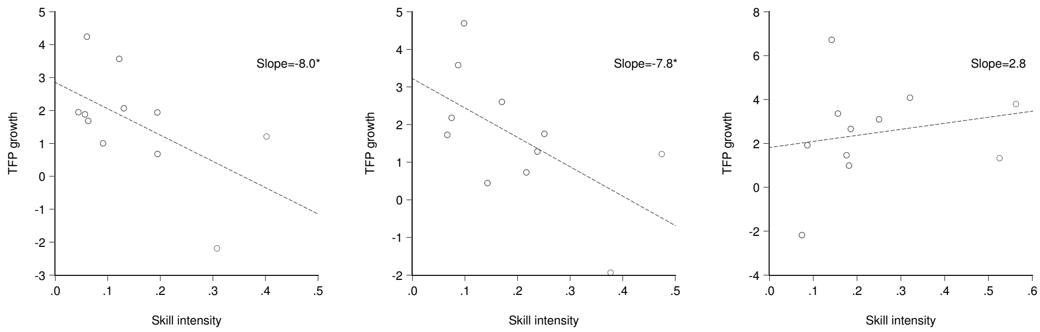


Fig. 2: The Oil and gas exploration sector



(a) Complements, $\sigma_i < 1$ (b) Substitutes, $\sigma_i > 1$

Fig. 3: The sector bias of SBTC. The y axis measures SBTC while the x axis measures skill intensity (H/L) in 1990. The OLS regression line specified in equation (2) is included. Significance of the slope coefficient is indicated by $*$ at the 10 per cent significance level and by $**$ at the 5 per cent significance level.



(a) 1975-1986 (b) 1987-1997 (c) 1998-2007

Fig. 4: The Sector Bias of TFP. The y axis measures smoothed TFP growth while the x axis measures skill intensity (H/L) in (a) 1980, (b) 1990 and (c) 2000. The TFP series has been smoothed with the Hodrick-Prescott filter using the smoothing parameter $\lambda = 100$. The OLS regression line specified in equation (8) is included. Significance of the slope coefficient ϕ_2 is indicated by $*$ at the 10 per cent significance level and by $**$ at the 5 per cent significance level.

Table 7: VEqCM: Test for autocorrelation

	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
15 Consumption goods	9.66	7.95	8.19	5.27	5.97	9.90
	(0.38)	(0.54)	(0.52)	(0.81)	(0.74)	(0.36)
25 Misc. manufacturing	17.40**	11.98	2.78	8.92	5.18	5.72
	(0.04)	(0.21)	(0.97)	(0.44)	(0.82)	(0.77)
30 Energy intensive manufacturing	11.61	11.23	6.30	3.01	10.54	8.86
	(0.24)	(0.26)	(0.71)	(0.96)	(0.31)	(0.45)
45 Engineering products	6.79	7.68	8.11	5.65	8.12	4.91
	(0.66)	(0.57)	(0.52)	(0.77)	(0.52)	(0.84)
50 Oil platforms and ships	3.78	12.72	9.03	6.18	18.31**	8.63
	(0.93)	(0.18)	(0.43)	(0.72)	(0.03)	(0.47)
55 Construction	8.04	9.65	4.56	7.84	9.61	8.34
	(0.53)	(0.38)	(0.87)	(0.55)	(0.38)	(0.50)
63 Financial intermediates	23.66**	24.51**	7.55	7.07	6.54	7.90
	(0.00)	(0.00)	(0.58)	(0.63)	(0.68)	(0.54)
64 Oil and gas exploration	12.44	12.33	11.07	5.77	7.05	8.26
	(0.19)	(0.20)	(0.27)	(0.76)	(0.63)	(0.51)
71 Electricity	9.70	7.15	17.03**	8.14	8.76	6.95
	(0.38)	(0.62)	(0.05)	(0.52)	(0.46)	(0.64)
74 Domestic transportation	9.31	7.14	1.89	4.32	8.42	5.53
	(0.41)	(0.62)	(0.99)	(0.89)	(0.49)	(0.79)
81 Wholesale and retail trade	3.36	5.73	4.16	5.93	2.00	4.85
	(0.95)	(0.77)	(0.90)	(0.75)	(0.99)	(0.85)
85 Other private services	9.52	5.26	3.48	9.72	3.82	8.92
	(0.39)	(0.81)	(0.94)	(0.37)	(0.92)	(0.44)

Probability of rejecting the null hypothesis of no serial autocorrelation is given in brackets. Rejection at the 10 per cent significance level is indicated with * and ** indicates rejection at the 5 per cent significance level.