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A note on the effects of skill-biased technical change on productivity flattening

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Abstract

This paper examines the role of skill-biased technical change (SBTC) in the flattening of productivity growth and its effects on hours worked. We employ a structural macroeconometric analysis based on comprehensive micro data. The results show that 69 percent of the slowdown in productivity growth in Germany since the early 2000s can be explained by the flattening of SBTC. Furthermore, skill-biased technology shocks reduce hours, whereas skill-neutral technology shocks have a positive effect on hours in the long run.

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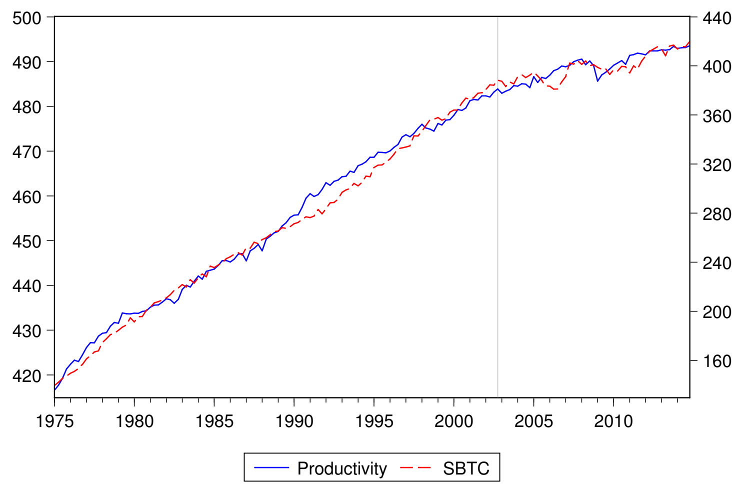
1 Introduction

Figure 1 shows a well-known but nonetheless eminent phenomenon: productivity growth has substantially weakened since the turn of the millennium. While the figure shows German data, the flattening of productivity growth has been discussed intensely as a global phenomenon (e.g., Summers (2015), Gordon (2016)), where the focus is on technical change in addition to demographics and the Great Recession.

A second trend that dominated debates on the development of labour markets and labour productivity is given by skill-biased technical change (SBTC). Phenomena such as automation and computerisation have often been associated with labour market outcomes such as skill-specific unemployment and increasing skill premia. Indeed, Germany is one of the major countries with a weakening of productivity and pronounced skill-specific labour market trends, e.g. in unemployment rates or wages.

Figure 1: Productivity and SBTC



Notes: Left scale: Seasonally adjusted productivity: GDP per hour worked, log × 100. Source: destatis. Right scale: Skill-biased technical change (SBTC) is measured according to (1). Source: Sample of Integrated Employment Biographies (SIAB). The vertical line denotes the timing of productivity flattening which arises approximately in 2002 q4 (see text for further information).

Given that SBTC played a major role in the last decades of the recent millennium, it comes as a question how SBTC is connected to the observed weakening of productivity growth. Along with productivity, Figure 1 shows our longitudinal estimate of SBTC, which we calculate from large-sample, high-quality administrative labour market data. Intriguingly, the SBTC measure bends down substantially at the beginning of the millennium. In the underlying paper, we seek to analyse in how far this has driven down productivity growth. We do so by extending a small structural vector autoregressive model (SVAR) of productivity and hours worked by our SBTC measure. While we identify technology shocks as the only ones exerting long-run effects on productivity, skill-neutral as opposed to skill-biased technology shocks are defined as not affecting SBTC in the long run.

From the model results, we determine that the flattening of SBTC since the early 2000s explains 69 percent of the drop in productivity growth rates. Additionally, our model allows shedding light on a further unsettled debate, namely the employment effects of technical change (e.g., Gali (1999), Christiano et al. (2004)). In particular, as Balleer and van Rens (2013) we find skill-neutral and skill-biased technology shocks to have opposite effects on hours worked.

2 Variable Selection and Data

We will explicitly model SBTC to disentangle the productivity effects of SBT shocks (i.e., shocks favouring the skilled over unskilled workers) from SNT (skill-neutral technology) shocks. To measure SBTC, we use the theoretical framework of a production function that can be derived within a growth model with horizontal innovation that endogenises the bias of new technologies (see Gancia and Zilibotti (2009), Acemoglu (2002) or the pioneering work of Katz and Murphy (1992), for instance). This model allows us to infer SBTC from observable variables (the skill premium and the relative factor supplies) and from a parameter that can be estimated (the elasticity of substitution between skilled and unskilled workers):

$$ln\left(\frac{A_H}{A_L}\right) = \frac{\sigma}{\sigma - 1}\left[ln\left(\frac{w_H}{w_L}\right) + \frac{1}{\sigma}ln\left(\frac{H}{L}\right)\right], \tag{1}$$

where A_L and A_H are the factor-augmenting technology terms of low- and high-education labour supplied inelastically at time t, L and H denote the respective number of workers, w_H and w_L the average wages, and σ is the elasticity of substitution between the factors. Equation (1) requires observations of both the skill premium and the relative factor supply, which we obtain from the Sample of Integrated Labour Market Biographies (SIAB). The data range from 1975Q1 to 2014Q4 and provide detailed information about an individual's (un)employment history on the German labour market. Particularly for measuring gross wages, this dataset provides data with high quality and precision compared to survey data. As a consequence, using the administrative data described above to estimate SBTC substantially improves the precision and reliability with which the variable can be approximated. In Appendix A1, we explain in detail how we calculate SBTC from the micro data.

The dotted line in Figure 1 shows the development of SBTC after seasonally adjusting, converting the monthly data into quarterly data and multiplying by 100. SBTC is steepest through the 1990s but markedly flattens in the subsequent decade. Presumably, the strong wave of computerisation including the introduction of the internet spread in the 1980s and 90s and phased out afterwards. In addition, the new digitalisation wave connected to notions such as artificial intelligence, big data or industry 4.0 had not yet started; compare Beaudry et al. (2010) for technology waves.

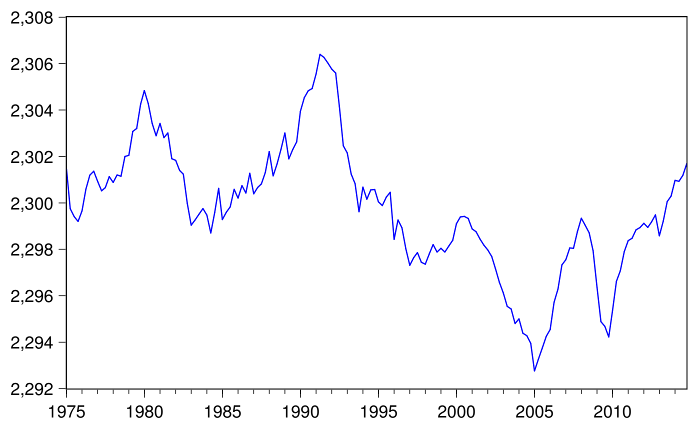
For productivity and hours, we rely on overlapping German and West German macroeconomic time series in 1991, thus providing a factor for adjusting the level shift after 1992Q1 due to German reunification. A seasonally adjusted productivity time series measured in terms of real GDP per hours worked is obtained from destatis[1]. The solid line in Figure 1 shows the development of productivity after taking logs and multiplying by 100. Beyond

[1]see https://www.destatis.de/DE/Themen/Wirtschaft/Volkswirtschaftliche-Gesamtrechnungen-Inlandsprodukt/_inhalt.html. We take the variable *Arbeitsproduktivität je Erwerbstätigenstunde* from Fachserie 18 Reihe 1.3 (since 1992) and from Fachserie 18 Reihe S.28 (before 1992).

the Great Recession of 2008/2009, we observe a clear flattening of productivity growth after approximately 2002 (see vertical line). We show below that the flattening of SBTC is a major reason behind the much-discussed weakening of productivity growth.

We use total hours worked from the IAB working time accounts. Hours is a holistic measure of labour market activity considering both the number of workers and the employees' working time. Figure 2 shows the log $\times$ 100 of seasonally adjusted hours worked by all dependent workers. It clearly mirrors the downturn of the German labour market over the 1990s and its recovery since 2005, interrupted only temporarily by the Great Recession.

Figure 2: Hours worked



Notes: Seasonally adjusted hours worked by all dependent workers, log $\times$ 100. Source: IAB working time accounts.

3 Model and Identification

Our model must fulfil several requirements. First, we are interested in the response of productivity and hours to technology shocks *over time*, so the model must be dynamic. Second, we want to isolate skill-neutral from skill-biased technology shocks. This requires a structural model identified on economic grounds. Third, since technology shocks can be discriminated by their steady-state-effects, the dynamic model must formally incorporate the long run.

ADF tests confirm that our variables should be treated as non-stationary. This leads to modelling the variables in first differences (Δ). To capture very general dynamic interactions of the variables without imposing strong structural assumptions a priori we start with a VAR of lag length q:

$$\Delta y_t = c + \sum_{i=1}^{q} A_i \Delta y_{t-i} + u_t \ , \qquad (2)$$

where y_t contains the $n = 3$ endogenous variables SBTC, productivity (p) and hours (h). A_i are $n \times n$ coefficient matrices, and u_t is n-dimensional white noise. We allow for a $n \times 1$ vector of constants c.

The VAR in (2) represents the reduced form of an underlying structural system. The correlated residuals in u_t are not economically interpretable but are usually specified as linear combinations of structural shocks. Formally, this can be written as

$$u_t = Be_t \ , \tag{3}$$

where B is an $n \times n$ parameter matrix, and e_t represents the vector of structural disturbances that are of interest in our analysis, namely skill-neutral and skill-biased technology shocks. B contains the initial impacts of the shocks on the respective variables, with diagonal elements normalised to unity. Under the standard assumption of zero cross-correlations between the different structural shocks, $n(n-1)/2 = 3$ restrictions are needed to identify the structural form.

In general, we seek to identify the structural shocks while letting the data speak as flexibly as possibly, avoiding any unnecessary theoretical assumptions on how the economy operates. For this purpose, we make use of long-run restrictions as introduced by Blanchard and Quah (1989). We do so in two steps:

1. With regard to our research question, we are interested in the effects of skill-neutral and skill-biased technology shocks. The remaining innovation is assumed to have no long-run impact on productivity and SBTC. This is in line with the standards in the growth literature stating that the only long-term drivers of productivity are technology shocks.

2. Our two technology shocks are discriminated by means of the definition of skill bias: SBTC is driven only by SBT shocks in the long run but not by normal, i.e., skill-neutral, technology shocks. Examples include the widespread usage of computers and robotics at workplaces or other skill-complementing or low-skill replacing technologies. Thereby, using long-run restrictions allows a maximum of data-driven dynamics at finite horizons.

4 Results

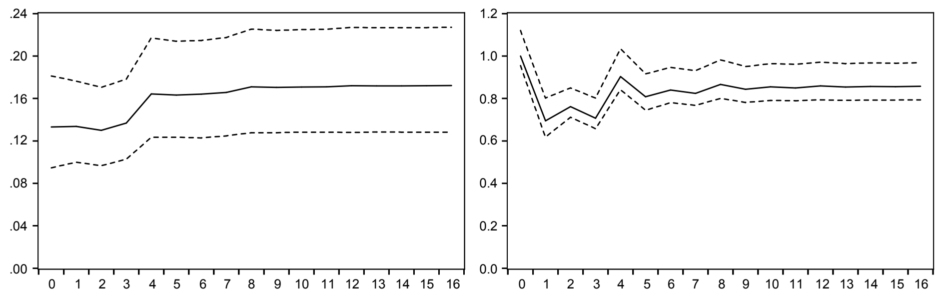
We choose the optimal lag length $q = 4$ according to Akaike's Information Criterion (AIC) and secure parsimony by sequentially excluding the A_i-elements that lead to worse AIC values. We apply LM-tests and find no evidence of remaining residual autocorrelation. Due to the constraints in A_i, the set of regressors is not the same in each of the equations which would lead to inefficient estimates in case of OLS. As a consequence, the white noise covariance matrix Σ_u is used to compute a GLS-type estimator. After obtaining the dynamics of the model from the reduced form (Equation (2)), the structural form is estimated by maximum likelihood given the restrictions described above (compare Lütkepohl (2005)). Further details on the estimation method are provided in Appendix A2.

From the structural model, we estimate impulse responses and 2/3 confidence intervals[2] using the bootstrap of Hall (1992) with 2,000 replications, as shown in Figures 3 and 4 for a

[2]Compare also Balleer and van Rens (2013) or Blanchard and Quah (1989) who use similar confidence levels.

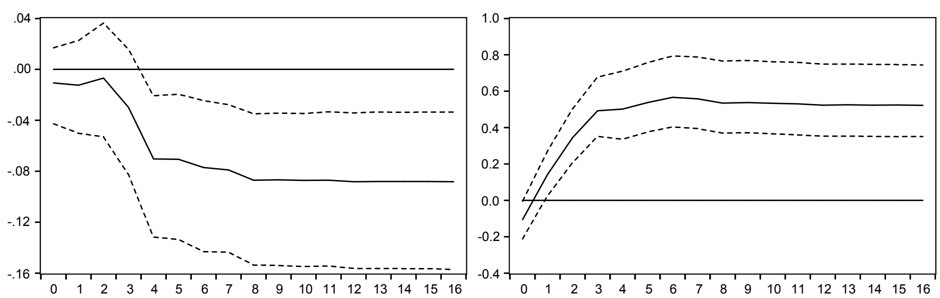
horizon of 16 quarters. We consider 1 unit shocks. Since all variables were multiplied by 100, this implies a technology shock connected to an immediate 1 percent productivity impact and a SBT shock connected to an immediate 1 percent impact on SBTC (i.e., the relation of the factor-augmenting technology terms of the high- and low-skilled). Robustness checks are provided in Appendix A3.

Figure 3: Responses of p to skill-biased and skill-neutral technology shocks



Notes: The solid line shows the responses of productivity to 1% skill-biased (left panel) and skill-neutral (right panel) technology shocks up to 16 quarters. The dotted lines denote 2/3 confidence intervals.

Figure 4: Responses of h to skill-biased and skill-neutral technology shocks



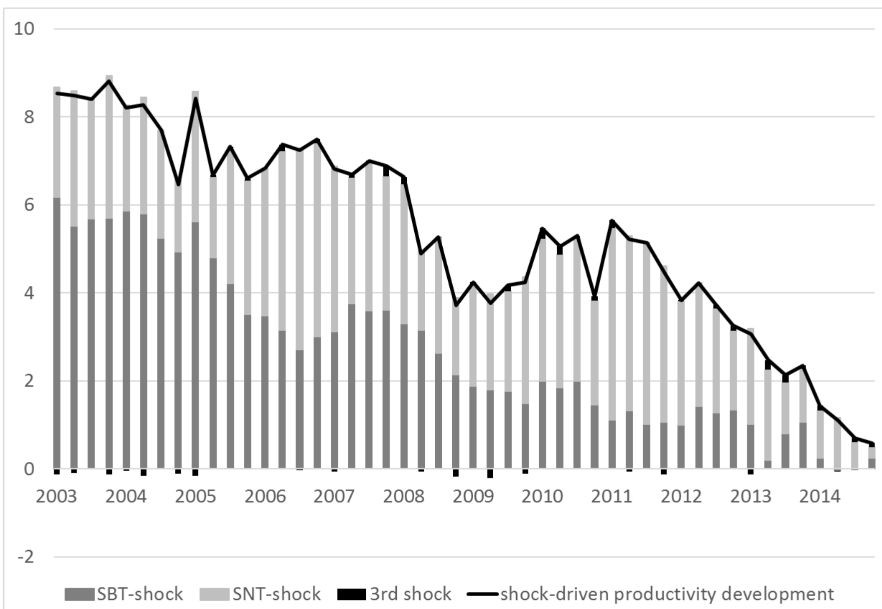
Notes: The solid line shows the responses of hours to 1% skill-biased (left panel) and skill-neutral (right panel) technology shocks up to 16 quarters. The dotted lines denote 2/3 confidence intervals.

As expected, both skill-biased and skill-neutral technology shocks increase productivity (Figure 3). With regards to our main research question, the long-run reaction of productivity following a 1 percent impulse in SBTC amounts to 0.17 percent. Since the standard deviation of a structural SBT shock is 2.28, a typical impulse in SBTC changes productivity by 0.39 percent, which is a major effect for shocks at a quarterly frequency. The economic relevance of SBTC for productivity will be addressed in more detail in the following paragraph.

Now, to gauge the economic impact the flattening of SBTC had on productivity, we calculate a historical decomposition of the shock-driven part of productivity. We look concretely at the period after 2002 q4, where we observe the above-mentioned clear weakening of productivity growth (Figure 1). We choose 2002 q4 because the difference in average quarterly productivity growth before and after this point in time reaches a maximum (besides the period surrounding the Great Recession).

Figure 5 shows by how much the shock-driven part (i.e., beyond deterministics) of productivity development (solid line) after 2002q4 can be explained by SNT (bright grey bars) and SBT (dark grey bars) shocks, respectively. While negative SNT shocks clearly played a role in explaining the productivity slowdown, the major part of it can be attributed to a series of negative SBT shocks that took place after 2002q4: the dark grey bars strongly diminish over the depicted period. The respective contributions of the two shocks amount to 69 percent (SBT shocks) and 33 percent (SNT shocks). The results do not change substantially if the timing of the productivity flattening is moved a couple of quarters forward or backward. For all possible split dates ranging between 2001Q4 and 2003Q4, the share of SBTC-driven productivity development ranges between 65 and 75 percent. Technically, the third shock (black bars) is part of our historical decomposition, too. However, with a contribution of -2 percent during the period after 2002q4 it plays virtually no role, which is in accordance with our identification strategy presented in Section 3.

Figure 5: Historical decomposition of productivity



Furthermore, we can apply the share of SBTC-driven productivity flattening (69 percent) on the average growth rate difference of productivity until and after 2002q4 (which is 1.62 percentage points per year). In doing so, we conclude that productivity growth would have been 1.12 percentage points higher per year if the series of mostly dampening SBT shocks during this period had not occurred.

Contrary to productivity, hours worked are affected in opposite ways by skill-biased and skill-neutral technology shocks (Figure 4). Hours are clearly reduced following a 1 unit SBT shock. This is consistent with high-skilled workers being more productive than low-skilled workers. Then, if the relative demand for high-skilled is increased, fewer hours are required to produce a given output. The income effect of SBTC seems not to offset the displacement or substitution effect (Moore and Ranjan (2005)). Put differently, if less productive workers are substituted with more productive ones following an SBT shock, total hours decrease while their production impact rises. By the same token, one can think of SBTC invoking skill mismatch and thus long-lasting structural unemployment (Restrepo (2015)).

By contrast, we find a clear increase in hours following a 1 percent skill-neutral technology shock. The effect is insignificant in the short run (compare also Evans and Marshall (2009)) but increases until the third quarter to approximately 0.5 percent. It is in line with results from Christiano et al. (2004), among others, but stands in contrast to the persistent negative effects reported in Gali (1999) and subsequent studies. It should be noted that these latter results are based on a single technology shock that implicitly captures both skill-neutral and skill-biased technology shocks (compare also Balleer and van Rens (2013)). Since the hours effect of the latter has been shown to be negative above, the responses to overall (intermingled) technology shocks will be smaller than the responses to skill-neutral technology shocks.

5 Conclusion

We analysed the effects of SBTC on productivity flattening and hours worked. A historical decomposition of productivity shows that 69 percent of the slowdown in productivity growth in Germany since the early 2000s can be explained by the flattening of SBTC. Furthermore, SBT shocks reduce hours, whereas SNT shocks have a positive effect in the long run. In disentangling the effects of skill-biased and skill-neutral technology shocks, our analysis contributes to a more comprehensive understanding of the relationship of technology to productivity and the labour market.

In fact, a new wave of SBTC would contribute to overcoming the prevalent productivity slack, but may at the same time come as a challenge for employment development.

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Appendix A1: Details on SBTC

Equation (1) sets the theoretical basis for calculating SBTC. It requires observations of the skill premium and the relative factor supply, which we obtain from the Sample of Integrated Labour Market Biographies (SIAB) of the IAB, and σ, the elasticity of substitution between high- and low-education workers. The steps necessary for obtaining these ingredients are explained in the following.

When determining labour supply, we count all employees and unemployed (including participants in active labour market policy measures) who have completed vocational training or higher education as being high-skilled and all workers without a degree as being low-skilled. While this classification seems to differ from the usual college vs. no college perspective, for the German case, we find it to be appropriate due to the special role of the dual system of vocational training (Müller and Wolbers (2003)). Indeed, it represents the main part of jobs that require a college degree in other countries. Furthermore, the permeability and cooperation between the vocational training system and tertiary education has increased substantially (compare Wolter and Kerst (2015)). In addition, the unemployment rates of workers with vocational training are far closer to the academics than to those without any degree (compare Röttger et al. (2018)). I a sense, our approach is similar to the unskilled/skilled classification used in Dustmann and Meghir (2005). The shifts in the labour supply variables in 1992 (reunification) and 2005 (statistical effects of the Hartz reforms) were adjusted in ARIMA models with dummies.

To calculate the skill premium, one must estimate, for each period of time, the average wages for high-education and low-education workers, after controlling for demographic factors. We rely on information from full-time workers because part-time wages cannot be pinpointed due to a lack of information about the hours worked (beyond the full-time/part-time information). Wages above the social security contribution ceiling are imputed following Gartner (2005). We run monthly Mincer-type regressions of wage on age, squared age, seniority[3], squared seniority and dummies for gender, nationality and East-Germany, which also controls for composition effects. Hence, non-SBTC-related causes for wage differentials are controlled for, whereas variables such as education, sectors or firm size are left out on purpose in the Mincer regressions because SBTC unfolds its distortive character along these dimensions. The resulting residuals from the regressions are used to calculate w_H and w_L of Equation (1), i.e., the average (adjusted) wages for high-education and low-education workers, respectively.

There is broad consensus in the literature that the elasticity of substitution between high- and low-education workers, σ, ranges between 1.4 and 2 (see, e.g., Katz and Murphy (1992) or Angrist (1995)). Möller (2000)'s finding of $\sigma \approx 1.7$ for German data will be our preferred estimate for this study. This value is also in accordance with other studies (see, for instance, Hamermesh (1993) or Bound and Johnson (1992)). Nonetheless, below we run robustness checks on the involved parameter.

[3]For workers who first appear in the data set in 1975 (West) or 1992 (East), the seniority variable is left-censored. Then, we proxy seniority by potential work experience according to age and education.

Appendix A2: Estimation

We estimate Equation (2) after excluding the A_i-elements that lead to worse AIC values. This is done by sequentially deleting those regressors which lead to the largest reduction of AIC until no further reduction is possible (see, e.g., Brüggemann and Lütkepohl (2001)). This strategy is equivalent to sequentially eliminating those regressors with the smallest absolute values of t-ratios until all t-ratios (in absolute value) are greater than some threshold value. Note that a single regressor is eliminated in each step only, and after each step, new t-ratios are computed.

In a next step, the resulting reduced-form model is then estimated by feasible generalized least squares (GLS). For this purpose, the three individual equations of the system are estimated by OLS. The residuals are used to estimate the white noise covariance matrix $\hat{\Sigma}_u = T^{-1} \sum_{t=1}^{T} \hat{u}_t \hat{u}_t'$. This estimator is then used in the next step to compute the GLS estimator.

The structural form is estimated by maximum likelihood using a scoring algorithm (see Breitung et al. (2004)). Estimation of the Blanchard-Quah model is done by a Choleski decomposition of the matrix $(I_k - \hat{A}_1 - ... - \hat{A}_q)^{-1} \hat{\Sigma}_u (I_k - \hat{A}_1' - ... - \hat{A}_q')^{-1}$, where I_k is a $k = 3$-dimensional identity matrix.

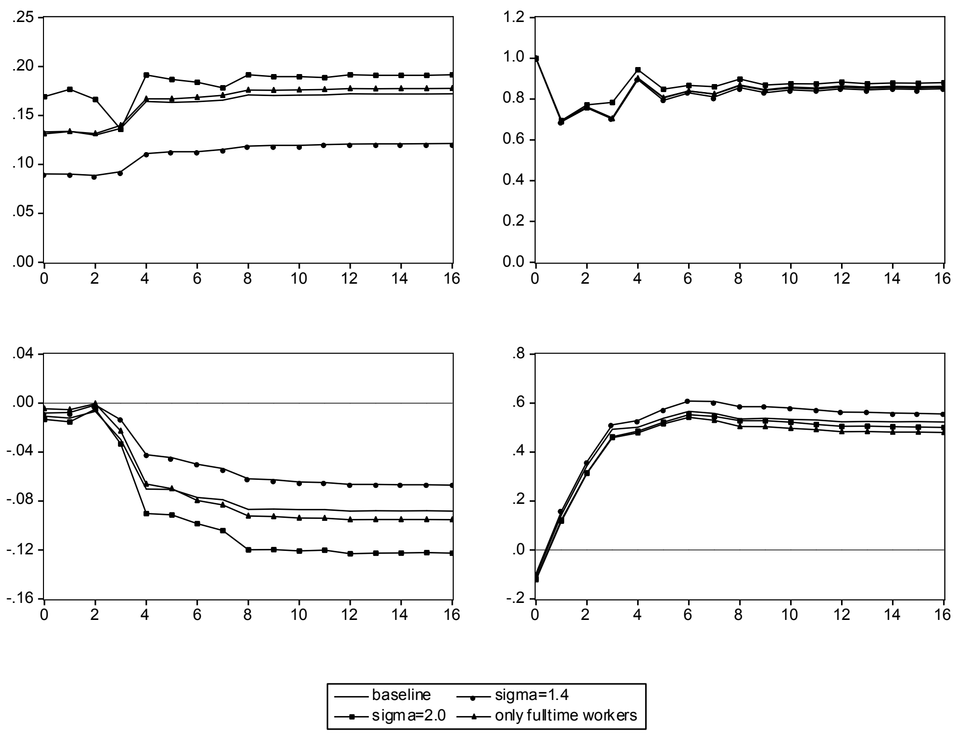
Once the SVAR model has been estimated, the impulse response analysis can be carried out using the Wold moving average representation. Furthermore, with the help of the structural residuals, one can calculate a historical decomposition of the variables of interest.

Appendix A3: Robustness checks

Since SBTC is a crucial variable in our investigation, we run several robustness checks with respect to its calculation.

First, we change the value of σ, the elasticity of substitution between skilled and unskilled labour. There is broad consensus in the literature that the elasticity of substitution between high- and low-education workers, σ, ranges between 1.4 and 2. Katz and Murphy (1992), for instance, find a value of $\sigma \approx 1.4$ for US data, whereas Angrist (1995)'s results on Palestinian skill premia imply $\sigma \approx 2$. However, the dynamics of SBTC do not change substantially of σ is set to 1.4 or 2.0 instead of 1.7. Figure 6 shows that also the impulse responses shown in Section 4 are quite robust even if using the boundaries of the usual range of this parameter.

Figure 6: Robustness checks: Responses of p and h to SBT and SNT shocks



Notes: The graph shows robustness checks of the responses of productivity (upper panels) and hours (lower panels) to skill-biased (left panels) and skill-neutral (right panels) technology shocks up to 16 quarters.

Second, instead of including part-time workers in H and L, i.e., in the supply components of Equation (1), we use full-time workers only. This is to prove that it does not matter how one deals with the issue of not having hourly wages for part-timers available: One can exclude part-timers only for the calculation of w_H and w_L, but include them in H and L (our baseline version presented in the main part of this study). Or one can calculate SBTC with full-time workers only. However, the latter method has almost no effect on the impulse responses as the lines with the triangles in Figure 6 show.

In order to check stability of the SBTC effects on productivity and hours, we performed a subsample analysis by splitting the sample at the time of the German reunification (1991q4). While the impulse responses of productivity and hours to SBT shocks in the two subsamples show some moderate differences regarding their exact form, the total (i.e., long-run) effects are very similar. We conclude that an analysis over a long time span is warranted.