Labour Market Effects of Wage Inequality and Skill-Biased Technical Change in Germany

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Contents

Abstract

This paper analyses the relationship between wage inequality and labour market development. Relevant economic theories are ambiguous, just as public debates. We measure the effects of wage inequality, skill-biased and skill-neutral technology on hours worked, productivity and wages in a novel structural vector error correction framework identified by economically motivated long-run restrictions. Results show that skill-biased technology shocks reduce hours worked but increase inequality, productivity and wages. Structural inequality shocks also have a negative impact on hours worked, but additionally reduce productivity. These effects are particularly pronounced at high inequality levels and for inequality below the median wage.

Zusammenfassung

Ziel dieser Arbeit ist es, die Beziehung zwischen Ungleichheit und der Arbeitsmarktentwicklung in Deutschland seit 1975 näher zu beleuchten. Die wichtigsten Theorien sowie auch die empirische Evidenz sind sich zu diesem Thema nicht einig. Unser strukturelles Vektorfehlerkorrekturmodell modelliert explizit den qualifikationsverzerrenden technologischen Fortschritt als Quelle von Ungleichheit. Mithilfe von nicht-rekursiven Langfristrestriktionen werden die Effekte von Ungleichheitsschocks, qualifikationsverzerrenden (und -neutralen) Technologieschocks auf Arbeitsvolumen, reale Lohnkosten und Produktivität identifiziert. Deskriptive Evidenz zeigt, dass der jahrzehntelange Anstieg der Lohnungleichheit im Jahr 2010 gestoppt wurde und sich sogar umkehrte. Dafür ist hauptsächlich die sinkende Ungleichheit in der unteren Hälfte der Lohnverteilung verantwortlich. Die Impuls-Antwort-Analysen verdeutlichen, dass qualifikationsverzerrende Technologieschocks sich negativ auf das Arbeitsvolumen auswirken, die Lohnungleichheit, Lohnkosten und Produktivität allerdings erhöhen. Ungleichheitsschocks haben ebenfalls einen negativen Effekt auf das Arbeitsvolumen, reduzieren zusätzlich aber die Produktivität.

JEL classification: C32, I24, J24, J31

Keywords: inequality, wages, productivity, hours, SBTC, SVEC

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1 Introduction

Recent years witnessed intensifying debates on increasing economic inequality worldwide. This brings the question of the effects of inequality on economic growth or the labour market to the fore. However, as vast as the range of literature on this issue, as differing are the theoretical hypotheses and channels linking inequality to the macroeconomic variables of interest. On the one hand, there are theoretical considerations stating that wage dispersion is a necessary precondition, i.e. the price, for higher incentives, investment, growth rates and employment chances. On the other hand, a range of theories expect a higher level of inequality to impede the opportunities of an important share of the labour force to participate on educational advancement, signifying an obstacle to growth, productivity and employment development. Empirical evidence ranges from finding results in favour of the first (e.g. Forbes (2000), Bowles and Park (2005)) over ambiguous results (e.g. Persson and Tabellini (1994)) to those in favour of the latter (e.g. Panizza (2002)).

However, the lion's share of existing research links inequality to labour market outcomes only indirectly, e.g. by investigating the effects on economic growth, investment, or political stability (see, for instance, Cingano (2014) or Alesina and Perotti (1996)). Studies that directly investigate the relationship between inequality and labour market outcomes are scarce. Fitzenberger and Garloff (2008), for example, examine the impacts of wage disparity on the level of unemployment. Furthermore, country-specific measures of inequality are available only on a yearly frequency which makes in-depth structural analyses of short-run and dynamic effects difficult. Instead, existing literature often focusses on the cross-sectional dimension via multiple country analyses (see, for instance, Forbes (2000)). Naturally, relationships for single countries cannot be inferred from these studies. Another strand of the literature (e.g. Kölling (2014)) focuses on firm level data and links wage dispersion within companies to bargaining power, productivity, the profit rate and competitiveness. However, the conclusions to be made concern employment effects at the firm's level only and are difficult to transfer to the aggregate level.

We contribute to the literature by proposing a structural macroeconometric framework for analysing economic and labour market effects of wage inequality. Within this framework, causal effects can be identified for single countries, i.e. without recourse to cross-sectional methods. The model provides high flexibility in that it minimises the set of identifying assumptions and allows estimating fully dynamic (i.e., short-, medium- and long-run) impacts. In addition, it enables us to simultaneously model the effects of further structural shocks such as skill-biased (and skill-neutral) technological change.

We can rely on a decent number of observations at the longitudinal section using the integrated employment biographies (IEB), a unique administrative dataset by the Federal Employment Agency in Germany. The data range from 1975 to 2014 and allow us to collect labour market information of every single employee during his or her employment career. Hence, we can spot changes in overall inequality not only once per year, but at any point in time. Logically, inequality is no longer the limiting variable in terms of frequency. As a consequence, the full range of quarterly information stemming from variables such as productivity, hours or wages is at our disposal for an in-depth structural macroeconometric investigation. This provides the opportunity for an in-depth analysis of inequality effects in one of the world's most sizeable labour markets that also features an exemplary rise of inequality through time, including heated debates on the topic.

We calculate the Gini coefficient as measure of wage inequality. The results show an upward trend in wage inequality that prevailed for decades but has come to an end and even reversed since 2010, a result also found by Weber (2015). We find that this reversion in wage dispersion is mainly driven by a reduction of inequality in the lower half of the wage distribution.

For identification purposes, we construct a structural vector error correction model (SVECM), i.e., a dynamic cointegrating model with economically motivated short- and long-run restrictions. The analysis is embedded in a framework including major driving forces of the labour market and inequality, productivity shocks and skill-biased technical change (SBTC). For this purpose, we residually measure SBTC from time series of the skill premium and the relative labour supply. Importantly, the ambiguity of empirical results on the effects of inequality could stem from the fact that wage dispersion itself, besides other factors, can be driven by inherently efficiency-enhancing forces, SBTC representing the prime case (see Katz and Murphy (1992) or Juhn et al. (1993), for instance). Hence, we allow the effects of structural inequality shocks on the labour market variables of interest being discriminated from the effects of SBTC.

Results based on the impulse responses show that skill-biased technology shocks increase productivity and wages, but reduce hours worked and drive up inequality. Indeed, in our SBTC measure we find a substantial flattening of the trend since the early 2000s. This can be identified as a major reason behind the much-discussed weakening of productivity development and also facilitated the most recent decline of inequality in Germany. Structural inequality shocks also have a negative impact on hours worked, but additionally reduce productivity. These adverse effects are stronger in the second half of the sample that is characterised by higher inequality levels. Allowing for different impacts of inequality below and above the median wage shows that both types of wage dispersion have negative labour market effects, somewhat stronger for the former. Furthermore, we find that (skill-neutral) technology shocks have a positive long-run effect on hours worked. The opposing effects of skill-biased and skill-neutral technology shocks can contribute to a more comprehensive understanding of the relationship of technology and the labour market (cf. Balleer and van Rens (2013)).

The remainder of the paper is structured as follows: Different theories linking inequality to growth or labour market variables are discussed in section 2, which also addresses the role of SBTC. Section 3 discusses the variable selection and introduces the data used in this paper. Section 4 presents our macroeconomic model, the identification strategy and the estimation procedure. The results based on the impulse responses as well as robustness checks are laid out in section 5. The last section concludes.

2 Theoretical background

2.1 Inequality effects in the literature

The following paragraphs present a short overview of the mechanisms postulated in the literature analyzing the relationship between inequality and economic growth or – though only scarcely existing – between inequality and the labour market.

Theoretical considerations consistent with the incentive hypothesis postulate that wage dispersion is a necessary precondition, i.e. the price, for higher investment, growth rates and employment chances. Mirrlees (1971) or Lazear and Rosen (1981), for instance, state that higher dispersion leads to higher incentives for harder work, more investment and higher willingness to take risks to benefit of high rates of return. This provides a direct link to aggregate productivity: High skill premia could motivate more people to improve their educational status. Given that high-education workers are more productive, aggregate productivity is influenced, too.

Another strand of the literature (e.g. Kaldor (1955)) theoretically postulates a positive relationship between inequality and growth through a different mechanism. In short, it is based on the finding that the rich have a lower propensity to consume than the poor. In this context, higher dispersion raises aggregate savings and hence more capital is accumulated. The Solow model presented in Bourguignon (1981) puts a formalized framework to this hypothesis. The author shows that there are multiple steady states each of which is associated with a different degree of inequality if savings are a convex function of income. However, the more unequal steady states are the ones with higher aggregate output.

By contrast, theories in line with the opportunities hypothesis expect a higher level of inequality to impede the opportunities of an important share of the labour force to participate on educational advancement, signifying an obstacle to employment development. Galor and Zeira (1993) formalized the so-called *human capital accumulation theory*. It depends on imperfect financial markets in which the level of income (or wealth) determines whether an individual can afford profitable investments. At the educational market, the poor do not receive the optimal level of education even though the rate of return on education is high. This type of under-investment is not only negative at the individual level, but also for the society, and harmfully affects future productivity and growth.

Another strand of the literature such as the *endogenous fiscal policy theory* (see Persson and Tabellini (1994), for example) links inequality to institutions: High wage dispersion leads voters to insist on higher tax rates, more regulation and anti-business policies all of which could harm growth through reduced incentives to invest. Related to this theory is the political instability argument, especially for countries with substantial poverty. Alesina and Perotti (1996), for instance, argue that extreme inequality may lead to social unrest and hence be a drag on growth. Nel (2003)'s findings do not support this hypothesis in a clear way. He finds no statistically significant effects of inequality on political stability. However, he argues that high levels of inequality change potential investors' risk perceptions, which negatively affects future growth prospects.

The theories presented so far link inequality to the labour market only indirectly and more in the longer term. Furthermore, one may argue that a channel via personal educational investment might be less relevant in view of a comprehensive public infrastructure in industrialised (compared to developing) economies. Nonetheless, arguments in the spirit of the opportunities hypothesis open the possibility for short- and medium-run effects as well. The opportunities hypothesis, beyond general education, could also operate through participation in further training, which is by far the weakest for low-wage earners. By the same token, the wage also reflects the value of a job, including longer-term perspectives and development opportunities. I.e., arguments in line with the opportunities hypothesis extend to the quality of jobs, which has immediate consequences for labour market development. Concretely, inequality not only can impede opportunities to participate on educational advancement but also create a sector of persistent low-quality jobs with limited productivity dynamics and poor career opportunities. This can further be linked to negative employment effects since in such a sector typically layoff risks are higher, productivity might fall short of a more or less rigid wage level, structural problems and unemployment hysteresis are more prevalent and labour force participation is limited.

Studies that directly investigate the relationship between inequality and labour market variables are scarce. Bowles and Park (2005), for instance, investigate how incentives to emulate the rich can influence an individual's decision between labour and leisure, so that greater inequality can lead to longer work hours. The short- and medium-run effects of inequality-reducing interventions are often seen to depend on the economy's level of market failure. While inequality-reducing measures such as minimum wages (e.g. Acemoglu and Pischke (1999) or Agell and Lommerud (1997)), unemployment benefits (e.g. Atkinson (1999) or Acemoglu and Shimer (1999)) or employment protection (e.g. Pissarides (2001)) can have detrimental effects on efficiency and the labour market outcome in perfectly competitive markets, they might lead to an increase in efficiency and employment in presence of a certain level of market failure, e.g. monopsonistic or even monopolistic markets, or frictions in the labour market. Fitzenberger and Garloff (2008), for instance, examine the impacts of wage disparity on the level of unemployment, distinguishing between two hypotheses. The frictional hypothesis postulates that both income inequality and unemployment increase if the bargaining power of companies increases, while the heterogeneity hypothesis links the wage of an employee to his/her marginal productivity. A compression of wages, e.g. by minimum wages, leads to high employment barriers, signifying high entry rates to unemployment and low exit rates out of unemployment. The results do not clearly support either hypothesis. However, the authors state that the frictional hypothesis seems to perform better since they find no negative correlation between unemployment within age/education cells and within-cell wage dispersion.

A further set of theories links wage inequality to a firm's productivity, profit rate and competitiveness (see, e.g. Kölling (2014)). In theory, there should be a positive relationship among these variables if efficiency and tournament wages increase the firm's productivity, while there should be a negative relationship if wage inequality violates fairness beliefs (compare Akerlof and Yellen (1988)) and reduces workers' motivation as well as the firms' attractiveness and innovation potential. Under the assumption that the successful companies grow stronger while the unsuccessful ones shrink or close down, one could translate these firm-level based theories into considerations at the aggregate level.

To summarize, the wide range of research trying to theoretically capture the mechanisms through which inequality impacts growth allows both negative or positive effects. Empirical work that aimed at discriminating between these channels has often been ambiguous or inconclusive. Since existing literature is often occupied with multiple country analyses, relationships for single countries cannot be inferred. In contrast, we will construct a framework for investigating inequality effects within single countries, focussing on Germany. In this, we seek to estimate the overweighing effect inequality exerts on the labour market through varied mechanisms. Thereby, the ambiguity of empirical results on the effects of inequality could also stem from the fact that wage dispersion itself, besides other factors, can be driven by inherently efficiency-enhancing forces. In this context, SBTC represents the prime case in the literature (see Katz and Murphy (1992), Juhn et al. (1993), for instance). The next subsection provides a more detailed discussion on this issue.

2.2 The role of SBTC

According to Acemoglu (2002) or Moore and Ranjan (2005), amongst others, the rapid computerization at workplaces and the contemporaneous increase in wage dispersion during the past several decades is not a mere coincidence. If computers, robotics and the widespread usage of the internet complement skilled workers and replace lower skilled labor-intensive tasks, SBTC can be seen as direct source of an increasing skill premium and wage inequality.

However, inequality not only exists in terms of qualification, but alongside many other dimensions such as gender, race, regions, sectors, or age. As Card and DiNardo (2002) point out, SBTC is not able to explain the development of other dimensions of wage dispersion such as racial or gender wage gaps. Logically, inequality can be driven by other sources as well, for instance by the introduction or changes of minimum wages, by gender-, region- or sector-specific policy measures promoting or restricting certain parts of the workforce, by migration flows or by changes in the bargaining power of unions. We argue that these sources are conceptually different from SBTC since they do not directly aim at favouring the skilled over the unskilled. By the same token, SBTC has an inherent efficiency-increasing nature, distinguishing it from other sources of inequality.

We explicitly model SBTC as source of inequality in order to isolate structural inequality shocks from technology shocks favoring the skilled over unskilled workers. This requires measuring SBTC so that it can be controlled for in our structural model. We use the theoretical framework introduced by Katz and Murphy (1992) that allows to residually infer SBTC from observable variables (such as the skill premium and the relative factor supplies) and from parameters that can be estimated (the elasticity of substitution between skilled and unskilled workers). The approach borrows from Solow (1957)'s way of residually quantifying factor-neutral technical change from measures of aggregate output, capital and labour and an estimate of the elasticity of output to capital. We follow Acemoglu (2002) and provide a more general view to this framework using a CES production function for the aggregate economy:

$$Y(t) = [(A_l(t)L(t))^\rho + (A_h(t)H(t))^\rho]^{\frac{1}{\rho}}, \tag{1}$$

where $\rho \leq 1$. $L(t)$ and $H(t)$ denote the number of low-education and high-education workers supplying labour inelastically at time t, A_l and A_h are the respective factor-augmenting technology terms. The elasticity of substitution between the two factors is defined as $\sigma \equiv 1/(1-\rho)$. Assuming competitive labour markets, the skill premium reads as follows:

$$\frac{w_h}{w_l} = \left(\frac{A_h}{A_l}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{H}{L}\right)^{\frac{-1}{\sigma}}. \tag{2}$$

Taking the natural logarithm on both sides and solving for relative skill productivity yields:

$$ln\left(\frac{A_h}{A_l}\right) = \frac{\sigma}{\sigma-1}\left[ln\left(\frac{w_h}{w_l}\right) + \frac{1}{\sigma}ln\left(\frac{H}{L}\right)\right]. \tag{3}$$

As Violante (2016) points out, one can directly measure SBTC from Equation (3) given an estimate of σ, and given time series on the skill premium and relative factor supplies. In section 3 we will discuss how to feed this theoretical framework with data.

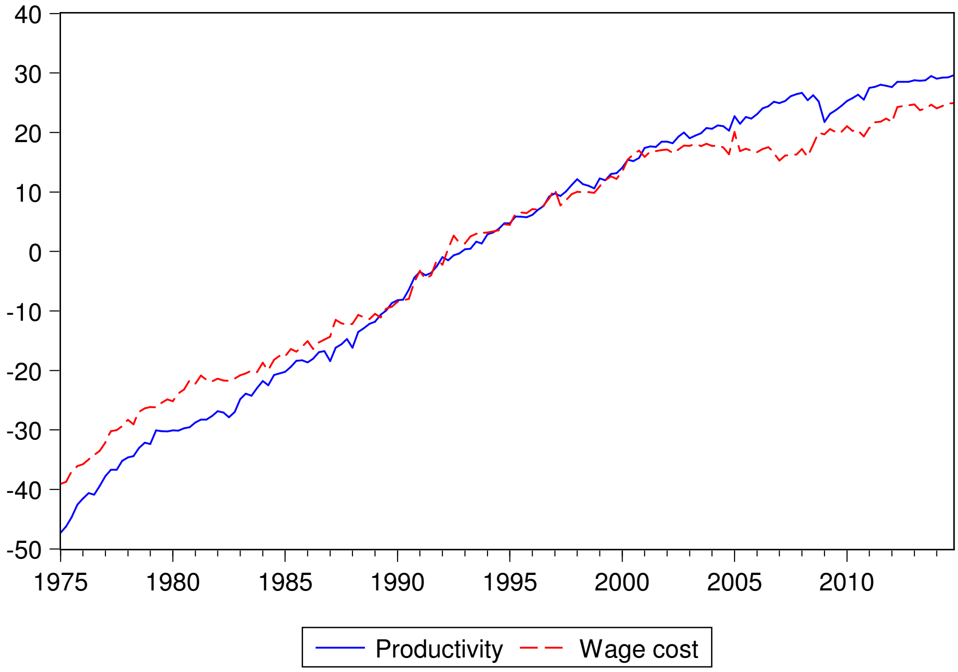
3 Variable Selection and Data

In our model of the economy and the labour market we use five variables: productivity, wages, hours worked, SBTC, and inequality. We measure these variables as explained in the subsequent paragraphs. All data are either available at a quarterly frequency or are converted from monthly frequency. They range from 1975Q1 to 2014Q4 so that the total number of observations amounts to 160. For adjusting the structural level shift in 1992Q1 due to the German reunification, we could rely on an overlap of the German and West German macroeconomic time series in 1991, providing a factor that we applied to the time series after the shift. This section explains the respective data sources and methods used for data preparation.

Productivity

Productivity is both an important factor involved by the hypotheses discussed in section 2 and a key factor in modern theories of the labour market (e.g.Mortensen and Pissarides (1994)). Therefore, we include this variable in our structural model. We use seasonally adjusted productivity from the Federal Statistical Office (Destatis) in Germany. Productivity is measured in terms of real GDP per hours worked by the whole working population (hours being described below). The solid line in Figure 1 shows the development of productivity after taking logs and multiplying by 100. Besides the normal business cycle fluctuations, the slump during the Great Recession of 2008/2009 is clearly visible. By the same token, we observe a certain flattening of productivity growth from about 2002 onwards.

Figure 1: Productivity and wages



Notes: The graph shows the log × 100 of seasonally adjusted productivity (solid line) in terms of GDP per hour worked (working population), and the log × 100 of seasonally adjusted real wage cost in terms of salaries and wages per hour worked (dependent workers). Nominal wage cost have been converted to real terms by usage of the GDP deflator. For both variables, the respective structural breaks in 1992 due to the German reunification have been eliminated and the respective sample means have been subtracted.
Source: destatis.

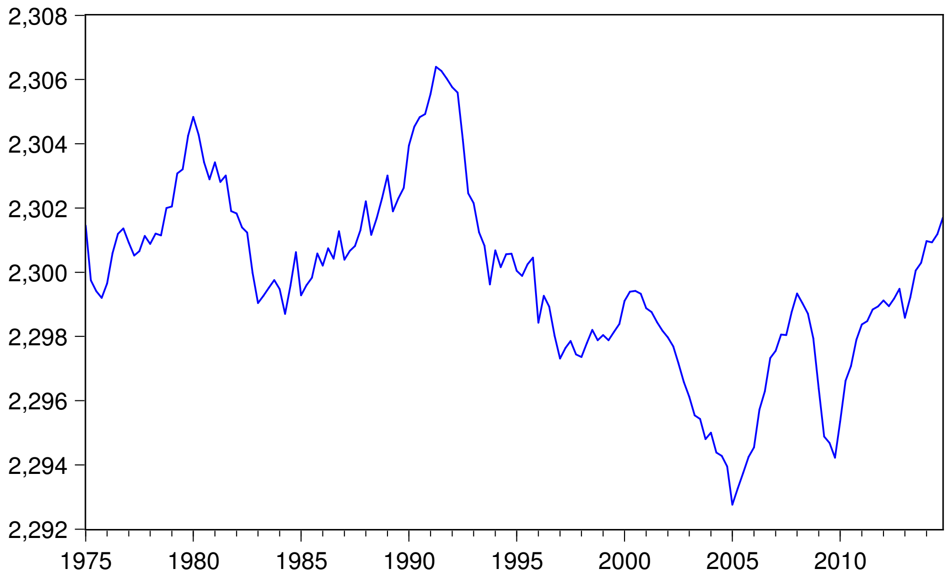
Wages

The second variable in our model is real wage cost as published by the Federal Statistical Office. It comprises the dependent workers' gross hourly wages and salaries plus the employers' social security contributions. The variable represents the wage level as distinct from wage inequality discussed below. The time series is seasonally adjusted and converted to real terms through the GDP deflator. The dashed line in Figure 1 shows the log × 100 of real wage cost in Germany since 1975Q1. The graph might suggest the existence of a long-run relationship between productivity and wages. A gap has been opening during the wage moderation phase mainly through the 2000s, but in recent years (also beyond the sample) real wage growth again exceeded productivity growth. Based on cointegration tests, we will allow for such a relation in our model. Cointegration between productivity and wages is economically equivalent to the presence of a covariance-stationary labour share. More detailed information on our structural model is presented in section 4.

Hours

Our preferred variable for measuring the labour market quantity effects of inequality and SBTC is total hours as calculated by the Institute for Employment Research (IAB) in Nuremberg. It is a holistic measure of labour market activity that, in contrast to the number of dependent workers, considers the employees' working time and hence is able to capture structural effects such as the changing importance of part-time work or minijobs. This choice is in parallel to large strands of literature measuring influences of technical change on the macroeconomy, e.g. Gali (1999). 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 the recovery since 2005 that is interrupted only temporarily by the Great Recession.

Figure 2: Hours



Notes: The graph shows the log $\times$ 100 of seasonally adjusted hours worked by all dependent workers. The structural break in 1992 due to the German reunification has been eliminated.
Source: IAB working time accounts.

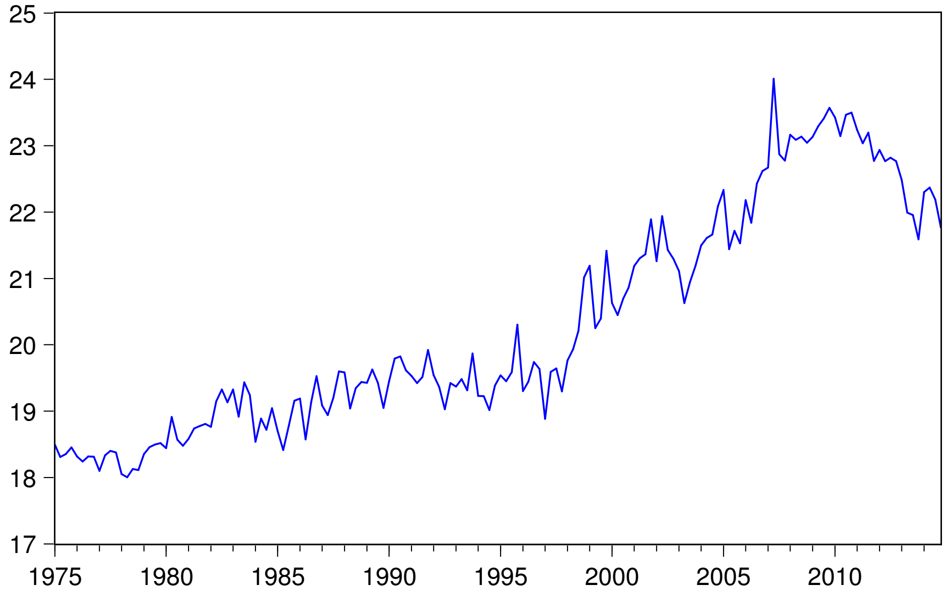
Inequality

We choose the Gini coefficient G given by Equation (4) as our measure of wage inequality.

$$G = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} |w_i - w_j|}{2N \sum_{i=1}^{N} w_i}, \tag{4}$$

where N denotes the total number of cross-section individuals. Hence, G is equivalent to half of the average absolute wage difference of all pairs of employees at a certain point in time, divided by the average wage in order to normalize for scale. Thus, the Gini coefficient takes the whole wage structure into account. It can take on values between 0 (in case every worker earns the same) and nearly 1 (in case all wages go to a single worker). From a different perspective, G equals 2 times the area between the 45° line signifying a perfectly equal wage distribution and the actual wage distribution given by the Lorenz curve. We use the IEB as data source that allows us to collect wage information of 100 percent of the workers in order to avoid noisy fluctuations in the data. In contrast to SBTC (explained below), we use unconditional wages to measure inequality preventing us from ignoring specific sources of inequality.[1]

Figure 3: Inequality



Notes: The graph shows the seasonally adjusted Gini coefficient × 100 based on full time workers subject to social security contributions aged 15 to 64. Level shifts in January 1978, January 1984 and January 1992 have been eliminated. The monthly data were converted to quarterly frequency. Further information in the text. Source: IEB.

The IEB data set provides us with the unique opportunity to generate a time series of inequality at a quarterly frequency so that it is not the limiting factor in macroeconometric research any more. The key advantage is that the large data set provides us with a high number also of intrayear observations. Usually, an employer reports the individual worker's data relevant for the social security system once per year (annual report). In this case, the reported wage reflects the total payment received by the worker during the calendar year. However, the timing of individual wage changes due to promotion or tariff changes within a year is not reflected in annual reports which – if not taken care of – would lead to an underestimation of the intrayear wage dynamics. However, this problem can be tackled if a worker changes his or her job after January or before December, or if there is an intrayear switching of, say, the health insurance company. These or similar events affecting the social security system require additional reports from which information on the *true* wage dynamics within a calendar year can be deduced. Naturally, annual reports reflect more stable employment episodes that often span several years whereas intrayear reports are based on shorter and, on average, worse paid employment episodes. This has an influence on the values of the Gini coefficient. As a consequence, for every calendar year, we choose the respective inequality value of January (which includes both all annual reports and current intrayear reports falling onto January) as anchor value around which the

[1] This overall measure also includes sectoral composition effects. From the viewpoint of robustness, controlling such effects in micro-level wage regressions would explain only a small part of inequality development; compare Möller and Hutter (2011).

intra-year fluctuations from February to December are built. This combines the appropriate level of inequality that would appear in an annual time series and the full intrayear variation which is crucial in any dynamic model.

Figure 3 shows the seasonally adjusted Gini coefficient after converting the monthly time series into quarterly data and multiplying by 100. Note that, in addition to the reunification break, level shifts in 1978Q1 and 1984Q1 due to a break in the way annual special payments are reported have been eliminated as well. The figure reveals that the well-documented upward trend in wage inequality that prevailed for decades has come to an end and even reversed since 2010, a result also found by Weber (2015). The flattening of SBTC shown below (Figure 4) is likely to have facilitated this trend reversal. However, this change is clearly not big enough to account for the marked reduction of inequality. This underlines that inequality is driven by other sources as well.

Skill-Biased Technical Change

Subsection 2.2 delivers the theoretical framework for measuring 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. This data set provides detailed information about an individual's (un)employment history on the German labour market. Basically, SIAB is a 2 percent random sample of the population collected in the Integrated Employment Biographies (IEB) that comprises all (un)employed persons in Germany between 1975 to 2014.

Concerning wages, 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).[2] In case of multiple employment, only reports of the main job are included. When determining labour supply, we count all employees and unemployed (including participants of active labour market policy measures) with completed vocational training or higher education as being high-skilled and all workers without completed vocational training or high school degree as being low-skilled (H and L in Equation (3)). At first, this classification seems to differ from the college vs. no college perspective. However, for the German case we find it appropriate due to the special role of the dual system of vocational training in Germany (compare Müller and Wolbers (2003)). Indeed, it comprises the main part of jobs that require a college degree in other countries. 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, we run monthly Mincer-type regressions of wage on age, squared age, seniority, squared seniority and dummies for gender, nationality and East-Germany.[3] Note that variables such as education, sectors or firm size are left out in the

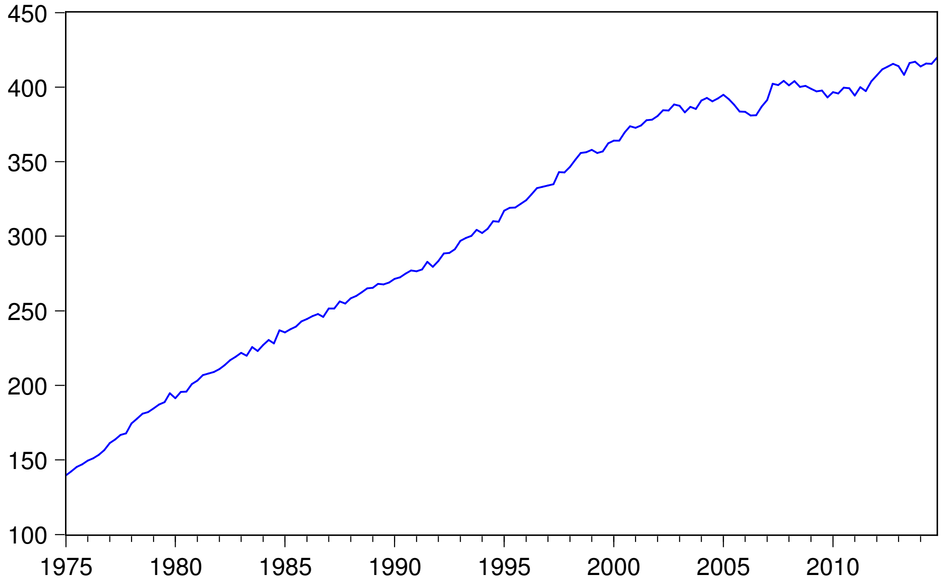
2 In 2011, the format of the part-time attribute in employers' reports to social security changed. However, none of the variables relying on wage information from the IEB (i.e., SBTC and the Gini coefficient above) contains relevant shifts in this period. Logically, adjusting for breaks would leave the results unchanged.

3 Whenever wage information stemming from SIAB or IEB is used, wages above the social security contribution ceiling are imputed following Gartner (2005). 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.

regressions. This fits the needs of our analysis since alongside these dimensions SBTC unfolds its distortive character.[4] The resulting residuals from the regressions are used to calculate w_h and w_l of Equation (3), i.e. the average (adjusted) wages for high-education and low-education workers, respectively.

As described above, wage information stemming from annual reports would understate the true intrayear dynamics. This is why, in order to calculate w_h and w_l, we use the wage information of annual reports only once per year (in January) whereas for February to December, we make use of wage information stemming from intrayear reports. The number of workers supplying high-education or low-education labour, H and L, can be calculated without further issues since the data set mirrors the true stock of employed and unemployed persons at any point in time.

Figure 4: Skill-Biased Technical Change



Notes: The graph shows the seasonally adjusted relative skill productivity $\times$ 100 as measured by Equation (3). The monthly data were converted to quarterly frequency. Further information in the text.
Source: SIAB.

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 $\sigma \approx 2$. Möller (2000)'s finding of $\sigma \approx 1.7$ for German data naturally 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)). The robustness checks in section 5.4 reveal that the resulting impulse responses are robust with respect to different elasticities of substitution.

Figure 4 shows the development of seasonally adjusted SBTC with $\sigma = 1.7$ after converting the monthly time series into quarterly data and multiplying by 100. SBTC is steep-

[4] Leamer (1996), for instance, emphasize the effect of the sectoral bias in technical change on wage rates.

est through the 1990s, probably connected to the general computerisation. However, it markedly flattens in the subsequent decade. This could be explained by the phasing out of the first wave of computerisation and the fact that the new digitalisation wave did not yet start (compare also Beaudry et al. (2010) for technology waves). We will show below that the flattening can be identified as a major reason behind the much-discussed weakening of productivity growth.

4 Methodology

4.1 Model Setting

Several features of the interdependence of inequality and the labour market require specific traits of the econometric model: First, we are interested in the response of, say, hours or productivity to inequality shocks *over time*, so the model needs to be dynamic, covering the short, medium and long run. Second, we want to isolate structural inequality shocks from Skill-Biased Technology (SBT) shocks which in return must be disentangled from skill neutral technology shocks. This requires a structural model to be identified by statistical and economic reasoning. The presence of technology shocks leads us to form a dynamic structural model with long-run restrictions that do not preempt the results with respect to the hypothesized effects.

The long-run and the structural dimensions will be introduced below. Regarding the dynamic model, we start with a VAR. This has the advantage to capture very general interaction of the variables without imposing strong structural assumptions a priori. The VAR with lag length $q+1$ reads

$$y_t = c_0 + c_1 t + \sum_{i=1}^{q+1} A_i^* y_{t-i} + u_t \ , \tag{5}$$

where y_t contains the $n = 5$ endogenous variables log of productivity (p), log of wages (w), log of hours worked (h), $SBTC$ and inequality (I). A_i^* are $n \times n$ coefficient matrices and u_t is an n-dimensional vector of white noise errors. As deterministic terms, we allow for a $n \times 1$ vector of constants c_0 and a linear trend. In choosing the model size, we seek to limit the complexity and empirical requirements, while upholding economic interpretability in the sense of being able to address the core research questions.

Augmented Dickey-Fuller (ADF) tests confirm that our variables should be treated as non-stationary. This leads to modelling the variables in first differences. However, as visualized in Figure 1, there could exist a cointegrating relation between p and w. In this case, the labour share $(wN)/(pN)$ is covariance-stationary. Indeed, this is supported by an ADF test for the labour share which rejects non-stationarity with a p-value of 3 percent. Therefore, we allow for a level relationship, which generalizes a first-difference specification. Here, we also allowed for a linear trend just as in Equation (5), which might already be suggested by the time series developments in Figure 1. In case of long-run comovement, the variables contain common non-stationary components. According to Johansen (1995), the commonness of $n-r$ such stochastic trends is reflected by a reduced rank of $A^*(1)$, with $A^*(L) = I_n - \sum_{i=1}^{q+1} A_i^* L^i$. Consequently, one can write $A^*(1) = -\alpha\beta'$, where β spans the space of the r cointegrating vectors, and α includes the corresponding adjustment coefficients. Granger's representation theorem leads to the VECM

$$\Delta y_t = \alpha[\beta' y_{t-1} + c_1^*(t-1)] + c_0 + \sum_{i=1}^{q} A_i \Delta y_{t-i} + u_t \ , \tag{6}$$

with $A_i = -\sum_{j=i+1}^{q+1} A_j^*$, $i = 1, \ldots, q$. Note that $\beta' = \begin{pmatrix} 1 & \beta_2 & 0 & 0 & 0 \end{pmatrix}$ in our case since the cointegration involves only p and w. The linear trend with coefficient c_1^* is restricted to the cointegration space (compare Johansen (1995)).

4.2 Identification

The VECM in Equation (6) represents the reduced form of an underlying structural system. In particular, the correlated residuals in u_t do not represent economically interpretable innovations. Instead, they are usually specified as linear combinations of some structural shocks. Formally, this can be written as

$$u_t = Be_t \ , \tag{7}$$

where B is an $n \times n$ parameter matrix, and e_t represents the vector of structural disturbances. B contains the initial impacts of the shocks on the respective variables, with diagonal elements normalised to be non-negative.

Evidently, B introduces $n^2 = 25$ unknown coefficients into the model, which cannot be determined form the reduced form without further elaboration. First, the variances of e_t are normalised to one and the cross-correlations between the different structural shocks are assumed zero (as is standard in structural VAR models). This reduces the number of unknowns by $n(n+1)/2 = 15$, still leaving $n(n-1)/2 = 10$ restrictions to impose for identification of the structural form. We address this issue by a set of long-run restrictions.[5] From the VECM moving average representation (Johansen (1995)) one gets the matrix of the long-run effects of the reduced-form residuals u_t:

$$\Xi^* = \beta_\perp(\alpha'_\perp(I_n - \sum_{i=1}^{q} A_i)\beta_\perp)^{-1}\alpha'_\perp \ , \tag{8}$$

with $\perp$ denoting the orthogonal complement (thus $\alpha'\alpha_\perp = 0$, where both α and $\alpha_\perp$ have full column rank). In detail, the ith row of Ξ^* contains the long-run impacts of each of the n residuals in u_t. Accordingly, the long-run matrix associated to the fundamental shocks e_t

[5] In some of our robustness checks below, identification is obtained through a combination of short- and long-run constraints.

results as $\Xi := \Xi^* B$. The elements of this matrix equal the structural impulse responses that are reached when the adjustment processes following a shock are finished.

Once the structural coefficients are identified, they provide the basis for the impulse response analysis which will be presented in section 5. In the following, we discuss the long-run restrictions imposed in order to disentangle the structural shocks of interest. As pointed out above, 10 linearly independent restrictions either in B or in Ξ are needed to exactly identify the model. We define $\xi_{i,j}$ as the long-term effect of the ith variable on the jth structural shock. For the moment, we implement only long-run restrictions to identify the structural shocks.[6] Thereby, we confine ourself to a minimal set of restrictions, in line with the flexible character of our model.

Essentially, we are only interested in the effects of technology shocks, SBT shocks and inequality shocks. For the time being, the remaining two innovations are identified as shocks to labour demand and supply (that can of course also be affected by the following three shocks), disentangling them by the standard neoclassical assumption $\xi_{h,w} = 0$. However, in a robustness check, we also simply leave the correlation of the w- and h-residuals unidentified. While we are not especially interested in these shocks, importantly they cover independent sources of variation in the wage *level*, thus facilitating the identification of pure wage inequality shocks that concern the wage *structure*. In any case, the two shocks are assumed to have no long-run impact on productivity (p) and relative skill productivity ($SBTC$). This is in line with the standards in the growth literature stating that the only relevant long-term drivers of productivity are technology shocks.

A crucial variable of interest is inequality that is defined as being affected only by its own shocks and – since SBTC is a potential source of I – by SBT shocks. Logically, the usual (i.e., skill-neutral) technology shocks do not drive inequality in the long run (just as the other two aggregate level shocks). Structural inequality shocks can occur, for instance, through changes in the employers' hiring preferences that lead to substandard employment, the introduction or changes of minimum wages, through de-regulation of temporary employment, or through labour market reforms in general (e.g. the Hartz reforms, compare Klinger and Weber (2016)). Furthermore, globalisation or outsourcing (which are not necessarily linked to technological change) have impact on inequality, if they favour workers in exporting sectors more than those in non-exporting sectors. In sum, on the present model's level of aggregation, inequality-driving forces are divided into SBTC and structural inequality shocks, where the latter comprise inequality-relevant factors. Of course, not all of these factors will have exactly identical economic effects, but we aim at identifying an *overall effect of inequality*. Even if one of its factors should have effects strongly different from the overall shock, then at least we can say that this factor cannot be quantitatively important for the development of inequality.

By contrast, $SBTC$ is defined as being driven only by SBT shocks. Examples could be the widespread usage of computers or robotics at workplaces or other skill-complementing

[6] Also Balleer and van Rens (2013), for instance, avoid short-term restrictions to identify SBTC. They argue that the assumption that wages are proportional to marginal products might not hold in the short run if there are frictions in the wage determination process.

or low-skill replacing technologies. This is in line with explicitly modelling SBTC as source of inequality, the reasoning followed in our modelling framework. Notwithstanding, the constraint $\xi_{SBTC,I} = 0$ could be questioned if a higher endowment with high-education workers – also connected to higher inequality ceteris paribus – leads to a bigger market for skill-biased technologies in the long run (i.e., directed technical change, compare Acemoglu (1998)). Therefore below we run robustness checks on the involved restriction.

The third shock of interest is the normal, i.e. skill-neutral, technology shock. This shock is defined as having no long-run impact on SBTC and on inequality which yields the two remaining constraints required for identification. To summarize, the restrictions read as follows:

$$\Xi = \begin{pmatrix} \xi_{p,p} & 0 & 0 & \xi_{p,SBT} & \xi_{p,I} \\ \xi_{w,p} & \xi_{w,w} & \xi_{w,h} & \xi_{w,SBT} & \xi_{w,I} \\ \xi_{h,p} & 0 & \xi_{h,h} & \xi_{h,SBT} & \xi_{h,I} \\ 0 & 0 & 0 & \xi_{SBTC,SBT} & 0 \\ 0 & 0 & 0 & \xi_{I,SBT} & \xi_{I,I} \end{pmatrix}. \tag{9}$$

4.3 Estimation

Estimation of Equation (6) requires some further discussion. First, we choose the optimal lag length according to the Akaike Information Criterion (AIC) and find $q = 2$. Second, we try to keep the model as parsimonious as possible by sequentially excluding the elements in the adjustment vector α and in A_i of lagged endogenous variables that lead to worse AIC values. Third, as mentioned in section 3, we allow for an economically motivated cointegration relation between p and w.

The estimation method involves two stages (compare, e.g., Lütkepohl (2005)). In the first stage, β is estimated. The equation is then estimated by OLS and the cointegration relation is extracted by normalizing the coefficient of the first variable (p) to 1. In the second stage, the restrictions on the elements of A_i can be accounted for. The term $\beta' y_{t-1}$ is treated as an additional variable. 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. Applying LM-tests, no evidence of remaining residual autocorrelation was found.

After obtaining the dynamics of the model from the reduced form (Equation (6)), the structural form is estimated by maximum likelihood given the restrictions in Equation (9).

5 Results

5.1 Impulse Responses

From the structural model, we estimate impulse responses and confidence intervals using the bootstrap of Hall (1992) with 2.000 replications. Figures 5 to 7 show the impulse responses for a horizon of 16 quarters together with 2/3 confidence intervals. We consider 1 unit shocks. As all variables were multiplied by 100, this implies a technology shock connected to an immediate 1 percent productivity impact, an 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) and an inequality shock connected to an immediate impact of 1 point on the Gini coefficient (scaled between 0 and 100).

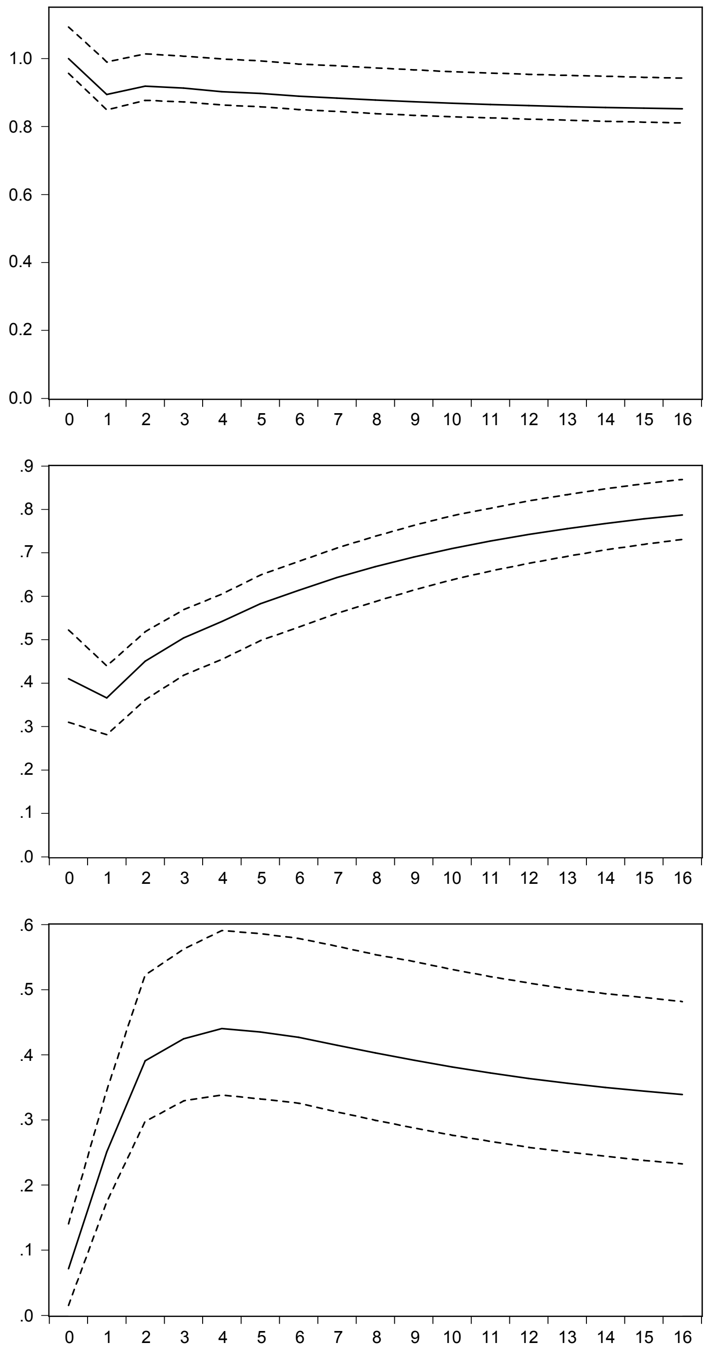
As expected, skill-biased technology shocks increase productivity (Figure 6, upper panel). Along with productivity, also wages rise (middle panel). However, hours worked are clearly reduced by the SBT shock (lower panel). This is consistent with high-skilled workers being more productive than low-skilled workers: Then, if the relative demand for high-skilled is increased, less hours are required for producing a given output. Put differently, the income effect of SBTC seems not to offset the displacement or substitution effect (compare Moore and Ranjan (2005)). In other words, if less productive workers are substituted with more productive ones following an SBT shock, total hours can decrease while their production impact rises. There is only a weak rebound visible in the impulse response, which could reflect reallocation of labour following an initially distortionary shock. In this context, one might hypothesise that adjustment to technical change in the German labour market has been limited due to sclerotic structures. However, the labour market reforms in 2003-2005 could have changed this by improving flexibility and reallocation capacity. Indeed, when estimating the model only until 2002, we measure an even more negative hours reaction to SBT shocks without any rebound. Logically, the period after the reforms is inclined to more advantageous SBT effects.

Figure 8 shows that inequality is positively affected by SBT shocks. This confirms the role of SBTC as source of inequality and can be taken as a plausibility check for our identification scheme. A 1 percent shock to SBTC increases the Gini coefficient (scaled between 0 and 100) by about 0.011. While this value seems rather limited, the large range of the SBTC variable over the sample (Figure 4) compared to the other variables must be taken into account. In fact, SBTC increased from 1978 (the inequality minimum) until 2009 (the inequality maximum) by 215.4 points. We can hypothetically neutralise this rise by negative shocks summing to the same size, slightly scaled down by 1/1.02, since the long-run impulse response of SBTC to a SBT-unit-shock is 1.02. Then, the total effect on inequality would have been -2.40 points.[7] In other words, without SBTC, the Gini coeffcient would have increased only by 3.16 instead of 5.57 points.

By the same token, we can calculate the contribution of the flattening of SBTC to the decrease in productivity growth since about 2001. SBTC rose from 1975 until 2000 on average by 2.27 points per quarter, afterwards only by 0.82 points. We can neutralise this weakening by shocks of $2.27 - 0.82 = +1.45$, again to be scaled down by 1/1.02, per quarter since 2001 and apply the total impulse response of productivity to SBTC shocks of 0.09 (which is reached rather quickly, compare Figure 6). Then productivity growth would have been 0.13 percentage points higher per quarter (or 0.53 percentage points per year).

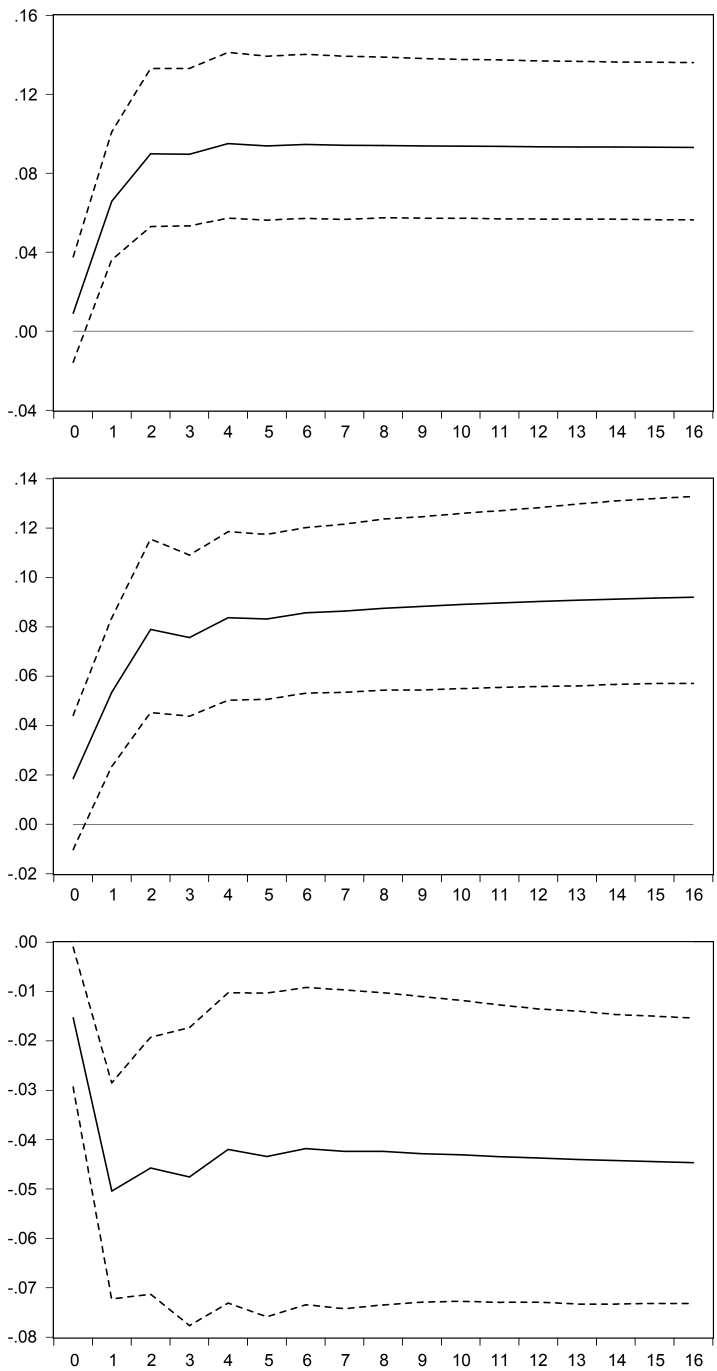
[7] Recall that according to our identification, in the long run only SBT shocks affect SBTC. Therefore the secular rise in SBTC can only be neutralised by these shocks.

Figure 5: Responses of p, w and h to technology shocks



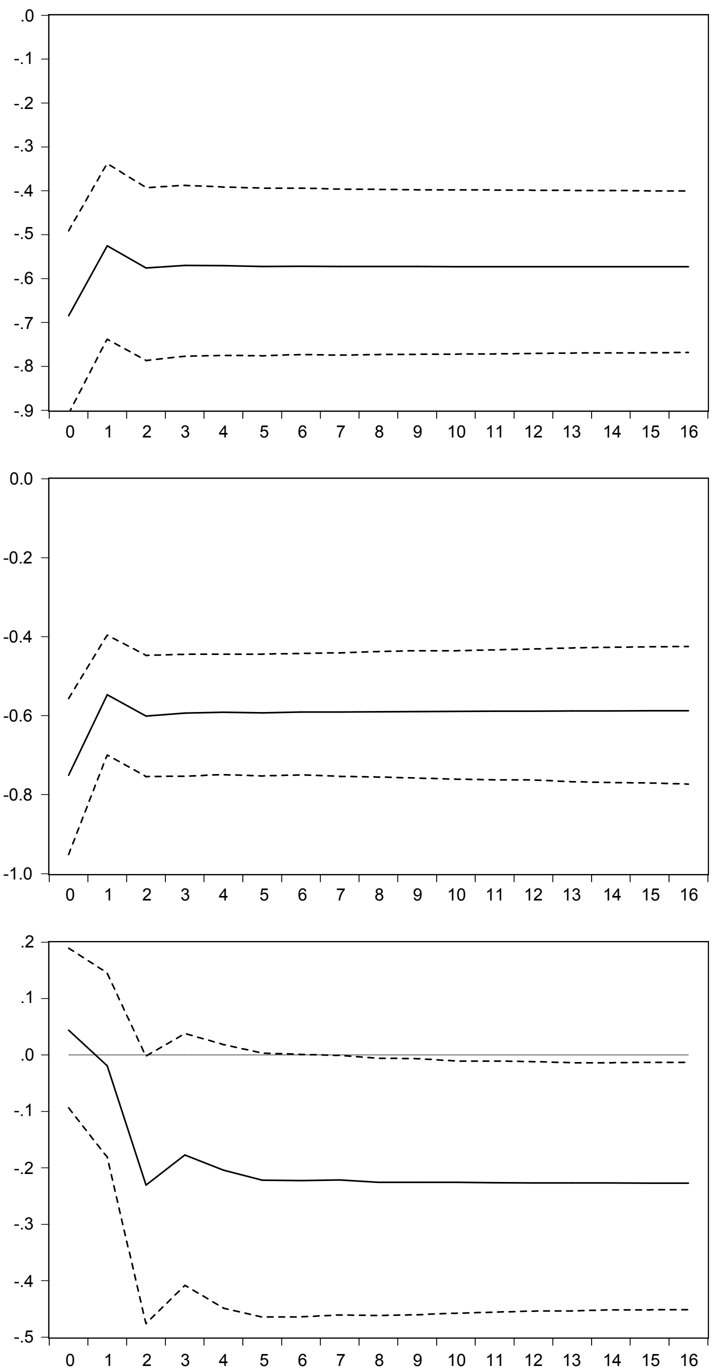
Notes: The solid line shows the responses of productivity (upper panel), wages (middle panel) and hours (lower panel) to 1% (skill-neutral) technology shocks up to 16 quarters. The dotted line denotes Hall (1992)'s 2/3 bootstrapped confidence interval.
Source: Own calculations.

Figure 6: Responses of p, w and h to SBT shocks



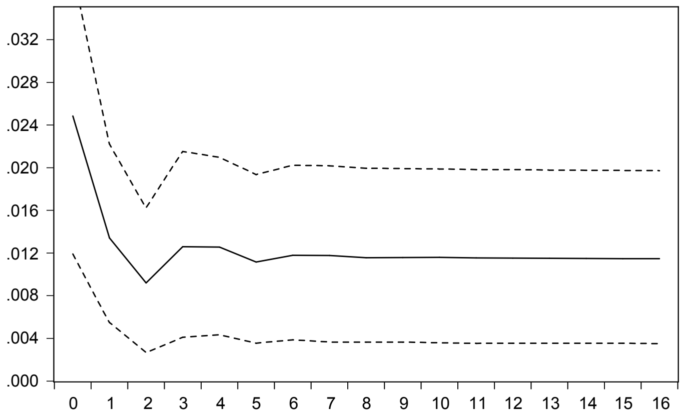
Notes: The solid line shows the responses of productivity (upper panel), wages (middle panel) and hours (lower panel) to 1% SBT shocks up to 16 quarters. The dotted line denotes Hall (1992)'s 2/3 bootstrapped confidence interval.
Source: Own calculations.

Figure 7: Responses of p, w and h to inequality shocks



Notes: The solid line shows the responses of productivity (upper panel), wages (middle panel) and hours (lower panel) to 1 unit inequality shocks up to 16 quarters. The dotted line denotes Hall (1992)'s 2/3 bootstrapped confidence interval.
Source: Own calculations.

Figure 8: Responses of I to SBT shocks



Notes: The solid line shows the responses of wage inequality to 1% SBT shocks up to 16 quarters. The dotted line denotes Hall (1992)'s 2/3 bootstrapped confidence interval.
Source: Own calculations.

This explains a substantial part of the average growth rate difference of productivity before and after 2001, which amounts to 1.45 percentage points per year.

(Skill-neutral) technology shocks naturally increase productivity and wages (Figure 5, upper and middle panels), the latter partly with delay. Notably, we also find an increase for hours worked (lower panel). This positive effect following a 1 percent technology shock is weak in the short run but increases until the fourth quarter to about 0.4 percent, before it again reverses. It goes hand in hand with the above-mentioned delayed wage reaction and is in line with results from Christiano et al. (2004), amongst others. However, it stands in contrast to the persistent negative effects reported in Gali (1999) and subsequent literature. In this context, note 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)). The hours effect of the latter has already been shown to be negative above. Logically, responses to overall (intermingled) technology shocks will incline more towards the negative area. Indeed, if we eliminate $SBTC$ and inequality from the system and thus estimate a small standard model, the response of hours to the technology shock is negative on impact and insignificant in the following. However, the positive hours effect reached in the complete model is more in line with the expectation from standard search and matching theory that plain productivity shocks foster vacancy creation and therefore employment. This emphasizes the advantage of an approach that disentangles skill-neutral and skill-biased technology shocks in order to allow for different effects on the labour market.

As SBTC, structural inequality shocks have a negative impact on hours worked (Figure 7, lower panel). In addition, they reduce productivity (upper panel) and wages (middle panel). These variables drop by 0.57 percent, hours by just under half as much, following a shock of one point in the Gini coefficient scaled between 0 and 100. This implies that relevantly sized employment and productivity impacts appeared in the past: As above, we can neutralise the SBTC-independent rise of inequality of 3.16 points between 1978 and

2009 by negative inequality shocks summing to the same size and apply the total impulse responses.[8] Then, the productivity level would have been 2.97 percent higher, and hours 1.18 percent. The results indicate that inequality has adverse impacts on the labour market as implied by the opportunities hypothesis. However, the fact that the responses materialise rather fast supports the reasoning that besides a mechanism via educational investment, channels of the quality of jobs, development perspectives, participation in further training or fairness beliefs may prove relevant, just as theories considering frictions and market failures. Moreover, there appear to be no counterbalancing effects in terms of efficiency (i.e., productivity) gains, quite the contrary.

In sum, the investigation implies that higher inequality harms employment and productivity in Germany. Naturally, as in all empirical models, these results must not be extrapolated too far beyond the range of observed data. For instance, one cannot infer that complete equality would bring about the most beneficial effects.

5.2 Upper and Lower Inequality

A comparison of the respective origins of the incentive hypothesis and the opportunities hypothesis leads to the conclusion that the latter has been designed mainly for developing countries since it explicitly addresses the opportunities of *the poor*. Barro (2000) and Castelló-Climent (2010), for instance, investigate the effects of inequality on growth separately for rich and poor countries and find the relationship to be positive in the former and negative in the latter. Transferred into the context of industrialized countries, this could imply that the two contradicting hypotheses are not equally important in different parts of the wage distribution (see, e.g., Voitchovsky (2005)).

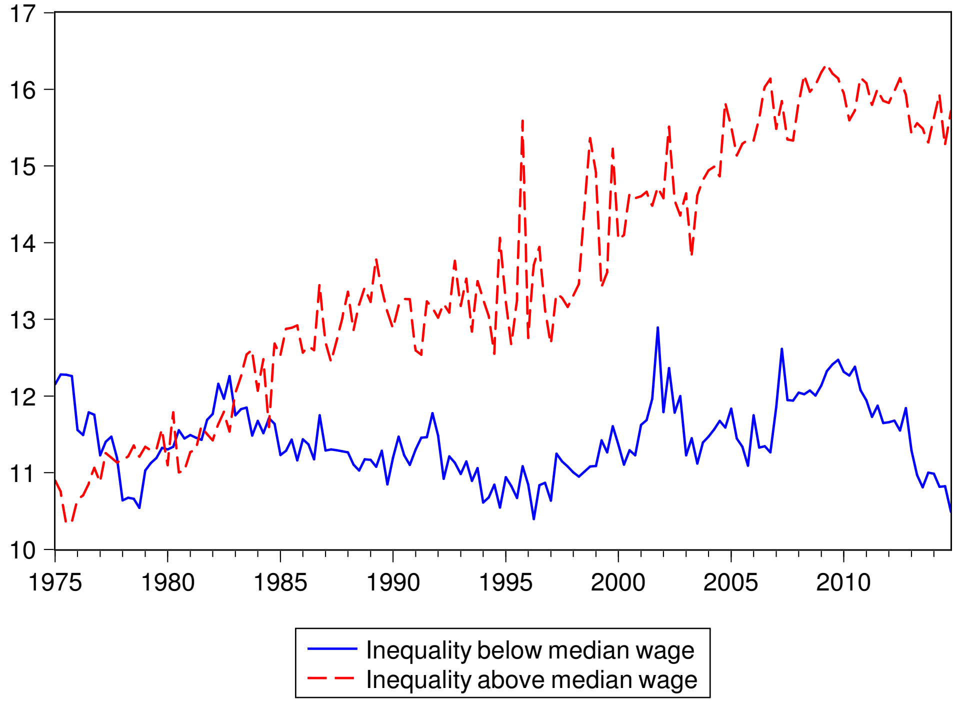
In order to shed more light onto this issue, we calculate inequality above ("upper inequality", I_u) and below ("low inequality", I_l) the median. This is done by applying Equation (4) separately to all individuals earning less (I_l) or more (I_u) than the median wage, respectively. Figure 9 shows that the increase in total inequality seems to be driven mainly by an increase in wage dispersion above the median, at least until the mid-nineties, while the marked decrease in inequality since 2010 comes from reduced wage dispersion below the median (I_l). The two different dynamics by which total inequality is driven raises the question whether the respective shocks have different impacts in our structural model.

In order to investigate potential differing effects, we add the two inequality variables in our model (in place of overall inequality). Thereby, we model no causal effects between the two inequality measures. While their residuals can be correlated, it appears plausible to trace this correlation back to common factors rather than to bilateral spillover effects. Technically, this is implemented by allowing for correlation between the structural residuals ϵ_{I_l} and ϵ_{I_u}, which does not influence the impulse responses.

Figures 10 and 11 show the resulting responses to the respective structural shocks. The negative labour market effects of inequality shocks are prevailing for both upper and lower

[8] The long-run impulse response of inequality to its own shocks is only 3/5 of the initial shock size. Therefore, the necessary shock size of 3.16 points has to be scaled up by 5/3.

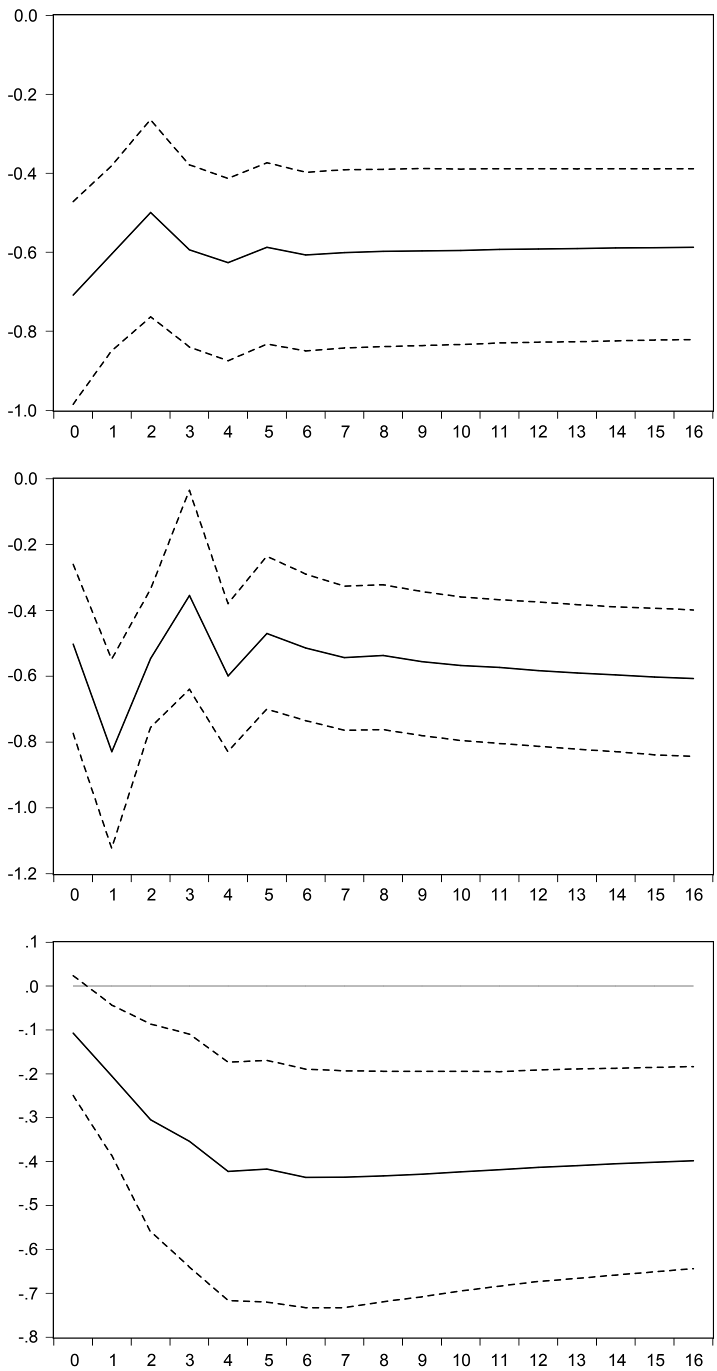
Figure 9: Inequality above and below the median wage



Notes: The graph shows the seasonally adjusted Gini coefficient below (solid line) and above (dotted line) the median wage based on full time workers subject to social security contributions aged 15 to 64. Level shifts in January 1978, January 1984 and January 1992 have been eliminated. The monthly data were converted to quarterly frequency. Further information in the text.
Source: IEB.

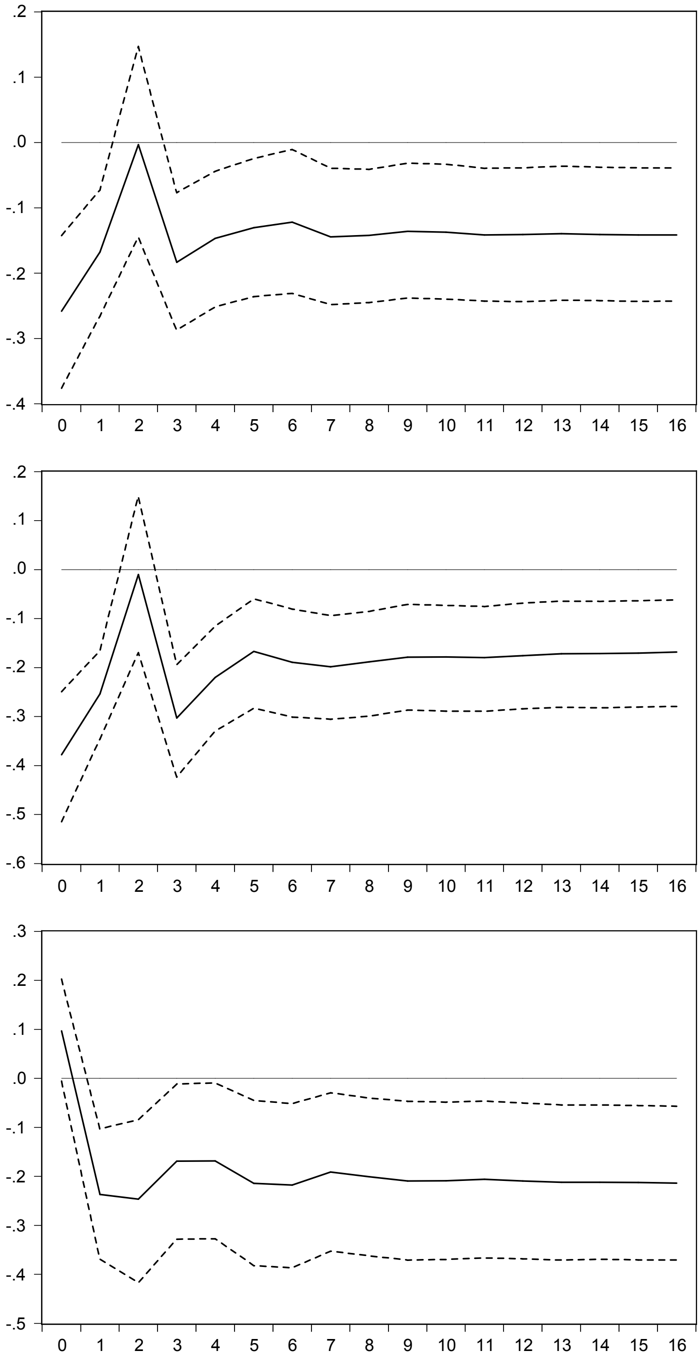
inequality. However, the latter has stronger (negative) effects on productivity, wages and hours than overall inequality. An explanation could be connected to the relevance of the opportunities and incentive hypotheses for higher and lower wage groups. The former points to the situation of low-income earners: inequality can impede opportunities to participate on educational advancement and create a sector of persistent low-quality jobs with limited productivity dynamics. Therefore, the opportunities hypothesis is likely to strengthen the adverse effects of lower inequality. In contrast, the incentive hypothesis might be more relevant for higher income jobs, where career paths and development chances are more prevailing. Logically, this would dampen negative effects of I_u.

Figure 10: Responses of p, w and h to I_l-shocks



Notes: The solid line shows the responses of productivity (top), wage inequality (middle), and hours (bottom) to 1 unit shocks in wage inequality below the median wage up to 16 quarters. The dotted line denotes Hall (1992)'s 2/3 bootstrapped confidence interval.
Source: Own calculations.

Figure 11: Responses of p, w and h to I_u-shocks



Notes: The solid line shows the responses of productivity (top), wage inequality (middle), and hours (bottom) to 1 unit shocks of wage inequality above the median wage up to 16 quarters. The dotted line denotes Hall (1992)'s 2/3 bootstrapped confidence interval.
Source: Own calculations.

5.3 Effects at high and low levels of inequality

Inequality is often thought of as influencing the economy differently depending on its level (e.g. Voitchovsky (2005) , Galor and Moav (2004) and Banerjee and Duflo (2003)). In detail, the balance of different effects might change with the overall level of inequality. If rather low levels prevail, higher inequality might have positive effects via higher incentives or employment chances. In contrast, once inequality lies too high, further increases might be harmful when educational opportunities are narrowed, problems in lower segments in two-tier labour markets become urging and political opposition grows. Then, the negative effects would dominate.

When considering the development of wage inequality in Figure 3, a strong increase can be observed from 1997 onwards. Therefore, we conduct two separate estimations for the samples 1975-1997 and 1997-2014. This choice also seems plausible when considering a Chow sample-split test: While p-values for the null hypothesis of no structural break are high for break points in the first part of the sample, they are close to zero from 1997 onwards.

Comparing the impulse responses of productivity, wages and hours in each of the two subsamples, it becomes evident that inequality shocks are more harmful in the second period where the inequality level was higher. A one unit shock to the Gini coefficient lowers productivity and wages by 0.59 percent, only slightly more than in the overall sample. However, the hours reduction due to structural inequality shocks is -0.78 percent and hence three times stronger compared to the effect estimated for the whole sample. In contrast, in the first subsample inequality shocks have more muted effects: They reduce productivity and wages by just above 0.3 percent. The effect on hours worked is even positive, but statistically insignificant. Of course, for evaluating the current situation the estimates from the later period are relevant. This implies that further increases in inequality might be quite harmful, while employment could benefit from a moderate reduction.

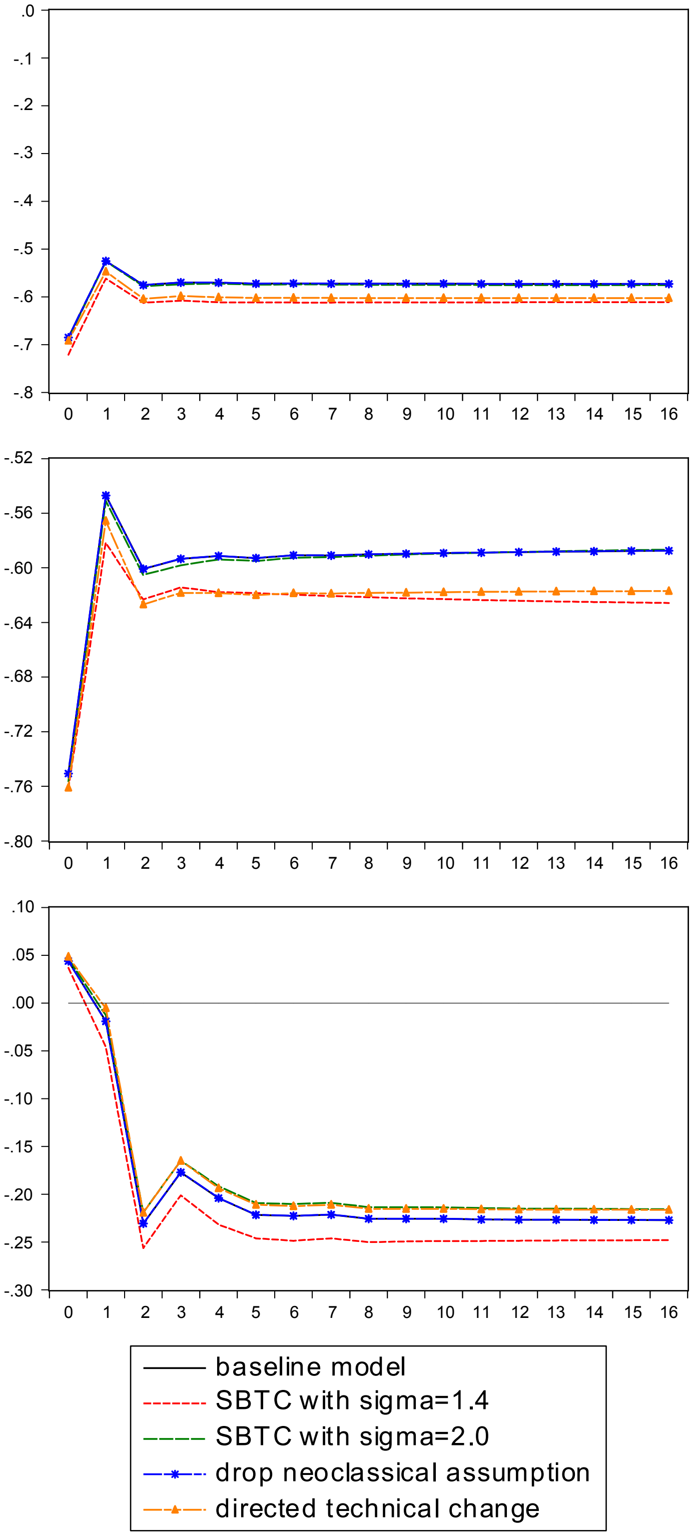
We repeat the experiment from above and calculate the contribution of changes in inequality for labour market development, now from 1997 onwards until 2009. Thus, we neutralise the SBTC-independent rise of inequality between 1997 and 2009 (3.50 Gini points) by negative inequality shocks summing to the same size and apply the new total impulse responses. We find that the productivity level would have been 2.95 percent higher, and hours 3.90 percent.

5.4 Robustness Analysis

Since we provide evidence for the effects of inequality in a novel econometric framework, robustness checks gain particular importance. We pursue the following steps:

- We change the elasticity of substition σ to 1.4 or to 2.0 when calculating the SBTC time series.
- We drop the neoclassical assumption $\xi_{h,w} = 0$, instead leaving the residuals connected to wages and hours unidentified.

Figure 12: Robustness checks: Responses of p, w and h to inequality shocks



Notes: The graphs show robustness checks with respect to the responses of p, w and h to 1 unit inequality shocks up to 16 quarters. See text for more details.
Source: Own calculations.

- We relax the long-run restriction on the impact of inequality shocks on SBTC and replace it by the respective zero restriction in the short-run matrix B. This requires only the weak assumption that the potential triggering of the development of skill-biased technologies according to directed technical change does not pass off within a single quarter.

Figure 12 shows the resulting impulse responses of p, w and h to inequality shocks, compared to the baseline model (solid lines) described in section 4. The reactions of p and w are a bit stronger when using $\sigma = 1.4$ for measuring SBTC (dotted lines) or when allowing for directed technical change (triangles). The reactions of h are marginally weaker for $\sigma = 2.0$ (dashed lines) and for the setting with directed technical change and – again – a bit stronger for $\sigma = 1.4$. The reactions are virtually unaffected by dropping the neoclassical assumption $\xi_{h,w} = 0$ (cross symbols). In total, Figure 12 shows that our results are rather robust to alternative settings and identification schemes.

6 Conclusion

In the underlying study we analysed the effects of inequality, skill-neutral and skill-biased technical change (SBTC) on the economy and the labour market. We explicitly model SBTC as source of inequality to isolate structural inequality shocks. We put forward a dynamic cointegrating framework with theory-based (short- and) long-run restrictions for identifying the impacts of inequality on productivity, wages and hours worked.

A structural impulse response analysis revealed that skill-biased technology shocks increase productivity and wages, but reduce hours worked and raise inequality. Structural inequality shocks also have a negative impact on hours worked, but additionally reduce productivity. These adverse effects are stronger in the second half of the sample that is characterised by higher inequality levels. We find that inequality both above and below the median wage have negative labour market effects, somewhat stronger for the former. Furthermore, by separating skill-biased technology shocks, we can show that skill-neutral technology shocks have a positive long-run effect on hours worked. In general, the results indicate that inequality has negative impacts on the labour market as implied by theories in line with the opportunities hypothesis (cf. Galor and Zeira (1993)) or theories allowing for market failures and frictions (cf. Acemoglu and Pischke (1999)). Moreover, there appear to be no counterbalancing effects in terms of efficiency (i.e., productivity) gains, quite the contrary.

The results imply that the rising wage inequality in Germany since the 1990s should not be seen as a precondition for the German labour market upswing of the recent ten years. Instead, higher inequality appears to harm employment and productivity. The employment upswing is more likely connected to those components of the reforms that aimed at enhancing the efficiency of the labour market functioning (compare Launov and Wälde (2016) and Klinger and Weber (2016)) as well as to other factors such as the upward trend of the service sector and high immigration in recent years. Wage moderation as such could also have played a role in strengthening labour demand, but according to our analysis wage inequality was an obstacle to labour market development. However, the development of declining inequality since the end of the Great recession is likely to have contributed to expanding employment during a period where a lowering speed due to the phasing-out of the Hartz-reform effects was already expected.

In disentangling the effects of skill-biased and skill-neutral technology shocks (see also Balleer and van Rens (2013)), our analysis contributes to a more comprehensive understanding of the relationship of technology and the labour market (see, e.g. Christiano et al. (2004), Gali (1999)). Furthermore, the results on SBTC can be taken as a warning signal for the current wave of – intelligent and interconnected – digitalisation. According to research results for Germany, this will raise the qualification needs (Wolter et al. (2016)). As far as the development is connected to an essentially skill-biased technical change, there appears to be a risk of negative employment effects. This underlines the key role of qualification.

The general construction of the model framework paves the way for further economic analyses of inequality. Measuring economic effects of inequality based on data from other countries could shed light on the degree of generality or conditionality of the results. Moreover, the functional form could be extended in order to capture potential nonlinearities in the relationship of inequality and labour market outcomes. Finally, additional differentiation in modelling inequality shocks could elaborate further on the concrete mechanisms at work.

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